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IMPROVING INFLATION FORECASTS FROM THE SURVEY OF PROFESSIONAL FORECASTERS IN CHILE

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Resumen

En este artículo evaluamos las proyecciones de inflación provenientes de la Encuesta de Expectativas Económicas del Banco Central de Chile. Nuestro análisis, para el período 2000-2008, detecta un exceso de autocorrelación en los errores de predicción y un sesgo estadísticamente significativo hacia el final de la muestra. Este sesgo y autocorrelación posibilita mejorar las proyecciones de inflación mediante la incorporación de un buen predictor de los errores. Los resultados de un ejercicio fuera de muestra indican que el ajuste por autocorrelación permite reducir el sesgo y el error cuadrático medio de las proyecciones de inflación hasta en un 34% y un 29% respectivamente. En general estas reducciones son estadísticamente significativas.

Abstract

We evaluate inflation forecasts from the Survey of Professional Forecasters (SPF) of the Central Bank of Chile. Forecast errors for the period 2000-2008 show an excess of autocorrelation and a statistically significant bias at the end of the sample. We take advantage of the bias and autocorrelation structure of the forecast errors to build new and more accurate inflation forecasts. We evaluate these new forecasts in an out-of sample exercise. The new forecasts display important reductions in bias and Mean Square Prediction Error. Moreover, these reductions are, in general, statistically significant.

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1. Introduction

In this paper we analyze the bias and serial autocorrelation properties of the prediction errors from the Survey of Professional Forecasters (SPF) of the Central Bank of Chile. Additionally, with an out-of-sample exercise, we evaluate a very simple way of improving these forecasts.

Our results indicate that inflation forecasts from the SPF are biased downward and show an excess of autocorrelation. We take advantage of this bias and autocorrelation structure of the forecast errors to build new and more accurate inflation forecasts. More precisely, we show that when we adjust inflation forecasts using the autocorrelation structure of the forecast errors and their bias, we generate new forecasts which result in lower bias and Mean Square Prediction Error (MSPE). Differences in bias and MSPE are, in general, statistically significant at usual confidence levels.

While the dominant strategy to assess two forecasting methods lies upon MSPE´s comparisons, some literature raises other ways of evaluation that could be even more useful[1]. In particular, it might be important to evaluate bias and autocorrelation of forecasts errors. Ideally we would like those errors to behave like optimal prediction errors, which could only be achieved in an ideal situation when the amount of information about the data generating process is significant. According to this, under quadratic loss, optimal prediction errors k periods ahead should have a null bias and a $MA(k\text{-}1)$ moving average structure, which in other words means that the serial autocorrelation of order k or higher should be zero. In particular, an optimal prediction error one step ahead should follow a white noise process, showing no serial correlation.

Deviations from this optimal pattern might be used to adjust the prediction errors. In fact, if prediction errors k periods ahead showed a $MA(q)$ moving average structure with $q>k\text{-}1$, then the prediction errors would be predictable. Consequently, the original forecasts could be adjusted using the useful information contained in previous forecast errors.

Öller and Barot (2000) point-out that bias and autocorrelation evaluations have been called "weak informational efficiency tests". These type of tests are framed within a family of tests aimed at evaluating rationality of economic agents[2]. Despite this remark, some late literature show that evidence of bias and autocorrelation in prediction errors is not necessarily a symptom of inefficiency or irrationality. Actually, bias and autocorrelation may be the result of an optimal strategy from agents facing asymmetric loss functions (see as example Patton and Timmermann, 2007; Capistrán 2007 and Capistrán and Timmermann, 2008).

[1] An interesting discussion regarding different metrics to evaluate forecasts can be found in McCracken M. and K. West (2002)

[2] We wish to highlight Mincer and Zarnowitz's (1969) contributions. They propose simple methods to evaluate the efficiency and bias of a given series of predictions. Likewise, Granger and Ramanathan (1984) and Chong and Hendry (1986) propose encompassing tests to evaluate if the data contained in certain forecast can, at least, partially explain forecast errors from another forecasting method.

Many papers question the quality of economic predictions from different agents. For instance, Joutz and Stekler (2000), analyzing the predictions of the Federal Reserve of the U.S. found that inflation forecast errors show autocorrelation. Notwithstanding this fact, Joutz and Stekler (2000) do not propose methods to correct forecasts by making use of the information contained in previous forecast errors. More recently, Capistrán (2007) shows that inflation predictions of the Federal Reserve of the U.S. considerably underestimated actual inflation within a certain sampling period, while overestimating it in the following sampling period. Additionally, Capistrán (2000) points-out that information available from private agents' forecasts seems to have been not considered by the Federal Reserve's forecasts.

For the Euro zone, Bowls and al. (2007) analyze the economic predictions carried out by a number of private analysts. Among other things, they find that for the period running from the first quarter of 1999 until the last quarter of 2006, analysts have tended to considerably underestimate inflation and overestimate economic growth.

Loungani (2001) is another interesting publication analyzing the quality of economic forecasts. Compared to the previous papers, Loungani takes into consideration economic growth forecasts for a group of industrialized and developing countries for the period 1989 – 1998. Forecasts were gathered from *Consensus Forecasts.* Loungani shows evidence of bias in forecasts from developing countries, and evidence of inefficient use of information for both the group of industrialized and the group of developing countries.

As aforesaid, there are numberless studies evaluating private analysts', central banks and other institutions forecasts. Nevertheless, there are only a small number of studies analyzing data from Chile. Chumacero (2001) is an example. He finds strong evidence of bias when evaluating the economic growth forecasts of a group of private analysts. In turn, Albagli et. al. evaluate inflation and growth prediction errors from the Central Bank of Chile (CBCH), private analysts and other central banks. Their results, regarding inflation, show that from 2000 to 2002, the CBCH's prediction errors were considerably lower than those of private analysts[3].

Most of the papers that assess forecasts according to its efficiency do not involve in out-of-sample exercise aimed at evaluating potential improvements in the construction of new forecasts based upon the information not used in the original forecasts[4]. As distinct from these papers, we have shown that the bias and excess of autocorrelation detected in SPF's forecasts can be used to generate new, more accurate forecasts. This is significant, since a simple finding of bias and excess of autocorrelation in an in-sample exercise does not ensure these can be used to actually improve forecasts in real time.

[3] Nadal (2001) implement an out-of-sample evaluation of some inflation models for Chile. Nevertheless, he gives no evaluation of the Central Bank of Chile forecasts, private analysts or other institutions.
[4] One important exception is Capistrán and Timmermann (2007).

The rest of the paper is organized as follows: section II describes some properties of an optimal prediction error. The third section describes the strategy used to compare bias and MSPE between forecasts. Section IV evaluates SPF's prediction errors in terms of bias and autocorrelation. Section V shows the benefits, in terms of bias and MSPE reduction, achieved when the bias and excess of autocorrelation of prediction errors are used to construct new forecasts. This is done with an out-of -sample exercise. Finally, Section VI gives a short summary and offers some conclusions.

2. Optimal Prediction Error

Wold's second theorem claims that every ergodic, weakly stationary and purely not deterministic series may be expressed as an infinite linear combination of zero mean innovations ε_t with equal variance. Thus, if Y_t is a series having these characteristics, the following is true:

$$Y_t = \sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i}$$

where

$$\sum_{i=0}^{\infty} \psi_i^2 < \infty; \quad \psi_0 = 1$$

and we have also assumed for simplicity that Y_t is a zero mean process.

Consider an information set given by I_t. The best predictor under quadratic loss corresponds to the conditional expectation of the variable to be predicted with respect to I_t. Thus, if we denote this conditional expectation by $Y_t^f(h)$, we have

$$Y_{t+h} = \sum_{i=0}^{\infty} \psi_i \varepsilon_{t+h-i}$$

$$Y_t^f(h) = \sum_{i=0}^{\infty} \psi_i E(\varepsilon_{t+h-i} \mid I_t)$$

$$Y_t^f(h) = \sum_{i=h}^{\infty} \psi_i \varepsilon_{t+h-i}$$

The optimal prediction error under quadratic loss can be defined as the difference between the original series and the optimal predictor. This error, that we designate by $e_t(h,)$, can be expressed as follows:

$$e_t(h) = Y_{t+h} - Y_t^f(h)$$

$$e_t(h) = \sum_{i=0}^{\infty} \psi_i \varepsilon_{t+h-i} - \sum_{i=h}^{\infty} \psi_i \varepsilon_{t+h-i}$$

$$e_t(h) = \sum_{i=0}^{h-1} \psi_i \varepsilon_{t+h-i}$$

From these definitions we can easily demonstrate three properties:

1. Optimal prediction errors are unbiased.

In fact, it is enough to notice that

$$Ee_t(h) = E\left(\sum_{i=0}^{h-1} \psi_i \varepsilon_{t+h-i}\right)$$

$$Ee_t(h) = \sum_{i=0}^{h-1} \psi_i E(\varepsilon_{t+h-i}) = 0$$

2. Prediction errors $e_t(h)$ and $e_{t-l}(h)$ have a null correlation for $l > h-1$.

In fact, let us notice that

$$Ee_t(h)e_{t-l}(h) = E\left(\sum_{i=0}^{h-1} \psi_i \varepsilon_{t+h-i} \sum_{j=0}^{h-1} \psi_j \varepsilon_{t-l+h-j}\right)$$

$$= E\left(\sum_{i,j=0}^{h-1} \psi_i \psi_j \varepsilon_{t+h-i} \varepsilon_{t-l+h-j}\right)$$

$$= \sum_{i,j=0}^{h-1} \psi_i \psi_j E\left(\varepsilon_{t+h-i} \varepsilon_{t-l+h-j}\right)$$

As we want to evaluate a condition for $l > h$-1 we have that if i,j lies between 0 and h-1, then

$$t - l + h - j < t + 1 - h + h - j$$

$$t - l + h - j < t + 1 - j < t + 1$$

On the other hand, we also have that the following is true

$$t + h - i > t + h + 1 - h$$
$$t + h - i > t + 1$$

Then, if $l > h\text{-}1$ we note that sub indexes $t+h-i$ and $t-l+h-j$ can never take the same value, from this we can conclude that if $l > h\text{-}1$

$$Ee_t(h)e_{t-l}(h) = \sum_{i,j=0}^{h-1} \psi_i \psi_j E\left(\varepsilon_{t+h-i}\varepsilon_{t-l+h-j}\right) = 0$$

3. The optimal prediction error h steps ahead follows a *MA(h-1)* process**.** Under quadratic loss and using the information set $I_t = \{\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2,\ldots}\}$ we can conclude that the best predictor of the optimal prediction error h steps ahead is zero.

$$E(e_t(h) \mid I_t) = E(\sum_{i=0}^{h-1} \psi_i \varepsilon_{t+h-i} \mid I_t) = 0$$

3. Evaluation of Predictive Ability

To compare the predictive ability of two prediction methods we will focus on evaluating both the MSPE and the bias differences of forecasts. MSPE of forecast errors and their bias are defined as follows

$$MSPE(e) = E(e^2)$$
$$Bias(e) = E(e)$$

where e is the prediction error defined as the actual inflation minus its forecast. A forecasting method will be better than another as long as it has lower bias and lower MSPE. We use the approach proposed by Giacomini and White (2006) to statistically assess both bias and MSPE differences between two methods. We choose this approach over the usual one due to Diebold and Mariano (1995) and West (1996) because Giacomini and White (2006) tests are focused on evaluating a forecast method and not a forecasting model. Though subtle, for this paper this difference is very important because the obtained observations are inflation forecasts which are not necessarily associated to econometric models.

The Giacomini and White (2006) test statistic we use here is similar to a statistic primarily ascribed to Diebold and Mariano (1995) and West (1996) with the two following considerations: First, there is no correction associated to parametric uncertainty, because the purpose is not the evaluation of a model with population parameters, but a forecasting method. Secondly, when using a HAC estimate of the relevant variance of our core statistic, lags are not selected according to the optimal behavior of forecast errors because they may contain a more complex autoregressive structure. For every practical effect, we used HAC estimation according to Gallant (1987) with automatic lag selection according to Newey and West (1994)[5].

Following Giacomini and White (2006), we formulate the following statistic:

$$t_{n(\tau)} = n(\tau)\frac{\overline{\Delta L_{n(\tau)}}}{\sigma_{n(\tau)} / \sqrt{n(\tau)}}$$

with

$$\overline{\Delta L_{n(\tau)}} = \frac{1}{n(\tau)}\sum_{t=1}^{n(\tau)} \Delta L_t$$

where τ is the forecast horizon, $n(\tau)$ is the number of forecasts for that specific horizon, ΔL is the differential loss between two predictions and $\sigma_{n(\tau)}$ is a HAC estimate of the asymptotic variance of the $t_{n(\tau)}$ statistic numerator, duly weighted by the square root of $n(\tau)$.

Under the null hypothesis of equal predictive ability, the $t_{n(\tau)}$ statistic is asymptotically normal.

4. Analysis of SPF's Prediction Errors

The Survey of Professional Forecasters (SPF) collects monthly inflation forecasts from about thirty private forecasters. Inflation forecast series at one and three months ahead are collected from this survey for each individual forecaster. The Central Bank of Chile maintains a public access database that shows the median of these forecasts. The following analysis is based on the time series properties of the publicly available series of forecast errors. We analyze the period from February 2000 to May 2008. We remove any possible seasonal pattern by taking log differences between the current forecast and its twelfth lag.

Tables 1 and 2 show that forecasting errors display a statistically significant bias in the last half of the sampling period, reaching a value of 11 and 47 base points at one and three months ahead, respectively.

[5] We also carried out an analysis using HAC estimation following Newey and West (1987). Results were very similar to those obtained following Gallart (1987).

Table 1
Bias in Forecast Errors
One Month Ahead Forecasts

Sample	Bias	Standard Error	t-statistic	P-value
2000M2-2008M5	*0.03*	*0.04*	*0.87*	*0.39*
2000M2-2004M1	*-0.04*	*0.04*	*-1.10*	*0.28*
2004M2-2008M5	*0.11*	*0.05*	*2.03*	*0.05*

Table 2
Bias in Forecast Errors
Three Months Ahead Forecasts

Sample	Bias	Standard Error	t-statistic	P-value
2001M11-2008M05	*0.13*	*0.16*	*0.83*	*0.41*
2001M11-2005M02	*-0.21*	*0.18*	*-1.15*	*0.26*
2005M03-2008M05	*0.47*	*0.21*	*2.21*	*0.03*

Tables 3 and 4 below show that MA(1) and MA(7) processes are, respectively, good statistic representations of the one and three steps ahead prediction errors. These results are in sharp contrast with the optimal structure of forecast errors under quadratic loss. Actually, as previously indicated, optimal prediction errors should display a MA(0) and MA(2) structure one and three steps ahead, respectively. Accordingly, this is an evidence of an excess of autocorrelation in the SPF's forecast errors.

Table 3
Moving Average Structure
One Month Ahead Forecast

Variable	Coefficient	Standard Error	t-statistic	P-value
C	*0.03*	*0.04*	*0.91*	*0.37*
MA(1)	*0.49*	*0.08*	*6.36*	*0.00*

Table 4
Moving Average Structure
Three Months Ahead Forecast

Variable	Coefficient	Standard Error	t-statistic	P-value
C	*0.32*	*0.32*	*1.01*	*0.31*
MA(1)	*1.56*	*0.13*	*12.49*	*0.00*
MA(2)	*1.21*	*0.21*	*5.68*	*0.00*
MA(3)	*0.65*	*0.25*	*2.54*	*0.01*
MA(4)	*0.66*	*0.22*	*3.00*	*0.00*
MA(5)	*0.90*	*0.17*	*5.36*	*0.00*
MA(6)	*0.85*	*0.15*	*5.69*	*0.00*
MA(7)	*0.55*	*0.08*	*7.23*	*0.00*

Consistently with the aforementioned, the following table 5 shows that one step ahead prediction errors can be satisfactorily predicted by a linear function of the first lag of this variable. This is clearly incompatible with properties of optimal prediction errors. Let us recall that under quadratic loss, a one step ahead optimal prediction error is white noise, and consequently is unpredictable. Likewise, table 6 shows an analogue result for 3 months ahead prediction errors. We see that these errors can be satisfactorily predicted by a linear function of lags lying in the set of information available at the moment of prediction.

Table 5
Predictability of Prediction Errors
One Month Ahead Forecast

Variable	Coefficient	Standard Error	t-statistic	P-value
C	*0.02*	*0.03*	*0.84*	*0.40*
F(1)	*0.35*	*0.11*	*3.20*	*0.00*

F(k) is a linear function of the lag k of the dependent variable.

Table 6
Predictability of Prediction Errors
Three Months Ahead Forecast

Variable	Coefficient	Standard Error	t-statistic	P-value
C	*0.18*	*0.16*	*1.17*	*0.25*
F(3,4,5,9)	*0.10*	*0.06*	*1.74*	*0.09*

F(l,k,j,m) is a linear function of lags l,k,j,m of the dependent variable.

Tables 1 to 6 account for SPF's prediction errors sub optimal condition under quadratic loss. These tables show an excess of autocorrelation for these errors which potentially could be used to achieve an improvement of SPF's forecasts.

Notwithstanding the evidence displayed in tables 1 to 6, the traditional analysis of autocorrelation functions (ACF) of SPF's prediction errors show somewhat ambiguous results. Though ACF of one step ahead prediction errors is not consistent with a white noise structure, the ACF of 3 steps ahead prediction errors seems consistent with a MA(2) type of structure.

Table 7
Autocorrelation Function of Prediction Errors

One Step Ahead Prediction Errors		Three Step Ahead Prediction Errors	
Absolute Value ACF	Critical Values	Absolute Value ACF	Critical Values
0.33	0.16	**0.78**	0.19
0.02	0.16	**0.42**	0.28
0.06	0.16	0.20	0.30
0.08	0.16	0.17	0.30
0.20	0.16	0.16	0.30
0.15	0.16	0.06	0.30
0.12	0.16	0.12	0.30
0.16	0.16	0.25	0.30
0.17	0.16	0.24	0.30
0.00	0.16	0.10	0.30
0.26	0.16	0.06	0.30
0.13	0.16	0.11	0.30

In bold: 10% statistically significant values.

In short, the evidence shown is clear to point-out that SPF's one step ahead prediction errors show an excess of autocorrelation that potentially can be used to improve these forecasts. Evidence is somewhat ambiguous in the three steps ahead prediction errors, because two out of three of our exercises are consistent with the hypothesis of autocorrelation in excess, while one exercise is inconsistent.

5. Forecasting Forecast Errors

In the previous section, we showed that one step ahead prediction errors display bias and excess of autocorrelation. We also showed bias evidence and mixed evidence of excess of autocorrelation for three step ahead prediction errors. In this section we assume that an excess of autocorrelation is present for both series. By making use of the excess of autocorrelation and bias we are able to build forecasts of prediction errors that can be added to the original inflation forecasts to generate new real time inflation forecasts. Let us introduce some notation. Let Y_{t+h} be actual inflation at time $t+h$. Forecasts for Y_{t+h} built with information until time t will be called $Y^f_t(h)$. Prediction errors are called e_{t+h}. Then we have that

$$Y_{t+h} = Y_t^f(h) + e_{t+h}$$

Let $e^f_t(h)$ be a good predictor of e_{t+h}, then

$$e_{t+h} = e_t^f(h) + \varepsilon_{t+h}$$

and

$$
\begin{aligned}
Y_{t+h} &= Y_t^f(h) + e_t^f(h) + \varepsilon_{t+h} \\
Y_{t+h} &= Ye_t^f(h) + \varepsilon_{t+h} \\
Ye_t^f(h) &= Y_t^f(h) + e_t^f(h) \qquad (1)
\end{aligned}
$$

where Ye^f_t *(h)* denotes a new predictor that adds the e^f_t *(h)* prediction error to the original forecast Y^f_t (h). If our forecasts of the forecast errors are appropriate, we can expect the final prediction error to decrease.

To evaluate this strategy in an out-of-sample fashion we proceed as follows: We split the full sample of forecasts errors in an estimation window of size *R*, and a prediction window of size $P=T+1-R-(h-1) = T+2-R-h$, where $T+1$ is the number of available observations and *h* is the forecast horizon. We take the first *R* available observations and fit the *AR(p)* process for the forecast errors that minimize the Akaike information criterion[6]. Next, we build *h* steps ahead forecasts for the forecast errors. With this prediction, the *h* steps ahead inflation forecasts are adjusted according to equation (1). Finally, we repeat this procedure removing the first observation and adding observation $R+1$ to the estimation window to fit another *Ar(p)* process. In other words, the autoregressive model is always selected based on a rolling strategy with *R* observations. Therefore *P* new forecasts of inflation are constructed. These adjusted forecasts are compared to the original forecasts in terms of bias and MSPE reductions.

Since results may be sensitive to the initial selection of the size of the estimation window *R*, tables 8-11 show out-of-sample MSPE and bias reductions obtained for different choices of the size of the estimation window.

We would like to emphasize that estimation of the *AR(p)* processes is carried-out using a variant of a Stein estimator. It is essentially estimated by OLS and then the OLS vector is multiplied by a reduction factor $\lambda(p) = \lambda^p$ where *p* is the order of the selected autoregressive process. For the purpose of this work, we consider $\lambda=0.90$[7].

[6] For the 3 steps ahead forecast errors this automatic selection procedure yielded unstable results. Therefore, we picked an AR(1) process as a good autoregressive representation.

[7] The case $\lambda=1$ corresponds to OLS estimation. By using this OLS estimator results are similar but slightly milder.

Table 8
MSPE Decline in Prediction Error
One Month Ahead Forecasts

R	MSPE	Percentage Decline	t-statistic	P-value
30	*0.08*	*12.06*	*1.45*	*0.07*
40	*0.08*	*7.43*	*0.85*	*0.20*
50	*0.08*	*15.35*	*1.53*	*0.06*
60	*0.09*	*14.05*	*1.52*	*0.06*
70	*0.09*	*17.17*	*1.74*	*0.04*
80	*0.12*	*17.01*	*1.89*	*0.03*

Total number of predictions is P=100-R

Table 8 shows MSPE reductions for one month ahead forecasts. This table shows that regardless of the size of the estimation window (R), there is always a decline in out-of-sample MSPE. This reduction ranges from 7.43% to 17.17%, being for most of the cases statistically significant at the 10% or 5% significance value. Note that p-values decrease along with the size of the observations used for the first estimation. We assume this happens because it is by the end of the sample period that main reductions in forecast errors are achieved. This is showed in Figure 1.

Figure 1
One Month Ahead Prediction Errors

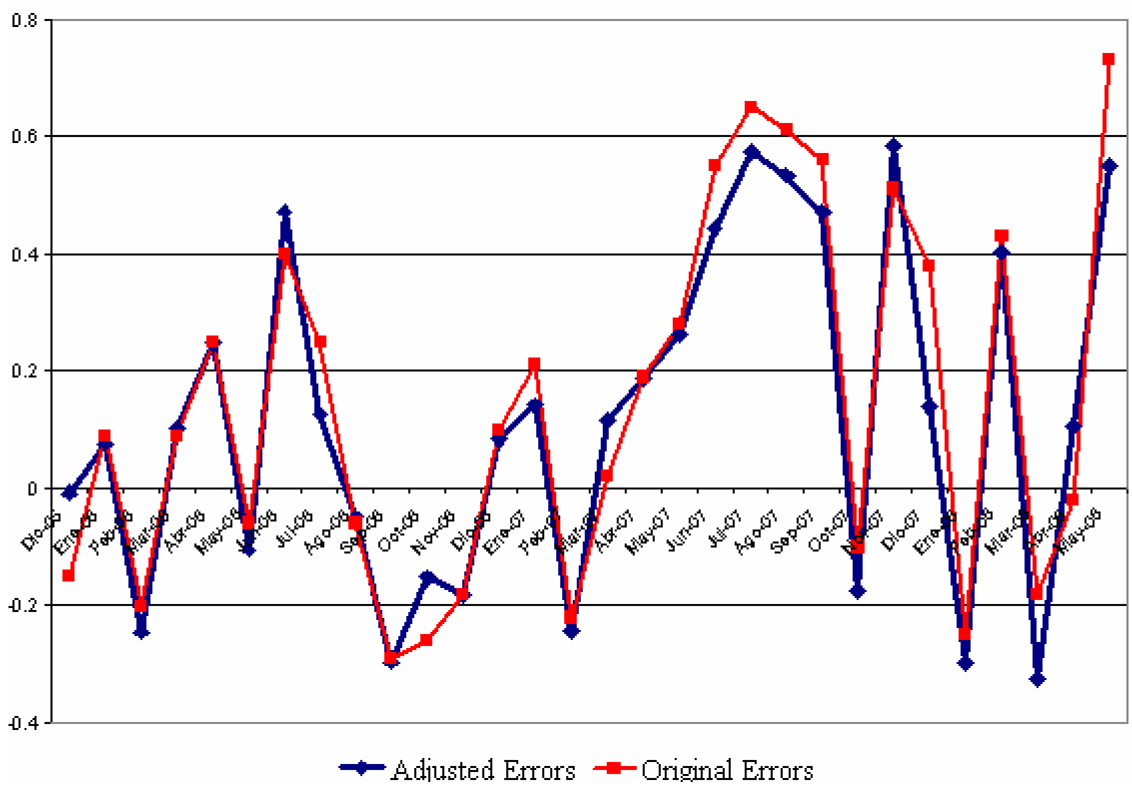

Table 9 shows that bias also declines when corrections by autocorrelation are made. Bias decline ranges from 10.87% to 27%. When the size of the portion used to estimate the AR(p) process is higher than *50*, bias reductions are also statistically significant with a significance level of 95%.

Table 9
Bias Decline in Prediction Error
One Month Ahead Forecasts

R	Bias	Percentage Decline	t-statistic	P-value
30	*0.05*	*27.00*	*1.16*	*0.12*
40	*0.04*	*23.80*	*1.21*	*0.11*
50	*0.09*	*10.87*	*0.98*	*0.16*
60	*0.11*	*17.17*	*1.92*	*0.03*
70	*0.12*	*18.26*	*1.95*	*0.03*
80	*0.17*	*16.74*	*2.23*	*0.01*

Total number of predictions is P=100-R

Table 10
MSPE Decline in Prediction Error
Three Months Ahead Forecast

R	MSPE	Percentage Decline	t-statistic	P-value
30	*0.61*	*16.87*	*1.07*	*0.14*
40	*0.64*	*24.56*	*1.53*	*0.06*
50	*0.77*	*24.56*	*1.68*	*0.05*
60	*1.00*	*29.54*	*2.39*	*0.01*

Total Number of predictions is P=79-R-2

Table 10 is analogue to table 8 but show results for three months ahead forecasts. In this case corrections made by bias and autocorrelation reduce the out-of-sample MSPE at least by 16.87%. Likewise, this reduction is statistically significant at usual significance levels when the size of the estimation window is higher than *30*. We assume this happens because it is by the end of the sample period that main reductions in forecast errors are obtained. Figure 2 depicts this regularity clearly.

Figure 2.
Three Months Ahead Prediction Errors

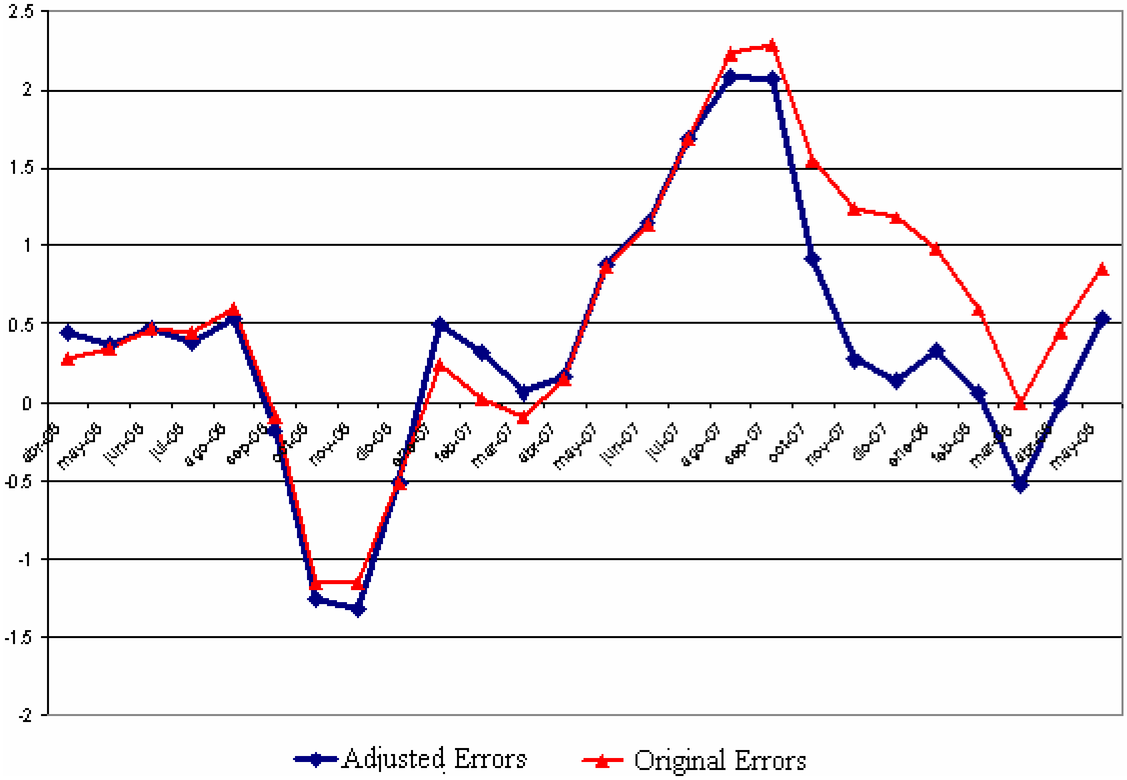

Table 11
Bias Decline in Prediction Error
Three Months Ahead Forecast

R	Bias	Percentage Decline	t-statistic	P-value
30	*0.23*	*34.90*	*1.76*	*0.04*
40	*0.32*	*32.99*	*1.90*	*0.03*
50	*0.37*	*34.66*	*2.01*	*0.02*
60	*0.71*	*25.42*	*2.50*	*0.01*

Table 11 shows that bias also declines when corrections by bias and autocorrelation are made in the case of three steps ahead forecast errors. The bias decline ranges from 25.42% to 34.90%. Likewise, this reduction is statistically significant at usual significance levels.

6. Summary and Conclusions

We have shown that the median inflation forecast from the Central Bank of Chile's Survey of Professional Forecasters differs from optimal forecasts by displaying a downward bias and autocorrelation in excess. This is especially evident in the last half of the sampling period.

We take advantage of the bias and autocorrelation structure of the forecast errors to build new and more accurate inflation forecasts. We evaluate these new forecasts in an out-of sample exercise. The new forecasts display important reductions in bias and Mean Square Prediction Error. Moreover, these reductions are, in general, statistically significant. For the construction of the new forecasts we have relied in an extremely simple strategy based upon the estimation of an appropriate AR(p) model. This leads to believing that the use of a more complex strategy in real time could achieve even much better results.

Compared to other papers aimed at evaluating forecasts according to their bias and autocorrelation in excess, we have shown that bias and the excess of autocorrelation detected in SPF's forecasts can be used to generate new, more accurate forecasts. This is important, since a simple finding of bias and excess of autocorrelation in an in-sample exercise does not ensure they can be actually used to improve forecasts in real time. It is only by carrying out an out-of-sample exercise that this question can be properly answered.

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