SESSIONE VI
MODELLI DI PREVISIONE A BREVE E MEDIO TERMINE

Una valutazione preliminare della performance previsiva di EZEO

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The track record of the EZEO forecasts: a first assessment

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Sommario

In questo lavoro, analizziamo per la prima volta la performance previsiva dello Eurozone Economic Outlook (EZEO). L'EZEO è una pubblicazione trimestrale redatta congiuntamente dall'Istituto tedesco IFO, l'istituto francese Insee e l'istituto di Statistica Nazionale italiano Istat. Le previsioni rilasciate dall'EZEO vengono valutate in termini di accuratezza, efficienza e non distorsione.

Parole chiave: Confronto tra previsioni, Funzione di perdita

Abstract

In this paper, we analyse, for the first time, the track record of the forecast published in the Euro Zone Economic Outlook (EZEO). The EZEO is a quarterly publication jointly prepared by the German institute IFO, the French institute Insee, and the Italian institute Istat. EZEO's forecast are assessed in terms of accuracy, efficiency and unbiasedness.

Keywords: Forecast accuracy, Unbiasedness, Efficiency, Diebold and Mariano test,.

Introduction

Economic forecasts are widely used as a basis for economic policy analysis and decision-making. It is important to enquire, therefore, into the reliability of such forecasts. This in turn calls for a regular assessment of their performance.

In this paper we analyse, for the first time, the track record of the forecast published in the Euro Zone Economic Outlook (EZEO). The EZEO is a quarterly publication jointly prepared by the German institute IFO, the French institute Insee, and the Italian institute Istat. Ideally, EZEO's forecasts we examine here are free from political pressures which could instead influence those from national governments and/or international institutions which operate under political preassure.

In this exercise, EZEO's forecast are assessed in terms of accuracy, efficiency and unbiasedness assuming both a linear and a quadratic loss function; we commit to extend this analysis to not symmetric loss function in a further version of the paper.

The paper is organised as follows: in the next section we discuss our empirical strategy, then we discuss the EZEO dataset and methodology and in the third section an evaluation of the EZEO forecasts is presented. Finally, some conclusions and suggestions for further analysis are exposed.

I. Empirical strategy

The aim of this paper is to assess EZEO's forecast accuracy. To achieve this goal, our empirical strategy is to compare, for each vintage, the forecast conditional on the information available at that time with the latest observed realization of the relevant target variable.

Evaluation of forecast accuracy is first assessed in terms of root mean squared error (RMSE) other than mean error (ME) and mean absolute error (MAE), and then by considering forecast error characteristics (efficiency, unbiasedness). As an additional test we perform the Diebold and Mariano (1995) test of forecast comparison with respect to a naïve model.

There are a number of notions of forecast rationality. These include those of unbiasedness and efficiency, and are examples of forecast-evaluation criteria based on the relationship between the predictions and outcomes. 'Weak' rationality often refers to the consistency of forecasts or, in other way, to the absence systematic bias in forecasts. Efficiency (or 'strong' rationality) requires that the forecast errors are uncorrected with other series or information available at the time the forecasts are performed.

Rationality is tested under a number of assumptions of forecasters' objectives. If the latters are quadratic, then testing for rationality simply amounts to testing if the forecast errors have zero mean, and are uncorrelated with any information available at the time that the forecast was made. The most popular form of these tests is the Theil-Mincer-Zarnowitz regression (see, for example Zarnowitz, 1985).

One strand of the literature has argued that asymmetric losses in which positive and negative forecast errors may be weighted differently might better represent the forecasters objectives (see, for example Patton and Timmermann, 2007). In particular, Elliot, Komunjer, and Timmermann (2005) (EKT hereafter) and Capistran and Timmermann (2009) found evidence for asymmetric loss in the ECB's Survey of Professional Forecasters (SPF) forecasts of output and inflation. Under asymmetric loss, forecast efficiency tests based on the Theil-Mincer-Zarnowitz regressions result being biased. EKT (2008) quantify the extent of the bias and its impact on the size and power of standard rationality tests.

In the following, we focus on the concepts of unbiasedness and efficiency. Tests of unbiasedness are often based on a regression equation of the form:

$$A_{t+h} = a + \beta P_{(t+h|T)} + e_{t+h} \qquad (1)$$

where $P_{t+h|T}$ is the h-step ahead forecast of A_{t+h} made at period T. Suppose that h is fixed and T varies, time runs from $T+1-h$ to $T+H-h$, and that a forecast is made at each value of $T=(1,\ldots,t)$, giving a sample of dimension H. Notice that for $h>1$, the forecast horizon will exceed the sampling frequency, so that forecasts overlap in the sense that they are made before knowing the error in the previous forecast. Thus, rationality does not rule out serial correlation in the error process e_{T+h} of a moving average of order $h-1$.

Unbiasedness is often referred as testing the null of a=0 in the equation:

$$e_{t+h} = a + \varepsilon_{t+h} \qquad (2)$$

which implicitly imposes that $\beta=1$ in terms of equation (1) and the error term coincides with the forecast error. As noted by Holden and Peel (1990), unbiasedness condition is satisfied more generally by

$$[a = (1 - \beta)E[e]_{t+h}] = 0 \qquad (3)$$

Testing for joint null hypothesis $a=0$ and $\beta = 1$ in equation (1) represents a sufficient but not a necessary condition for unbiasedness.[1] $a=0$ in (2) can be also considered as a test of weak efficiency if projection errors are also uncorrelated with informative data series. In the case of a systematic relationship between forecasts and their errors, this could be exploited to help predict future errors (see Mincer and Zarnowitz, 1969).

Forecast efficiency is an important characteristic because it ensures that all the information are used and, once a forecast error is made, it does not feed into the next forecast. Efficiency is defined as the condition that $\beta=1$ in the OLS regression of equation (1), so that the residual variance in the regression is equal to the variance of the forecast error. To see this,

$$e_{t+h} = A_{t+h} - \beta P_{t+h} = a + (\beta - 1)P_{t+h} + \varepsilon_{t+h} \qquad (4)$$

so that

$$[Var[e]_{\perp}(t+h]) = [(\beta - 1)^{\uparrow}2\, Var[P]_{\perp}(t+h)] + [Var[\varepsilon]_{\perp}(t+h)] + 2\beta\, [-1)Cov[P]_{\perp}(t+h), \varepsilon_{\perp}(t+h$$

where $\beta = 1$ implies $Var[e_{T+h}]=Var[\varepsilon_{T+h}]$ whatever the value of a. If $a=0$, as well as $\beta = 1$, then:

$$MSFE = \mathrm{E}[e_{t+h}^2] = [Var[e]_{t+h}] = [Var[\varepsilon]_{t+h}]$$

The properties of unbiasedness and efficiency are often presented as minimum requirements for optimal or rational forecasts. However, the identification of the unbiasedness property with optimality requires a symmetric loss function, as in the case of quadratic costs (Zellner, 1986).

As for the descriptive statistics, three evaluation criteria are used to assess forecasting accuracy: the Mean Error (ME), the Mean Absolute Forecast Error (MAE) and the Root Mean Squared Forecast Error (RMSE). MAE is the average over the evaluation sample of the absolute values of the differences between forecasts and the corresponding actual observations and measures the average magnitude of the errors in the set of forecasts, without considering their direction. RMSFE measures the spread of the forecast error distribution. It is similar to the standard deviation of the error term, except that it explicitly focuses on the forecast error.

Following Artis and Marcellino (2001), we also compare EZEO's consensus forecasts to those from a naïve model, a random walk without drift, which implies, in case the null hypothesis is not rejected, that the optimal forecast of a given quarter being equivalent to the latest available realization. Comparison vis-à-vis the benchmark models is carried out by applying the Diebold and Mariano test of equal predictive accuracy,

$$DM = H^{-\frac{1}{2}} \frac{\sum_{j=1}^{H} d_j}{\sigma_d}$$

[1] While the coefficient estimates obtained from ordinary least squares (OLS) on (1) will remain unbiased, the estimate of the covariance matrix of the parameter estimates (necessary for tests of the significance of the parameters in (1)) will be inconsistent. This is typically dealt with by using the Hansen and Hodrick (1980) correction.

where $d_j=g(e_{1j}) - g(e_{2j})$, g is the loss function of interest corresponding to a quadratic loss when $g(e)=e^2$ and to an absolute loss for $g(e)=|e|$, e_1 and e_2 are the errors from the two competing forecasts and σ_d is the standard deviation of d. In order to obtain a consistent estimate, we follow the recommendations of Diebold and Mariano (1995) and Harvey, Leybourne, and Newbold (1997) and use an unweighted sum of the sample autocovariances up to $h-1$, that is

$$2\pi\widehat{f_d(0)}=\hat{\gamma}_0 + 2\sum_{\tau=1}^{h-1}\hat{\gamma}_\tau$$

with $\hat{\gamma}_\tau$ being the lag-k sample autocovariance. Moreover, we apply the small sample correction suggested by Harvey et al. (1997), and use critical values from the t distribution with $H-1$ degrees of freedom.

Against this background, the chosen naïve models constitute a valid benchmark, because of their robustness to breaks (see, for instance, Clements and Hendry, 1999). A possible remedy in this case is 'intercept correction', that is the practice of those forecasters who use formal econometric models for forecasting, by adding a constant term equal to the lagged forecast error to model's equations. In EZEO experience, this method has been never implemented.

Section III presents empirical evidences on both forecast efficiency and forecast evaluation. Forecast efficiency is an important characteristic because it ensures that all the information are used and, once a forecast error is made, it does not feed into the next forecast. As a first check for serial correlation in the forecast errors, we analyse autocorrelation coefficients up to two lags. Their significance is tested using the Ljung-Box with a nominal threshold of 0.05, so that *p-values* below that values indicates that the null hypothesis of absence of autocorrelation in the forecast errors is rejected at the 5% level of significance.

II. The EZEO dataset

The EZEO forecast is the result of a consensus among the three institutes mentioned above. Each institute bases its own forecast on time-series models using auxiliary indicators coming from business surveys produced by national institutes, Eurostat, and the European Commission. The joint forecast covers, for the period Q1 2004-Q4 2014, Industrial production, GDP, Consumption, Investment (since 2006), and inflation. For these variables, the EZEO provides a three quarter ahead and the economic outlook is the result of a coordinated effort of the three main eurpean agencies, namely Istat for Italy (ISAE up to 2010), Insee for France, IFO for Germany. Concerning national accounts, predictions of chained linked, seasonally and working day adjusted times series are performed. Industrial production forecast is provided in terms of seasonally and working day adjusted series.

The EZEO outlook is published on a quarterly basis in correspondence of the diffusion of Eurostat second release of national accounts.

III. A preliminary evaluation of the EZEO forecast

In this paper we intend to assess the potential coming from the combination of forecasts for the special case of the Eurozone Economic Outlook Consensus forecast. Table 1 shows the main forecast error metrics (i.e. ME, RSME, MAE) both for the three Institute forecast (Insee, IFO, Istat) and the consensus forecast. All the error metrics indicates that EZEO Consensus forecast outperforms all the forecasts produced by the single institutes at

all steps but in three cases. In fact, the second forecaster (F2) has a smaller RMSE for consumption and investment at 1 step-ahead and for investment 3 step-ahead.

Insert Table 1

Regarding unbiasedness and weak efficiency, Table 2 resumes the results for Consensus and the three institutes participating to the EZEO forecast. The first column (*unb.1*) of each set of results shows the *p-value* of the *F* statistic jointly testing $\alpha_{0=}0$ and $\alpha_1=1$ in (1), while column 3 (*unb.2*) reports the *p-value* for $\beta_0=0$ in (2). Unbiasedness is rejected, at the conventional 5% significance level, in just 20 out of 120 total cases (all the three steps and both definitions). 10 out of this 20 cases are referred to investment, signaling the forecast of this specific variable particularly challenging.

The corresponding weak efficiency test for the two unbiasedness definitions above are (*wef.1* and *wef.2*), in general, not rejected 1 step-ahead, but refused further ahead signaling a strong persistence (correlation) in the error far in the future.

Comparing unbiasedness and weak efficiency between Consensus and all the other forecasters shows an overall slightly better performance for the INSEE 1 step-ahead, but for the unbiasedness 2 and 3 step-ahead Consensus forecasts results being more accurate.

Insert Table 2

An additional preliminary analysis of the forecast performances can be done comparing the forecast of the consensus and the national forecasters with a naïve model, and in particular with a random walk (RW) without a drift. Here we use the test suggested by Diebold and Mariano (1995) for the absolute and quadratic loss. In the case where the statistic is negative the loss associated with the naïve model is larger than that of the "genuine model".

Table 3 shows the value of the t-statistic of the DM test for the absolute (*t-alf*) and quadratic (*t-qlf*) loss function with the corresponding p-value on the right of each statistic. In almost all the cases the *t-value* is negative, meaning that the naïve model loss would be larger than the genuine model, but the *p-value* rejects the null Hypothesis of no difference between the two models in few cases only. In particular, it is bit reassuring noticing that at least for 1 step-ahead forecast Consensus represents a better model for all variables even if only for the absolute loss function, while results for 2 and 3 step-ahead are mixed. For inflation the genuine models appear statistically better than the RW, while for the other variables the two competing forecasts do not show significant difference.

Conclusions and future research

According to our preliminary analysis, all the error metrics indicates that the EZEO consensus forecast outperforms all the single forecasters at all steps with few exceptions.

Regarding unbiasedness and weak efficiency we found that Unbiasedness is rejected in just 20 out of 120 total cases interestingly enough all the three steps and both 10 out of this 19 cases are referred to investment, signaling the forecast of this specific variable particularly challenging.

The weak efficiency test for the unbiasedness definitions are, in general, not rejected 1 step-ahead, but refused further ahead signaling a strong correlation in the error far in the future. Comparing unbiasedness and weak efficiency between Consensus and all the other forecasters shows an overall better performance for the consensus.

Given the availability of updated figures as the time passes by, we intend to further

analyse in the near future the role of financial crisis and post financial crisis in determining projection errors. Forecasting the timing, depth and ramifications of the global financial crisis has proven exceptionally difficult. Particular challenging was the identification of imbalances and their unsustainability entering the crisis, the timing of their unwinding and the likely impact on real activity. A source of possible problems for some of EZEO's forecasts could be the presence of structural breaks over the forecast period due to un-modelled changes in economic policy. While the pre-crisis period was one of relative economic stability, changes in the global economy and financial system in the early to mid-2000s contributed to the subsequent difficulties of forecasting once the crisis began. This period was one of increasing globalisation and integration of real and financial activity, with expanded financial leverage and risk-taking attitudes favoured by a low interest rate environment.

Furthermore, a broad part of literature on forecasting accuracy deals with the testing of potential improvements coming from forecast's combination, both in terms of methods and forecasters. The concepts of forecast combination and forecast encompassing are closely related. Each country prediction represents an independent forecast (for a specific target variable) competing with other Institute's predictions. And Consensus forecast may be considered as kind of averaging with unknown country-specific weights. In this framework, forecast encompassing may be used to determine whether one of a pair of forecasts contains all the useful information for prediction. If both models contain some incremental information, there is potential to combine both forecast. By contrast, only one of the models is retained and the other may be discarded as it does not contribute to rise overall efficiency. In this way, we can evaluate if forecast encompassing enhance predictive power vis-à-vis EZEO Consensus forecast and assess if each of the single-country forecast is encompassed by rival predictions.

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Appendix 1

Table 1: Basic measures of forecast accuracy

	1 step ahead											
	Consensus			F1			F2			F3		
	ME	*RSME*	*MAE*	*ME*	*RSME*	*MAE*	*ME*	*RSME*	*MAE*	*ME*	*RSME*	*MAE*
infl	0.0500	0.2166	0.1167	0.0663	0.2776	0.1912	0.0625	0.2535	0.1775	0.0588	0.3226	0.2262
gdp	-0.0016	0.3250	0.2353	-0.0417	0.3985	0.2766	0.0008	0.3511	0.2503	-0.0092	0.3596	0.2520
ipi	0.0489	1.0669	0.6250	0.0198	1.2797	0.8354	NA	NA	NA	0.0123	1.3083	0.7872
cons	-0.0309	0.2657	0.2080	-0.0909	0.2799	0.2140	-0.0078	0.2653	0.2083	-0.0678	0.3440	0.2732
inv	-0.1354	0.7494	0.6223	-0.4414	1.0755	0.7836	-0.1627	0.7225	0.6049	-0.1081	0.8675	0.6919
	2 steps ahead											
	ME	*RSME*	*MAE*	*ME*	*RSME*	*MAE*	*ME*	*RSME*	*MAE*	*ME*	*RSME*	*MAE*
infl	0.1317	0.3969	0.3073	0.1154	0.4633	0.3462	0.1308	0.4605	0.3513	0.1449	0.4740	0.3654
gdp	-0.0497	0.5752	0.3769	-0.0675	0.6072	0.3888	-0.0482	0.6013	0.4018	-0.0559	0.5987	0.3860
ipi	-0.0419	2.0104	1.1832	-0.1135	2.0647	1.2146	NA	NA	NA	-0.0930	2.2487	1.2840
cons	-0.0491	0.3107	0.2499	-0.1619	0.3592	0.2824	-0.0276	0.3290	0.2723	-0.0737	0.3461	0.2749
inv	-0.4318	1.3192	0.9671	-0.6199	1.4816	1.0753	-0.4724	1.3427	1.0039	-0.3912	1.3780	0.9952
	3 steps ahead											
	ME	*RSME*	*MAE*	*ME*	*RSME*	*MAE*	*ME*	*RSME*	*MAE*	*ME*	*RSME*	*MAE*
infl	0.2100	0.6569	0.4950	0.1895	0.7248	0.5263	0.1763	0.7496	0.5763	0.2566	0.8045	0.5987
gdp	-0.0928	0.6657	0.4140	-0.0948	0.6988	0.4321	-0.0807	0.6808	0.4415	-0.1140	0.7078	0.4602
ipi	-0.2002	2.2844	1.1982	-0.0891	2.4005	1.2655	NA	NA	NA	-0.2549	2.2954	1.2359
cons	-0.0776	0.3832	0.2915	-0.2263	0.4389	0.3183	-0.0541	0.3900	0.3034	-0.1094	0.4215	0.3239
inv	-0.7021	1.6347	1.1507	-0.8242	1.7962	1.2221	-0.6440	1.5424	1.1636	-0.7311	1.6695	1.1471

Table 2: Unbiasedness and efficiency (p-value)

	Consensus				F1				F2				F3			
1 step ahead																
	unb.1	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*
infl	0.1474	0.8234	0.1364	0.8459	0.1371	0.6091	0.1329	0.7021	0.1977	0.4660	0.1202	0.5429	0.1534	0.1962	0.2544	0.3025
gdp	0.0053	0.4046	0.9750	0.0506	0.0069	0.9489	0.5150	0.1737	0.0788	0.6033	0.9887	0.2975	0.1482	0.0750	0.8738	0.0311
ipi	0.0321	0.0896	0.7705	0.0084	0.0951	0.0207	0.9234	0.0045	NA	NA	NA	NA	0.8931	0.0046	0.9533	0.0106
cons	0.7283	0.1167	0.4571	0.1651	0.2220	0.3135	0.0800	0.3765	0.8779	0.0995	0.8546	0.1381	0.0548	0.0110	0.2165	0.1210
inv	0.1653	0.5596	0.3065	0.8983	0.0422	0.5359	0.0243	0.3691	0.2435	0.1106	0.2005	0.5238	0.3884	0.7432	0.4825	0.7624
2 steps ahead																
	unb.1	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*
infl	0.0901	0.0103	0.0318	0.0441	0.1846	0.0002	0.1212	0.0126	0.0853	0.0025	0.0758	0.0233	0.1103	0.0000	0.0551	0.0001
gdp	0.3487	0.0057	0.5867	0.0023	0.2460	0.0053	0.4948	0.0014	0.6430	0.0084	0.6226	0.0050	0.4645	0.0023	0.5663	0.0014
ipi	0.9911	0.0011	0.8958	0.0067	0.9407	0.0004	0.7362	0.0019	NA	NA	NA	NA	0.3557	0.0004	0.8000	0.0144
cons	0.6022	0.0011	0.3178	0.0031	0.0218	0.0407	0.0141	0.1145	0.6047	0.0015	0.6068	0.0061	0.2832	0.0009	0.1867	0.0123
inv	0.1610	0.0731	0.0630	0.0584	0.0724	0.0680	0.0239	0.0893	0.1378	0.1037	0.0447	0.0964	0.2829	0.0649	0.1094	0.0683
3 steps ahead																
	unb.1	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*	*unb.1*	*wef.1*	*unb.2*	*wef.2*
infl	0.0574	0.0000	0.0416	0.0004	0.1228	0.0000	0.1079	0.0000	0.0468	0.0000	0.1494	0.0011	0.0151	0.0000	0.0478	0.0009
gdp	0.6818	0.0003	0.3784	0.0004	0.6238	0.0002	0.4040	0.0003	0.7698	0.0007	0.4665	0.0008	0.4418	0.0002	0.3207	0.0007
ipi	0.1965	0.0000	0.5859	0.0000	0.0912	0.0001	0.8224	0.0000	NA	NA	NA	NA	0.4092	0.0000	0.5009	0.0000
cons	0.1288	0.0001	0.2041	0.0013	0.0002	0.0512	0.0050	0.0148	0.0745	0.0002	0.3993	0.0015	0.0078	0.0002	0.1105	0.0018
inv	0.0517	0.0100	0.0142	0.0135	0.0368	0.0047	0.0140	0.0150	0.0582	0.0136	0.0174	0.0147	0.0453	0.0089	0.0122	0.0163

Table 3: Diebold and Mariano test

	Consensus				F1				F2				F3			
1 step ahead																
	t-alf	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*
infl	-3.2364	0.0024	-1.9259	0.0612	-2.2379	0.0312	-1.6038	0.117	-2.4798	0.0177	-1.7415	0.0897	-2.0794	0.0444	-1.7805	0.083
gdp	-2.2028	0.0334	-1.4588	0.1524	-1.5823	0.1219	-1.0994	0.2785	-2.4006	0.0214	-1.5203	0.1367	-2.1864	0.035	-1.369	0.179
ipi	-2.6475	0.0115	-1.5886	0.12	-1.6951	0.0982	-1.3172	0.1957	NA	NA	NA	NA	-2.2155	0.0328	-1.3645	0.1804
cons	-3.1095	0.0034	-3.0336	0.0042	-1.5753	0.1268	-1.6726	0.106	-3.1745	0.003	-3.0574	0.0041	-0.8924	0.3778	-0.9211	0.3628
inv	-3.5832	0.0011	-3.1823	0.0033	-1.8702	0.0723	-1.3927	0.1751	-3.6387	0.001	-3.2359	0.0029	-2.9819	0.0055	-2.884	0.0071
2 steps ahead																
	t-alf	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*
infl	-2.9455	0.0055	-2.2632	0.0294	-2.6458	0.012	-2.0986	0.0429	-2.8145	0.0079	-2.2525	0.0305	-2.61	0.0131	-2.1063	0.0422
gdp	-1.4884	0.1449	-1.203	0.2364	-1.3528	0.1846	-1.0394	0.3055	-1.3736	0.1781	-1.1842	0.2441	-1.4286	0.1617	-1.0996	0.2788
ipi	-1.2658	0.2133	-1.1247	0.2678	-1.0047	0.3217	-1.0022	0.3229	NA	NA	NA	NA	-1.0242	0.3126	-1.0269	0.3113
cons	-1.0814	0.2863	-0.899	0.3743	0.2075	0.8373	0.3696	0.7148	-0.5331	0.5973	-0.44	0.6626	-0.3422	0.7342	0.0523	0.9585
inv	-3.1605	0.0037	-2.1897	0.0367	-1.9567	0.0616	-1.3683	0.1834	-3.0019	0.0055	-2.2031	0.0357	-2.9215	0.0067	-1.9126	0.0657
3 steps ahead																
	t-alf	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*	*t-alf*	*p-value*	*t-qlf*	*p-value*
infl	-2.9047	0.0062	-2.1503	0.0383	-2.9511	0.0057	-2.0868	0.0445	-2.7996	0.0084	-2.3098	0.0271	-2.3104	0.0271	-1.7655	0.0865
gdp	-1.6228	0.1131	-1.3273	0.1925	-1.6084	0.1167	-1.2143	0.2328	-1.5043	0.1415	-1.3305	0.1919	-1.3081	0.1994	-1.1792	0.2463
ipi	-2.0604	0.0466	-1.4235	0.1632	-2.2633	0.0301	-1.4556	0.1547	NA	NA	NA	NA	-1.9481	0.0597	-1.4516	0.1558
cons	-1.1245	0.2683	-0.8325	0.4106	-0.9692	0.3426	-0.2354	0.816	-0.9288	0.3596	-0.7891	0.4355	-0.3542	0.7254	0.1103	0.9128
inv	-1.4145	0.1686	-1.2787	0.2119	-1.1747	0.2521	-0.9081	0.3733	-1.4577	0.1565	-1.7672	0.0885	-1.4504	0.1585	-1.157	0.2574