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How Useful Are Forecasts of Corporate Profits

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How Useful Are Forecasts Of Corporate Profits?

*Dean Croushore**

Investors' forecasts of corporate profits affect the prices of corporate stock. When a corporation announces that earnings won't be as large as expected, its stock price immediately drops. Similarly, when investors think a firm will earn higher profits than they previously thought, the company's stock rises in value. This positive relationship between forecasts of corporate profits and stock prices must be true for the stock market as a whole. That is, if investors forecast higher overall corporate earnings, that should lead to higher overall stock prices. In the 1990s, stock prices have grown substantially, in part because of forecasts of higher levels of corporate profits.[1] But how accurate are those forecasts?

To investigate the accuracy of forecasts of overall U.S. corporate profits, we need to have a consistent set of forecasts. One such set comes from

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[1]For a discussion of how stock prices are related to corporate profitability in the 1990s, see the article by John Cochrane and the article by John Carlson and Kevin Sargent. U.S. data show strong correlations between stock prices, corporate profits, and forecasts of corporate profits.

the Survey of Professional Forecasters (SPF), which has collected forecasts of corporate profits and many other macroeconomic variables for over 30 years. The survey is widely respected by academic researchers, and they often use it for investigating the quality of forecasts of various macroeconomic variables, especially inflation.[2] In general, the forecasters who participate in the survey are actively involved in forecasting as a part of their jobs. The forecasters include many Wall Street economists, along with chief economists at Fortune 500 companies, a number of bank economists, and some economic consultants. It's the type of group you'd expect to have a pretty good idea about corporate profits as well as the macroeconomic variables (such as inflation and output growth) they are asked to forecast.

DATA PROBLEMS

If we look at the raw data on the growth of corporate profits in the U.S. economy, we see that profits are very volatile over time (Figure 1).[3] Notice that, on an annualized basis, corporate profits have occasionally risen from one quarter to the next at a rate of over 100 percent. Data on most macroeconomic variables, such as the economy's output or its industrial production, aren't nearly as volatile. To eliminate some of the volatility, we'll look at the growth in corporate profits over a year, not at quarterly data.[4] The annual data series is a lot less volatile.

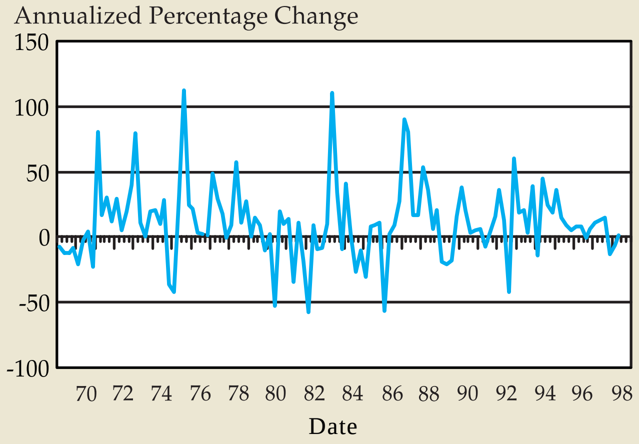
Unfortunately, attempts to analyze the forecasts of the growth of corporate profits are subject to a problem that's also true of many other variables — the data have been modified over time. That is, the data a forecaster or stockholder faced at a particular point in time look quite different from the data available today.

For example, let's take a look at the reported values for the growth of corporate profits from 1986 to 1987. If we look at the national income data in May 1988, the growth rate of corporate profits from 1986 to 1987 was reported as 8.5 percent. In July 1988, the numbers underwent a minor revision, and the growth rate rose to 10.2 percent. But in July 1989, new IRS tabulations of data from corporate tax returns led the Bureau of Economic Analysis (BEA), the statistical

[4]The variable we'll use is the growth rate in the annual average level of corporate profits from one year to the next.

FIGURE 1

Quarterly Corporate-Profits Growth



[2]For a look at some of the details of the survey and how it's run, see my 1993 article; to find out how accurate the inflation forecasts from the survey are, see my 1996 article. I use the SPF, rather than the Blue Chip survey or the IBES survey, because it began in 1968, much earlier than the other surveys.

[3]The precise variable we're examining is nominal (i.e., not adjusted for inflation) after-tax corporate profits (without inventory valuation and capital consumption adjustments) as reported in the *Survey of Current Business* from the national income and product accounts.

agency that compiles the national income accounts, to substantially reduce the value of corporate profits for both 1986 and 1987, but more so for 1986. As a result, the growth rate of corporate profits from 1986 to 1987 rose to 23.2 percent.

An even bigger change came in December 1991, when the BEA, among other changes, reclassified the bad-debt losses of financial institutions as financial transactions; those losses were no longer included in the national income accounts and were not to be viewed as reducing corporate profits. The result was a very large recalculation of corporate profits, especially for 1987, when financial firms recorded very large bad-debt losses. The impact was to increase the growth rate of corporate profits for 1987 to 44.4 percent. Minor revisions since then have reduced the growth rate to 43.5 percent.

So, occasionally the data for corporate profits are revised quite extensively. Most of the time, the revisions aren't as extensive as they were for 1987, but they can still be substantial.

Getting around this problem of data revisions is not easy. We're going to attempt to do so using the following technique: we're going to take data sets that were created not long after the forecasts were formulated, because information available *at that time* is what affected stock prices. First, we've created a special set of data, called a real-time data set.[5] Based on data published in the *Survey of Current Business* from 1965 to the present, this data set contains the data available to a forecaster in mid-November each year, the same time at which the Survey of Professional Forecasters is taken. These data sets show us what the official data looked like at the time. This real-time data set is a better source for the numbers forecasters were trying to predict than the data set available today, because some of the changes in corporate-profits data involved redefinitions of the items included in corporate profits; forecasters couldn't have foreseen those changes.

How well do the year-ahead forecasts compare to the data, using the real-time data set? To find out, we'll first plot the forecast for the growth of corporate profits over a one-year period, then compare it to the actual value in the real-time data set (Figure 2).[6] You can see that the forecasts and actual growth rates move together

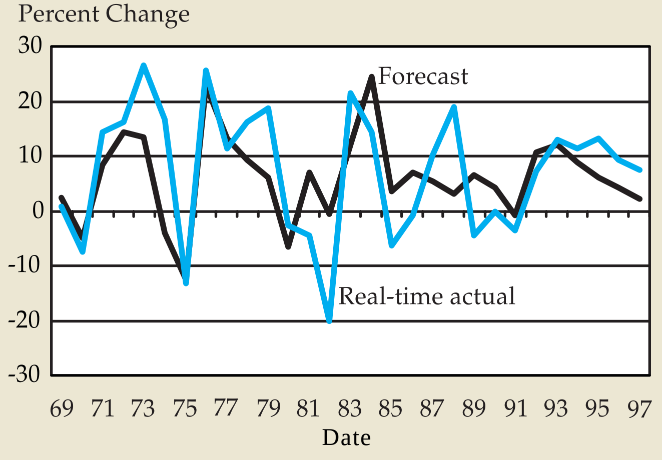
[5]Details on this data set can be found in my 1999 paper with Tom Stark.

[6]The forecasts are taken from the November Survey of Professional Forecasters each year, from 1968 to 1996. The forecast variable is the growth rate of corporate profits from the year in which the survey was taken to the following year, based on annual average data. For example, the November 1968 survey forecasts how much higher profits are expected to be in 1969 than they were in 1968.

FIGURE 2

Corporate Profits

(SPF Forecasts and Real-Time Actuals)

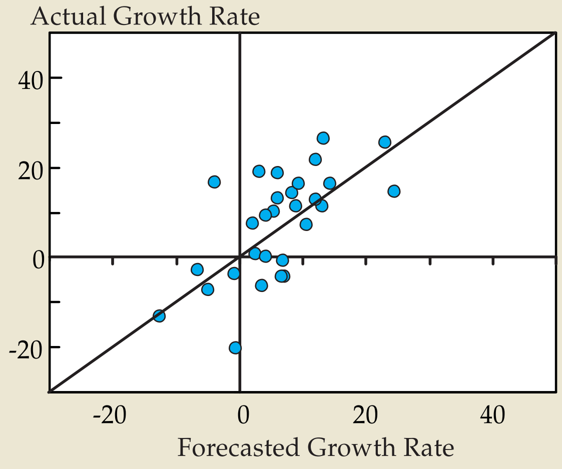


pretty well in the 1970s, despite the oil-price shocks in that period. Overall, the forecasts were not too bad in the 1980s. The forecasters missed the downturn in profits from 1980 to 1982, and their forecasts didn't capture the volatility in profits in the late 1980s, but they did get the average about right. Forecasts in the 1990s haven't been too bad either; they were just a bit too pessimistic about the growth of profits from 1994 to 1997.

Another way to see the relationship between the forecasts and the real-time actual data is to use a scatter plot that compares the actual data with the forecasts (Figure 3). If the forecasts are accurate, the points in the scatter plot should lie along the 45-degree line shown in the figure. A data point close to that 45-degree line means that the growth rate being forecast is close to the actual growth rate of corporate profits. The further away a point is from the 45-degree line, the greater the error and the poorer the forecast.

From the scatter plot, it looks like the forecasts for the growth rate of corporate profits are pretty good. The data points are close to the 45-degree line, with a few exceptions, which means the forecast errors are usually fairly small.

FIGURE 3
Corporate Profits
(SPF Forecasts and Real-Time Actuals)



STATISTICAL TESTS FOR FORECAST QUALITY

Although examining figures that plot the forecasts along with the actual values is interesting and graphically illustrates how good the forecasts are, we can also use statistical theory to perform more formal tests of the quality of the forecasts. Economists have developed a number of tests that forecasts must pass to be considered high quality.

All of the tests that follow look at the relationship between the forecasts and the actual values and allow for the fact that no forecast is perfect. After all, the economy is very difficult to predict, and many things can cause a forecast to go awry. We're going to look at two different ideas about forecast quality: (1) high-quality forecasts should be rational, and (2) high-quality forecasts should be better than simple alternatives.

A forecast is said to be rational when forecast errors are not predictable in advance. If they were, it would be possible to create a better forecast. For example, if I knew that the forecasters, on average, predicted a growth rate of corporate profits that was three percentage points too high, I could make a better forecast by taking the survey's prediction and subtracting three percentage points. For a forecast to be considered rational, no such method of changing a forecast must lead to a better forecast.

The second test of forecast quality is a forecast's ability to beat simple alternative forecasts. We should expect forecasts from our survey to be significantly better (in the sense of having smaller errors) than some simple alternative methods of forecasting. For example, suppose we found that the forecast errors from the Survey of Professional Forecasters were larger, on average, than the errors from a forecast that assumes corporate profit growth will be 10 percent every year. Then we'd think, with good reason, that the survey's forecast was poor because it was worse than a naive forecast.

We begin by testing to see if the survey forecasts are rational. We need statistical theory in these tests because, as noted above, there will always be errors in forecasts. The statistical question is: are the forecast errors unpredictable enough that we should consider the forecasts rational? Or are they so predictable that we should reject the notion of rationality for the forecasts? The average error in the forecasts for the growth rate of corporate profits was one percentage point. But in this case, the one-percentage-point average error is not statistically significant, because the growth rate of corporate profits is so variable from year to year that finding a one-percentage-point error isn't surprising or unusual. So one could not convincingly argue that the forecasts aren't rational just because on average they are slightly higher than actual growth of profits.

A common statistical test for rationality is a test for unbiasedness, which uses a technique known as regression analysis. The regression analysis determines whether the points lie along the 45-degree line in the scatter plot (Figure 3).[7] In this case, the test doesn't reject the hypothesis that the forecasts are unbiased; visually, there is a rough balance between the points below the 45-degree line and those above. This result suggests that the forecasts are potentially useful and can't be easily improved upon.

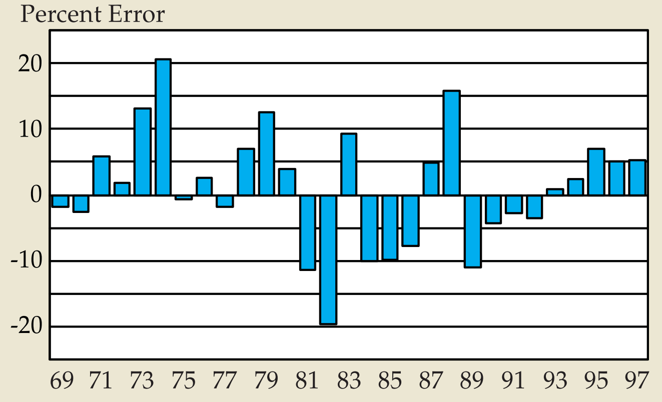
If we look at a plot of the forecast errors (the actual value for the growth rate of corporate profits minus the forecast at each date), we see they are occasionally large (Figure 4). But the forecast errors don't show any predictable pattern, which means it would be difficult for someone to make a better forecast than the one provided by the survey forecasters.

[7] To perform this test, we regress the actual value for corporate-profits growth each year on a constant and the forecast value. If the forecast were perfect, the constant term would be zero, and the coefficient on the forecast would be one. But, of course, there are certain to be some errors in the forecasts, which cause the coefficients to differ from zero and one, so we must use statistical theory to see how different from zero and one the coefficients are. Thus, we run a statistical test to see whether the constant term is significantly different from zero and the coefficient on the forecast is statistically different from one. If they are significantly different from zero and one, we say the forecast isn't rational. Our tests show they are not significantly different from zero and one. Further details on the statistical tests in this article can be found in the Appendix.

FIGURE 4

SPF Corporate Profit Forecast Errors

(Real-Time Actuals)



A variety of statistical tests that examine the forecasts show the forecast errors to be unpredictable and balanced, a sign of good-quality forecasts. The various tests run on the forecasts include the sign test, which examines whether there are the same number of positive and negative forecast errors; the Wilcoxon signed-rank test, which examines whether the magnitude of positive and negative forecast errors are the same; the zero-mean test, which examines whether the forecast errors are significantly different from zero; and the Dufour test, which looks to see if the forecast error for one year is independent of the forecast error from the previous year. The forecasts pass all these tests with flying colors (Table 1).[8] The table provides the value of the test statistic, along with the critical value to which that test statistic is to be compared, and whether the test supports the rationality of the forecasts. If the value of the test statistic is less than the critical value, the test supports the notion that the forecasts are rational.[9]

In summary, all the tests support the view that the forecasts of corporate-profits growth from the Survey of Professional Forecasters are rational.

The second type of test for forecast quality compares the forecasts from the survey to some alternative forecasts. One alternative is to form a naive forecast, in which the forecast for next year's growth rate of profits equals the value from last year. Another possibility is to forecast that corporate-profits growth equals its long-run average. Yet another possibility is to assume that corporate-profits growth simply equals its average over the last five years. When we try these alternatives, however, the errors are always much worse than the errors from the survey forecasts.

A good summary measure of overall forecast accuracy is the root mean squared error of the forecast.[10] When we look at the root mean squared error of the survey forecasts, compared to the alternative forecasts, we see that the survey has a lower root mean squared error than any of the alternatives (Table 2).

Although the survey forecasts pass all these statistical tests, we are left wondering a bit about these results, because the forecast errors are some-

TABLE 1
Tests for Forecast Rationality

Test	Value of Test Statistic	Critical Value	Rational?
Unbiasedness test	0.23	3.37	yes
Sign test	0.56	1.96	yes
Wilcoxon signed-rank test	0.07	1.96	yes
Zero-mean test	0.64	2.04	yes
Dufour test	1.32	1.96	yes

Note: The test is consistent with rationality of the forecast when the value of the test statistic is less than its critical value.

[8]The first line of the table reports the test results that show the forecast is unbiased. Additional information about the other tests can be found in the Appendix.

[9]To see how the forecasts would fare in these tests using today's data, as opposed to the real-time data set, see *Corporate Profits Data Today.*

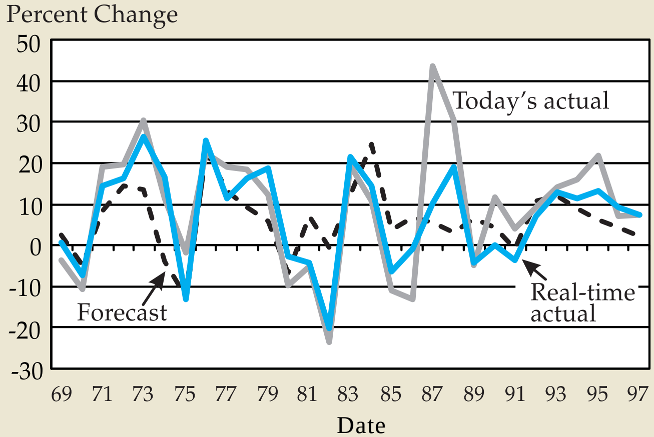
[10]The root mean squared error is calculated by taking the forecast errors at each date, squaring them, adding them together, dividing by the number of data points, and taking the square root.

Corporate Profits Data Today

How much difference would it make to use today's data on corporate profits, instead of the real-time data set used in this article? The choice of which data to use makes a difference, especially at particular dates. If we plot the data from today over time and compare it to the real-time data, we see that the new definitions and recalculations of the data are important, especially at certain dates, such as 1987 (Figure). The figure shows that the difference in the growth rate of corporate profits between the different data sets is as much as 33 percentage points!

How much difference would this have made to our statistical tests? Using the latest vintage of the data would increase the average forecast error to three percentage points (higher than the one-percentage-point average error based on the real-time data). Despite that, when we run all the statistical tests reported in Table 1 and the alternative forecasts reported in Table 2, using the latest data, the forecasts still pass all the tests, but not by as large a margin.

Corporate Profits
(SPF Forecasts and Actuals)



times large. It's not clear why that should be the case. But a close look at the data reveals a good reason why the forecasts pass the tests despite the occasional large errors: corporate profits are very volatile, as we saw in Figure 1. Forecasting a variable this volatile is bound to lead to large forecast errors, as we've seen. However, large forecast errors don't indicate that the forecasts are bad, just that the variable itself is inherently volatile.

TABLE 2
Tests for Improving Forecasts

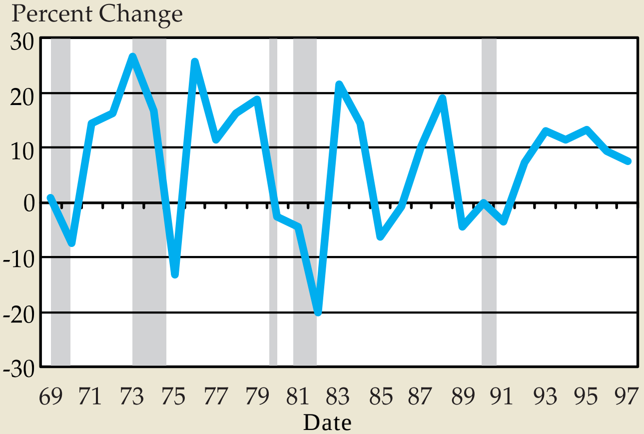
Alternative	Root Mean Squared Error
Survey	8.9
Naive	15.8
Constant Average Value	11.9
Five-Year Moving Average Value	13.5

WHY ARE CORPORATE PROFITS SO VOLATILE?

The main source of volatility in corporate profits seems to be the business cycle. Recessions cause corporate profits to decline substantially (Figure 5). As you can see from the figure, the recessions (the shaded periods in the figure) that began in 1969, 1973, 1980, 1981, and 1990 led to significant declines in the growth rate of corporate profits.

Other sources of volatility in corporate profits include: (1) changes in the value of the dollar against other currencies; (2) changes in the in-

FIGURE 5
Corporate Profits
(Real-Time Actuals)



porate profits until the economy came out of the recession in late 1982 and began growing strongly in 1983.[12]

SUMMARY

Corporate profits are quite volatile. Even so, forecasts of corporate profits from the Survey of Professional Forecasters pass a variety of statistical tests that show they're rational and better than simple alternative forecasting methods. The forecasts line up reasonably well with actual values.

The value of the stock market may have risen over the past few years partly because of forecasts of high corporate profits. The results reported here, concerning the forecasts of corporate profits from the Survey of Professional Forecasters, suggest that such forecasts have been fairly accurate, though certainly not perfect, over the last 30 years.

What is the forecast for corporate profits for this year? In the Survey of Professional Forecasters from the fourth quarter of 1998, the forecasters projected that corporate profits would rise just 0.8 percent in 1999, after declining in 1998. This represents a significant slowdown from the growth rate of corporate profits throughout the earlier part of the 1990s.

flation rate; and (3) changes in tax laws.

Changes in the value of the dollar against other currencies can influence corporate profits, since large corporations depend heavily on profits from foreign operations, which are affected by the exchange rate. When the dollar rises against foreign currencies, profits earned abroad in foreign currencies convert to fewer dollars, so the dollar profits of international corporations decline.

Uncertainty about profits can also stem from changes in the inflation rate. Inflation introduces a number of distortions into our accounting systems, and those systems can't deal with inflation perfectly. For example, the manner in which accounting methods handle the value of inventories can make a significant difference in nominal profits. As a result of problems like this, changes in the inflation rate make profits hard to predict.[11]

Changes in tax law obviously influence after-tax corporate profits, though sometimes the effects aren't apparent for several years. Corporate taxes were cut in 1981, in the middle of a recession, but the effects didn't show up in cor-

[11]There is some controversy about this issue, since the biggest increases in inflation were accompanied by large increases in oil prices and economic recession. As a result, it's hard to tell whether corporate profits really fall because of inflation alone.

[12]For more on the sources of volatility in corporate profits, see the article by John Duca.

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APPENDIX

For the interested reader, this appendix explains the tests discussed in this article in more detail (see Table 1 in the text). More information about all these tests can be found in the 1996 article by Diebold and Lopez.

BIAS TESTS

The first test discussed in the paper is a test for *unbiasedness.* A set of forecasts over time is unbiased if a regression of the actual values (the dependent variable) on a constant term and the forecasted values (the independent variable) yields coefficients that are not significantly different from 0 for the constant term and 1 for the forecast term. That is, the regression is:

$$\pi_t = \alpha + \beta\, \pi_t^f + \varepsilon_t,$$

where π_t is actual profits and π_t^f is the forecast at each date t. The bias test is simple and sensible: over a long sample period, you'd expect $\hat{\alpha}$ to be close to zero and $\hat{\beta}$ to be close to one. When we estimate this equation, we get the following results:

$$\underset{}{\pi_t} = \underset{(2.15)}{1.380} + \underset{(0.216)}{0.949}\ \pi_t^f, \qquad \bar{R}^2 = 0.21,\ \text{D.W.} = 0.17,\ F = .23,\ F^* = 3.37,$$

where $\bar{R}^2$ is the adjusted R^2 statistic, D.W. is the Durbin-Watson statistic, numbers in parentheses are standard errors, F is the value of the test statistic for the joint hypothesis that α is zero and β is one, and F* is the critical value of that statistic. Since F < F*, we don't reject the null hypothesis.

Sign Test. If a forecast is optimal, the forecast errors should be independent with a zero median. The sign test examines this null hypothesis by examining the number of positive forecast errors in the sample, which has a binomial distribution. Since the studentized version of the statistic is standard normal, we assess its significance with the normal distribution. The test statistic has a value of 0.56, less than the critical value of 1.96, so we don't reject the null hypothesis that the forecast errors have zero median.

Wilcoxon Signed-Rank Test. The Wilcoxon signed-rank test is related to the sign test, since it has the same null hypothesis, but requires distributional symmetry. It accounts for the relative sizes of the forecast errors, not just their sign. The test statistic is the sum of the ranks of the absolute values of the positive forecast errors, where the forecast errors are ranked in increasing order. The studentized value of the statistic is normally distributed. The test statistic has a value of 0.07, while the critical value is 1.96, so we don't reject the null hypothesis.

Zero-Mean Test. Optimal forecasts should pass a simple test: the mean of the forecast errors should be zero. The mean of the forecast errors divided by its standard error is 0.64, which is less than the critical value of 2.04, so we don't reject the null hypothesis that the mean of the forecast errors is zero.

Dufour Test. Dufour adapts the Wilcoxon signed-rank test and applies it to the product of successive forecast errors. This is a stringent test of the hypothesis that the forecast errors are white noise and serially independent, in particular that they are symmetric about zero. The value of the test statistic is 1.32, less than the critical value of 1.96, thus we don't reject the null hypothesis that forecast errors are white noise.