

ON THE IMPORTANCE OF THE ARRIVAL OF NEW INFORMATION*

RESPECTO A LA IMPORTANCIA DEL ARRIBO DE NUEVA INFORMACIÓN

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Abstract

This paper develops a framework for evaluating the importance of the arrival of new information for forecasting, estimation, and decision making. By fusing known and recently developed statistical tests and concepts, the paper provides guidelines for detecting outliers, influential observations, innovations, and possible breaks in the end of the sample. The methodology is applied to analyze the Chilean CPI inflation.

Key words: *News, Innovation, Outlier, Influential analysis.*

Resumen

Este trabajo desarrolla un marco conceptual para evaluar el impacto de nueva información para realizar proyecciones y estimaciones. Combinando conceptos y tests recientemente desarrollados, se provee una guía para la detección de potenciales observaciones extremas, observaciones influyentes, innovaciones y quiebres en la parte final de la muestra. La metodología desarrollada se aplica a la serie de inflación en Chile.

Palabras clave: *Noticias, Innovaciones, Observaciones extremas, Análisis influyente.*

JEL Classification: *C52, C53.*

* I would like to thank Pablo Pincheira, Klaus Schmidt-Hebbel, and the participants of the Meeting of the Chilean Economic Association and the Conference on Computational and Financial Econometrics for useful comments and suggestions. Financial support from Fondecyt (Nº 1095034) is gratefully acknowledged. The usual disclaimer applies.

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1. INTRODUCTION

The arrival of new information is valuable for decision makers. It may reinforce past perceptions or cast doubts on them.

Processing new information efficiently is also important. Decision makers may wish to examine more carefully the structure of their models if the actual realizations differ greatly from their forecasts and use them with more confidence when these differences are small.

Consider the model:

$$(1) \quad y_t = m(x_t, \theta) + u_t,$$

where y is the variable of interest, $m(\cdot)$ is the model used to forecast it, x_t is a vector of variables assumed to be known at t , θ is a vector of parameters, and u_t is an innovation¹.

With an estimate of θ , (1) can be used to produce forecasts. In particular, given a loss function and the (postulated or estimated) distribution of u , point, interval, and density forecasts can be obtained analytically or approximated numerically.

Decision makers may be interested in possible sources of large forecast errors. If they occur, were they due to specific events that are deemed to be unlikely to be repeated in the future? Are they signals of forecast failures in the model used? Is the structure of the Data Generating Process (DGP) changing? How would an extreme event affect forecasts in the future?

This paper provides tools for answering these questions when evaluating some characteristics of short-term (one-step ahead) forecasts², by assessing when new information can be categorized as a surprise (section 2), an outlier (section 3), an influential observation (section 4), or a signal of a structural break (section 5). Each section presents an empirical application for the Chilean CPI inflation.

2. NEWS AND SURPRISES

Decision makers may be interested in evaluating whether the current realization constitutes a surprise. Surprise is defined as an event that presents an important departure from what was forecasted.

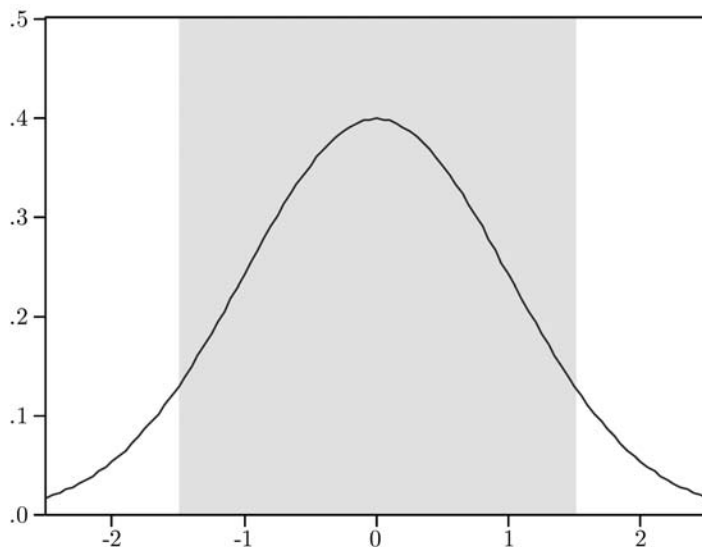
The simplest way to operationalize this concept is to consider the one-step ahead distribution function forecast (F), and to evaluate:

$$(2) \quad \Pr[y < y_t] = F_t(y_t).$$

¹ A random variable is an innovation if it is orthogonal to (unpredictable with respect to) any other variables in the information set. In this case, the information set includes past observations of y and past and present observations of x . An innovation is also a white noise as it is orthogonal to its own past (see Clements and Hendry, 1998).

² Although the methods discussed below could, in principle, be extended to analyze longer-term forecasts.

FIGURE 1
DEFINING A SURPRISE USING DENSITY AND INTERVAL FORECASTS



The realization y_t is considered to be a surprise when the probability of its occurrence is low, which would happen if the actual realization is on either of the extremes of the forecast density. Consequently, a surprise is defined as an event outside a forecasted confidence interval of coverage $1-\alpha$, where the level α is determined by the decision maker (see Figure 1). Low values of α would imply that the decision maker is only willing to equate surprises with extreme events. High values of α would trigger considering the current event as a surprise more frequently. If the confidence interval has the proper coverage (which can be tested), surprises should occur $\alpha\%$ of the times and their occurrences should not be correlated³.

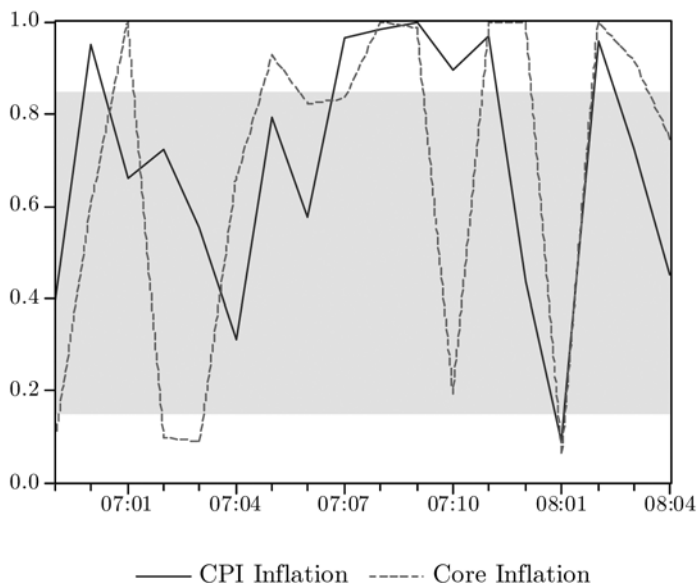
Applying this concept is simple once a model $m(\cdot)$ is chosen and its parameters estimated. As the focus is centered on one-step ahead forecasts, the models postulated for each time series are simple $AR(p)$ processes, where p is chosen using a pre-specified information criterion for the full sample.

³ Christoffersen (1998) describes an intuitively simple way to evaluate interval forecasts. Formally, for a sequence of interval forecasts with ex-ante coverage probability p , the ex-post coverage q corresponds to the fraction of times in which the observed outcome lies in the forecast interval. If in n observations there are n_1 outcomes falling in the forecast interval, we have that $q = n_1/n$. We can test that the interval has the correct coverage (p) by using the binomial distribution and forming the corresponding Likelihood Ratio Test:

$$LR = 2 \left[n_1 \ln \frac{q}{p} + (n - n_1) \ln \frac{1 - q}{1 - p} \right],$$

which is asymptotically distributed as a chi-square with one degree of freedom.

FIGURE 2
ONE-STEP AHEAD FORECAST PROBABILITIES WITH A 70%
CONFIDENCE INTERVAL



Once p is chosen, the model is estimated using $t-1$ observations and the parameter estimates and residuals are used to obtain a one-step ahead forecast density. Next, the actual realization of the variable in period t is used to compute $F_t(y_t)$ in (2).

Figure 2 presents the values of $F_t(y_t)$ estimated for CPI and Core Chilean inflations. The shadowed area presents the coverage consistent with $\alpha = 0.3$. The figure suggests that both measures of inflation were “surprisingly” high in the second semester of 2007. However, according to the model, the inflation rates observed in April 2008 (8.3% and 8.1% respectively) were not surprises.

When a “surprise” (as defined above) is detected, the questions posed in the Introduction arise. How should surprises be treated? Can its potential impact be assessed? The next sections discuss some potential avenues to address these questions.

3. OUTLIERS

Outliers are considered to be aberrant observations. That is, observations that are strikingly different from others in the sample. Outliers are considered to be exceptional events that do not belong to the DGP. In those instances, they should be detected and removed.

Although including an outlier may present problems for conducting reliable inference and forecasting, it is not at all clear that if an event happened in the past, it will not happen again in the future. In that case, that observation would provide valuable information and should not be discarded. Alternative (robust) procedures may be used to minimize their detrimental effect on forecasting. Because of these problems, outlier detection is not as prevalent a practice in economics as it is in statistics.

Outliers are often categorized as Additive Outliers (AO) and Innovation Outliers (IO). Following Franses (1998), let y_t be the observed series and x_t be the outlier-free series. If y has one AO at time $t = \tau$, it can be described as:

$$y_t = x_t + \omega I_t^\tau,$$

where ω is the size of the outlier and I_t^τ is an indicator dummy variable that takes the value of 1 when $t = \tau$ and 0 otherwise. In this case, the outliers are considered as measurement errors. If, for example, x follows an AR(1) process, a scatter plot of y_t against y_{t-1} would present two irregular points⁴.

If we consider again an AR(1) process, an IO at time τ is defined as:

$$y_t = \rho y_{t-1} + \omega I_t^\tau + u_t.$$

In this case, the predicted value for y_t would be ρy_{t-1} for $t \neq \tau$. However, when $t = \tau$, the predicted value should be $\rho y_{t-1} + \omega$. In this case, a scatter plot of y_t against y_{t-1} would present only one irregular point⁵.

Several statistical procedures have been proposed to test for aberrant observations. The most common (and simplest) is to include the dummy variable indicator I_t^τ for different values of τ and test the null hypothesis $H_0: \omega = 0$. However, as τ is not known, sequential testing may have a non-standard distribution.

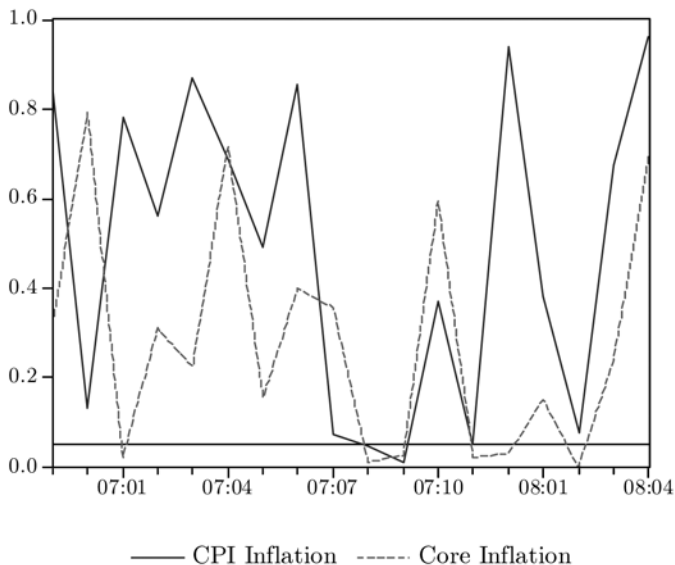
Figure 3 presents the p -values of the test for IO estimated for CPI and Core Chilean inflations. In each case, the autoregressive structure is not confined to be an AR(1) process. Given a particular level for the test (say 5%), few candidate IO are detected. This is due in part to the fact that the level chosen favors the null.

The case for AO is more difficult to make as, if its source is a one-time measurement error, it would be easy to spot. The troubling feature of outliers is that they are supposed to be events that do not provide information of the structure. Apart from trivial cases, this claim is difficult to back.

⁴ One with the pair $(y_\tau, y_{\tau-1})$ and the other with the pair $(y_{\tau+1}, y_\tau)$.

⁵ On the pair $(y_\tau, y_{\tau-1})$.

FIGURE 3
P-VALUE OF THE TEST OF INNOVATION OUTLIER



Note: The horizontal line is located at the standard 5% level.

4. INFLUENTIAL OBSERVATIONS

The estimate of θ in (1) is important for forecasting y_t . If $m(\cdot)$ were linear in θ , OLS would be the most likely candidate for estimating θ . As this method seeks to prevent a few large residuals at the expense of incurring into many relatively small residuals, a few observations can be extremely influential in the sense that dropping them from the sample would change some elements of θ substantially.

A systematic way to find those influential observations in linear models is as follows⁶:

Let $\hat{\theta}^{(t)}$ be the estimate of θ obtained when omitting the t -th observation. It can be shown that:

$$\hat{\theta}^{(t)} - \hat{\theta} = -\left(\frac{1}{1-p_t}\right)(X'X)^{-1}x_tu_t, \quad p_t = x_t'(X'X)^{-1}x_t,$$

$$0 \leq p_t \leq 1 \text{ and } \sum_{t=1}^T p_t = k.$$

⁶ This procedure can also be used for non-linear models.

Thus, the average of p_t is equal to the saturation ratio kT (see Hayashi, 2000). Consider:

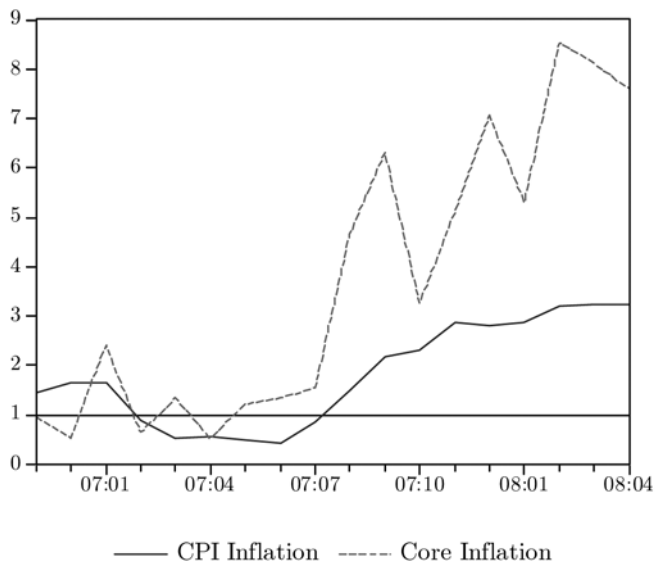
$$d_t = \frac{Tp_t}{k},$$

which on average should be equal to 1. High values of d_t would signal that observation t is influential.

Figure 4 presents the values of d_t estimated for CPI and Core Chilean inflations up. For each month, d_t in (3) is computed by considering that the sample ends on the corresponding month. The figure suggests that, as the inflation rate rose significantly beginning on the second semester of 2007, these last observations are becoming increasingly influential on the estimation of the model and, if used, should modify short term forecasts.

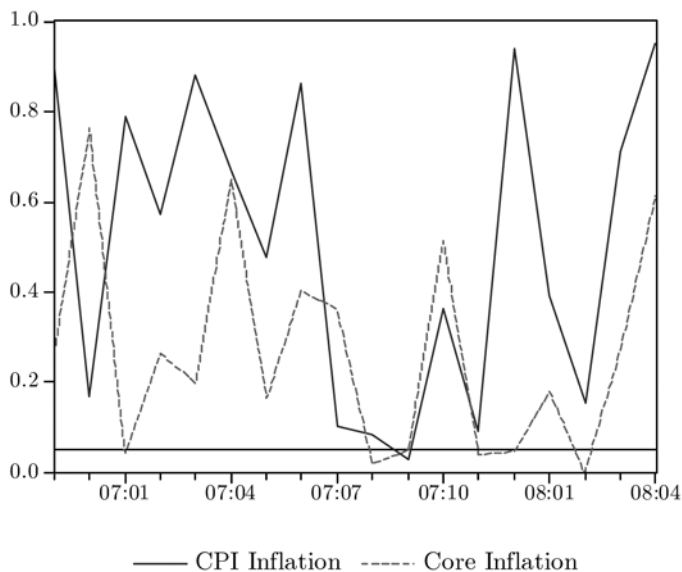
What should be done with influential observations? If they “belong” to the model, they provide valuable information that is not available from the rest of the sample. If they are considered to be atypical of the rest of the sample, and unlikely to be observed again, one could consider providing them a special treatment. In either case, when influential observations are detected, practitioners may be advised to use robust estimation techniques such as LAD (Least Absolute Deviation), where the influential observations are considered, but their weight is not as dominant as with OLS.

FIGURE 4
INFLUENTIAL ANALYSIS



Note: The horizontal line is located at $d_t = 1$.

FIGURE 5
P-VALUES FOR END-OF-SAMPLE BREAKS



Note: The horizontal line corresponds to the 5% level.

4. BREAKS

Detecting if the latest observation “belongs” to the model is not trivial. As noted by Andrews (2003), the well-known Chow test only applies in a linear regression model with normally distributed iid errors and strictly exogenous regressors. As model (1) would hardly fit these characteristics, an alternative test is required.

Andrews (2003) presents a generalization of the conventional F test (termed the S test) which allows for a more general structure. Its null hypothesis is the absence of breaks against the alternative of a break in the last n observations, where n may be as small as one (that is, a break in the last observation).

In linear models with serially uncorrelated errors, the test considers computing the difference between the sum of squares of the residuals of the constrained and unconstrained model (which conform the S test) and to compute its critical value through a subsampling-like method (see Andrews, 2003).

Figure 5 presents the p -values for testing the null hypothesis of stability against the alternative of a break in the last observation. The results suggest that the first observations of high inflation in the second semester of 2007 could have been considered as evidence of instability (particularly in the case of Core inflation). Once they are included in the model, there is no evidence that the most recent observations detect instability in the model.

5. CONCLUDING REMARKS

This paper provides tools for evaluating the informational content of new information by comparing observed outcomes and short-term forecasts.

This comparison is useful as it can help to answer questions such as when is the outcome truly unexpected and what to expect in such case.

By carefully assessing how influential recent observations have been, forecasters and decision makers can make wiser choices.

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