Seasonality in macroeconomic prediction errors. An examination of private forecasters in Chile

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Abstract

It is argued that the errors of the Chilean private forecasters' macroeconomic projections are affected by seasonality in the sense that there are differences in the errors across months with respect to the signs as well as size. The latter is confirmed by statistical tests. The differences are apparent in monthly inflation rates, which are highly seasonal, and in annual output growth rates, where the main part of the seasonality is eliminated. A tentative explanation is that forecasters are affected by the weather when making their projections although more rigorous research is needed to determine the causes.

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1. Introduction

For the guidance of forward looking economic policies, reliable forecasts of macroeconomic variables are essential. Part of the reliability is related to the assessment of the forecast uncertainty, which also plays an important role in e.g. central banks' communications.[1] While several macroeconomic variables show clear seasonal patterns, to the knowledge of the author, no research has been conducted on possible seasonality in the errors of the forecasts of macroeconomic variables, even though past forecasts errors do contain useful information for the assessment of the uncertainty of a given forecast. If the forecasters are efficient, they use all available information, including perceived seasonality, such that forecast errors will not be affected by seasonality. Empirical evidence suggests, however, that forecasters in general are not efficient.[2]

The survey employed is performed monthly and, hence, Chile serves as a nice case study for assessing whether forecast errors of surveys are affected by seasonality. A small sample caveat is, however, in place as the number of observations for each month is relatively small and, hence, the interpretation of the results should be made in this context.

The study in hand adds to the existing literature on forecast uncertainty by examining the possibility that forecast errors are affected by seasonality. The median of monthly predictions of inflation and output growth rates from the Chilean survey of private forecasters are analyzed and the results suggest that there are indeed differences in the errors across months with respect to signs as well as sizes. This is not only the case for the monthly inflation rates, which affected by seasonality, but also for the annual growth rates of output, which suggests that it has little to do with the seasonality of the predicted series.

Why may forecast errors be seasonal? With respect to inflation, some literature argue that higher rates lead to higher inflation uncertainty[3] implying that forecasts errors in months with traditional high inflation rates may be larger. Another, and perhaps more important explanation, is that psychological behavior may affect the way forecasters make their projections. Forecasts rarely rely only on the outcomes of economic and econometric models, but rather they are influenced by, at times a great deal of, judgmental input. This

[1] At least 20 inflation targeting central banks publish fan chart with their projections according to Franta et al. (2014).

[2] See Pedersen (2015) for the case of Chilean private forecasters.

[3] See e.g. Golob (1994).

judgement is most likely affected by psychological factors such as the weather or indeed the time the forecast is made.[4] If this is the case, forecast errors would be different across months.

The rest of the paper is organized as follows: Section 2 describes the data employed, while section 3 investigates to what extent the macroeconomic forecast errors of the Chilean private forecasters are affected by seasonality. The last section offers some concluding comments.

2. Data description

The forecasts evaluated are of inflation and output growth rates of the Chilean Economic Expectation Survey (EES) conducted monthly by the Central Bank of Chile (CBC).[5] The period covers from January 2001 to December 2016,[6] i.e. a total of 192 observations or 16 for each month. Hence a small sample caveat is in place for the present analysis. To compare forecast accuracy, published data of the inflation rates are extracted from the web page of the CBC and first vintage output (IMACEC[7]) growth observations are from Pedersen (2013, updated). The question of inflation in the survey is asked as how much the consumer prices will increase in percentage the present month, while the IMACEC question concerns the annual growth rate for the previous one.[8] Hence, while the inflation rates in the survey are highly seasonal, the main part of the seasonality is eliminated in the annual output growth rates as shown in figure 1.

[Figure 1]

The CBC publishes the median response of the answers supplied by the forecasters and this is the measure that is analyzed in the present study. Due to this simple combination of the forecasts, one might expect that

[4] While no research has documented calendar or weather effects on forecast behavior, both have been documented to exist in financial markets. See e.g. Saunders (1993) on the effect of weather on the US stock market and Copeland and Wang (1994) on how the day of the week affects asset return. Bakar et al. (2014) find that the so-called Monday affect in asset prices can be explained by the mood.

[5] A description of the survey (in Spanish) is available in Pedersen (2011).

[6] The period refers to the months of publication of the actual data, not the months the questions were asked in the survey.

[7] IMACEC (for its abbreviation in Spanish) is the monthly indicator of Chilean economic activity.

[8] Up till January 2004 the question of the IMACEC was for two months ago, but due to changes of publication dates, from February 2004 it was changed to one month earlier. As a consequence, the historical survey observations do not include an IMACEC prediction for December 2003.

it is difficult to find evidence of seasonality.[9] Thus, if such evidence is found it indicates that the issue of seasonality in the forecast errors indeed should be taking into consideration when evaluating the uncertainty of a given forecast. All variables are expressed with an accuracy of one decimal in order to match the replies to the survey.

3. Are forecast errors seasonal?

A first assessment of the forecast errors by month is presented in figure 2 that presents the root mean square error (RMSE) and the root mean square relative error (RMSRE), which is included to control for the fact that, particularly, inflation rates are quite different across months as shown in figure 1. The two measures are calculated as:

$$RMSE_i = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{it} - \hat{y}_{it})^2}\,,\; RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_{it}-\hat{y}_{it}}{\frac{1}{n}\sum_{i=1}^{n} abs(y_{it})}\right)^2},$$

where n is the number of forecast errors available, $\widehat{y_{it}}$ is the forecast for month i in year t, y_{it} is the published value of the variable which is projected, and $abs(y_{it})$ is the absolute value of the published number. As both inflation and output growth are measured as percentage, the evaluation measures are in percentage points (pp). To supplement figure 2, the figures A1 and A2 in appendix A illustrates each of the forecast errors included in the analysis. Outliers exist for both inflation and output growth, e.g. connected with the 2008 financial crisis and the February 2010 earthquake in Chile. To evaluate the possible impact of individual observations, uncertainty is at this stage evaluated by leave-one-year-out jackknife calculations.[10]

[Figure 2]

With respect to inflation, forecast errors seem to be larger during the last months of the year, but when correcting for differences in the actual rate, they are also quite large the first two months. Hence, while this visual inspection does not tell anything about statistical significant differences in the forecast errors across month, it does indicate that there might be differences. The two lower panels of figure 2 show that also the

[9] See e.g. Timmermann (2006), and the references therein, for a discussion of the advantages of combining forecasts. In his empirical application he finds that the median forecast is quite good.

[10] See e.g. Miller (1974).

forecast errors for output growth seem to be quite different across months. April seems to be the hardest month to predict, but this is to a great extent due to the aftermath of the earthquake in 2010.

The next two subsections take a closer look at possible seasonality in the forecast errors. Subsection 3.1 evaluates the signs of the errors, while subsection 3.2 presents the results with respect to size. The third and final subsection discusses the results.

3.1. Signs of the forecast errors

Table 1 presents some descriptive statistics of the historical forecast errors. On average the forecasters seem to perform negative errors (overestimate) with respect to output growth, while it is not evident that there are any skewness in the CPI predictions.[11] There are, however, notable differences across the months such that errors tend to be negative at the end of the year for both growth and inflation.[12]

[Table 1]

With respect to inflation it is also noteworthy that June and December seem to be the hardest months to predict in the sense that they are the only ones where the median forecast is erroneous in all years.

A complementary question is whether the sizes of positive and negative errors are different. As shown in the figures A1 and A2 in appendix A, it is not evident that the sizes are markedly different, but to address this question in more details, the RMSE of positive and negative forecast errors of each month are compared in figure 3. Because of a very limited number of observations, a small sample caveat is particularly relevant at this point, and the exercise should be considered as merely illustrative.

For inflation there are a couple of positive peaks in May and September suggesting that positive error are higher than negative ones. For May, however, this result is mainly due to the 2008 observation, whereas the result is more robust for September. For output growth, there are positive peaks in April, September and December, and a negative one in, particularly, October. These peaks, however, seem to be somewhat dependent on one observation with the exception of December.

[11] In an analysis of the G-7 countries, Batchelor (2007) argues that there is a systematic bias in the real GDP forecasts of private forecasters and also in the inflation predictions, although to a lesser extent.

[12] Solferino and Waldmann (2010) argue that the signs of the forecast errors of the US Treasure bond yield can be predicted.

[Figure 3]

Given the evidence of the illustrative analysis presented in this subsection, it cannot be discarded that forecast errors are affected by some kind of seasonality with respect to the signs of the errors. The next subsection analyzes whether there are differences in the size of the errors across months.

3.2. Size of the forecasts errors

To evaluate whether the forecast errors shown in figure 2 are different in a statistical sense, the Diebold and Mariano (1995) and West (1996) test is applied with the small sample correction suggested by Harvey et al. (1997). The test is made for each pair of month, i.e., January vs. February, January vs. March etc., with absolute as well as relative errors. Hence, the test is based on the average forecast error

$$\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i,$$

where n is the number of available forecasts and d is the difference between the forecast errors of the different months. In the case of the absolute errors it is calculated as

$$d_t^{ij} = \left(e_t^i\right)^2 - \left(e_t^j\right)^2,$$

while it for the relative errors is computed as

$$d_t^{ij} = \left(\frac{e_t^i}{\frac{1}{n}\sum_{h=1}^{n} abs\left(y_h^i\right)}\right)^2 - \left(\frac{e_t^j}{\frac{1}{n}\sum_{h=1}^{n} abs\left(y_h^j\right)}\right)^2,$$

where i,j = 1,2,…, 12 are the months ($i \neq j$) and y^i and y^j denote the actual values. The result for the monthly inflation rates are reported in table 2.

[Table 2]

The evidence from table 2 suggests that, in a statistical sense, there are indeed differences in inflation forecasts across months, and they are most notably when the errors are adjusted by the size of the average inflation rates. In general terms, the tests support what is shown in figure 2, namely that the errors are particularly large in November and December, which are the months that generally present the lower rates (figure 1). This is in contrast to the literature that finds that inflation uncertainty is higher when the rate is higher. Also February and June are months with relative high forecast errors, but only in terms of the RMSRE of February the differences are statistical significant in more than half of the cases. It is not evident that any of the months have statistically significant lower forecast errors, even though the ones of March and July are relatively small. In general, the results are robust to leaving out individual observations as shown in table B1 in appendix B.

Table 3 reports the results for output growth and it shows that for the months of March, and to a lesser extend in statistical terms, April the forecast errors are the highest. Hence, even though April is the month with highest average forecast error, the evidence from the tests suggest that there are more statistical significant differences with respect to the other months in March. On the other hand, in January and December the median forecaster makes better predictions than in the other months. Also for the output growth forecasts these results are relatively robust with respect to leaving out individual observations as reported in table B2 in appendix B.

[Table 3]

3.3. Discussion of the results

In the previous two subsections it was argued that there are differences among forecast errors with respect to the size of the error as well as the sign. In other words, apparently forecast errors of the private forecasters in Chile are affected by seasonality. As pointed out in the introduction, there are several reason why the errors might be different from month to month.

Turning, firstly, to the results of the inflation forecasts, the large errors in November and December are mainly related to negative errors (table 1), which indicate that forecasters generally believe that the inflation rates will be higher than the outcomes. These are the late spring / early summer months in Chile where the prices of, particularly, fruits and vegetables typically fall and the forecasters seem to underestimate these falls. This could indicate over optimism related to demand effects maybe because of better weather. This is supported by the forecast errors of output growth the last four month of the year, i.e. the spring and early summer months. On the other hand, it is not evident that the relatively large errors in March are related to the signs.

In general, the evidence from the present analysis suggests that there are differences in the forecast errors across months and this information can be utilized to make a better assessment of the uncertainty related to the errors.

4. Concluding remarks

In this analysis it was shown that the errors of the Chilean private forecasters' macro predictions are affected by seasonality in the sense that the errors are different across month, in absolute and relative terms. Chile serves as a nice case study as the survey is conducted monthly and each time questions are asked for both inflation and output growth rates. Future research may reveal whether the results obtained also apply for other countries and variables.

A couple of tentative suggestions were made to explain why the forecast errors are seasonal, such as the effect of the weather. More rigorous analyses are, however, needed to quantify the extent to which this is the case and how other effects, e.g. the mood, impact forecasts. Finally, it cannot be discarded that the day at which the prediction is made also matters for the forecast error. These issue is left to future research.

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Appendix A. Forecast errors by month

[Figure A1]

[Figure A2]

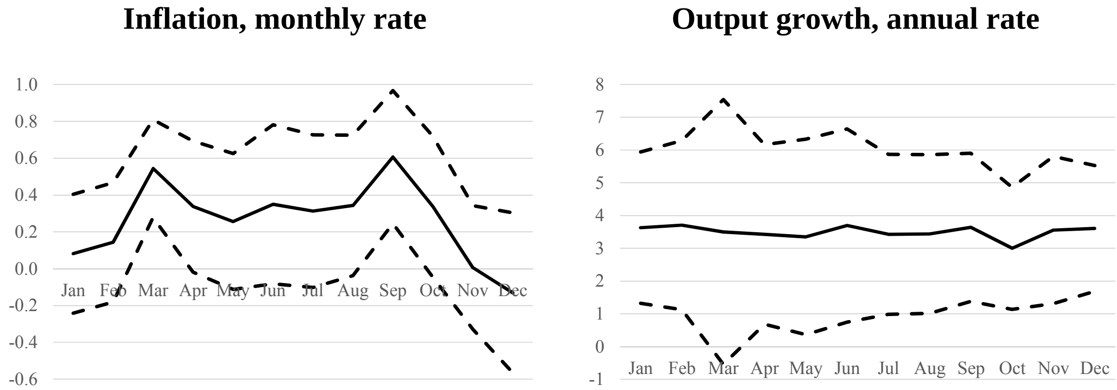
Appendix B, Leave-one-year-out robustness check

[Table B1]

[Table B2]

Figures

Figure 1. Average rates (%)

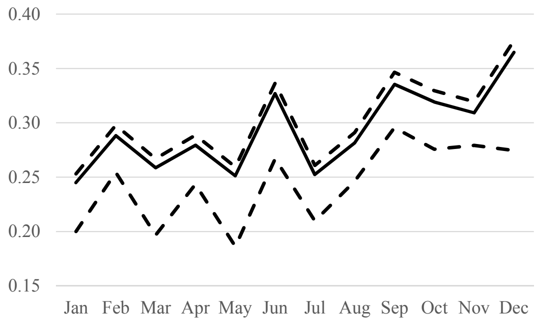


Note: Dotted lines are +/- one standard deviation.

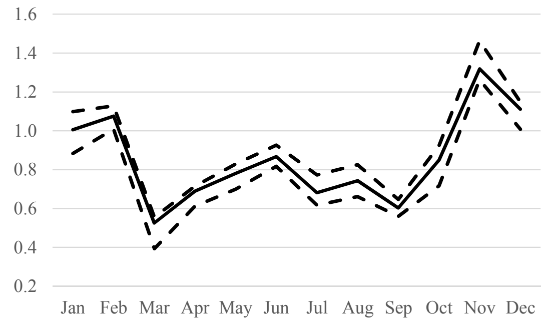
Figure 2. RMSE and RMSRE (pp)

Inflation

Absolute forecast errors

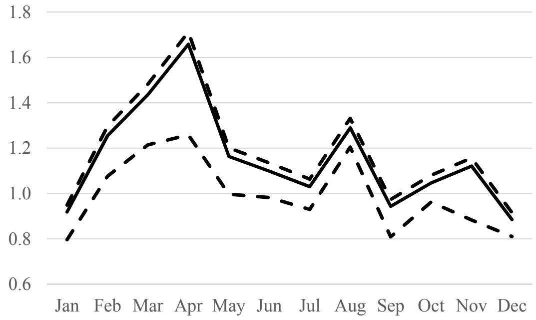


Relative forecast errors

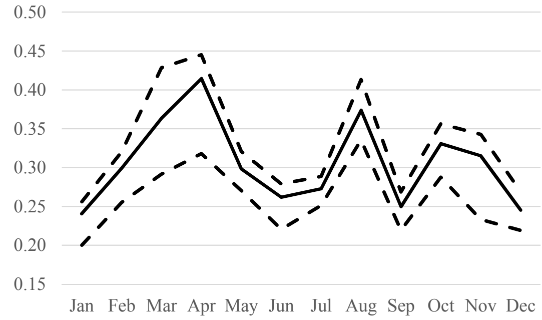


Output growth

Absolute forecast errors



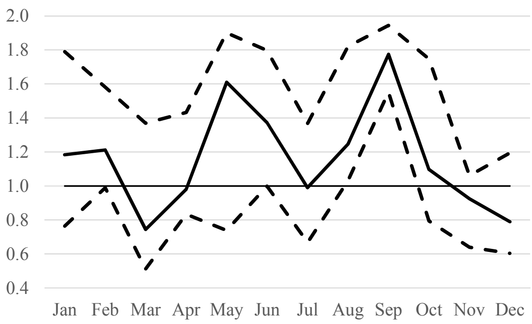
Relative forecast errors



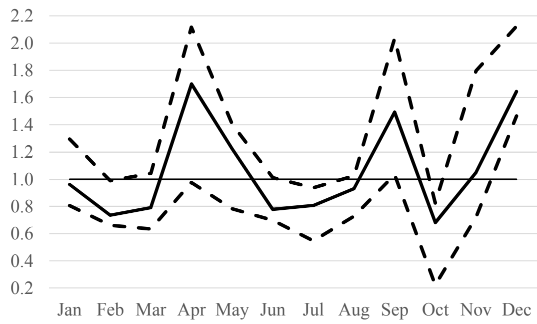
Note: Dotted lines are minimum and maximum values obtained with leave-one-year-out jackknife calculations.

Figure 3. RMSE ratios (pp)

Inflation

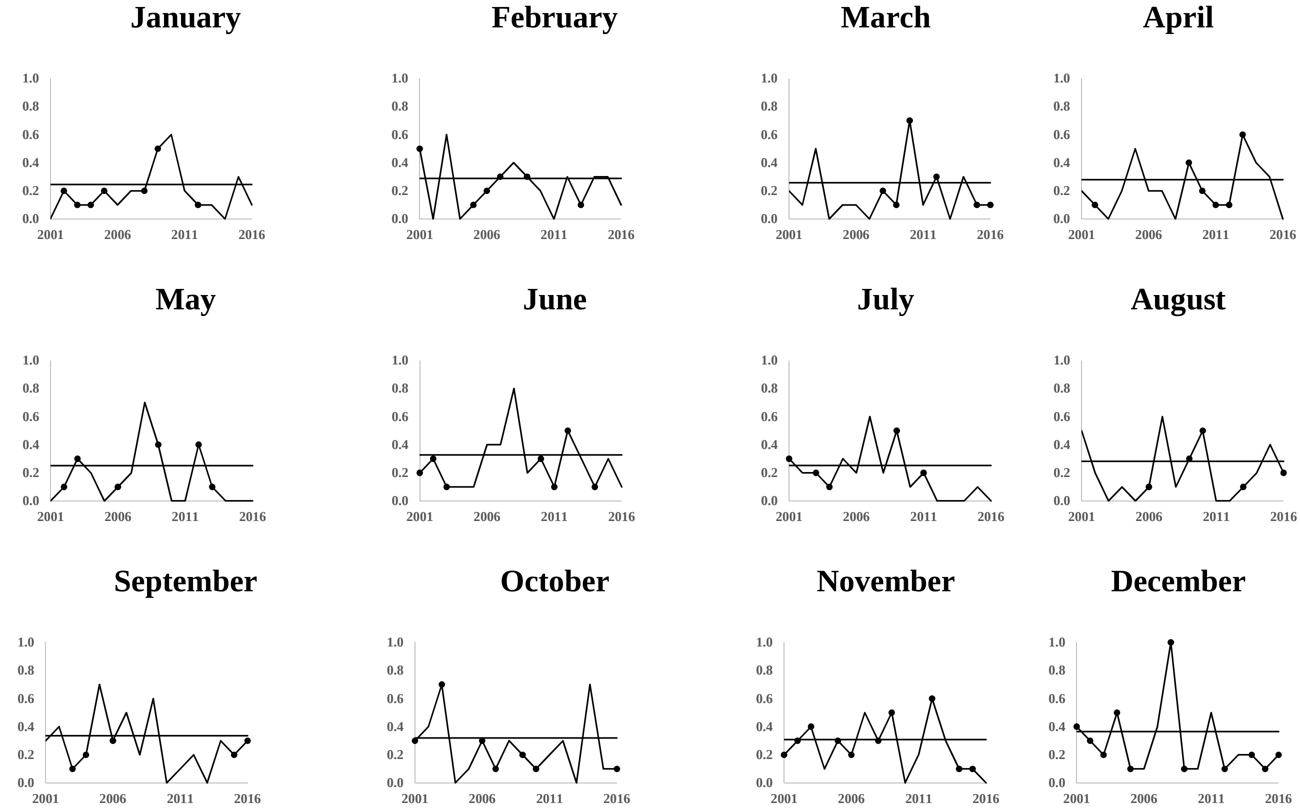


Output growth



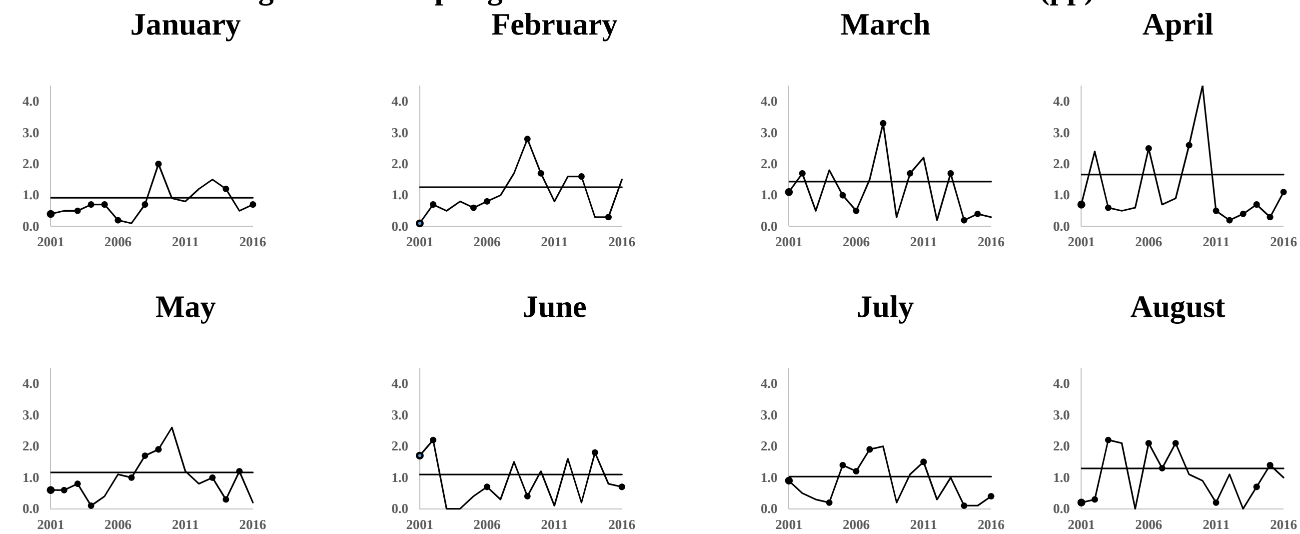
Note: Ratio of the RMSE of positive and negative forecast errors. A number higher than one indicates that the size of the negative errors on average is smaller than those of the positive ones.

Figure A1: Inflation. Absolute value of forecast errors (pp)

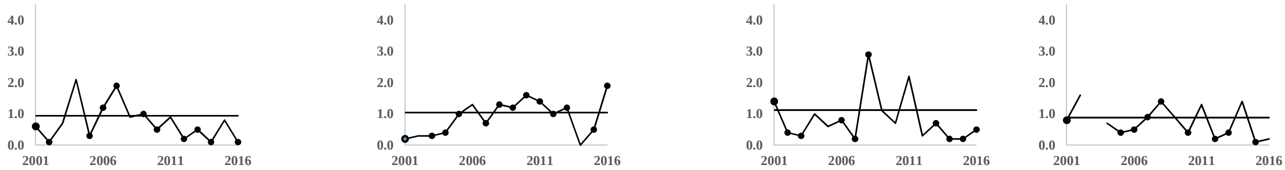


Note: Vertical lines are the RMSE and dots indicate that the forecast errors are negative (overestimation).

Figure A2: Output growth. Absolute value of forecast errors (pp)



September **October** **November** **December**



Note: See figure A1.

Tables

Table 1. Descriptive statistics forecast errors, 2001-16 (numbers)

Inflation	Sample (%)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Under est.	41	7	7	7	7	3	9	7	7	9	7	4	5
Over est.	42	7	6	6	6	6	7	5	5	5	7	10	11
No error	17	2	3	3	3	7	0	4	4	2	2	2	0
Output growth													
Under est.	40	7	9	7	6	6	9	8	5	5	3	6	6
Over est.	57	9	7	9	10	10	5	8	9	11	12	10	9
No error	3	0	0	0	0	0	2	0	2	0	1	0	0

Note: Numbers of under estimations (negative errors), over estimations (positive errors), and zero forecast errors.

Table 2. Inflation. RMSE and RMSRE ratios (pp)

	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	0.85	0.95	0.88	0.97	0.75	0.97	0.87	0.73	0.77	0.79	0.67
	0.93	**2.01***	1.50	1.31	1.17	1.51	1.38	1.73	1.20	**0.75****	0.90
Feb		1.11	1.03	1.15	0.88	1.14	1.02	0.86	0.90	0.93	0.79
		2.16***	**1.60***	1.40	1.25	**1.62*****	**1.48****	**1.85*****	**1.28****	**0.81****	0.97
Mar			0.93	1.03	0.79	1.02	0.92	0.77	0.81	0.84	0.71
			0.74	0.65	0.58	0.75	0.69	0.86	**0.60***	**0.37*****	**0.45****
Apr				1.11	0.85	1.11	0.99	0.83	0.88	0.90	0.77
				0.87	0.78	1.01	0.92	1.15	0.80	**0.50*****	**0.60***
May					**0.77*****	1.00	0.89	**0.75***	0.79	**0.81****	**0.69*****
					0.89	1.16	1.05	1.32	0.92	**0.58*****	**0.69*****
Jun						*1.29*	1.16	0.97	1.02	**1.06***	0.90
						1.29	1.18	**1.48***	1.02	**0.64*****	**0.77****
Jul							0.90	**0.75****	0.79	0.82	**0.69*****
							0.91	1.14	0.79	**0.50*****	**0.59****
Aug								0.84	0.88	0.91	0.77
								1.25	0.87	**0.55*****	**0.65****
Sep									1.05	1.08	0.92
									0.69	**0.44*****	**0.52****
Oct										1.03	0.87
										0.63***	0.75
Nov											0.85
											1.20***

Notes: First row of each month contains ratios for absolute forecast errors, while the second includes those of the relative ones. Ratios lower than one indicate the forecast of the column month one average is better than that in row month. For example, (Jan,Feb) = 0.85 in the first row and (Jan,Feb) = 0.93 in the second row show that both the RMSE and RMSRE of January are smaller than those of February. ***: $p < 0.01$; **: $p < 0.05$, *: $p < 0.10$. Bold numbers indicate that the ratio is statistical different from one when applying a 10% confidence level. Numbers in Italic indicate that the test could not be calculated because the long-run variance matrix was not positive definite.

Table 3. Output growth. RMSE ratios of absolute and relative forecast errors.

	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	**0.73***	**0.64****	**0.55***	0.79	0.84	0.89	0.71	0.97	0.88	0.82	1.04
	0.80	**0.66****	**0.58***	0.81	0.92	0.88	**0.64***	0.96	**0.73****	0.76	0.98
Feb		0.87	0.76	1.08	1.14	1.22	0.97	1.33	1.20	1.12	1.42
		0.82*	0.72	1.00	1.14	1.10	0.80	1.20	0.90	0.95	1.22
Mar			0.87	**1.23***	1.31	**1.39*****	1.11	**1.52****	**1.37***	**1.28*****	**1.62*****
			0.88	1.22	**1.39***	**1.33*****	0.97	**1.46****	1.10	**1.15*****	**1.48****
Apr				**1.43***	1.51	1.61	1.29	1.76	1.59	1.48	**1.87***
				1.39*	1.58	1.52	1.11	1.66	1.25	1.32	1.69
May					1.06	1.13	0.90	1.23	1.11	1.04	1.31
					1.14	1.09	0.80	1.19	0.90	0.95	1.22
Jun						1.07	0.85	1.16	1.05	0.98	**1.24***
						0.96	0.70	1.05	0.79	0.83	1.07
Jul							0.80	1.09	0.98	0.92	1.16

	0.73*	1.09	0.82	0.87	1.11
Aug		*1.37*	1.23	1.15	**1.46***
		1.50***	1.13	1.19	**1.52***
Sep			0.90	0.84	1.07
			0.76	0.79	1.02
Oct				0.93	1.18
				1.05	**1.35***
Nov					1.27
					1.29

Note: See table 2.

Table B1. Inflation. Results of leave-one-year-out exercises (numbers).

	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	16(1)	14(1)	15(0)	13(0)	16(1)	14(0)	15(0)	16(3)	16(1)	16(1)	16(3)
	13(1)	16(11)	16(1)	6(0)	6(0)	16(3)	16(1)	16(3)	15(0)	15(8)	14(0)
Feb		16(1)	13(0)	16(1)	15(1)	15(1)	13(0)	15(1)	15(0)	15(0)	15(1)
		16(16)	16(11)	16(8)	16(1)	16(16)	16(16)	16(16)	16(14)	16(8)	9(0)
Mar			14(0)	13(1)	16(1)	12(1)	14(0)	16(2)	16(1)	16(1)	16(1)
			16(4)	16(1)	16(9)	16(5)	16(9)	15(1)	16(14)	16(16)	16(16)
Apr				14(1)	15(0)	15(0)	10(0)	16(1)	15(0)	15(0)	15(0)
				11(0)	16(0)	12(0)	10(0)	16(0)	16(3)	16(16)	16(5)
May					16(16)	8(0)	15(1)	16(11)	16(1)	16(14)	16(16)
					7(0)	10(2)	9(0)	16(1)	8(0)	15(15)	16(15)
Jun						*3(2)*	15(2)	13(0)	12(0)	13(8)	16(2)
						3(3)	16(2)	16(16)	11(0)	9(9)	16(12)
Jul							16(0)	16(16)	16(1)	16(1)	15(14)
							16(0)	15(0)	16(1)	16(16)	15(15)
Aug								16(0)	14(0)	15(0)	15(3)
								16(1)	14(0)	16(16)	16(12)
Sep									13(0)	15(0)	15(1)
									16(3)	16(16)	16(16)
Oct										14(0)	15(0)
										16(10)	16(2)
Nov											15(2)
											11(8)

Notes: Times of a maximum of 16 that the RMSE ratios are in accordance with the results reported in table 2. Numbers in bracket are times the results are statistical significant. Numbers in italic are for the cases where the test could not be calculated because of non-positive definite long-run variance matrix.

Table B2. Output growth. Results of leave-one-year-out exercises (numbers)

	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	16(16)	16(16)	16(13)	16(3)	16(1)	14(0)	16(6)	13(0)	16(1)	15(2)	14(0)
	16(7)	16(15)	16(12)	16(3)	15(0)	15(0)	16(14)	12(0)	16(16)	15(6)	8(0)
Feb		15(4)	16(2)	15(2)	15(0)	16(0)	11(0)	16(1)	16(0)	15(2)	16(4)
		15(15)	16(3)	10(0)	15(0)	14(0)	16(1)	16(0)	16(1)	13(1)	16(0)
Mar			15(0)	16(7)	16(4)	15(15)	15(0)	16(15)	16(12)	13(13)	16(16)
			15(0)	16(5)	16(10)	15(14)	10(0)	16(15)	15(1)	13(12)	16(16)
Apr				16(13)	16(0)	16(2)	15(0)	16(2)	16(4)	16(1)	16(14)
				16(13)	16(0)	16(1)	15(0)	16(2)	15(0)	15(1)	16(6)
May					14(0)	15(0)	16(1)	16(0)	15(0)	14(0)	16(1)
					15(0)	15(0)	16(1)	16(0)	15(0)	13(1)	16(0)
Jun						13(0)	16(0)	16(0)	13(0)	12(0)	16(15)
						12(0)	16(6)	13(0)	16(1)	15(1)	15(4)
Jul							16(6)	15(1)	12(0)	15(0)	16(1)
							16(14)	15(1)	16(1)	15(3)	16(0)
Aug								*6(6)*	16(0)	16(0)	16(9)
								14(14)	15(0)	16(0)	16(12)
Sep									15(1)	15(1)	14(0)
									16(3)	15(1)	12(0)
Oct										14(0)	16(1)
										13(1)	16(9)
Nov											16(2)
											16(3)

Notes: Notes: Times of a maximum of 16 that the RMSE ratios are in accordance with the results reported in table 3. See table B1.