Earnings Forecasts from Firm-Level Regressions: Implications for Research and Practice

Reginald Edwards*

This Draft: 1 September 2014

Abstract

Analyst forecasts are used in research on valuation, cost of capital, and more. In this paper I deconstruct this supposed advantage of analysts over statistical forecasts. I develop and evaluate a novel statistical forecasting framework for earnings. I reinterpret and reevaluate estimates of firms' implied cost of capital and market-level risk premia that rely on analyst forecasts by using a statistical forecast. I examine if the main strength of the purported superioty of analyst forecasts is concentrated in the period prior to the passage of Regulation Fair Disclosure (Reg FD). My work posits a model of earnings that has many of the desirable properties of analyst forecasts, but less bias and is applicable to more firms and years. This model is thus more useful to both researchers and practitioners.

1 Introduction

The maintained assumption in accounting research is that analyst forecasts of firms' earnings are superior to forecasts from statistical models and represent a more accurate proxy for the

*Ross School of Business, University of Michigan (`reggie@umich.edu`).

market's expectations of future corporate earnings. Thus, analyst forecasts are used in research on valuation, cost of capital, and more. In this paper I deconstruct this supposed advantage of analysts over statistical forecasts. I develop and evaluate a novel statistical forecasting framework for earnings. I reinterpret and reevaluate estimates of firms' implied cost of capital and market-level risk premia that rely on analyst forecasts by using a statistical forecast. I examine if the main strength of the purported superioty of analyst forecasts is concentrated in the period prior to the passage of Regulation Fair Disclosure (Reg FD). And, lastly, I evaluate a trading strategy that hinges on disagreement between the statistical forecast of earnings and analysts' expectations.

My work here is largely descriptive (and proscriptive) in nature and has a methodological purpose. The use of analyst forecasts of earnings as proxies for the market's expectations of earnings has been questioned in recent years. My work posits a model of earnings that has many of the desirable properties of analyst forecasts, but less bias and is applicable to more firms and years. This model is thus more useful to both researchers and practitioners.

The accounting literature stands in contrast to many fields of economics and finance in the preeminence of expert judgment (that of equity research analysts) over statistical forecasts in the realm of corporate earnings. Researchers and practitioners often use statistical forecasts to augment or obviate professional, human forecasts of inflation (Faust and Wright (2013)), GDP (Chauvet and Potter (2013)), interest rates (Duffee (2013)), oil prices (Alquist, Kilian and Vigfusson (2013)), and real estate prices (Ghysels et al. (2013)). Indeed, these forecasts are often found to be superior to human forecasts on various measures of performance evaluation and better proxies for market expectations.

Research that relies on analyst forecasts of earnings suffers from three flaws: (1) analyst forecasts are known to be upwardly biased; (2) there is evidence suggesting analysts don't attempt to accurately forecast earnings and investors don't necessarily rely on these forecasts explicitly for information about long-term cash flows; and (3) since the availability of machine- readable analyst forecasts only dates back to the early 1980s, the research sample is necessarily limited. The statistical forecasts of earnings from firm-level regressions that I develop here overcomes the first and last points. By demonstrating that the forecasts from my model are associated with higher returns I provide support for the notion that some market participants may be able to derive more accurate from the past history of earnings than is given by blindly following analyst forecasts. To fully address the second point, the forecasts from my model must be used to derive implied cost of capital estimates and market risk premia.

My work here contributes to the literature in two ways. The first is methodological in nature. I deconstruct the notion that analysts forecasts are the best estimates of earnings, develop a superior statistical framework for forecasting earnings, and discuss the implications for resarch design for using the analyst forecasts instead of the statistical forecasts. The second contribution is more applied. I show how using a statistical forecast of earnings can be used to gain an edge over market participants that rely on analyst forecasts.

2 Literature Review

2.1 Statistical Earnings Forecasts

Research on understanding and forecasting the time-series properties of earnings can be traced back to at least the 1960s (Little (1962)). The earliest studies in accounting [e.g., Ball and Watts (1972), Brooks and Buckmaster (1976)] concluded that earnings follow a random-walk process and little could be gained from statistical earnings forecasts. Later, Brown (1993) lays out a coherent path for future research into earnings forecasts. A decade later, Kothari (2001) declares that this literature was "fast becoming extinct" due to the ready availability of analyst forecasts. However, Bradshaw et al. (2012) contribute to a recent resurgence in focus on the forecastability of earnings and the usefulness and appropriateness of such forecasts to researchers and practitioners.

Hou, van Dijk and Zhang (2012) represent an important step towards more sophisticated models of earnings based on economically sound predictor variables. In the spirit of Fama and French (2000), they develop a cross-sectional regression-based forecast of earnings. My work here builds on and differs from theirs in key ways. The most prominent difference is in estimation methodology and forecaste evaluation. Hou, van Dijk and Zhang (2012) estimate their pooled regression over all firms for one year at a time. They then average the in-sample coefficients and use the averaged coefficients to forecast earnings one to five years ahead. Hou, van Dijk and Zhang (2012) also use GAAP earnings (from Compustat) as opposed to "street" earnings-per-share (from IBES) to build their model, thus making it difficult to compare the forecast accuracy of their model with that of analysts.

2.2 Analysts' Earnings Forecasts

Analysts are generally seen to have two advantages over statistical models with respect to forecasting earnings: (1) analaysts have access to more recent data (the *timing advantage*, and (2) analysts have access to proprietary information stemming from their access to management, customers, and suppliers (the *information advantage.*) With respect to the information advantage analysts are said to posses, it is likely that this would deteriorate subsequent to the passage of Regulation Fair Disclosure (Reg. FD.) Reg. FD was designed to prohibit select groups of investors and analysts from gaining access to exclusive information from management. Indeed, Gintschel and Markov (2004) find that analyst forecasts are less informative after the passage of Reg. FD. Thus, findings of analyst superiority over time-series models are likely to attenuate over time.

Moreover, analyst forecasts tend to exhibit well-documented and predictable biases. Empirical evidence suggests that analysts issue more optimistic (upwardly biased) forecasts when (1) issuing buy recommendations [Eames, Glover and Kennedy (2002)], (2) forecasting lower earnings [Francis and Philbrick (1993)], and (3) when the target firm's earnings are less predictable [Das, Levine and Sivaramakrishnan (1998)]. It is also unclear whether and to what extent investors as a whole rely on analyst forecasts to form expectations about future earnings and, thus, price. Given these considerations, it is natural to consider if statistical models of earnings that replicate much of the decision process undertaken by individual analysts can improve upon analyst forecasts.

2.3 Implications for Implied Cost of Capital Estimates

An expectation of a firm's future earnings is the key input into estimates of that firm's cost of capital as implied by its prevailing market price (Gebhardt, Lee and Swaminathan (2001)). Reverse-engineering the cost of capital is essential for internal capital budgeting and external investment evaluation. Also, aggregates of firm-level cost of capital estimates have been shown to have risk-return characteristics that more closely follow standard asset pricing theory (Lee, So and Wang (2011)). Standard in the literature is the use of analyst forecasts of earnings and long-term growth rates. However, since it is unclear whether the objective function of analysts is designed to produce accurate earnings forecasts, especially longer than one year out (see, e.g. Givoly, Hayn and Yoder (2011)), it may be inappropriate to use analyst forecasts for cost of capital estimates.

2.4 Implications for the Equity Risk Premium

Proxies for the market's expectations of corporate earnings are necessary to estimate the market-wide equity risk premium. Claus and Thomas (2001) were among the first to realize the importance of the proxy used and incorporated analyst expectations into their analysis of the equity risk premium. They subsequently find a much lower equity risk premium than the prevailing estimate. However, inferences based on analyst forecasts, which have been shown to be optimistic, are hardly benign. Easton and Sommers (2007) document that even a seemingly small upward bias in the expected earnings figure used can lead to large estimates of the equity risk premium. They suggest that, given the extent of optimism in analyst forecasts, the size of the equity premium may not be puzzling.

3 Research Design

3.1 Earnings Forecasts

In this paper, I model and forecast firm-level earnings for one ("FY1" in IBES), two ("FY2"), and three years ahead ("FY3"). Forecasts are made at the date of announcement of base-year earnings. For example, forecasts of a firm's earnings for 2002, 2003, and 2004 are made on the date in which the company releases earnings in 2001, using publicly data available up until that date.

The statistical model I build here tries to capture the information process undertaken by analysts while seeking to avoid overfitting to the data in-sample. When analysts forecast companies' earnings they incorporate past earnings data, industry trends, macroeconomic context, and expert judgment about the firm in consideration. Because analysts generally focus on a handful of firms, it stands to reason that a firm-level modeling approach will have advantages over a statistical approach based on aggregate cross-sectional relationships.

The naive firm-level statistical model of earnings is the first-order autoregressive ("AR(1)") approach. A major advantage this method has over the regression-based approach in this paper is it requires very little data to estimate. Because of the loss of degrees of freedom from each additional regressor, I restrict the model to firms with at least 15 years of data. This captures half of the universe of available firm-years. For firms with fewer than 15 years of data I use the classic AR(1) model. Forecasts using simple, lagged values of earnings tend to be downwardly biased out-of-sample because earnings generally grow at 50 basis points per year. Moreover, the earnings of all firms in the economy must mechanically be positively related to the growth of the economy as a whole, in aggregate. To capture the varying effects of firm-level growth, I include return on equity (ROE) as a predictor. To capture the effects of economy-wide growth I include macroeconomic factors–GDP growth, the unemployment rate U, and the inflation rate. Many in accounting and finance (e.g., Fama and French (2000)) have noted that negative earnings are particularly informative about future earnings over and above the level of earnings itself. Therefore, I include an indicator variable for negative earnings, NE_t, to capture this effect.

Hou, van Dijk and Zhang (2012) note that accruals booked by firms in one period must necessarily eventually reverse and therefore may be informative about future earnings. While the authors in that study use a measure of total accruals, I specifically include change in accounts receivables and accounts payables over the prior period as predictors of future earnings.[1] Standard asset pricing theory posits that a firm's stock price impounds market expectations of future cash flows, thus changes in price today should, to a large extent, reflect changes in market-level expectations of earnings. To capture potentially useful price-based information I include the year-over-year change in a firm's stock price, ΔP_t as of the forecasting date. To accomodate a potential level effect, I also include the firm's price-to-earnings ratio.

Finally, to accomodate the findings in Hou, van Dijk and Zhang (2012), I include (the natural logarithm of) sales, dividends, and assets in the model. Given, the factors motivated above, I estimate the following model of firm earnings,

$$\begin{aligned} E_{t+\tau} = \beta_0 + \beta_1 E_t + \beta_2 assets_t + \beta_3 dividends_t + \beta_4 NE_t + \\ \beta_5 \Delta P_t + \beta_6 sales_t + \beta_7 PE_t + \beta_8 \Delta AP_t + \\ \beta_9 \Delta AR_t + \beta_{10} U_t + \beta_{11} GDP_t + \beta_{12} INFLATION_t + \varepsilon \end{aligned} \tag{1}$$

As an additional step to improve the potential out-of-sample performance of the model I take advantage of two common observations from the economic forecasting literature (see West (2006) for a review): (1) combinations of models tend to outperform individual models,

[1] In untabulated analyses I include, instead, accruals directly. The results are markedly worse.

and (2) forecasting performance usually worsens the farther out the forecast target. To incorporate the first consideration I use a bayesian model averaging framework (Jennifer A. Hoeting and Volinsky (1999)) to combine the model with the rich predictor set with the simple AR(1) model. As Gerakos and Gramacy (2013) note, the simple autoregressive model is in many cases very comparable to models with large predictor sets. To incorporate the second consideration I weight the AR(1) model more strongly in the bayesian model averaging framework for models of two-year-ahead earnings than the model of one-year-ahead earnings and more strongly in the models of three-year-ahead earnings than the model of two-year-ahead earnings.

4 Data

4.1 Data Overview

To estimate, test, and evaluate my model I make use of data on analyst forecasts of firms' annual (fiscal year-end) earnings for one, two, and three years ahead (IBES); firm-level balance sheet (Compustat) and market (CRSP) data; and U.S. macroeconomic data.[2] The earnings figure used is the *pro forma* figure from IBES ("ACTUAL") rather than that reported on the income statement. This is to make the model directly comparable with analyst forecasts. Summary statistics for the variables of interest are given in Table 1.

My use of the appropriate macroeconomic data merits discussion. For GDP, I Use nominal, quarterly, seasonally adjusted, year-over-year change in GDP. For forecasting, I use the GDP and inflation figure from the quarter prior to that in which the analyst(s) forecast. For example, forecasts made in the first quarter (January, February, or March) rely on data from the fourth quarter of the previous year. For unemployment, I use the unemployment rate from the month prior to the month in which the analyst made the forecast. These steps

[2] Macroeconomic data are from the St. Louis Federal Reserve Bank webiste: `http://research.stlouisfed.org/fred2/`.

serve to make sure that the inputs to the statistical model are only data that were available at the time of forecasting.

4.2 Sample Selection

My final sample is a subset of the entire intersection of IBES, CRSP, and Compustat firms with continuous earnings data, limited via the following steps. I exclude small cap firms (i.e., those firms with a market value of equity of less than one billion dollars.)[3] I exclude firms whose earnings are negative over the entire observation period I exclude utilities (whose profitability is regulated) and firms in the financial industry. I calculate accruals calculated using the balance sheet approach (as in e.g. Richardson et al. (2005)). Some firms (e.g. General Electric) choose note to report "Current Assets" as a separate line-item on their balance sheets. Therefore, I proxy for current assets as the sum of cash, total receivables, and inventories.

5 Results

5.1 Univariate Results

As a preliminary step, to investigate the marginal contribution of each variable over the traditional AR(1) specification, I compute OLS regressions of the form

$$EPS_t = \alpha_0 + \alpha_1 EPS_{t-1} + \alpha_2 X_{t-1} + \varepsilon.$$

In the "univariate" equation above, X_{t-1} is the lagged observation of a predictor. Table 2 below shows summary statistics for the firm-level univariate regressions. As the table shows, next-year earnings are, on average, increasing in all factors after controlling for the effect of

[3] If a firm subsequently goes above a billion dollar valuation it is included in the sample from that point on.

current-year earnings. Next-year earnings are decreasing in the unemployment rate, likely driven by decreased demand from consumers; my measure of inflation, which represents primarily increased costs faced by businesses; and the current-year PE ratio. As Cochrane (2011) notes, high prices relative to past earnings generally indicate lower future returns.

Table 3 shows summary statistics for R^2 values of these regressions. Predictors with high incremental R^2 values may be predictive in subsequent out-of-sample tests and the values may serve to limit the set of predictors. In particular, the lower in-sample explanatory power of *Accruals* compared with ΔAP and ΔAR serve as partial motivation for the former to be replaced by the latter two in the multivariate model.

5.2 Earnings Forecasts

To assess how the model performs by target year (the target firm's fiscal year end in which earnings will be announced), I compute mean squared prediction errors (MSPE) for all target years. The results in Table 4 show MSPE by target year for the model, mean analyst forecast, and median analyst forecast. All three estimates do extremely poorly during the dotcom bubble bursting period. [4]

Does private information help analyst forecasts? Table 5 presents comparisons of the model's accuracy before and after implementation of Regulation Fair Disclosure. As noted in prior literature (e.g. Gintschel and Markov (2004)) analyst forecasts are worse in the post-Reg FD period. The performance of the model forecasts does not change in any consistent way pre- and post-Reg FD.[5]

The effects of *ex ante* uncertainty on forecasts. Table 6 presents comparisons of the accuracy of model and consensus forecasts during information environments characterized by high and low uncertainty. Both the model and analyst forecasts perform better during

[4]MSPE comparisons for two-year-ahead and three-year-ahead forecasts have been omitted.

[5]In this section and all others, "consensus" forecasts refer to the mean analyst estimate. Results with median analyst estimates are qualitatively similar.

periods characterized by low analyst dispersion.[6] For the one-year-ahead forecasts, the model performs relatively better than consensus forecasts.

5.3 Earnings Forecasts as Trading Signals

Most studies that compare time series forecasts to analyst forecasts use a loss function (evaluation criterion) that is some form of relative prediction error or bias. To better quantify the significance of divergence between the consensus forecasts of earnings and the model forecast, I examine the returns to an investor who uses the divergence in analyst and model forecasts as a signal. As a first step, I calculate buy and hold returns ($BAHR$) for each firm from the forecast date to one month and, separately, two months after the target date (i.e., the date at which forecasted earnings are revealed.) I do this for all forecasts (one-, two-, and three-year-ahead forecasts.) I then compute the divergence between the model forecasts and the consensus forecast, $DIFF$, as the model forecast less the consensus forecast. $DIFF$ is calculated for each forecast horizon. For each forecast target and returns horizon I run a regression of the form

$$BAHR_{t+\tau} = \alpha_0 + \alpha_1 DIFF_i + \varepsilon. \tag{2}$$

Table 7 shows the coefficient and p-values from each of these regressions. For the forecasts of FY1 earnings, buy-and-hold returns are positively and statistically significantly related to the degree of divergence between model forecasts and consensus analyst forecasts. Note, however, that returns have not been adjusted for standard asset pricign risk factors.

Next, I rank and group each forecast into deciles by the level of divergence. As Figures 1 and 2 show, the buy-and-hold returns over the forecast horizon for the forecast of FY1 earnings is increasing in the level of divergence between the model and the consensus forecast.

[6] Dispersion is measured as the standard deviation of analyst forecasts. High (low) dispersion periods are those with a standard deviation above (below) the median. Results are not sensitive to choice of percentile.

This indicates that the stock returns of firms for which the model forecasts higher earnings than analysts are higher than those for which analysts are more optimistic than the model suggests.

6 Conclusions and Extensions

Research that relies on analyst forecasts of earnings suffers from three flaws: (1) analyst forecasts are known to be upwardly biased; (2) there is evidence suggesting analysts don't attempt to accurately forecast earnings and investors don't necessarily rely on these forecasts explicitly for information about long-term cash flows; and (3) since the availability of machine- readable analyst forecasts only dates back to the early 1980s, the research sample is necessarily limited. The statistical forecasts of earnings from firm-level regressions that I develop here overcomes the first and last points. By demonstrating that the forecasts from my model are associated with higher returns I provide support for the notion that some market participants may be able to derive more accurate from the past history of earnings than is given by blindly following analyst forecasts. To fully address the second point, the forecasts from my model must be used to derive implied cost of capital estimates and market risk premia. If the forecasts represent a better proxy for market-level expectations then they may lead to estimates that better conform to the risk-return relationship predicted by modern asset pricing theory. I leave this step for future work.

References

Alquist, Ron, Lutz Kilian, and Robert J. Vigfusson. 2013. "Chapter 8 - Forecasting the Price of Oil." In *Handbook of Economic Forecasting.* Vol. 2, Part A of *Handbook of Economic Forecasting*, , ed. Graham Elliott and Allan Timmermann, 427 – 507. Elsevier.

Ball, Ray, and Ross Watts. 1972. "Some Time Series Properties of Accounting Income." *The Journal of Finance*, 27(3): pp. 663–681.

Bradshaw, Mark T., Michael S. Drake, James N. Myers, and Linda A. Myers. 2012. "A re-examination of analysts' superiority over time-series forecasts of annual earnings." *Review of Accounting Studies*, 17(4): 944–968.

Brooks, LeRoy D., and Dale A. Buckmaster. 1976. "Further Evidence of the Time Series Properties of Accounting Income." *The Journal of Finance*, 31(5): pp. 1359–1373.

Brown, Lawrence D. 1993. "Earnings forecasting research: its implications for capital markets research." *International Journal of Forecasting*, 9(3): 295 – 320.

Chauvet, Marcelle, and Simon Potter. 2013. "Chapter 3 - Forecasting Output." In *Handbook of Economic Forecasting*. Vol. 2, Part A of *Handbook of Economic Forecasting*, , ed. Graham Elliott and Allan Timmermann, 141 – 194. Elsevier.

Claus, James, and Jacob Thomas. 2001. "Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets." *The Journal of Finance*, 56(5): pp. 1629–1666.

Cochrane, John H. 2011. "Presidential Address: Discount Rates." *The Journal of Finance*, 66(4): 1047–1108.

Das, Somnath, Carolyn B. Levine, and K. Sivaramakrishnan. 1998. "Earnings Predictability and Bias in Analysts' Earnings Forecasts." *The Accounting Review*, 73(2): pp. 277–294.

Duffee, Gregory. 2013. "Chapter 7 - Forecasting Interest Rates." In *Handbook of Economic Forecasting*. Vol. 2, Part A of *Handbook of Economic Forecasting*, , ed. Graham Elliott and Allan Timmermann, 385 – 426. Elsevier.

Eames, Michael, Steven M. Glover, and Jane Kennedy. 2002. "The Association between Trading Recommendations and Broker-Analysts' Earnings Forecasts." *Journal of Accounting Research*, 40(1): pp. 85–104.

Easton, Peter D., and Gregory A. Sommers. 2007. "Effect of Analysts' Optimism on Estimates of the Expected Rate of Return Implied by Earnings Forecasts." *Journal of Accounting Research*, 45(5): pp. 983–1015.

Fama, Eugene F., and Kenneth R. French. 2000. "Forecasting Profitability and Earnings." *The Journal of Business*, 73(2): pp. 161–175.

Faust, Jon, and Jonathan H. Wright. 2013. "Chapter 1 - Forecasting Inflation." In *Handbook of Economic Forecasting*. Vol. 2, Part A of *Handbook of Economic Forecasting*, , ed. Graham Elliott and Allan Timmermann, 2 – 56. Elsevier.

Francis, Jennifer, and Donna Philbrick. 1993. "Analysts' Decisions As Products of a Multi-Task Environment." *Journal of Accounting Research*, 31(2): pp. 216–230.

Gebhardt, William R., Charles M. C. Lee, and Bhaskaran Swaminathan. 2001. "Toward an Implied Cost of Capital." *Journal of Accounting Research*, 39(1): pp. 135–176.

Gerakos, Joseph, and Robert B. Gramacy. 2013. "Regression-based earnings forecasts." *Chicago Booth Research Paper*, 12(26).

Ghysels, Eric, Alberto Plazzi, Rossen Valkanov, and Walter Torous. 2013. "Chapter 9 - Forecasting Real Estate Prices." In *Handbook of Economic Forecasting*. Vol. 2, Part A of *Handbook of Economic Forecasting*, , ed. Graham Elliott and Allan Timmermann, 509 – 580. Elsevier.

Gintschel, Andreas, and Stanimir Markov. 2004. "The effectiveness of Regulation FD." *Journal of Accounting and Economics*, 37(3): 293 – 314.

Givoly, Dan, Carla Hayn, and Timothy R. Yoder. 2011. "Do Analysts Account for Earnings Management?" *Working Paper.*

Hou, Kewei, Mathijs A. van Dijk, and Yinglei Zhang. 2012. "The implied cost of capital: A new approach." *Journal of Accounting and Economics*, 53(3): 504 – 526.

Jennifer A. Hoeting, David Madigan, Adrian E. Raftery, and Chris T. Volinsky. 1999. "Bayesian Model Averaging: A Tutorial." *Statistical Science*, 14(4): 382417.

Kothari, SP. 2001. "Capital markets research in accounting." *Journal of accounting and economics*, 31(1): 105–231.

Lee, Charles M. C., Eric C. So, and Charles CY Wang. 2011. "Evaluating Implied Cost of Capital Estimates." *Working Paper.*

Little, I. M. D. 1962. "Higgledy Piggledy Growth." *Bulletin of the Oxford University Institute of Economics & Statistics*, 24(4): 387–412.

Richardson, Scott A., Richard G. Sloan, Mark T. Soliman, and rem Tuna. 2005. "Accrual reliability, earnings persistence and stock prices." *Journal of Accounting and Economics*, 39(3): 437 – 485.

West, Kenneth D. 2006. "Chapter 3 Forecast Evaluation." In . Vol. 1 of *Handbook of Economic Forecasting*, , ed. C.W.J. Granger G. Elliott and A. Timmermann, 99 – 134. Elsevier.

Appendix: Tables and Figures

	mean	med	min	max	stdev
EPS	1.722	1.290	-13.940	89.610	2.751
Total Assets	10742.531	2411.400	0.808	797769.000	35031.631
Accruals	-0.033	-0.036	-5.224	1.864	0.127
Dividends	3.193	0.212	0.000	18000.000	218.575
Dividend Payer	0.238	0.000	0.000	1.000	0.426
Negative Earnings	0.048	0.000	0.000	1.000	0.215
$\Delta Price$	0.103	0.047	-2.033	9.529	0.539
PE Ratio	56.994	22.298	-57200.000	151250.000	1617.267
GDP	0.045	0.047	-0.032	0.124	0.024
ROE	0.986	0.156	-312.626	5822.013	70.802
Unemployment	0.063	0.056	0.038	0.108	0.018
Inflation (PPI)	0.003	0.004	-0.053	0.030	0.012
Sales	9545.757	2290.295	-7.237	470171.000	29433.901
AR	1692.512	303.298	0.000	418777.000	11146.256
AP	914.879	150.639	0.000	149813.000	3876.577
Age	15.779	13.000	5.000	32.000	8.262
$\Delta Sales$	1108.466	186.751	-172892.000	278188.000	8293.066
ΔAR	170.144	21.981	-40708.000	60942.000	1680.019
ΔAP	103.539	10.448	-83588.000	71555.000	1272.733

Table 1: Summary statistics of EPS and independent variables.
Age is number of years company is in the sample.

	mean	med	min	max	stdev
EPS_{t-1}	0.8365	0.8903	-0.1384	1.2728	0.2621
Total Assets	0.0002	0.0001	-0.0012	0.0026	0.0005
Log Assets	0.0316	0.0225	-0.8275	0.3838	0.0877
Accruals	1.0163	0.1647	-27.7192	50.3953	5.7010
Dividends	-3.3222	0.0219	-868.1679	21.1498	56.1218
Dividend Payer	0.3611	0.2075	-5.5520	4.9040	0.9422
Negative Earnings	0.5258	0.2546	-4.6542	7.1198	1.4530
$\Delta Price$	0.4812	0.2580	-1.1649	5.5304	0.7044
PE Ratio	-0.0096	-0.0020	-0.2723	0.0525	0.0261
GDP	3.9724	1.8984	-37.5517	144.6891	13.6927
ROE	1.9134	0.8492	-7.8009	18.1838	3.3770
Unemployment	-1.0157	0.1596	-192.9481	67.0008	21.0969
Inflation (PPI)	10.4296	4.8584	-108.8861	157.9932	22.9823
Sales	0.6885	0.4160	-2.7407	7.1705	1.0305
AR	0.0598	0.0324	-0.7462	0.6187	0.1225
AP	0.0656	0.0444	-0.9054	0.6850	0.1384
$\Delta Sales$	0.0004	0.0001	-0.0018	0.0066	0.0008
ΔAR	0.0014	0.0004	-0.0107	0.0359	0.0041
ΔAP	0.0020	0.0006	-0.0202	0.0523	0.0069

Table 2: Estimated coefficients from regressions of the form $EPS_t = \alpha_0 + \alpha_1 EPS_t + \alpha_2 X_{t-1} + \varepsilon$.

	mean	med	min	max	stdev
EPS_{t-1}	0.6694	0.7516	0.0018	0.9981	0.2900
assets	0.6877	0.7636	0.0055	0.9982	0.2804
Accruals	0.6923	0.7505	0.0124	0.9983	0.2675
Dividends	0.6953	0.7653	0.0090	0.9984	0.2763
Dividend Payer	0.6948	0.7748	0.0066	0.9983	0.2813
Negative Earnings	0.6797	0.7575	0.0164	0.9981	0.2806
$\Delta Price$	0.7313	0.7866	0.0351	0.9981	0.2419
PE Ratio	0.7395	0.8049	0.0343	0.9983	0.2372
GDP	0.7046	0.7792	0.0199	0.9983	0.2639
ROE	0.7535	0.8151	0.0268	0.9982	0.2284
Unemployment	0.7065	0.7794	0.0081	0.9984	0.2649
Inflation (PPI)	0.7032	0.7696	0.0181	0.9982	0.2663
Sales	0.7444	0.8100	0.0012	0.9982	0.2450
ΔAR	0.7195	0.7980	0.0168	0.9983	0.2639
ΔAP	0.7190	0.7868	0.0192	0.9981	0.2609

Table 3: R^2 values from regressions of the form $EPS_t = \alpha_0 + \alpha_1 EPS_t + \alpha_2 X_{t-1} + \varepsilon$.

Year	Model	MEANEST	MEDEST
1990	14.440	20.250	18.662
1993	0.116	0.152	0.176
1994	0.096	0.137	0.137
1995	0.166	0.037	0.031
1996	0.122	0.002	0.000
1997	0.180	0.554	0.606
1998	1.018	0.196	0.201
1999	4.547	5.233	5.126
2000	0.542	0.379	0.324
2001	41.042	19.687	19.687
2002	1701.955	1832.864	1828.333
2003	0.152	0.151	0.148
2004	0.263	0.365	0.359
2005	2.929	2.737	2.749
2006	0.593	0.211	0.209
2007	0.771	1.316	1.389
2008	18.404	11.094	11.298
2009	0.592	1.357	1.303
2010	1.658	1.379	1.381
2011	1.016	0.367	0.378
2012	2.357	1.612	1.618

Table 4: Mean squared prediction error of model forecast, mean analyst (MEANEST) forecast, and median analyst forecast (MEDEST). Forecasts are of one-year-ahead earnings.

	Pre-Reg FD		Post-Reg FD	
Forecast horizon	Model	Consensus	Model	Consensus
1-Year Ahead	2.365	2.466	27.479	28.159
2-Year Ahead	2.255	1.905	4.163	3.672
3-Year Ahead	0.732	2.574	3.889	4.256

Table 5: Mean squared prediction error comparison of "model" and "consensus" earnings forecasts.

	Low Dispersion		High Dispersion	
Forecast horizon	Model	Consensus	Model	Consensus
1-Year Ahead	1.45	0.774	90.436	94.511
2-Year Ahead	8.133	7.853	0.874	0.371
3-Year Ahead	1.409	0.860	5.155	4.986

Table 6: Mean squared prediction error comparison of "model" and "consensus" earnings forecasts.

	BAHR $\tau + 1$ month		BAHR $\tau + 2$ months	
Forecast horizon, τ	Coeff.	*P-Value*	Coeff.	*P-Value*
1-Year Ahead	0.06825**	0.0334	0.06903**	0.0329
2-Year Ahead	0.02169	0.344	0.02610	0.259
3-Year Ahead	-0.02812	0.216	-0.02903	0.205

Table 7: Buy-and-hold returns for FY1 ($\tau = 12$), FY2 ($\tau = 24$), and FY3 ($\tau = 36$) forecasts. Return horizons are one month and two months after the forecast target date.

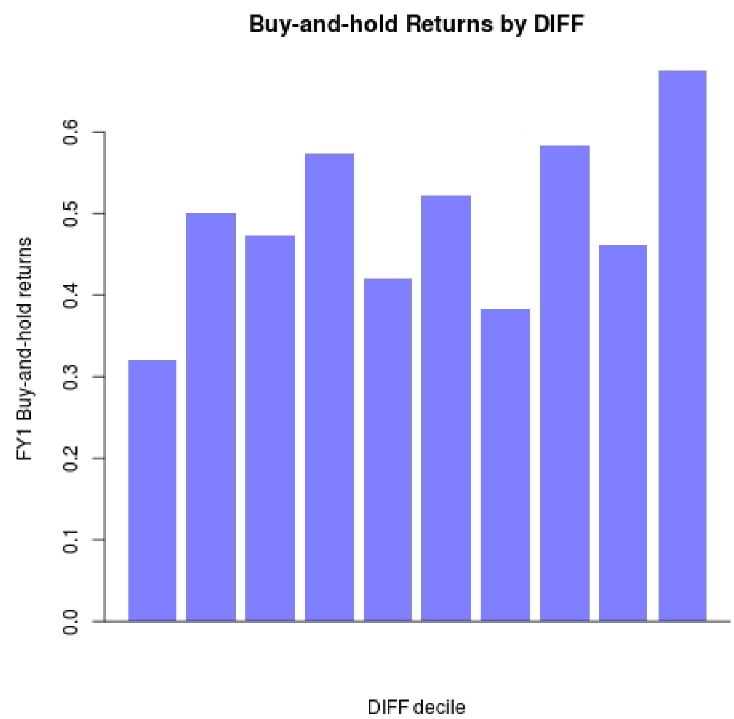

Figure 1: Buy-and-hold returns by $DIFF$ decile for one-year-ahead model. $DIFF$ is the model forecast of earnings less the consensus forecast.

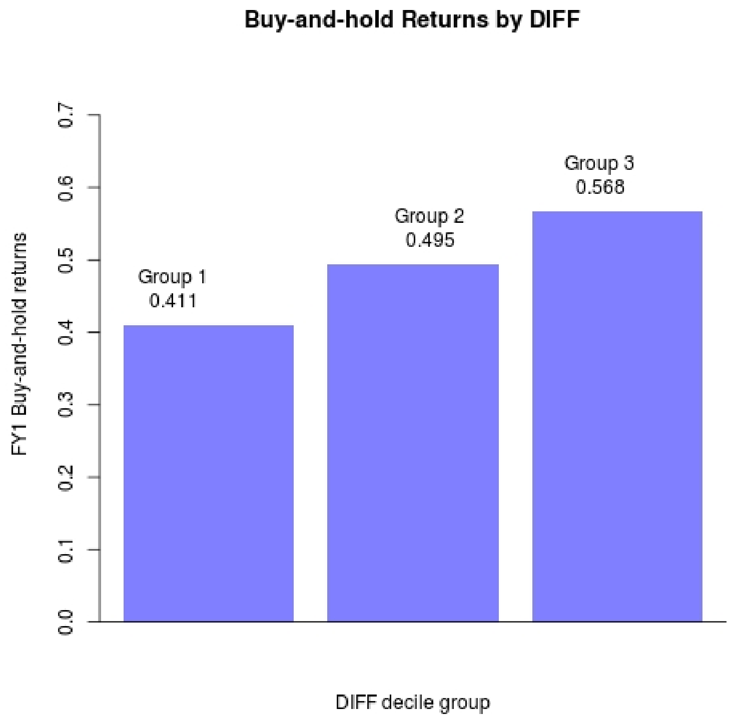

Figure 2: Buy-and-hold returns by $DIFF$ decile for one-year-ahead model. $DIFF$ is the model forecast of earnings less the consensus forecast. Group 1: first and second decile. Group 3: ninth and 10th deciles.