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COMMUNICATIONAL BIAS IN MONETARY POLICY: CAN WORDS FORECAST DEEDS?

Pablo Pincheira Mauricio Calani

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Agustinas 1180
Teléfono: (56-2) 6702475; Fax: (56-2) 6702231

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COMMUNICATIONAL BIAS IN MONETARY POLICY: CAN WORDS FORECAST DEEDS?

Pablo Pincheira Brown
Gerencia de Investigación Económica
Banco Central de Chile

Mauricio Calani Cadena
Gerencia de Investigación Económica
Banco Central de Chile

Resumen

La comunicación de los bancos centrales con el público es una práctica creciente que complementa las decisiones de política monetaria en lo que a tasas de interés se refiere. En este trabajo examinamos un tópico particular de las prácticas comunicacionales del Banco Central de Chile y que resume la apreciación del Consejo acerca de la más probable evolución futura de la Tasa de Política Monetaria (TPM). Mostramos que esta apreciación, que denominamos “Sesgo Comunicacional”, contiene información útil respecto del futuro de la TPM. Esto es mostrado evaluando la capacidad que tiene el sesgo comunicacional de anticipar los cambios de dirección futuros de la TPM, y comparar esta capacidad con la de varios modelos disponibles en la literatura. Nuestros resultados indican que el Banco Central de Chile, en el período analizado, ha mostrado coherencia entre el dicho y el hecho. De hecho, el sesgo comunicacional predice los cambios en la TPM de manera más precisa que un camino aleatorio y que el azar. También mostramos que el sesgo comunicacional permite mejorar la capacidad predictiva de un modelo discreto basado en una regla de Taylor con persistencia. Finalmente, también mostramos que el sesgo comunicacional tiene información útil que permitiría a los agentes del sistema financiero mejorar las proyecciones de corto plazo de la TPM contenidas en la curva forward.

Abstract

Communication with the public is an ever-growing practice among central banks and complements their decisions of interest rate setting. In this paper we examine one feature of the communicational practice of the Central Bank of Chile (CBC) which summarizes the assessment of the Board about the most likely future of the monetary policy interest rate. We show that this assessment, known as communicational bias or simply c-bias, contains valuable information regarding the future stance of monetary policy. We do this by comparing, against several benchmarks, the c-bias’s ability to correctly forecast the direction of monetary policy rates. Our results indicate that the CBC has (in our sample period) matched words and deeds. The c-bias is a more accurate predictor of the future direction of monetary policy rates than a random walk and a uniformly-distributed random variable. It also improves the predictive ability of a discrete Taylor-Rule-type model that uses persistence, output gap and inflation-deviation-from-target as arguments. We also show that the c-bias can provide information to improve monetary policy rate forecasts based on the forward rate curve.

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Correspondence: Agustinas 1180. Santiago-Chile. Tel: (562) 670-2874, Fax: (562) 670-2836. E-mail: ppinchei@bcentral.cl; mcalani@bcentral.cl.

1 Introduction

"[...] a successful communication strategy requires a central bank to be credible. And this, in turn, means matching words with deeds."

Mario Draghi (2008)

The implementation of monetary policy based on overnight interest rates setting, is usually complemented with a strong set of communicational tools that, first, inform markets about the reasons underlying current decisions, and second, indicate the most likely path of future monetary policy rates, given the appraisal of the current economic environment. Inflation Targeting (IT) countries have been leaders in incorporating these set of tools which usually comprise periodical "Inflation Reports", "Financial Stability Reports", formal speeches and minutes released immediately after Monetary Policy Meetings (MPM)[1]. In the case of Chile, the second oldest inflation targeter country, these minutes usually include a paragraph signaling the most likely future path of monetary policy rates. This signal is called the "Communicational Bias" (c-bias) and can be regarded as a forecast of the future direction of monetary policy rates. How good of a forecast is it? We cannot tell a priori, and that is the objective of this paper: to evaluate the ability of the c-bias to forecast the future direction of monetary policy rates in Chile.

Why should we be interested in assessing the forecasting accuracy of the c-bias? the answer relies on its role on shaping expectations. The consensus Neo-Keynesian model predicts that current economic developments and more importantly, key variables such as the exchange rate and long-term interest rates are dependent (among other things) on the expectation of the future evolution of monetary policy [2]. Furthermore, it is through these forward-looking variables that part of the transmission mechanism for taming inflation operates (Svensson, 2003). If the c-bias is informative about future developments, then it should be relevant for expectations, and therefore it should have an impact on economic outcomes. This impact may be subtle and hard to identify using econometrics in small samples. Nevertheless, a necessary condition for this impact to exist, is that of a strong enough relationship between future MPR and the c-bias. Should this relationship fail, then the link between c-bias and economic outcomes would lack of logical support. Then, by focusing on the ability of the c-bias to predict future changes in monetary policy rates, we are, first, evaluating

[1] Equivalent to the FOMC meeting of the Federal Reserve Board of the U.S.

[2] See Galí (2008) for an excellent treatment of the basic New-Keynesian model that has become standard in monetary policy analysis.

the c-bias in its own merit and, second, we are testing for a necessary condition for the c-bias to have an impact on economic outcomes.

We evaluate the c-bias' forecasting ability using several different benchmarks. First we consider a random walk (in level and first differences) and a uniformly distributed random variable that considers three equally likely scenarios: tightening, easing and silent (neutral) c-bias. We also consider the case of a taylor-rule-type model including predictors such as the output gap, inflation deviation from target and persistence of monetary policy rate (MPR). Finally, we consider market expectations derived from the forward rate curve. We mainly engage in two exercises. First we carry out a horse race between the c-bias and different benchmarks. In those few cases in which the c-bias does not outperform its competitors, we also evaluate if the c-bias can improve the predictions of the competing strategy.

Our results indicate that the c-bias predicts more accurately future MPR changes than a martingale model in level and differences. Similarly, the c-bias strongly outperform random forecasts generated by a uniformly-distributed random variable. Moreover, the (pseudo-out-of-sample) predictive ability of a more sophisticated model that considers inflation and output (as central banks do) can be outperformed by its c-bias augmented version, even though this latter model is less parsimonious. Finally, the c-bias is equally accurate as the forward rate curve to forecast future changes in MPR. Nevertheless, we show that the predictive accuracy of the forward curve could be improved by using information from the c-bias.

We make a contribution to the literature in different directions. First, we assemble a database for a qualitative variable which is, to our knowledge, novel among emerging economies. Second, we contribute to the literature that evaluates central bank's performance under Inflation Targeting. This literature has focused on evaluating several dimensions of Central Bank's performance through macroeconomic final outcomes only, and not through time-consistency in matching words and deeds; which would be key to establishing a credible policy framework[3]. This last feature, although widely recognized, has been confined to the theoretical arena[4].

[3]Macro outcomes usually comprise inflation and output volatility, shock resilience, inflation level convergence and sacrifice ratios. Among others, excellent reference papers are Ball and Sheridan (2005), Corbo, et al. (2002), Cecchetti et al (2006), and Mishkin and Schmidt-Hebbel (2007).

[4]Agénor (2002), for instance, proposes transparency as an unresolved analytical issue in the design of inflation-targeting regimes. Walsh (2007), using a simple new Keynesian framework concludes that policy's impact is significantly affected by the way policy announcements alter expectations.

Additional distinctive features of this paper are the use of out-of-sample tests of predictive ability and the use of an ordered response model to characterize the evolution of MPR. This model is used to properly take into consideration that MPR is a discrete rather than a continuous time series. In fact, during the sample period, the lowest common multiple for MPR changes is 25 basis points. This a feature that, to our knowledge, has not been taken into account in the related literature.

The rest of the paper is organized as follows. In the next section we present a literature review and a description of the importance of communicational tools for monetary policy. In section 3 we describe the c-bias used at the Central Bank of Chile and the way in which we deal with the qualitative aspects of the data. Section 4 describes the chosen methodologies. Section 5 presents our empirical results and section 6 concludes and summarizes the implications for the conduction of monetary policy.

2 Monetary Policy Implementation and its Communicational Toolkit

Expectations about future MPR may play a major role in the conduction of monetary policy (see Woodford, 2005); for current overnight interest rates may not be as important as the expectation of their persistence and future changes. In fact, the Neo-Keynesian standard model gives expectations a prominent role to macroeconomic outcomes' determination. But under what circumstances does central bank's communication provide extra information to shaping expectations beyond that already contained in observed macroeconomic variables? Under rational expectations and perfect (symmetric) information: none. If one assumes rational expectations, any systemic pattern in the way the policy is being conducted should be correctly inferred from the central bank's behavior. Nevertheless, do private agents can perfectly do so? Models in which there is not perfect information but in which agents must make inference about how the central bank operates give a significant role to transparency and more importantly to communication as a tool to overcome the information gap. See Woodford (2005) and more recently Blinder et al. (2008) for a general discussion and Cukierman and Meltzer (1986) and Orphanides and Williams (2005) for precise theoretical models in which providing information to private agents is not only non-trivial but also welfare-improving.

The extent to which any economy departs from rational expectations and perfect information is an empirical issue. Thus, it is no wonder that plenty of articles have been written in this arena. The growing attention to IT countries, which have given huge steps towards increasing transparency and accountability, has only made the topic even more appealing. This is because IT countries usually complement the adoption of this regime with several publications and press releases (Batini and Laxton, 2007).

The empirical analysis of communicational tools on macroeconomic outcomes has been mainly focused on its impact on interest rates and the yield curve (Blinder et al., 2008). For the U.S. Gürkaynak et al. (2005), attempt precisely to separate the effects of current MPR changes from the effects of the FOMC announcements and statements; which they label as "current policy" and the "future path policy" effects. Using a principal-components approach they conclude that previous studies that focused only on current change of MPR missed most of the story, as the second factor (future policy) accounts for more than three quarters of the total effect on longer maturity interest rates. Following similar insights, Andersson et al. (2006) examine a wide set of "monetary policy signals", including publication of inflation reports and executive speeches from the Riksbank. They conclude that current monetary policy actions have their greatest effect on the short end of the yield curve and that signaling appears to have some effects on longer interest rates. Siklos and Bohl (2007) examine if communication is important for explaining interest rate movements by the Bundesbank in a Taylor-rule type equation. They find that the communication variable they construct is robust and significant. This communicational variable is based on the number of speeches on a particular matter for which an auxiliary equation is estimated. This last equation, however, has on its left side the number of speeches and on the right hand current and past values of interest rate changes. Thus, there is a chance that their empirical work might not be quantifying the impact of communication on future interest rates but the impact of past policy changes on current policy.

Rosa and Verga (2007) and Lapp and Pearce (2000) are more related to the present paper in the sense that they both focus on the predictive ability of communicational tools of monetary policy on future policy changes. Lapp and Pearce (2000) study the (in-sample) predictive ability of the Bias in the FOMC. They conclude that the Bias has some power to predict future changes in the Fed fund rates. They show that bias toward tightening implies (on average) a positive change in the fed funds rate of 11 bp, in contrast to a negative change of 37 bp after an easing bias. Rosa and Verga (2007) analyze the recent experience of the ECB using the introductory statements of its president in his monthly press conference. They map wording into an index using the frequency of words associated to the tightness of monetary policy.

They show this index is positively and significantly correlated to subsequent Repo rate changes. Moreover, they show that ECB's rethoric is a complement, rather than a substitute, to measures of activity and exchange rate movements within an empirical reaction function. They fail, however, to show that the ECB´s rethoric can be a better predictor than the Euribor rates. Finally, they regress the change of Euribor rates on the change of one month forward rates and the first difference of the communication index, both of which result positively related with the dependent variable.

3 Communicational Bias in Chile

The Central Bank's Board makes monthly monetary policy decisions at monetary policy meetings. In these meetings, which are announced six months in advance, the Board sets the level of the monetary policy rate (MPR) which is the target rate in accordance to which liquidity is provided to the financial industry (Central Bank of Chile, 2007). This operational implementation is supported by extensive communication of the central bank with the public. In particular, policy decisions are immediately communicated after the respective monetary policy meeting in an official news release or minute.

These minutes can be broken down into three sections: first the policy decision is announced; second, the arguments behind such decision in terms of domestic and international economic events are sketched; and finally, the last paragraph of the minute is devoted to providing hints about the "most likely course of future monetary policy" if conditions were not to deviate far from the baseline scenario. It is this last signal which we call communicational bias. The Central Bank of Chile publishes these statements as of September 1997. However, it is only from 2000 that it does so every month without interruptions. On top of that, in August 2001 the Central Bank of Chile changed its target instrument from an inflation-indexed monetary policy rate to a nominal interest rate[5]. It is for this last reason that we decide to work with monthly data from August 2001.

A clear signaling about the most likely future evolution of monetary policy can be extracted from some of the statements. But, in general, the correct signaling could be subject to readers' prejudice or misinterpretation. To avoid this potential problem we recur to the very same people who participated (with or without voting right) in MPM, and ask them to classify the message therein into the following categories:

[5] A fact that implied a large decline in interest rate volatilities, see Fuentes et al. (2003)

strong upwards bias, moderate upwards bias, no change, moderate downwards bias, strong downwards bias and no-bias. In 63% of the cases opinions are coincident, only one statement is classified in three different categories and the rest of the cases share two categories. It is for these latter cases that we recur to the opinion of other staff economists at the Central Bank of Chile and reach a consensus on the message every statement provides. Given that some of our categories have very few or lack of observations we collapse them into the following three categories that are shown in Figure 1: upward bias (including the previous strong and moderate upwards bias categories), neutrality (including the previous no change and no bias categories) and downward bias (including the previous strong and moderate upwards bias categories).

Three stylized facts arise naturally. First we can see that neutral bias is the most frequent state (50% of the time), closely followed by 38% of tightening bias. Easing bias, in contrast, is only present 12% of the time. Second, the c-bias is highly persistent. Out of 92 months, only 21 display changes. Third, the last third of the sample is different from the first two in terms of persistence. Indeed, in the first two thirds the average maintenance time is 5 months and the peak of unchanged c-bias is 24 months. This contrasts with the last third of the sample in which the average and peak maintenance time are only 3 and 5 months respectively.

When not neutral, the c-bias is a natural predictor of future changes in the direction of MPR. However, if neutral, the c-bias cannot be interpreted as a forecast of some future policy decision. In fact, out of the 46 months in which the c-bias is neutral, only once the original category obtained was a "no change" label. The rest of the time the c-bias was absent and therefore no forecast was released. According to this, we will test the predictive ability of the c-bias only when this variable is different from neutral. We will do this following the conditional predictive ability framework of Giacomini and White (2006).

The rest of the paper will precisely be devoted to examine more rigorously the statistical ability of the c-bias to forecast future MPR changes. As mentioned above, this should be the first critical test to examine if the c-bias may have an impact on expectations about future policy, and through them, on key economic variables that affect current macroeconomic outcomes.

4 Methodology

Our aim is to evaluate the ability that the c-bias may have to predict future changes of MPR. First we check if the c-bias contains any relevant information about future MPR at all, and if this is the case, we evaluate if it has additional information to that contained within standard economic macro and financial variables.

Our empirical exercise entails one particular modeling challenge. Both, c-bias and MPR changes, are discrete variables, which makes traditional continuous models-based forecasts difficult to interpret and analyze. Jansen and de Haan (2006) are, to our knowledge, the first to take into consideration the discrete characteristic of the data, but they do not perform formal predictive ability test, and rely on the goodness of fit (pseudo-R^2) of their estimations. In this paper we explicitly consider the discrete nature of the data and use the formal out-of-sample predictive ability test proposed by Giacomini and White (2006) with several benchmarks. Before presenting the results, we briefly summarize the intuition behind the test in Giacomini and White (2006).

4.1 The Giacomini and White Conditional Approach

In this section we follow closely Giacomini and White (2006). Let us consider two competing parametric forecasting models for the conditional expectation of a scalar time series y_{t+1}. We denote the forecasts from these two models as $y^1_{t+1}(\beta_1)$ and $y^2_{t+1}(\beta_2)$, where β_1 and β_2 denote population parameters of the two competing models. For a given loss function $\mathcal{L} = \mathcal{L}(y_{t+1}, y^i_{t+1}(\beta_i))$, $i = 1, 2$ the traditional unconditional approach attributed to Diebold and Mariano (1995) and West (1996) suggests a test of equal forecast accuracy as follows

$$H_0 : \mathbb{E}[\mathcal{L}(y_{t+1}, y^1_{t+1}(\beta_1)) - \mathcal{L}(y_{t+1}, y^2_{t+1}(\beta_2))] = 0 \tag{1}$$

whereas the conditional approach suggests the following testing strategy

$$H_0 : \mathbb{E}[\mathcal{L}(y_{t+1}, y^1_{t+1}(\widehat{\beta}_{t1})) - \mathcal{L}(y_{t+1}, y^2_{t+1}(\widehat{\beta}_{t2}))|\mathcal{F}_t] = 0 \ a.s. \ for \ all \ t \geq 0 \tag{2}$$

where $\widehat{\beta}_{t1}$ and $\widehat{\beta}_{t2}$ denote parameter estimates of β_1 and β_2 with information up until time t. The implementation of the conditional approach relies on the fact that (2) is equivalent to

$$\mathbb{E}[h_t(\mathcal{L}(y_{t+1}, y^1_{t+1}(\widehat{\beta}_{t1})) - \mathcal{L}(y_{t+1}, y^2_{t+1}(\widehat{\beta}_{t2})))] = 0$$

for all $\mathcal{F}_t-$measurable function h_t.

4.2 One-Step Ahead Conditional Test

When $\tau = 1$, the sequence $h_t \Delta \mathcal{L}_{R,t+\tau}$ is a martingale difference sequence if the null is true. Giacomini and White (2006) propose the following statistic for the test of equal conditional predictive ability

$$T^h_{P_n,R} = P_n(\overline{Z'}_{P_n,R}\ \widehat{\Omega}^{-1}_{P_n}\overline{Z}_{P_n,R}) \tag{3}$$

where

$$\begin{aligned}
\overline{Z}_{P_n,R} &= \frac{1}{P_n}\sum_{t=R}^{T} Z_{R,t+1} \\
Z_{R,t+1} &= h_t \Delta L_{R,t+1} \\
\widehat{\Omega}_{P_n} &= \frac{1}{P_n}\sum_{t=R}^{T} Z_{R,t+1} Z'_{R,t+1}
\end{aligned}$$

Giacomini and White (2006) provide conditions under which the asymptotic distribution of $T^h_{P_n,R}|H_0$ is Chi-square.

$$T^h_{P_n,R}|H_0 \xrightarrow{D} \chi^2_q \quad as \;\; P_n \to \infty$$

Notice that when the dimension of the testing function h_t is one, the test is asymptotically normal.

4.3 Multi-Step Conditional Test

When $\tau > 1$ Giacomini and White (2006) propose the following statistic for the test of equal conditional predictive ability

$$T^h_{P_n,R,\tau} = P_n(\overline{Z'}_{P_n,R}\ \widetilde{\Omega}^{-1}_{P_n}\overline{Z}_{P_n,R}) \tag{4}$$

where

$$\begin{aligned}
\overline{Z}_{P_n,R} &= \frac{1}{P_n}\sum_{t=R}^{T-\tau} Z_{R,t+\tau+1} \\
Z_{R,t+\tau+1} &= h_t \Delta L_{R,t+\tau}
\end{aligned}$$

and $\widetilde{\Omega}_{P_n}$ is a HAC estimate of the variance of $Z_{R,t+\tau+1}$.

Giacomini and White (2006) provide conditions under which the asymptotic distribution of $T^{h}_{P_n,R,\tau}|H_0$ is Chi-square.

$$T^{h}_{P_n,R,\tau}|H_0 \xrightarrow{D} \chi^2_q \quad as \quad P_n \to \infty$$

Again, when the dimension of the testing function h_t is one, the test is asymptotically normal.

We test conditional predictive ability using a very simple testing function h_t :

$$h_t(\text{c-bias}_t) = \begin{cases} 1 & \text{if c-bias}_t \text{ is not neutral} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

so we evaluate the predictive ability of the c-bias when it is actually a forecast.

4.4 Interpretation of the Test in Our Environment

C-bias is by itself a predictor of the direction of change of the MPR but without a specific horizon. We will assume that behind this c-bias there is a latent predictor of future MPR that we will call $b_t(k)$ and is defined as follows:

$$b_t(k) = \begin{cases} \infty & \text{if} \quad \text{c-bias}_t \text{ is upward biased for all } k = 1, 2, ... \\ 0 & \text{if} \quad \text{c-bias}_t \text{ is neutral for all } k = 1, 2, ... \\ -\infty & \text{if} \quad \text{c-bias}_t \text{ is downward biased for all } k = 1, 2, ... \end{cases}$$

Let us consider a generic loss function

$$\begin{aligned} \mathcal{L} &: \mathbb{R}^2 \longrightarrow \mathbb{R} \\ \mathcal{L} &= \mathcal{L}(Y_{t+k,} y^p_t(k)) \end{aligned}$$

where $y^p_t(k)$ is a predictor of Y_{t+k} which uses available information up to t. Often, this loss function can be expressed in terms of an increasing function of the difference between the predictor and the variable it attempts to predict

$$\mathcal{L}(Y_{t+k}, y^p_t(k)) = l(Y_{t+k} - y^p_t(k))$$

Even though the most commonly used loss function is quadratic, it is also common to use a loss function based on the direction of change, such as

$$\mathcal{L}(Y_{t+k}\ , y^p_t(k)) = \left\{ \begin{array}{ll} 1 & \text{if} \quad sign(Y_{t+k}\ - Y_t) \neq sign(y^p_t(k) - Y_t) \\ 0 & \text{otherwise} \end{array} \right\}$$

where

$$sign(X) = \left\{ \begin{array}{ccc} 1 & \text{if} & X > 0 \\ -1 & \text{if} & X < 0 \\ 0 & \text{if} & X = 0 \end{array} \right\}$$

In particular we will have

$$\mathcal{L}(Y_{t+k}\ , b_t(k)) = \left\{ \begin{array}{ll} 1 \quad \text{if} \quad sign(Y_{t+k}\ - Y_t) \neq sign(b_t(k) - Y_t) \\ 0 \qquad\qquad\qquad\qquad \text{otherwise} \end{array} \right\}$$

then, the expected value of this loss function is

$$\mathbb{E}\mathcal{L}(Y_{t+k}, b_t(k)) = \Pr(sign(Y_{t+k} - Y_t) \neq sign(b_t(k) - Y_t))$$

which is nothing but the probability of the predictor $b_t(k)$ missing the direction of change of the future variable Y_{t+k}, which is the same as the probability of a wrong prediction by the c-bias of the future change in MPR. Let C denote the event in which $\{\text{c-bias}_t \neq \text{neutral}\}$ and let

$$\Delta\mathcal{L}_{t+k,t} = (\mathcal{L}(Y_{t+k}, y_t^p(k))) - \mathcal{L}(Y_{t+k}, b_t(k))$$

then

$$\begin{aligned} \mathbb{E}\mathcal{L}(Y_{t+k}, b_t(k))h_t &= \Pr\left[\{(sign(Y_{t+k} - Y_t) \neq sign(b_t(k) - Y_t)\} \cap C\right] \\ &= \Pr\left[\{(sign(Y_{t+k} - Y_t) \neq sign(b_t(k) - Y_t)|C\} \Pr\left[C\right]\right] \end{aligned}$$

therefore

$$\begin{aligned} \mathbb{E}[(\Delta\mathcal{L}_{t+k,t}\ )h_t] &= \mathbb{E}\left[h_t(\mathcal{L}(Y_{t+k}, y_t^p(k)))\right] - \mathbb{E}\left[h_t\mathcal{L}(Y_{t+k}, b_t(k)))\right] \\ &= \Pr\left[\{(sign(Y_{t+k} - Y_t) \neq sign(y_t^p(k) - Y_t)|C\} \Pr\left[C\right]\right] - \\ &\quad \Pr\left[\{(sign(Y_{t+k} - Y_t) \neq sign(b_t(k) - Y_t)|C\} \Pr\left[C\right]\right] \end{aligned}$$

$$\begin{aligned} \mathbb{E}[h_t\Delta\mathcal{L}_{t+k,t}\ ] &= \Pr\left[C\right] \Pr\left\{(sign(Y_{t+k} - Y_t) \neq sign(y_t^p(k) - Y_t)|C\right\} \\ &\quad - \Pr\left[C\right] \Pr\left\{(sign(Y_{t+k} - Y_t) \neq sign(b_t(k) - Y_t)|C\right\} \end{aligned}$$

This expression shows that the expected value of the loss function difference times the testing function h_t is proportional to the difference in the rate of failure in predicting the direction of change of future MPR, conditioned on the Board actually communicating a forecast. Most of our analysis uses this econometric framework, comparing rates of failure of two competing predictors.

In the next two subsections we show explicitly that the null of the Giacomini and White (2006) approach translate into very simple conditions for two leading cases amongst our benchmarks. We analyze the special case of the uniform distribution and the case of a martingale difference model for monthly changes in MPR.

4.5 The Special Case of the Uniform Distribution

One of the benchmarks we are using to compare the predictive ability of the c-bias is a "pure luck" model. In other words we would like to see if the assessment of the Board is better than pure luck. Therefore we consider a model in which statements about the future stance of monetary policy are generated independently by a random number generator. This random device associates equal probabilities (of $\frac{1}{3}$) to the possible future outcomes: tightening, easing and no change. An obvious problem with these forecasts is that we did not observe them during the sample period. Nevertheless, a little algebra allows us to properly write down the null hypothesis in Giacomini and White (2006) for this "pure luck" model in a very simple manner.

Proposition 1 *Let us consider the following random forecasting device:*

$$\begin{aligned} r(Y_t) &= \left\{ \begin{array}{ccc} Y_t+\epsilon & \textit{with} & \Pr(r(Y_t)=Y_t+\epsilon)=\frac{1}{3} \\ Y_t & \textit{with} & \Pr(r(Y_t)=Y_t)=\frac{1}{3} \\ Y_t-\epsilon & \textit{with} & \Pr(r(Y_t)=Y_t-\epsilon)=\frac{1}{3} \end{array} \right\} \\ \epsilon &> 0 \end{aligned}$$

where Y_t represents the actual MPR at time t. This random device provides forecasts for the future level of monetary policy. Then the null hypothesis in Giacomini and White (2006) could be expressed as follows:

$$H_0 : \mathbb{E}[\mathcal{L}(Y_{t+k}, b_t(k))] = \frac{2}{3}$$

for the unconditional case, and

$$\begin{aligned} H_0 &: \mathbb{E}[\mathcal{V}(Y_{t+k}, b_t(k))] = 0 \\ \mathcal{V}(Y_{t+k}, b_t(k)) &= \frac{2}{3}h_t - h_t\mathcal{L}(Y_{t+k}, b_t(k)) \end{aligned}$$

when the testing function h_t is given by

$$h_t(\textit{c-bias}_t) = \begin{cases} 1 & \textit{if c-bias}_t \textit{ is not neutral} \\ 0 & \textit{otherwise} \end{cases}$$

Proof. See the appendix. ■

4.6 The Special Case of the Martingale Difference Model for Changes in MPR

We also explore the predictive ability of the c-bias with respect to another simple benchmark: a martingale difference model for monthly changes in MPR. That is to say we consider the following model:

$$\begin{aligned} MPR_{t+1} - MPR_t &= MPR_t - MPR_{t-1} + \xi_{t+1} \\ \mathbb{E}(\xi_{t+1}|I_t) &= 0 \\ I_t &= \{\text{information available at time } t\} \end{aligned}$$

With this model, we have

$$\mathbb{E}(MPR_{t+k} - MPR_t|I_t) = k\,[MPR_t - MPR_{t-1}]$$

and therefore we have the following predictor for the monetary policy rate at time $t+k$:

$$y_t^p(k) \equiv \mathbb{E}(MPR_{t+k}|I_t) = MPR_t + k\,[MPR_t - MPR_{t-1}]$$

so

$$\mathcal{L}(MPR_{t+k}, y_t^p(k)) = \left\{ \begin{array}{lll} 1 & \text{if} & sign(MPR_{t+k} - MPR_t) \neq sign(k\,[MPR_t - MPR_{t-1}]) \\ 0 & & \text{otherwise} \end{array} \right\}$$

In the next section we will see the results of our horse race between the c-bias and all the benchmarks we are considering.

5 Empirical Results

Figure 2 shows the rate of success in predicting future changes of MPR using the c-bias. Yellow bars indicate the unconditional rate of success including those episodes in which the c-bias is neutral. The blue bars show the rate of success conditional on the CBCh issuing a signal (non neutral c-bias). As the c-bias is a forecast with no specific forecasting horizon, we explore predictability up to twelve months ahead, horizon we think is long enough to capture the policy relevant predictability of the c-bias. The blue bars show an increasing conditional rate of success peaking at more than 80% in the fourth month[6]. This rate of success is slightly lower at longer

[6] This is in contrast with the yellow bars which show a decreasing rate of succes as the forecasting horizons lenghtens. We do not pay much attention to these results because they are obtained assuming that a neutral c-bias is predicting a no change in MPR, which is not correct because most of the times (98%) a neutral c-bias coresponds to no signal whatsoever.

horizons. These high rates suggest that the c-bias is a strong signal of the CBCh future deeds. Nevertheless, with this simple analysis it is not clear whether this rate of success is something easy or hard to achieve. To have a clearer picture regarding this point, in this section we compare the c-bias as a predictor of the future direction of MPR vis à vis different models. We use the Giacomini and White (2006) framework outlined in the previous section and focus on the testing function given in (5)

5.1 Does communicational bias contain relevant information?

We start by considering a simple model assuming that the MPR follows a martingale difference process. Table (1) shows the results of this analysis. The core statistic in the second column of Table (1) is proportional to the difference in the rate of failure in predicting the direction of change of future MPR, conditioned on the Board actually communicating a forecast. The third and fourth column provide information about the standard errors and the corresponding t-statistics. A positive value of the core statistic means that the loss function associated to the martingale is greater than that associated to the c-bias, and consequently that the former has a higher failure probability in forecasting the direction of change of MPR than the latter. We see this is indeed the case for all forecasting horizons. Furthermore, results are statistically significant in favor of the c-bias for every single horizon with exception of the first one which is only marginally significant at usual significance levels. The c-bias variable then, seems to be more than irrelevant information.

A martingale difference model for the MPR, in essence predicts that future monetary policy rate will not change. An alternative basic benchmark would be to compare the predictive ability of the c-bias with a random experiment that imputes equal probabilities (of 1/3) to the possible future outcomes. These results are shown in Table (2) and only reinforce our previous conclusion: the c-bias does contain statistically significant information to predict future MPR for every single horizon.

Finally, we explore the predictive ability of the c-bias with respect to another simple benchmark: a martingale difference model for monthly changes in MPR. Table (3) shows our results when using the testing function (5). We can see that for all horizons, except the first one, the c-bias is statistically a better forecasts that this latter benchmark. Yet, at the first horizon, both methods are statistically indistinguishable.

5.2 Ordered Response Taylor Rule Model

C-bias predicts future changes of direction of MPR. But to what extent is not the c-bias just a proxy of macro variables that are commonly followed by central banks? Next, we turn to a much more acid test for c-bias' predictive ability. We take as a benchmark a discrete linear model inspired in a standard Taylor rule. We impose this structure based on the fact that we are assuming that future policy rates will change in discrete multiples of 25 b.p. as it has been usual in the past. Let $\Delta r_{t+k,t}$ stand for the possible MPR changes in the period ranging from t to $t+k$, and let k be the forecasting horizon. During k periods, MPR can change in any direction, and in several magnitudes. Let $J(k,t)$ be the number of possibilities of change in MPR, which depend on both, k and t. To make this clearer, take the MPR from July 2003 to June 2007, and let $k=2$. In such 4 year period and forecast horizon, Δr_h took 6 values {-1%, -0.5%, -0.25%, 0, +0.25%, +0.5%}, thus $J=6$. As the forecast horizon becomes larger, so does the number of possibilities of change, and its' extreme values. We use a ordered-probit model to generate our forecasts using information on inflation and output.

Ordered response models for $\Delta r_{t+k,t}$ can be derived from a latent variable model. Let $\Delta r^*_{t+k,t}$ be a latent variable

$$\Delta r^*_{t+k,t} = X_t\beta + e_{t+k} \qquad\qquad e_{t+k} \sim \mathcal{N}(0.1) \tag{6}$$

where β is $k \times 1$ and, X_t does not contain a constant. Let $\mu_1 < \mu_2 < \ldots\ \mu_J$ be threshold parameters, and define (for our example)

$$\begin{array}{llccl}
\Delta r = -1.00\% & \text{if} & & \Delta r^* & < \mu_1 \\
\Delta r = -0.50\% & \text{if} & \mu_1 < & \Delta r^* & < \mu_2 \\
\vdots & \vdots & & \vdots & \\
\Delta r = +0.50\% & \text{if} & & \Delta r^* & > \mu_{J-1}
\end{array} \tag{7}$$

Thus we can define the (conditional) probability distribution function for Δr_h very easily given that Δr_h can take a limited set of values.

$$\begin{array}{lcccl}
P(\Delta r = -1.00\%|\mathbf{x}) & = & P(\Delta r^* \leq \mu_1|\mathbf{x}) & = & P(\mathbf{x}\beta + e \leq \mu_1|\mathbf{x}) = \Phi(\mu_1 - \mathbf{x}\beta) \\
P(\Delta r = -0.50\%|\mathbf{x}) & = & P(\mu_1 < \Delta r^* \leq \mu_2|\mathbf{x}) & = & \Phi(\mu_2 - \mathbf{x}\beta) - \Phi(\mu_1 - \mathbf{x}\beta) \\
\vdots & & & & \\
P(\Delta r = +0.25\%|\mathbf{x}) & = & P(\mu_4 < \Delta r^* \leq \mu_5|\mathbf{x}) & = & \Phi(\mu_5 - \mathbf{x}\beta) - \Phi(\mu_4 - \mathbf{x}\beta) \\
P(\Delta r = +0.50\%|\mathbf{x}) & = & P(\Delta r^* > \mu_5|\mathbf{x}) & = & 1 - \Phi(\mu_5 - \mathbf{x}\beta)
\end{array}$$

We can estimate the parameters μ and β through Maximum Likelihood (ML) and use these ML estimates $\widehat{\beta}$ to compute fitted values for $\widehat{\Delta r_h^*}$, and the ML estimates $\widehat{\mu}$ to infer a discrete response of Δr_h.

5.2.1 Functional Forms

Assume the standard Taylor Rule (Taylor, 1993, Woodford, 2003)

$$i_t = c + \alpha(\pi_t - \overline{\pi}) + \beta(y_t - y_t^p) + \varepsilon_t \tag{8}$$

where $\overline{\pi}$ is the rate of inflation target, π_t is current inflation (change in the log CPI over the previous twelve months), i_t is the annualized policy rate (MPR), and $(y_t - y_t^p)$ is output gap, which we will abbreviate in y_t^G. Assume we can add persistence to the process to make a better description of the data (Judd and Rudebusch, 1998). Then, if we take persistence-augmented equation (8) for period $t+h$ and subtract from it equation (8) we obtain,

$$i_{t+h} - i_t = \rho(i_{t+h-1} - i_{t-1}) + \alpha(\pi_{t+h} - \pi_t) + \beta(y_{t+h}^G - y_t^G) + \varepsilon_{t+h} - \varepsilon_t \tag{9}$$

expression which clearly depends on unrealized data ($t+h > t+h-1 > t$). We need an expression that links $i_{t+h} - i_t$ to available data at time t. Thus we iterate on the first term in equation (9), assuming inflation and output gap can be approximated with AR(p) processes, and finding an expression in which $i_{t+h} - i_t$ depends only on data available at time t

$$\begin{aligned} i_{t+h} - i_t \;=\; & \rho^h(i_t - i_{t-h}) + \rho^{h-1}\alpha(\pi_{t+1} - \pi_{t-h+1}) + \rho^{h-1}\beta(y_{t+1}^G - y_{t-h+1}^G) \\ & + \cdots \\ & + \rho\alpha(\pi_{t+h-1} - \pi_{t-1}) + \rho\beta(y_{t+h-1}^G - y_{t-1}^G) \\ & + \alpha(\pi_{t+h} - \pi_t) + \beta(y_{t+h}^G - y_t^G) \\ & + \rho^{h-1}(\varepsilon_{t+1} - \varepsilon_{t-h+1}) + \ldots + \rho(\varepsilon_{t+h-1} - \varepsilon_{t-1}) + \varepsilon_{t+h} - \varepsilon_t \end{aligned}$$

now assume we can, for instance, approximate $(\pi_{t+1} - \pi_{t-h+1})$ with an AR(1) process. Then

$$(\pi_{t+1} - \pi_{t-h+1}) = \phi_\pi(\pi_t - \pi_{t-h}) + v_{t+1} \tag{10}$$

and we can do the same with the output gap $h-$period change,

$$(y_{t+1}^G - y_{t-h+1}^G) = \phi_y(y_t^G - y_{t-h}^G) + \omega_{t+1} \tag{11}$$

Iterating on these results, we can get rid off of unavailable information to date t in equation (9) and obtain

$$i_{t+h} - i_t = \widetilde{\rho}(i_t - i_{t-h}) + \widetilde{\alpha}(\pi_t - \pi_{t-h}) + \widetilde{\beta}(y_t^G - y_{t-h}^G) + \xi_{t+1,t+h} \tag{12}$$

where $\xi_{t+1,t+h}$ is a function of the shocks $\varepsilon_{t+1,..,}\varepsilon_{t+h;}\ \nu_{t+1,..,}\nu_{t+h}$ and $\omega_{t+1,..,}\omega_{t+h}$. We use this final expression in equation (6) as the model governing the latent variable in the determination of the discrete response Taylor Rule.

5.2.2 Predictive Ability Tests

Next we turn to using the model in (6) and (12) to generate threshold parameters μ_i. Then we use the fitted model with actual data and save the corresponding discrete forecast as in (7). The estimation procedure uses the first observations in the sample. We take a rolling estimation window of 40 observation. Then we compute 1 to 12 month ahead forecast to build pseudo-out-of-sample forecasts errors. We use the prefix pseudo because in this experiment we are not using the vintages of the output gap. We are working with revised data which is the only source of noise that makes our exercise different from a real time experiment[7].

Clearly, we confront a trade-off between estimation accuracy and the number of observations we can use in the predictive ability tests. We think that 40 observations (around 50%) of the sample is appropriate for estimation purposes. Figure 3 shows how the forecasts of the discrete Taylor rule look like. Unlike the simpler martingale models, this model can predicts positive as well as negative future changes of ΔMPR depending on the horizon for a given period in time t; e.g. we can see that for January 2005 the model predicts a small increase in the MPR that is reversed after 6 months and then gives room to a major monetary policy easing.

Next, we augment the model with the c-bias and obtain similar forecasts. In particular, we use the following model

$$i_{t+h} - i_t = \widetilde{\rho}(i_t - i_{t-h}) + \widetilde{\alpha}(\pi_t - \pi_{t-h}) + \widetilde{\beta}(y_t^G - y_{t-h}^G) + \theta Tb_t(k) + \xi_{t+h} \tag{13}$$

where

$$Tb_t(k) = \begin{cases} 1 & \text{if} \quad \text{c-bias}_t \text{ is upward biased for all } k = 1, 2, ... \\ 0 & \text{if} \quad \text{c-bias}_t \text{ is neutral for all } k = 1, 2, ... \\ -1 & \text{if} \quad \text{c-bias}_t \text{ is downward biased for all } k = 1, 2, ... \end{cases}$$

[7] Barbara Rossi and Claudio Soto pointed out that all our experiments were pseudo-out-of-sample because we did not get the real time version of the c-bias.

Once we have forecasts that exclude and include c-bias information, we compare the predictive ability of the two equations in Table (4). Positive values of the core statistic indicate that the non-augmented model is on average less accurate in predicting the direction of change of MPR than the c-bias-augmented model. We see that, with the exception of the first horizon, in which no statistically significant evidence is found, our statistic is indeed positive and we can confidently reject the null in favor of the c-bias for 2 to 8 and 12 months ahead.

5.3 The c-bias and the forward rate

In this section we compare the c-bias' predictive ability to that of the forward rate[8]. Results in Table (5) indicate that in those episodes in which the c-bias is not neutral the forward rate and the c-bias have statistically equal predictive ability, a result similar to that in Rosa and Verga (2007) for the EU[9]. This result means that on average the c-bias and the forward rate are equally accurate in predicting future changes in MPR. Nevertheless it is possible that the information in the c-bias could still be useful to improve the forward rate predictive ability. We assess this possibility next.

5.3.1 Could the c-bias improve forward-rate market expectations?

If the forward rate curve is the best predictor of MPR under quadratic loss, based on available information at time t, then other macro variables known up to t and useful for prediction should be orthogonal to its prediction error. If this should happen not to be true, we could improve the predictive ability of the forward rate by using these other variables. In particular, if the c-bias (when not neutral) contains valuable information to minimize this error, then the following conditional expectation should be different from zero.

$$\mathbb{E}[e_t^f(k)|\text{c-bias}_t \;\wedge\; \text{c-bias}_t \text{ is not neutral}] \neq 0 \tag{14}$$

where

$$e_t^f(k) = MPR_{t+k} - f_t(k)$$

[8] Data for the forward rates are based on the estimations of the yield curve performed by RiskAmerica. This data is available only after October 2002

[9] We also explore the ability od the c-bias to predict changes in MPR when the c-bias is neutral. Results in Table (6) indicate that in those episodes in which the c-bias is neutral, the forward rate is outperformed by the c-bias only in the first two horizons. The c-bias and the forward rate are statistically equal forecasts when predicting from 3 to 6 months ahead. At longer horizons the c-bias when neutral is outperformed by the forward rate.

represents the forward curve based forecasting error at time $t+k$, and $f_t(k)$ corresponds to the monetary policy rate forecast at time $t+k$ coming from the forward curve. It turns out that (14) is equivalent to

$$\mathbb{E}[e_t^f(k)|Tb_t(k) \wedge \{h_t = 1\}] \neq 0 \tag{15}$$

Under the assumption that the conditional expectation of $e_t^f(k)$ with respect to $Tb_t(k)$ is piecewise linear we have

$$\mathbb{E}[e_t^f(k)|Tb_t(k)] = \beta_1(k)d_{1t} + \beta_0(k)d_{0t} + \beta_{-1}(k)d_{-1t} \tag{16}$$

where

$$\begin{aligned} d_{1t} &= \left\{ \begin{array}{ll} 1 & \text{if c-bias}_t \text{ is upward biased} \\ 0 & \text{otherwise} \end{array} \right\} \\ d_{0t} &= \left\{ \begin{array}{ll} 1 & \text{if c-bias}_t \text{ is neutral} \\ 0 & \text{otherwise} \end{array} \right\} \\ d_{-1t} &= \left\{ \begin{array}{ll} 1 & \text{if c-bias}_t \text{ is downward bias} \\ 0 & \text{otherwise} \end{array} \right\} \end{aligned}$$

so

$$\mathbb{E}[e_t^f(k)|Tb_t(k); \{h_t = 1\}] = \left\{ \begin{array}{ll} \beta_1(k) & \text{if c-bias}_t \text{ is upward biased} \\ \beta_{-1}(k) & \text{if c-bias}_t \text{ is downward biased} \end{array} \right\} \tag{17}$$

therefore, evidence of statistically significant coefficients $\beta_1(k)$ and $\beta_{-1}(k)$ would indicate the rejection of the null hypothesis

$$H_0 : \mathbb{E}[e_t^f(k)|Tb_t(k) \wedge \{h_t = 1\}] = 0 \tag{18}$$

and therefore that the c-bias provides useful information for financial agents to predict MPR.

Figure (4) shows the results of this exercise; i.e. shows $\beta_1(k)$ and $\beta_{-1}(k)$, and their respective 10% HAC-confidence interval for one sided tests. Under the null hypothesis of forecast errors being indeed errors, then $\beta_1(k) = \beta_{-1}(k) = 0$. We find that a tightening c-bias is associated with under prediction of the forward rate for the first four consecutive months. That is, positive c-bias indicates that the forward rate should adjust upwards to re-center the mean of $e(t+h)$ back to zero. In terms of the beta coefficients, we find that $\beta_1(1)$, $\beta_1(2)$ and $\beta_1(3)$ are statistically different from zero indicating evidence of information contained in the c-bias that could be useful to improve forecasts from the forward curve. Similar results hold true when the c-bias signals an easing in monetary policy. In this case a downward c-bias is associated with over prediction of the forward rate for the first six consecutive months. Differing from the previous case, now the size of the revision suggested by our analysis is much bigger than before. In terms of the beta coefficients, we find that $\beta_{-1}(1)$, $\beta_{-1}(2)$, $\beta_{-1}(3)$, $\beta_{-1}(4)$ and $\beta_{-1}(5)$ are statistically different from zero indicating evidence of information contained in the c-bias that could be useful to improve forecasts from the forward curve.

We check for robustness of these results by augmenting equation (16), first, with the actual change in MPR and, second, with the actual change in MPR and one lag[10]. We do this because evidence of statistically significant coefficients might be the result of the omission of the actual change in MPR and this variable could be the real drive of our previous results. We run two additional augmented regressions and report in figure (5) robust estimates of the coefficients using a Bayesian Model Averaging (BMA) strategy following Brock and Durlauf (2001)[11]. We still find some statistically significant coefficients, but the evidence is weaker than before. Now a tightening c-bias is associated with statistically significant under prediction of the forward rate only at the first month. Similarly, an easing c-bias is associated with statistically significant over prediction of the forward rate only at the second and third months. In spite of this reduction in the number of statistically significant coefficients, our robust strategy indicate that the c-bias seems to contain valuable information to improve the short end forward curve's predictive ability.

6 Conclusions

Monetary Policy under Inflation Targeting relies heavily on the credibility a central bank can build over time. Presumably, this credibility enhances the efficiency of monetary policy and ultimately results in welfare gains. Thus, transparent communication with the public is an ever-growing practice among policy makers that complements their decisions of interest rate setting. In this paper we examine one feature of the communicational practice of the Central Bank of Chile contained in the press releases published immediately after monetary policy meetings: the assessment of

[10] Results from the first augmented regression show statistically significant coefficients only when the c-bias signal an easing in monetary policy. In this case $\beta_{-1}(2)$ and $\beta_{-1}(3)$ are statistically different from zero. In the second augmented regression, in addition to these two coefficients, we find that $\beta_1(1)$ is also statistically significant at the 10% significance level.

[11] A detailed description of the BMA strategy is attached in the appendix.

the Board about the most likely future of monetary policy (communicational-bias). We argue that should this variable provide information about future MP changes –beyond that incorporated in macroeconomic variables–, then it should be taken into account by economic agents when forming expectations and thereby affect key macroeconomic variables and asset prices. In this paper we test whether c-bias indeed provides such information, matching words and deeds in a 12-month-horizon forecasting exercise, by comparing forecast accuracy vis à vis several benchmarks.

We expand the previous literature in several ways. First, we assemble a novel database for a qualitative variable which is extremely rare among emerging economies. Second, our analysis is, to our knowledge, the first to use formal out-of-sample tests of predictive ability –in contrast to considering goodness of fit alone–. Third, we explore a new dimension in Central Bank performance: the time consistency of communication strategy.

Our results indicate that the c-bias is a strong signal of the CBCh future deeds, with a conditional rate of success peaking higher than 80% in the fourth month. We also show that the c-bias predicts more accurately future MPR changes than two martingale models and than a random "bias" generator. Furthermore, the pseudo-out-of-sample predictive ability of a more sophisticated model that considers inflation and output (as central banks do) can be outperformed by its c-bias augmented version at several horizons. Even though the c-bias is on average equally accurate as the forward rate curve in predicting future MPR changes, we also show that the c-bias contains useful information that should improve the forecasting ability of the short end of the forward curve.

These empirical results indicate that the accuracy of the c-bias in predicting the future direction of MPR is high, and that none of the alternative benchmarks we have considered in this paper are able to outperform the c-bias or the c-bias augmented version of the corresponding benchmark. This evidence is consistent with a strong ability of the c-bias to predict the future direction of MPR which is a necessary condition for the c-bias to have an impact on macro variables.

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A Proofs

A.1 Proposition 1

We are considering the following random forecasting device:

$$\begin{aligned} r(Y_t) &= \left\{ \begin{array}{ccc} Y_t + \epsilon & \text{with} & \Pr(r(Y_t) = Y_t + \epsilon) = \frac{1}{3} \\ Y_t & \text{with} & \Pr(r(Y_t) = Y_t) = \frac{1}{3} \\ Y_t - \epsilon & \text{with} & \Pr(r(Y_t) = Y_t - \epsilon) = \frac{1}{3} \end{array} \right\} \\ \epsilon &> 0 \end{aligned}$$

where Y_t represents the actual MPR at time t. It has a loss given by

$$\mathcal{L}(Y_{t+k}\,, r(Y_t)) = \left\{ \begin{array}{lcc} 1 & \text{if} & sign(Y_{t+k} - Y_t) \neq sign(r(Y_t) - Y_t) \\ 0 & & \text{otherwise} \end{array} \right\}$$

but

$$sign(r(Y_t) - Y_t) = \left\{ \begin{array}{ccc} sign(\epsilon) = 1 & \text{with} & \text{probability } \frac{1}{3} \\ sign(0) = 0 & \text{with} & \text{probability } \frac{1}{3} \\ sign(-\epsilon) = -1 & \text{with} & \text{probability } \frac{1}{3} \end{array} \right\}$$

Let us recall that

$$\mathbb{E}\mathcal{L}(Y_{t+k}\,, r(Y_t)) = \Pr(sign(Y_{t+k} - Y_t) \neq sign(r(Y_t) - Y_t))$$

and consider the following notation

$$\begin{aligned} S_{k,t} &= sign(Y_{t+k} - Y_t) \\ Sr &= sign(r(Y_t) - Y_t) \end{aligned}$$

then

$$\Pr(sign(Y_{t+k} - Y_t) \neq sign(r(Y_t) - Y_t)) = \Pr(S_{k,t} \neq Sr)$$

Let us calculate this probability:

$$\Pr(S_{k,t} \neq Sr) = \sum_{i=-1}^{1} \Pr((S_{k,t} \neq Sr)\,|Sr = i) \Pr(Sr = i)$$

but

$$\Pr(Sr = i) = \Pr(sign(r(Y_t) - Y_t) = i) = \frac{1}{3}, \quad i = -1, 0, 1$$

therefore

$$\begin{aligned}
\Pr(S_{k,t} &\neq Sr) = \frac{1}{3}\sum_{i=-1}^{1}\Pr((S_{k,t}\neq Sr)\,|Sr=i) \\
\Pr(S_{k,t} &\neq Sr) = \frac{1}{3}\sum_{i=-1}^{1}\Pr(S_{k,t}\neq i) \\
\Pr(S_{k,t} &\neq Sr) = \frac{1}{3}\left(\Pr\left[S_{k,t}\in\{0,1\}\right]+\Pr\left[S_{k,t}\in\{-1,1\}\right]\right)+ \\
&+\Pr\left[S_{k,t}\in\{-1,0\}\right] \\
\Pr(S_{k,t} &\neq Sr) = \frac{2}{3}\left(\Pr\left[S_{k,t}=-1\right]+\Pr\left[S_{k,t}=0\right]+\Pr\left[S_{k,t}\in 1\right]\right) \\
\Pr(S_{k,t} &\neq Sr) = \frac{2}{3}
\end{aligned}$$

Therefore, if we take the testing function $h_t = 1$, then the null hypothesis

$$H_0 : \mathbb{E}[\mathcal{L}(Y_{t+k}\ , r(Y_t)) - \mathcal{L}(Y_{t+k}, b_t(k))]h_t = 0 \tag{19}$$

is equivalent to

$$H_0 : \mathbb{E}[\mathcal{L}(Y_{t+k}, b_t(k))] = \frac{2}{3}$$

Let

$$\mathcal{X}(Y_{t+k}, b_t(k)) = 1 - \mathcal{L}(Y_{t+k}, b_t(k))$$

then

$$H_0 : \mathbb{E}[\mathcal{X}(Y_{t+k}, b_t(k))] = \frac{1}{3}$$

Notice that $\mathcal{X}(Y_{t+k}, b_t(k))$ is a Bernoulli random variable with expected value equal to the probability of the c-bias succeeding in predicting the direction of change in future monetary policy rates. Under regularity assumptions (see last footnote at the end of this proof) we will have that, given k:

$$\begin{aligned}
\frac{\sqrt{n}\frac{1}{n}\sum\limits_{t=1}^{n}\left[\mathcal{X}(Y_{t+k}, b_t(k)) - \frac{1}{3}\right]}{\overline{\sigma}} &\overset{A}{\rightsquigarrow} N(0,1) \\
\overline{\sigma}^2 &= \lim_{n\to\infty} var(\sqrt{n}\frac{1}{n}\sum_{t=1}^{n}\mathcal{X}(Y_{t+k}, b_t(k)) < \infty
\end{aligned}$$

We are not really interested in using the testing function $h_t = 1$. When using the relevant testing function

$$h_t = \left\{ \begin{array}{lc} 1 \quad \text{if} & \text{c-bias is not neutral} \\ 0 & \text{otherwise} \end{array} \right\}$$

the null hypothesis in (19) is different. We notice that

$$\mathbb{E}\mathcal{L}(Y_{t+k}\ , r(Y_t))h_t = \Pr((sign(Y_{t+k}\ - Y_t) \neq sign(r(Y_t) - Y_t)) \cap (h_t = 1))$$

this is nothing but the probability of making a mistaken forecast when the c-bias is not neutral. Let us consider the following set C

$$C = \{\text{c-bias}_t \neq \text{neutral}\} = \{h_t = 1\}$$

then

$$\begin{aligned} & \Pr((sign(Y_{t+k}\ - Y_t) \neq sign(r(Y_t) - Y_t)) \cap (h_t = 1)) \\ = \ & \Pr(\{S_{k,t} \neq Sr\} \cap C) \end{aligned}$$

so

$$\mathbb{E}\mathcal{L}(Y_{t+k}\ , r(Y_t))h_t = \Pr(\{S_{k,t} \neq Sr\} \cap C)$$

Let us calculate this probability:

$$\Pr(\{S_{k,t} \neq Sr\} \cap C) = \sum_{i=-1}^{1} \Pr(\{S_{k,t} \neq Sr\} \cap C | Sr = i) \Pr(Sr = i)$$

but

$$\Pr(Sr = i) = \frac{1}{3}, \quad i = -1, 0, 1$$

therefore

$$
\begin{aligned}
\Pr(\{S_{k,t} \neq Sr\} \cap C) &= \frac{1}{3}\sum_{i=-1}^{1} \Pr((\{S_{k,t} \neq Sr\} \cap C)\,|Sr = i) \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{1}{3}\sum_{i=-1}^{1} \Pr(\{S_{k,t} \neq i\} \cap C) \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{1}{3}\sum_{i=-1}^{1} \Pr(\{S_{k,t} \neq i\}\,|C) \Pr(C) \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{1}{3}\Pr(C)\sum_{i=-1}^{1} \Pr(\{S_{k,t} \neq i\}\,|C) \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{1}{3}\Pr(C)\left(\Pr\left[S_{k,t} \in \{0,1\}\,|C\right] + \Pr\left[S_{k,t} \in \{-1,1\}\,|C\right]\right) + \\
&\quad + \frac{1}{3}2\Pr(C)\Pr\left[S_{k,t} \in \{-1,0\}\,|C\right] \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{1}{3}\Pr(C)\left(2\Pr\left[S_{k,t} = -1|C\right] + 2\Pr\left[S_{k,t} = 0|C\right]\right) \\
&\quad + \frac{1}{3}2\Pr(C)\Pr\left[S_{k,t} \in 1|C\right] \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{2}{3}\Pr(C)\left(\Pr\left[S_{k,t} = -1|C\right] + \Pr\left[S_{k,t} = 0|C\right] + \Pr\left[S_{k,t} \in 1|C\right]\right) \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{2}{3}\Pr(C)\Pr\left[S_{k,t} \in \Omega|C\right]) \\
\Pr(\{S_{k,t} \neq Sr\}) &= \frac{2}{3}\Pr(C) = \frac{2}{3}\mathbb{E}h_t
\end{aligned}
$$

Therefore, the null hypothesis

$$H_0 : \mathbb{E}\left[\mathcal{L}(Y_{t+k}\,, r(Y_t)) - \mathcal{L}(Y_{t+k}, b_t(k))\right] h_t = 0$$

is equivalent to

$$H_0 : \frac{2}{3}\mathbb{E}h_t = \mathbb{E}[h_t\mathcal{L}(Y_{t+k}, b_t(k))]$$

Let

$$\mathcal{V}(Y_{t+k}, b_t(k)) = \frac{2}{3}h_t - h_t\mathcal{L}(Y_{t+k}, b_t(k))$$

then

$$H_0 : \mathbb{E}[\mathcal{V}(Y_{t+k}, b_t(k))] = 0$$

Under standard assumptions for the central limit theorem for dependent observations we will have that, given k[12]:

$$\frac{\sqrt{n}\frac{1}{n}\sum_{t=1}^{n}\left[\mathcal{V}(Y_{t+k}, b_t(k))\right]}{\overline{\sigma}} \overset{A}{\rightsquigarrow} N(0,1)$$

$$\overline{\sigma}^2 = \lim_{n\to\infty} var(\sqrt{n}\frac{1}{n}\sum_{t=1}^{n}\mathcal{V}(Y_{t+k}, b_t(k)) < \infty$$

B Bayesian Model Averaging

As Brock and Durlauf (2001) argue, the standard econometric approach in the literature relies upon the choice of a particular model M, which is considered a good approximation of the "true model". Given a data set D and the chosen model M, estimates of the parameters β of interest and their variances can be obtained. The analogous Bayesian strategy involves the calculation of the posterior density of the parameter $\mu(\beta \mid D, M)$.

Brock and Durlauf (2001) and many others analyze the problem of model uncertainty, which basically originates in the ignorance of the researcher about the true model. Under this type of uncertainty, any estimate of the parameters of interest β will be conditioned to the particular choice of a model M. Therefore, despite of the fact that the researcher is interested in the density $\mu(\beta \mid D)$, she will be only able to uncover $\mu(\beta \mid D, M)$.

To remove the model uncertainty problem, the Bayesian approach propose the definition of a space of possible models $\mathcal{M}$. Integrating out the dependence of $\mu(\beta \mid$

[12] These standard assumptions require $\mathcal{V}(Y_{t+k}, b_t(k))$ to be a stationary ergodic mixingale with γ_m of size -1. Let us recall that a sequence $\{Z_t\}$ such that $\mathbb{E}Z_t^2 < \infty$ is a mixingale if we can find sequences of nonnegative numbers $\{a_t\}$ and $\{\gamma_m\}$ such that

$$(\mathbb{E}(\mathbb{E}(Z_t|\mathcal{F}_{t-m})^2))^{1/2} \leq a_t\gamma_m$$

and

$$\lim_{m\to\infty}\gamma_m = 0$$

where $\{\mathcal{F}_t\}$represents a filtration for which $\{Z_t\}$ is an adapted process. See White (2001) for further details.

$D, M_m)$ on the particular model $M_m \in \mathcal{M}$ leads to the unconditional density $\mu(\beta \mid D)$. To do this, Bayes theorem provides the following expression

$$\mu(\beta \mid D) = \sum_{M_m \in \mathcal{M}} \mu(\beta \mid D, M_m)\mu(M_m \mid D)$$

which reduces to

$$\mu(\beta \mid D) \propto \sum_{M_m \in \mathcal{M}} \mu(\beta \mid D, M_m)\mu(D \mid M_m)\mu(M_m)$$

where $\mu(D \mid M_m)$ is the likelihood of the data given the particular model $M_m \in \mathcal{M}$, and $\mu(M_m)$ represents the prior density defined over $\mathcal{M}$. Basically these results show that the posterior density of the parameter β is a weighted average of the conditional densities of the parameter for different assumptions about the true model. This technique is in general called Bayesian Model Averaging. (BMA)

Leamer (1978) provides expressions for the conditional expectation and variance of β given the set of data D.

$$E(\beta \mid D) = \sum_{M_m \in \mathcal{M}} \mu(M_m \mid D)E(\beta \mid D, M_m)$$

and

$$var(\beta \mid D) = E(\beta^2 \mid D) - (E(\beta \mid D))^2 =$$
$$\sum_{M_m \in \mathcal{M}} \mu(M_m \mid D)var(\beta \mid D, M_m) + \sum_{M_m \in \mathcal{M}} \mu(M_m \mid D)(E(\beta \mid D, M_m) - E(\beta \mid D))^2 \tag{20}$$

where

$$\mu(M_m \mid D) = \frac{\mu(D \mid M_m)\mu(M_m)}{\sum_{M_m \in \mathcal{M}} \mu(D \mid M_m)\mu(M_m)}$$

therefore, the conditional variance of β given the set of data D in (20) is broken down into two additive components: an intra-model variance and an across-models variance.

For numerical implementation of the BMA technique, some approximations are commonly found in the literature. The Laplace approximation described by Volinsky et al (1997) is adopted in this paper. This approximation is shown in the following equation

$$\log(\mu(D|M_m)) \approx l - d_k \log(n) \tag{21}$$

where d_k represents the number of β parameters to estimate and l denotes the log-likelihood evaluated in the estimated parameters. (21) is called the Bayesian information criterion (BIC) approximation showed by Hoeting (1999).

As Brock and Durlauf (2001) suggest we compute estimates of $E(\beta \mid D, M_m)$ and $Var(\beta \mid D, M_m)$ simply by OLS and rely on a uniform prior distribution.

C Tables and Figures

Figure 1: Communicational Bias: Easing (-1), Tightening (1) and Neutral (0)

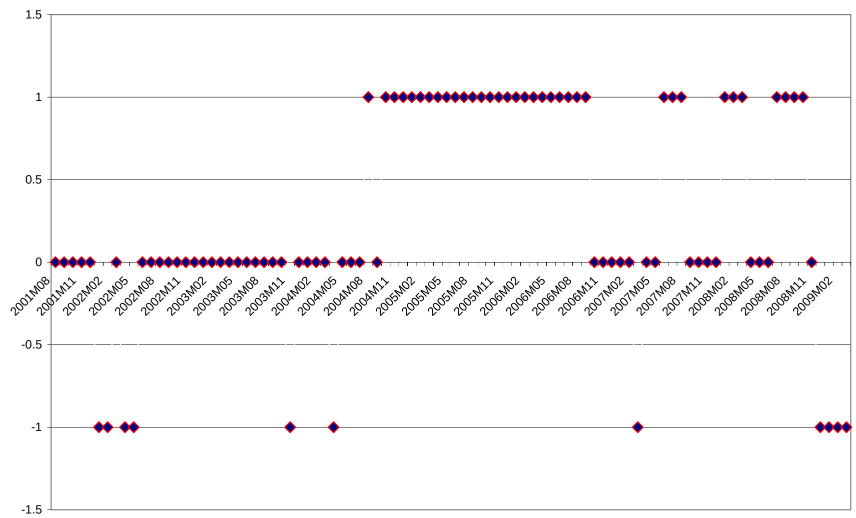


Figure 2: Conditional Success Probability of Communicational Bias

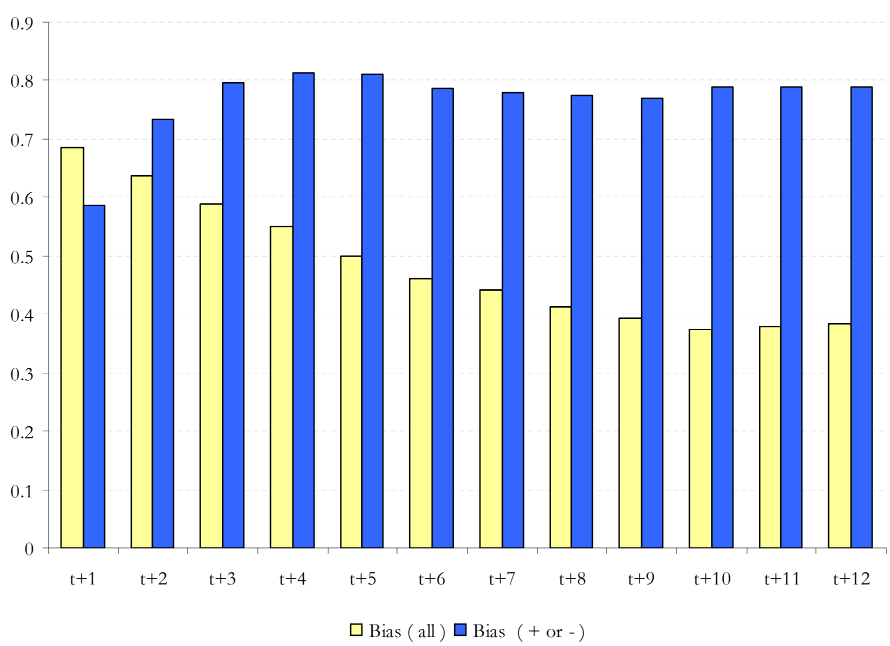


Figure 3: Forecasts (1 to 12 months ahead) of ΔMPR based on the discrete Taylor rule model.

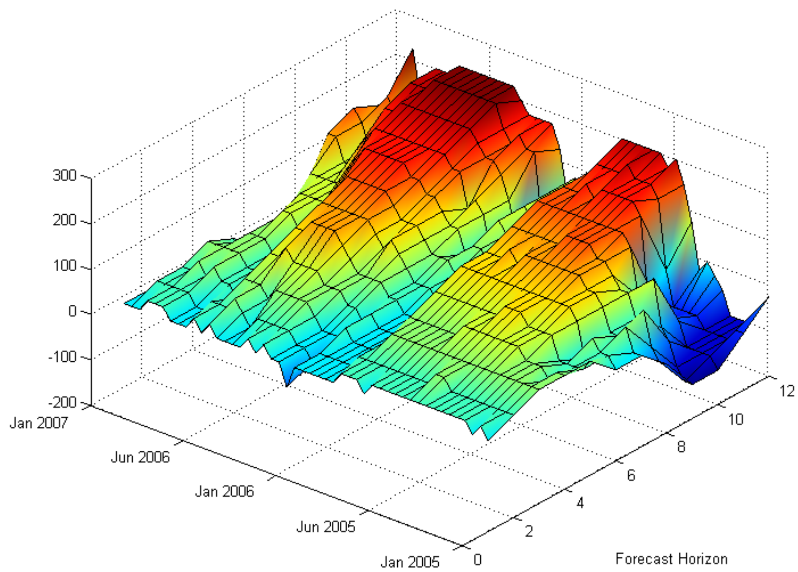
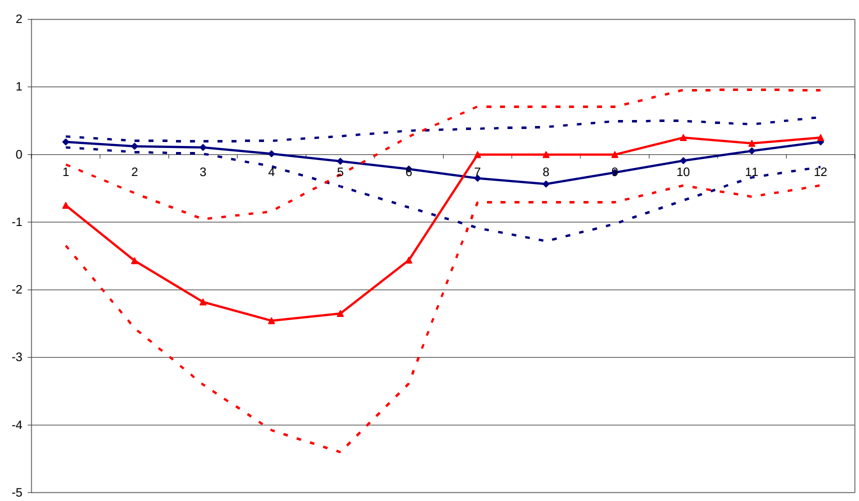


Figure 4: Coefficient estimates of forward rate forecast error regressed on communicational bias



blue line: upward bias   red line: downward bias

Figure 5: Coefficient estimates of forward rate forecast error regressed on communicational bias
Robust Estimates Using a Bayesian Model Averaging Approach

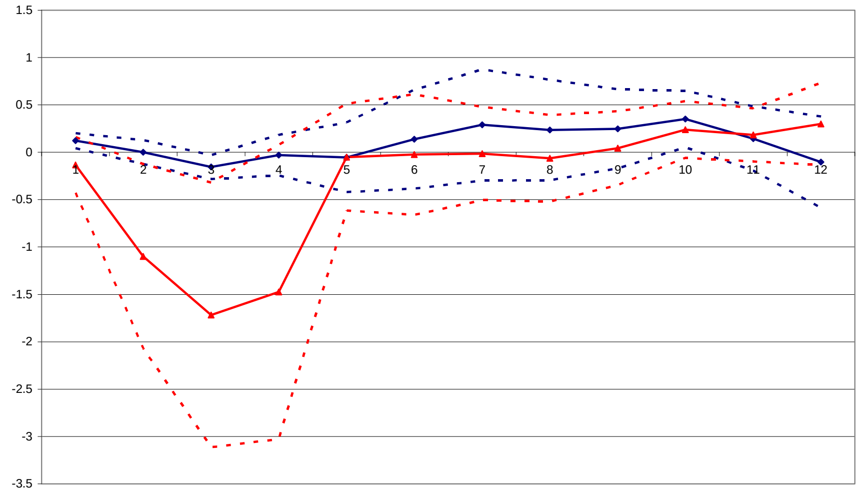


Table 1: Predictive Ability Test for the C-Bias Against a Martingale Model (1)

Forc. Hor.	Core Statistic (2)	Std. Error	T-statistic (DMW-GW)	P value
1	0.087	0.074	1.182	0.119
2	0.231	0.097	2.388	0.008
3	0.300	0.098	3.050	0.001
4	0.348	0.089	3.907	0.000
5	0.375	0.084	4.453	0.000
6	0.368	0.089	4.151	0.000
7	0.360	0.086	4.188	0.000
8	0.341	0.089	3.841	0.000
9	0.321	0.093	3.457	0.000
10	0.313	0.097	3.232	0.001
11	0.317	0.095	3.335	0.000
12	0.321	0.095	3.375	0.000

Notes:
(1) Benchmak model: Martingale: $\Delta(MPR) = 0$
(2) Positive values imply Martingale is less accurate
Monthly data: August 2001 to March 2009
Standard Errors using HAC (Newey-West 1987,1994)

Table 2: Predictive Ability Test for the C-Bias Against a Random Generator (1)

Horizon (months)	Core Statistic	Standard Error	T-statistic	P value
1	0.1268	0.0388	3.265	0.001
2	0.1978	0.0565	3.503	0.000
3	0.2259	0.0592	3.818	0.000
4	0.2322	0.0585	3.970	0.000
5	0.2273	0.0612	3.716	0.000
6	0.2184	0.0640	3.410	0.000
7	0.2132	0.0640	3.333	0.000
8	0.2078	0.0639	3.252	0.001
9	0.2024	0.0641	3.159	0.001
10	0.2088	0.0641	3.258	0.001
11	0.2114	0.0615	3.440	0.000
12	0.2140	0.0612	3.495	0.000

Notes:
One-tailed test
Monthly data: August 2001 to March 2009
Standard Errors using HAC (Newey-West 1987,1994)

Table 3: Predictive Ability Test for the C-Bias Against a Martingale Model for the Difference in MPR when the C-Bias is not Neutral (1)

Forc. Hor.	Core Statistic (2)	Std. Error	T-statistic (DMW-GW)	P value
1	0.033	0.050	0.653	0.257
2	0.077	0.058	1.331	0.092
3	0.111	0.053	2.112	0.017
4	0.157	0.049	3.233	0.001
5	0.170	0.044	3.835	0.000
6	0.172	0.045	3.850	0.000
7	0.151	0.043	3.514	0.000
8	0.129	0.048	2.674	0.004
9	0.131	0.049	2.680	0.004
10	0.120	0.053	2.274	0.011
11	0.122	0.050	2.443	0.007
12	0.136	0.047	2.878	0.002

Notes:
(1) Benchmak model: $\Delta(MPR) = \Delta(MPR_{-1})$
(2) Positive values imply benchmark model is less accurate
Monthly data: August 2001 to March 2009
Standard Errors using HAC (Newey-West 1987,1994)

Table 4: Ordered Response Taylor Rule Model

Horizon (months)	Core Statistic (2)	Std. Error	T-statistic (DMW-GW)	p-value
1	-0.020	0.082	-0.240	0.595
2	0.140	0.080	1.750	0.040
3	0.122	0.057	2.136	0.016
4	0.042	0.032	1.310	0.095
5	0.064	0.050	1.288	0.099
6	0.065	0.050	1.298	0.097
7	0.089	0.060	1.477	0.070
8	0.091	0.061	1.489	0.068
9	0.093	0.090	1.039	0.149
10	0.071	0.060	1.198	0.115
11	0.049	0.068	0.717	0.237
12	0.100	0.077	1.292	0.098

Notes:
(1) Ordered Response Taylor Rule Model v/s the same model augmented with the c-bias
Results Conditional to c-bias $\neq 0$
(2) Positive values indicate augmented model is more accurate
Monthly data January 2005- to March 2009
Standard errors using HAC (Newey-West 1987,1994)
One-tailed p value

Table 5: Predictive Ability Test for the C-Bias Against a the Forward Rate when the C-Bias is not Neutral (1)

Horizonte (meses)	Core statistic	Std. Error	T-statistic (DMW-GW)	P value
1	0.000	0.032	0.000	0.500
2	-0.013	0.028	-0.471	0.681
3	-0.026	0.030	-0.864	0.806
4	0.000	0.027	0.000	0.500
5	-0.014	0.030	-0.446	0.672
6	-0.014	0.031	-0.445	0.672
7	0.000	0.028	0.000	0.500
8	0.000	0.028	0.000	0.500
9	0.000	0.029	0.000	0.500
10	0.000	0.029	0.000	0.500
11	0.000	0.030	0.000	0.500
12	-0.015	0.026	-0.579	0.719

Notes:
(1) Alternative Model is the Forward Rate Curve
Positive Value indicates the Forward Rate is a less accurate predictor
Sample: 2002M10 to 2009M3
One tailed p-values

Table 6: Predictive Ability Test for the C-Bias Against the Forward Rate when the C-Bias is Neutral (1)

Horizonte (meses)	Core statistic	Std. Error	T-statistic (DMW-GW)	P value
1	0.333	0.062	5.348	0.000
2	0.143	0.097	1.473	0.070
3	0.013	0.105	0.125	0.450
4	-0.027	0.105	-0.254	0.600
5	-0.068	0.102	-0.662	0.746
6	-0.123	0.098	-1.264	0.897
7	-0.153	0.092	-1.663	0.952
8	-0.197	0.089	-2.218	0.987
9	-0.214	0.086	-2.503	0.994
10	-0.246	0.085	-2.897	0.998
11	-0.250	0.082	-3.046	0.999
12	-0.254	0.083	-3.059	0.999

Notes:
(1) Alternative Model is the Forward Rate Curve
Positive Value indicates the Forward Rate is a less accurate predictor
Sample: 2002M10 to 2009M3
One tailed p-values

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