# Forecast Bias of Government Agencies
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Forecasts of future economic activity underlie any budget revenue projection. However, the forecasters in a government agency may face incentives or pressures that introduce forecast bias. For example, agency forecasters may be rewarded for a rosy growth forecast that allows politicians to avoid politically costly program cuts or tax increases. Similarly they may be penalized for underforecasting economic growth. Where a reward system is asymmetric, it would make sense to observe biased forecasts.

This article evaluates real GDP forecasts of the Congressional Budget Office and the Office of Management and Budget. As a basis for comparison, the Blue Chip Consensus forecast is also evaluated. Tests in previous work assumed the forecast loss function was symmetric. This implies the political costs of a high or low GDP forecast are equal, so forecasts should be unbiased.

This article differs from previous work by conducting tests assuming the forecast loss function may not symmetric. Public choice models of political decisionmaking suggest government agencies such as the CBO and OMB face pressures that are likely to result in systematically biased forecasts. In this article, a flexible loss function allows for estimation of a parameter that captures the degree and direction of any forecast asymmetry. Elliott, Komunjer, and Timmermann (2005, 2008) show that failing to account for loss function asymmetry negatively affects tests that evaluate forecast accuracy and efficiency in the use of information available to forecasters.

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Evidence from the existing literature examining CBO and OMB forecast performance using the standard symmetric loss function is mixed. Some studies evaluate budget forecasts while others evaluate forecasts of economic activity, such as real GDP growth. Based on these efforts, three general conclusions can be drawn. First, short-run forecasts of GDP and revenues are generally unbiased while long-run forecasts of these variables have an upward bias.[1] Second, both short- and long-run forecasts of GDP and revenues usually fail tests of information use efficiency. Researchers find that forecasters do not use available information to improve their forecasts.[2] Third, despite what are likely to be different political pressures on different agencies, most of the studies find forecast biases to be similar across agencies.[3]

Using a flexible loss function to evaluate the CBO, OMB, and Blue Chip Consensus forecasts, I find significant evidence of asymmetry in the forecast loss functions. The CBO and the Blue Chip Consensus have a downward bias in their forecasts of real GDP growth two and five years out. The CBO forecast is consistent with the private sector consensus. The OMB forecast loss function is also asymmetric. However, the OMB bias is in the opposite direction. OMB forecasters overforecast real GDP growth at the two- and five-year horizons by 5 percent and 14 percent respectively. I argue that this finding is consistent with incentives facing the two agencies.

In addition, once the asymmetry of the forecast loss function is taken into account, the traditional finding that available information is not used in the forecasts is rejected in favor of the finding that government forecasters use available information efficiently. These results illustrate the importance of taking into account loss function asymmetries when evaluating the forecast performance of government agencies that are subjected to political pressures.

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[1]These studies include Kamlet, Mowery, and Su (1987), Plesko (1988), Belongia (1988), Miller (1991), Blackley and DeBoer (1993), Campbell and Ghysels (1995), McNees (1995), Auerbach (1999), Krause and Douglas (2005), and Corder (2005). Looking at Japanese data, Ashiya (2007) finds an upward bias in Japanese government forecasts of GDP. Frankel (2011a, 2011b) finds evidence of an upward bias in economic forecasts using a sample of 33 countries.

[2]Kamlet, Mowery, and Su (1987) find the forecasts of both agencies are efficient. Belongia (1988) conducts encompassing tests and finds private forecasts add information to the CBO forecast but not the executive branch forecast. This implies some inefficiency in the CBO forecast.

[3]McNees (1995) found executive branch forecasts to be less accurate than the CBO and the Federal Reserve.

This article is organized in the following manner. The first and second sections discuss testing procedures under symmetric and flexible loss functions. The third and fourth sections report the results of the tests under alternative loss functions. The fifth section articulates why loss functions would be expected to differ among the agencies in question. The article ends with a brief conclusion.

## Testing Forecast Accuracy with a Symmetric Loss Function

Underlying any forecast is a loss function. Standard forecast evaluations assume the forecast loss function to be quadratic and symmetric. A feature of this type of a loss function is that the optimal forecast is the conditional expectation, with the implication that forecasts are unbiased (Elliott, Komunjer, and Timmermann, 2005, 2008). I conduct a standard test of forecast performance by regressing the actual growth in real GDP over j periods ($\log Y_{t+j} - \log Y_t$) on the predicted growth in real GDP over j periods ($\log \hat{Y}_{t+j} - \log Y_t$):

$$(1)\ \log Y_{t+j} - \log Y_t = \alpha + \beta(\log \hat{Y}_{t+j} - \log Y_t) + \varepsilon_t,$$

where $\log Y_{t+j}$ and $\log \hat{Y}_{t+j}$ are the logarithm of real GDP and predicted real GDP in period $t+j$ respectively, $\alpha$ and $\beta$ are parameters to be estimated, and $\varepsilon_t$ is the error term, which should be uncorrelated for horizons beyond $j - 1$.[4] Under the unbiased forecast hypothesis, I test the joint null hypothesis that the parameter estimates are $\alpha = 0$ and $\beta = 1$. Rejecting the null hypothesis implies the forecasts are biased.

The second standard test examines if forecasters use available information efficiently. Past information about the economy should be uncorrelated with forecast errors. For this test, the forecast error ($\mu_t$) is regressed on information, such as past forecast errors ($\mu_{t-i}$), available at the time of the forecast:

$$(2)\ \mu_t = \nu + \tau_1 \mu_{t-1} + \tau_2 \mu_{t-2} + \xi_t,$$

where $\nu$, $\tau_1$, and $\tau_2$ are parameters to be estimated, $\xi_t$ is a white noise error term, and $\mu_{t-i}$ are past forecast errors. The joint null hypothesis tested in this case is $\nu = \tau_1 = \tau_2 = 0$. Rejecting the null hypothesis means past forecast errors could be used to reduce the current forecast error. If this is the case, researchers conclude that available information is not being used efficiently.

[4] See Mincer (1969).

## Testing Forecast Accuracy with an Asymmetric Loss Function

Elliott, Komunjer, and Timmermann (2005, 2008) develop a flexible loss function that provides an alternative method for evaluating forecasts. This approach allows the researcher to estimate a loss function parameter to determine the extent and direction of any asymmetry in the forecast loss function. As they show, ignoring asymmetry can bias forecast evaluation tests. Under certain conditions, a biased forecast can be optimal. If a low real economic growth forecast turns out to be politically more costly, an upward bias in the forecast is rational. This approach also provides an alternative test for how well forecasters use information available at the time of the forecast. Without accounting for purposeful bias in the forecast, we cannot effectively test whether forecasters use available information efficiently. Using this methodology, Elliott, Komunjer, and Timmermann (2005) find IMF and OECD budget deficit forecasts are optimal once the asymmetry is taken into account. Capistrán-Carmona (2008) uses this method to analyze the Federal Reserve's inflation forecast. In contrast to previous work, Capistrán-Carmona finds the Federal Reserve's forecasts to be optimal once the asymmetry of the forecast loss function is taken into account. Krol (2013) applies this approach to evaluate revenue forecasts for California. He finds a downward bias that implies optimistic revenue forecasts are politically costly. Also, forecasters use available information efficiently in contrast to much of the previous work in this area.

This article applies this approach to evaluate real GDP forecasts made each year by the Congressional Budget Office and the Office of Management and Budget. For a comparison, the Blue Chip Consensus forecast is also evaluated.

Equation 3 represents the flexible loss function used in this article:

$$(3) \quad L(\mu_{t+j}, \varphi) = [\varphi + (1 - 2\varphi) \; 1_{(\mu_{t+j} < 0)}] \; |\mu_{t+j}|^p,$$

where $L(\mu_{t+j}, \varphi)$ is the loss function that depends on the forecast error and asymmetry parameter $\varphi$, and $1_{(\mu_{t+j} < 0)}$ is an indicator variable that takes on a value of one when the forecast error $\mu_{t+j}$, is negative and zero otherwise. In order to identify $\varphi$, the parameter p is set equal to two making the loss function quadratic (Capistrán-Carmona 2008).

The relative cost of over- or underprediction can be calculated by $\varphi/(1 - \varphi)$ (see Capistrán-Carmona 2008). For example, if $\varphi = 0.6$,

then underpredicting real GDP is one and a half times more costly than overforecasting real GDP growth. When the asymmetry parameter of the loss function $\varphi$ is equal to 0.5, the loss function is symmetric. When $\varphi > 0.5$, underprediction is more costly than overpredicting real GDP growth. When $\varphi < 0.5$, overprediction is more costly than underpredicting real GDP growth.

The orthogonality condition of the optimal forecast under a flexible loss function and the estimate of $\varphi$ are derived by assuming the forecasters minimize the expected loss function conditional on the information set available at the time of the forecast. The orthogonality condition is

$$(4) \quad E[\omega_t \, (\mu_{t+j} - (1 - 2\varphi) \, |\mu_{t+j}| \,)] = 0.$$

When this condition holds, the forecasts are optimal. In Equation 4, $\omega_t$ is a subset of information available to forecasters at the time of the forecast and $(\mu_{t+j} - (1 - 2\varphi) \, |\mu_{t+j}|$ is the generalized forecast error, the actual forecast error adjusted for the degree of asymmetry and the absolute size of the forecast error. When the loss function is asymmetric, the orthogonality condition implies the generalized forecast error rather than the actual forecast error is independent of the information subset. Tests based on the actual forecast errors suffer from an omitted variable problem, resulting in biased coefficients and standard errors.

A Generalized Method of Moments estimator is used to get consistent estimates of $\varphi$ (Hansen, 1982). When more than one variable from the information set is used as an instrumental variable in estimation, the model is overidentified and a J-test can be used to test the orthogonality condition.

## Empirical Results with a Symmetric Loss Function

Regressions 1 and 2 are used to examine CBO, OMB, and Blue Chip two- and five-year GDP forecasts published at the beginning of each year from 1976 to 2008.[5] Regression 1 tests the null hypothesis that the forecast is unbiased. Regression 2 examines if information

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[5]Data on real GDP and forecasts come from CBO (2010). The crude oil price is the August and September value for West Texas Intermediate deflated by the CPI in that month. The August and September ten-year Treasury bond rate is the interest rate. The first and second quarter annualized growth rates are included in some versions of regression 2. These data come from FRED2 at the Federal Reserve Bank of St. Louis.

available at the time of the forecast is incorporated in the forecast. Since these forecasts are made during the fourth quarter of each year, I chose lags to ensure the data would be available at the time the forecast was made. For example, I use August and September crude oil prices.

Table 1, Panel A, reports the results on the unbiased forecast hypothesis. The unbiased forecast hypothesis is rejected for the five-year forecasts but not at the two-year horizon. This is similar to previous findings. The standard errors correct for the moving average property of the error term using the Newey and West (1987) approach. However, the Q-statistic still rejects white noise for the five-year forecasts.

Table 1, Panel B, reports results on how efficiently forecasters used available information. The first test includes a constant term and two lagged forecast errors. The second test includes a constant, two lagged real oil prices, two lagged ten-year Treasury bond interest rates, and two lagged real GDP annualized growth rates. Real oil prices represent an important supply shock. The Treasury bond rate captures general credit market conditions. Changes in real oil prices and bond rates both influence future real GDP growth. Lagged real GDP growth rates capture the recent performance of the variable forecasted.

P-values testing the joint significance of the impact of these alternative sets of variables on the forecast error are reported. Ninety-two percent of the tests reject the joint hypothesis that $\nu = \tau_1 = \tau_2 = 0$. These test results suggest the forecasts are not optimal, or that the loss functions are not symmetric.

## Empirical Results with an Asymmetric Loss Function

Table 2 reports GMM estimates of $\varphi$, the asymmetry parameter, p-values associated with the J-test of the orthogonality condition of Equation 4 and the test statistic for the null hypothesis, $\varphi = 0.5$.

The OMB value for $\varphi$ is significantly greater than 0.5 for all estimates. This implies OMB forecasters view underforecasting real GDP growth to be more costly than overforecasting it. In contrast, the CBO and Blue Chip Consensus values of $\varphi$ are significantly less than 0.5 for all estimates. CBO forecasts are conservative and consistent with private sector projections. OMB forecasters

TABLE 1
TEST RESULTS

Panel A: Test Results for Unbiased Forecasts Assuming a Symmetric Loss Function

| Forecast | α | β | P-value (1) | P-value (2) |
|---|---|---|---|---|
| CBO | | | | |
| 2 Years | 0.694 | 0.776 | .76 | .07 |
| | (.466) | (.01) | | |
| 5 Years | 3.43 | −0.154 | .03 | .00 |
| | (.015) | (.765) | | |
| OMB | | | | |
| 2 Years | 1.48 | .456 | .13 | .20 |
| | (.112) | (.107) | | |
| 5 Years | 3.43 | −0.138 | .02 | .00 |
| | (.006) | (.736) | | |
| Blue Chip | | | | |
| 2 Years | 0.844 | 0.784 | .66 | .39 |
| | (.471) | (.047) | | |
| 5 Years | 3.61 | −0.217 | .07 | .00 |
| | (.032) | (.720) | | |

NOTES: Coefficient p-values are reported in parentheses. P-value (1) tests the joint hypothesis that $\alpha = 0$ and $\beta = 1$. P-value (2) tests if the regression residuals using a Q-statistic are white noise. The sample period is 1976 to 2008.

Panel B: P-Values for Tests of Information Efficiency Assuming a Symmetric Loss Function

| | CBO2YR | OMB2YR | BCHIP2YR | CBO5YR | OMB5YR | BCHIP5YR |
|---|---|---|---|---|---|---|
| 1 | .004 | .028 | .000 | .000 | .000 | .000 |
| 2 | .015 | .051 | .007 | .184 | .012 | .047 |

NOTES: Row 1 includes a constant and two lagged forecast errors in the regression. Row 2 includes a constant, the September and August values of real oil prices (West Texas Intermediate deflated by the CPI in that month), similar lagged values of the ten-year Treasury bond interest rate, and the annualized real GDP growth rate for the first and second quarters. All variables come from the year preceding the budget. The sample period is 1976 to 2008.

## TABLE 2
## GMM ESTIMATES OF φ AND ORTHOGONALITY TESTS

| | CBO2YR | OMB2YR | BCHIP2YR | CBO5YR | OMB5YR | BCHIP5YR |
|---|---|---|---|---|---|---|
| One | | | | | | |
| φ | .432 | .589 | .231 | .384 | .797 | .129 |
| S.E. | .018 | .018 | .017 | .040 | .026 | .022 |
| J-Test | .044 | .043 | .061 | .131 | .197 | .232 |
| φ =.5 | −3.78* | 4.94* | −15.82* | −2.90* | 11.42* | −16.86* |
| Two | | | | | | |
| φ | .459 | .540 | .356 | .390 | .687 | .371 |
| S.E. | .015 | .013 | .014 | .033 | .020 | .034 |
| J-Test | .375 | .461 | .354 | .624 | .583 | .644 |
| φ =.5 | −2.73* | 3.08* | −10.29* | −3.33* | 9.35* | −3.79* |

NOTES: The asymmetry parameter is φ, S.E. is the standard error of φ, J-Test is the p-value for Hansen's orthogonality test, and φ=.5 is the test statistic for testing the null hypothesis φ = 0.5.
* indicates rejection of the null hypothesis at the 1 percent level.
Each estimate is based on an alternative set of instrumental variables. One includes a constant and two lagged forecast errors in the regression. Two includes a constant, the September and August values of real oil prices (West Texas Intermediate deflated by the CPI in that month), similar lagged values of the ten-year Treasury bond interest rate, and the annualized real GDP growth rate for the first and second quarters. All variables come from the year preceding the budget. The sample period is 1976 to 2008.

produce a more optimistic picture of the country's economic future compared to the CBO and private forecasters.[6]

A potential complication for interpretation of the results is that the OMB forecast assumes the president's policies will be approved. The CBO forecast assumes current policies remain in place. This could

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[6]Auerbach (1999) found both agencies made optimistic revenue forecasts during the 1986–93 period and pessimistic forecasts during the 1993–99 period. This suggests possible instability in the estimates. His sample and methodology differ significantly from this article. Also, his approach assumes a symmetric loss function. These sample periods are too short to estimate the model used in this article. To investigate for possible instability, I constructed a dummy variable for the 1993–99 period and reestimated the model. It had no impact on my results.

bias the OMB forecast upward compared to the CBO if the administration has a rosy perspective on the economic impact of its policies. Penner (2002) argues that the general uncertainties associated with making the forecast far outweigh any difference in policy assumptions.

Seventy-five percent of the forecasts fail to reject the orthogonality condition, indicating the forecasts are optimal. Unlike the results that assumed a symmetric loss function, forecasters appear to use available information efficiently once the asymmetry of the loss function is taken into account.

## Why Do Agency Forecast Loss Functions Differ?

This section discusses why the forecast loss functions are asymmetric (leading to biased forecasts) and why they might differ between government agencies. Before discussing reasons for government agency forecast bias, it is worth examining the private sector performance. In a comprehensive evaluation, Batchelor (2007) finds evidence of a bias in private sector forecasts of real GDP and inflation in the G7 countries. Laster, Bennett, and Geoum (1999) and Lamont (2002) discuss rational reasons why even private sector forecasters may bias their forecasts. They argue that forecasts may depend on factors other than just statistical accuracy.

In Laster, Bennett and Geoum (1999), the forecaster's wage depends on accuracy and firm publicity. Because most forecasters are not very accurate and because it is difficult to evaluate forecasts very well in real time, forecasters simply want to do better than competitors in a given period. As a result, forecasters maximize their wage and firm publicity by biasing their forecast away from the consensus forecast. They find evidence to support their model. Independent forecasters who benefit most from favorable publicity make the most extreme forecasts. Industries that require accuracy, like banking, are closer to the consensus and less extreme.

Lamont (2002) also argues that forecasts depend on more than statistical accuracy. Other factors influencing the forecast are wages, profits, marketability, and shock value. The incentive structure rewards reputation that takes time to develop, so they manipulate their forecasts in an attempt to build reputation. If your reputation and wage depend only on accuracy, then the forecast would equal the true expectation. However, if your reputation and wage depend on your ability relative to other forecasters, you might move your

forecast away from the consensus. In this model, forecasters cannot develop a reputation by making forecasts similar to the consensus. Once again, the forecast may be biased.

Because it takes time to build a reputation, as forecasters gain experience, the uncertainty about their ability falls and their reputation is enhanced. In this case, Lamont argues that how one does relative to other forecasts become less important and forecasts begin to differ more from the consensus, again biasing the forecast. He finds evidence supporting the idea that as forecasters age and establish a reputation, they begin to make more extreme forecasts and lose accuracy. Finally, Lim (2001) provides evidence of an upward bias in analysts' forecasts of corporate earnings in return for information.[7]

Government forecasts are also likely to depend on factors other than just statistical accuracy.[8] The economic outlook of the individuals responsible for the forecast and the views of politicians who control the agency can be expected to impact an agency forecast. Politicians may have considerable influence over forecasters because they control the agency's budget as well as promotions and salaries. Politicians may have the power to appoint agency directors and are a valuable source for a job referral when political parties change and agency personnel are looking for work. We would expect government officials to reward forecasters who produce a projection that makes it easier to carry out their program. In this case, a forecaster's wage or an agency's budget will be a function of both accuracy and the extent to which the forecast accommodates the preferences of the politicians who oversee the agency. This view helps us to understand why a government forecast might be biased in a particular direction, but does not help in understanding why the CBO and OMB loss functions and forecast biases differ.

Krause and Douglas (2005) argue that institutional design determines the degree to which forecasts are influenced by political motives. They argue that the less politically insulated an agency is, the more likely it will be influenced by political motives, potentially

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[7]Clatworthy, Peel, and Pope (2012) find that analysts' optimal earnings forecasts are biased under asymmetric loss functions even if actual earnings are symmetric. This reflects the fact that rewards and penalties of forecast errors are not symmetric.

[8] See Mueller (1997, 2003) and Rourke (1992) for a detailed discussion of bureaucratic behavior. For an application and evidence, see Svorny and Marcal (2002).

biasing forecasts of the economy. However, they do not find evidence to support this hypothesis in their own research, perhaps because they used a symmetric loss function. To explain their findings, they suggest that the professional credibility and reputation of a forecaster may offset at least some of the political pressure to slant a forecast in a particular direction.

Surely, economists working for the CBO and OMB benefit personally from unbiased forecasts which enhance their reputation and professional credibility, partially offsetting the political pressure to bias a forecast. A good forecasting performance can lead to lucrative private sector jobs. On the other hand, there are likely to be costs associated ignoring political pressures for a biased forecast. In addition to a reduction in agency funding and staff, economists who fail to respond to political pressures may simply be ignored and have little influence in the budgetary process.

The CBO and OMB are interesting agencies to study as their institutional designs differ. The OMB, as part of the executive branch, is controlled directly by the president and is likely to face significant pressure to bias its forecast. In contrast, the CBO, which reports to Congress rather than an individual or single party, is more independent. The CBO is accountable to members of both political parties who have different political goals. By design, the CBO budget is independent of congressional budget committees (Krause and Douglas 2005). Given the greater institutional independence of the CBO compared to the OMB, the costs associated with more objective forecasts should be lower, resulting in less optimistic forecasts.

Former OMB and CBO director Rudolph Penner (2002) argues that the CBO does not want to differ from the consensus outlook. According to Penner, large deviations from the consensus would make the CBO look partisan. Also, having a forecast that aligns with the consensus makes it easier to defend it before Congress. Furthermore, Penner points out that outside advisors contribute to the CBO forecast, which is likely to move the forecast in the direction of the consensus. Frankel (2011b) makes the more general argument that outside input can temper overly optimistic outlooks and limit the influence of politics.

The results in this article support these ideas. First, the OMB loss function suggests a low real GDP forecast is more costly to an administration than a rosy outlook. In a sense, the forecast is biased in a direction—upward—that helps the administration avoid politically

costly spending cuts or tax increases. Second, the greater independence from political pressure of the CBO and its desire to produce forecasts consistent with the private sector seems to hold. Both the CBO and the Blue Chip Consensus forecasts of real GDP growth have a similar downward bias.

## Conclusion

This article evaluates the accuracy of the CBO, OMB, and Blue Chip Consensus forecasts of real GDP growth. Assuming a symmetric loss function, the unbiased forecast hypothesis is rejected for the five-year forecast, but not the two-year forecast. For the two- and five-year horizons, information efficiency is usually rejected. However, tests for loss function asymmetry suggest these results are unreliable. The proper loss function in this case is a flexible loss function.

Estimates under a flexible loss function suggest that each agency's loss function is asymmetric. These estimates indicate a significant upward bias in the OMB forecast. This is interpreted to mean executive branch political pressure influences the forecast. In contrast, both the CBO and Blue Chip forecasts have a downward bias. The CBO economic outlook is consistent with the private sector forecast. In contrast to previous work, once the asymmetry of the loss function is taken into account, government forecasters appear to use information on the economy efficiently in arriving at their GDP forecasts.

These results differ from most of the literature on government forecast evaluation. By addressing the issue of intentional forecast bias, they highlight the roll political pressure and institutional design may play in economic forecasts.

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