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ABSTRACT

Understanding Analysts' Earnings Expectations: Biases, Nonlinearities and Predictability

This paper studies the asymmetric behavior of negative and positive values of analysts' earnings revisions and links it to the conservatism principle of accounting. Using a new three-state mixture of log-normals model that accounts for differences in the magnitude and persistence of positive, negative and zero revisions, we find evidence that revisions to analysts' earnings expectations can be predicted using publicly available information such as lagged interest rates and past revisions. We also find that our forecasts of revisions to analysts' earnings estimates help predict the actual earnings figure beyond the information contained in analysts' earnings expectations.

JEL Classification: C22 and G17
Keywords: analysts' earnings forecasts;, mixture model and predictability of forecast revisions

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The views, thoughts and opinions expressed in this paper are those of the authors in their individual capacity and should not in any way be attributed to Platinum Grove Asset Management LP or to Marco Aiolfi as a representative officer, or employee of Platinum Grove Asset Management LP.

The opinions herein are our own, and do not reflect the views of the Board of Governors of the Federal Reserve System.

1 Introduction

How financial analysts form expectations of corporate earnings is a question that has generated significant attention in accounting and finance. This interest is motivated by the importance of earnings expectations to discounted cash flow valuation models−and hence to asset prices−and the key role analysts play in disseminating earnings information to participants in the financial markets.[1] Financial analysts have been found to issue earnings forecasts that tend to be systematically upwards biased.[2] However, the extent to which a time-varying predictable component is present in analysts' forecast biases has not been addressed. Identifying economic state variables that predict biases is important since this may help our understanding of analysts' objectives and the extent to which they make full use of publicly available information.

Since we observe earnings forecasts more frequently (i.e. monthly) than the actual values of earnings (quarterly or annual), rather than studying forecast errors, we consider revisions to analysts' forecasts. This allows us to construct a contiguous time series with a larger set of observations. As shown by Pesaran and Weale (2006), if agents have squared loss and use information efficiently, revisions to their forecasts should follow a martingale difference process. We make use of this property and test if forecast revisions are in fact unpredictable.

Our empirical analysis uncovers strong evidence of asymmetries and persistence in the magnitude and signs of revisions to analysts' earnings expectations as measured by the consensus forecast which is the most widely accepted single measure of earnings expectations. It is well-known that negative revisions to analysts' earnings expectations occur more frequently than positive ones, but it is less known that the probability of a negative revision goes up if the previous revision was also negative. Furthermore, the magnitude of positive and negative revisions to analysts' earnings expectations is very different, with the average negative revision roughly twice as large and three times as volatile as the average positive revision.

Analysts' revisions reflect both the process whereby firms release information and the manner in which analysts form expectations. Consistent with recent studies such as Louis, Lys and Sun (2008), we argue that firms' news announcement behavior is important. In particular, we argue that the larger magnitude of negative revisions is related to the conservatism principle of accounting, leading negative news to be fully declared, while positive news is only partially declared and instead spread out over time until it can be verified. We present a simple stylized model in which negative news is immediately announced, while positive news is spread out over neighboring periods and show that this model generates a higher magnitude and greater standard deviation of negative news compared with positive news. Moreover, negative news is more persistent than positive news.

We incorporate our empirical findings in a dynamic three-state model that captures the persistence and asymmetry of positive, 'no change' and negative revisions to earnings expectations. This model accounts for the important feature of the consensus forecasts that they frequently do not change. Using the sign of the revision as the underlying state, the model comprises a three-state mixture of log-normal distributions and a single point (zero). State transitions are allowed to depend on the previous state as well as time-varying covariates. Since the state is observable, the model is straightforward to estimate by maximum likelihood methods.

We also study the effect on revisions to analysts' earnings expectations of past returns, past revisions, uncertainty about stock prices (captured by a 'realized volatility' measure) and the past T-bill rate. Three-state models that incorporate either past revisions to earnings expectations or the past T-bill rate are found to be capable of successfully predicting the direction of revisions to future earnings expectations (i.e. positive, no change or negative). Moreover, the ability of the three-state model to predict future revisions to earnings expectations is found to improve significantly over standard linear forecasting models that include these variables. Finally, we find that the forecasts of the consensus revisions from the three-state model predict not only the revision to analysts' earnings estimates but also the actual earnings figure announced by the firms once a year.

The paper is structured as follows. Section 2 provides details of the data set and establishes some stylized features of earnings revisions. Section 3 introduces the three-state model used to capture the different dynamics associated with negative, zero and positive revisions to earnings expectations and uses this to test for asymmetries and persistence in how analysts revise their earnings expectations. In turn, this model is used in Section 4 to explore whether revisions to analysts' earnings expectations are predictable and whether the *actual* earnings figures can be predicted by means of our forecasts of revisions in analysts' earnings expectations. Section 5 concludes.

2 Properties of Earnings Revisions

While the relation between earnings revisions and stock price movements has been studied extensively, there has been little analysis of the time-series dynamics of the consensus earnings estimates, i.e. the issue of how earnings estimates evolve over long spans of time.

Our paper addresses these issues by studying the properties of monthly revisions in analysts' earnings estimates for the 30 firms included in the Dow Jones index over a 20-year period. In so doing, we adopt a new perspective by considering revisions to the consensus earnings estimate every month and by studying how this is linked to the forecast horizon.

2.1 Data

Our data source on earnings forecasts is the unadjusted summary tapes of the Institutional Brokers' Estimate System (I/B/E/S). The sample spans the period from January 1986 to March 2008, a total of 267 months. In particular, we use the unadjusted summary tapes instead of the adjusted ones. In doing so, we are attempting to avoid overstatement of zero revisions which are induced by the rounding procedures present on the I/B/E/S summary adjusted tapes.

In order to make the forecasts in adjacent months comparable, we adjust forecasts for stock splits. More precisely, if a stock split happens in between months, we adjust the forecast of the previous month (without rounding it) to make it comparable to the next month. To calculate the adjustment factors used in this procedure, we combine the adjustment factors provided by I/B/E/S with the ones provided by CRSP to ensure that both dates and split ratios are correct.[3]

The advantage of using such a long time series is that it gives us the ability to better document systematic patterns in revisions to analysts' earnings expectations. We are interested in the behavior of earnings revisions at the individual firm level. To ensure sufficient analyst coverage throughout the long sample period studied here and keep the analysis manageable, we focus on the firms included in the Dow Jones 30 Index as listed in Table 1. Analyst coverage is excellent for each of these firms which on average is tracked by between 20 and 40 analysts. Moreover, since individual analysts usually do not provide a complete series of forecast updates, we follow Klein (1990), Chaney, Hogan and Jeter (1999), Easterwood and Nutt (1999) and others in modeling the consensus forecast (i.e., the cross-sectional average) in order to get a long contiguous time series. The consensus forecast is generally viewed as highly influential and is the most widely accepted single measure of earnings expectations (see, e.g., Brown et al (1985)). While individual analysts' forecasts may differ from the consensus expectation, the latter still explains a large fraction of the time-series variation in individual analysts' views.[4]

Time series of monthly revisions to analysts' earnings estimates are constructed as follows. Every third Thursday of the month (t)−the so-called statistical date−I/B/E/S lists all analysts' earnings estimates entered since the third Thursday of the previous month $(t-1)$. I/B/E/S then computes summary statistics (such as the consensus mean) over this set of individual analysts' estimates. We denote the consensus estimate of earnings for the current fiscal year recorded during month t for firm j by f_t^j.[5] At the end of the fiscal year, which we denote by T, firm j's actual earnings per share figure, A_T^j, is announced. Our analysis focuses on analysts' forecasts of earnings for the current fiscal year. When $t+1 \leq T$, the earnings revision for fiscal year T, Δf_{t+1}^j, is based on the difference between the adjusted earnings estimates on the statistical dates t and $t+1$. During months when the fiscal year changes we base the revision of the earnings forecast on a comparison of the previous month's forecast of earnings for fiscal year $T+1$ with the current month's forecast of this value. This allows us to create a contiguous time-series of monthly revisions to analysts' earnings forecasts.

Following studies such as Klein (1990) and Lys and Sohn (1990), we scale the earnings revision by a firm's initial split adjusted stock price, P_t^j, measured at the close on day t (the statistical date) and obtained from the CRSP daily files. The revision to the consensus estimate of firm j's earnings figure between months t and $t+1$ is thus computed as:[6]

$$\Delta f_{t+1}^j = 100 \times \left(\frac{f_{t+1}^j - f_t^j}{P_t^j} \right). \tag{1}$$

Hence we define the revision to the consensus earnings estimate as the change in the forecast of earnings per share from t to $t+1$, $f_{t+1}^j - f_t^j$, divided by the initial stock price per share, P_t^j, and multiplied by 100. Revision numbers can therefore be interpreted as a percentage of the stock price.

I/B/E/S reports the consensus estimate of earnings per share rounded to the nearest cent. For many of the months included in our sample, forecast revisions are zero since the arrival of new information between two neighboring months is insufficient to lead to an earnings revision in excess of one cent. While the earnings revision is unlikely to be exactly equal to zero, we follow common practice and record this as a zero observation. Such observations could be discarded, but doing so may lead to important biases. A 'no change' forecast may in fact contain valuable information about future revisions, particularly if periods with small revisions tend to be persistent (which we shall see is indeed the case).

Table 2 shows that close to 30% of the monthly revisions to the consensus earnings forecasts are smaller than one cent per share and hence get recorded as zero. This grand average conceals substantial variations across firms, however. The proportion of 'no change' revisions exceeds 50% for firms such as General Electric and Kraft Foods, while this proportion is 5%

for Alcoa, Chevron, General Motors and Exxon Mobil. The proportion of zeros for the median forecast revision is in line with earlier results by Kang, O'Brien and Sivaramakrishnan (1994) who find that 19-35% of their forecast revisions are zero.

2.2 Bias and Persistence in Revisions to Analysts' Forecasts

We next turn to the properties of the revisions to analysts' earnings forecasts. Figure 1 plots the time-series of monthly revisions to analysts' earnings expectations for two firms whose results we will explore in more details throughout the paper, namely 3M and Pfizer. Most revisions are quite small and lie in a range between -0.2 and 0.2 percent of the stock price. However, occasionally very large revisions occur, as in the case of Pfizer where some revisions exceed -0.5% of the stock price. The many months with small (zero) revisions are also apparent from this figure, particularly for Pfizer. Furthermore, revisions to earnings expectations appear to be persistent−positive revisions are more likely to follow if the previous revision was also positive. A similar finding holds for the negative revisions.

To capture such characteristics more systematically, Table 2 reports descriptive statistics for the time series of revisions to earnings expectations for each of the 30 firms. For all but three companies we have 267 monthly observations. The average revision to earnings expectations, at -0.044% of the stock price, is negative, but the proportion of positive and negative revisions, at 36 and 34 percent, respectively, is very similar.

Revisions to earnings expectations are also negatively skewed with large fat tails as revealed by the estimates of the third and fourth moments. The negative skew suggests that negative revisions are significantly larger than positive ones. Indeed, an interesting feature of the consensus revisions is that their properties differ depending on the sign of the revision. To demonstrate this, Table 2 reports the mean and standard deviation separately for positive and negative revisions. For 25 of 30 firms, negative revisions have a larger mean (in absolute terms) and the standard deviation of negative revisions exceeds that of the positive revisions. Moreover, these differences are economically large: the average negative revision is twice as large as the average positive revision, and a similar finding holds for the average standard deviation of negative versus positive revisions. Large negative revisions are hence far more common than large positive ones.

2.3 A Stylized Model for Earnings News under the Conservatism Principle

To help interpret the empirical evidence, we next present a simple and highly stylized model of firms' news announcement behavior. We assume that positive and negative news are equally likely and that news are drawn from a symmetric distribution. Suppose, however, that, consistent with the verifiability principle of accounting, firms treat negative and positive news differently. In particular, suppose that they fully declare negative news as it arrives, while only a portion of positive news, θ, gets declared, where $0 \leq \theta \leq 1$. The remainder of the (positive) news, $1-\theta$, gets declared with a one-period delay. Letting y_t be the news declared by the firm, while ε_t is the underlying innovation which only gets observed by the firm, we have

$$y_t = \varepsilon_t \mathbf{1}_{\varepsilon_t<0} + \theta\varepsilon_t \mathbf{1}_{\varepsilon_t\geq 0} + (1-\theta)\varepsilon_{t-1}\mathbf{1}_{\varepsilon_{t-1}\geq 0}, \tag{2}$$

where $\mathbf{1}_{\varepsilon_t<0}$ is an indicator function that is one if $\varepsilon_t < 0$, otherwise is zero. This is of course a highly stylized representation of the conservatism/verifiability principle. Nevertheless, it allows us to characterize the effect of firms' asymmetric smoothing behavior.

It follows immediately from this model that firms' declared earnings are more volatile for negative news than for positive news:

$$\begin{aligned} var(y_t|\varepsilon_t < 0) &= \sigma_\varepsilon^2 + (1-\theta)^2\pi\sigma_\varepsilon^2 \\ var(y_t|\varepsilon_t > 0) &= \theta^2\sigma_\varepsilon^2 + (1-\theta)^2\pi\sigma_\varepsilon^2, \end{aligned}$$

where $\pi = prob(\varepsilon_{t-1} \geq 0)$. As long as $\theta < 1$, we have $var(y_t|\varepsilon_t < 0) > var(y_t|\varepsilon_t > 0)$. Magnitude and persistence effects are harder to derive, but we can compute them numerically.

Table 3 shows the effect of varying the smoothing parameter, θ, on the magnitude (mean of the absolute value) of the negative and positive declared news, y, as well as on the standard deviation. Finally, we show the persistence of negative and positive news, measured, respectively, as $prob(y_t < 0|y_{t-1} < 0)$ and $prob(y_t \geq 0|y_{t-1} \geq 0)$. The table assumes that $\varepsilon_t \sim N(0,1)$ is identically and independently distributed over time.

When $\theta = 1$, there is no earnings smoothing and the positive and negative news have identical magnitude and dispersion and the persistence is the same for positive and negative news. However, in all other scenarios, the magnitude of the negative news is greater than that of positive news (comparing columns 2 and 3) and the standard deviation of negative news also exceeds that of positive news (columns 4 and 5). Moreover, the persistence of the negative news state, shown in columns 6 and 7, always at one-half, exceeds the persistence of the positive news state. Suppose that analysts closely follow the news released by companies, as argued by Louis, Lys and Sun (2008), and thus do not try to "undo" firms' earnings announcements. Then the properties of our simple model match the empirical findings for the earnings revisions in Table 2 and our results suggest that the observed asymmetric behavior of earnings revisions can be linked to the conservatism principle of accounting.

3 An Econometric Model for Revisions to Analysts' Earnings Expectations

In this section, we propose an econometric model that accounts for the different properties and dynamic behavior of negative and positive revisions noticed previously. The model also captures information revealed in draws from the 'no change' state (rather than discarding information on this state). Towards this end, we propose a dynamic three-state model whose state variable tracks revisions to analysts' earnings forecasts:[7]

$$s_{t+1} = \begin{cases} +1 & \text{if } \Delta f_{t+1} > 0 \\ 0 & \text{if } \Delta f_{t+1} = 0 \\ -1 & \text{if } \Delta f_{t+1} < 0 \end{cases} . \tag{3}$$

If $s_{t+1} = 1$, the revision to analysts' earnings expectations at time $t+1$ is positive, while conditional on $s_{t+1} = -1$, it is negative. Finally, if $s_{t+1} = 0$, the revision to the earnings expectation is zero (i.e. less than one cent per share). Treating small changes (zeros) separately is important if there are months where little or no news arrives. A model that pools 'no news' and news months is likely to be misspecified because it cannot fully capture the dynamics of earnings expectations in months with news which may be quite different from the dynamics in months with no news.

Revisions to analysts' earnings expectations are clearly not normally distributed (see Table 2). In particular, there are far more large negative revisions than we should expect under a normal distribution. To capture this aspect of the data, we assume that both positive and negative revisions to earnings expectations−the latter with their sign reversed so they become positive−are log-normally distributed. The log-normal distribution accommodates fatter tails than the normal distribution and is thus better suited for our data which clearly is affected by outliers.

Our earlier analysis indicated that the mean and variance of positive and negative revisions to earnings expectations are very different, so we do not want to impose that the parameters for positive and negative revisions are identical. In this spirit, we assume that positive revisions to earnings expectations are log-normally distributed with mean $\mu_{1,t}$ and variance σ_1^2, while (the absolute value of) negative revisions are log-normally distributed with mean $\mu_{-1,t}$ and variance σ_{-1}^2. The distribution of Δf_{t+1} conditional on s_{t+1} is thus described by the following mixture distribution:

$$g(\Delta f_{t+1}|s_{t+1}) = \begin{cases} \frac{1}{\Delta f_{t+1}\sqrt{2\pi\sigma_1^2}}\exp(\frac{-(\ln(\Delta f_{t+1})-\mu_{1,t})^2}{2\sigma_1^2}) & \text{if } \ s_{t+1}=1 \\ \mathbf{1}_{\Delta f_{t+1}=0} & \text{if } \ s_{t+1}=0 \\ \frac{1}{|\Delta f_{t+1}|\sqrt{2\pi\sigma_{-1}^2}}\exp(\frac{-(\ln(|\Delta f_{t+1}|)-\mu_{-1,t})^2}{2\sigma_{-1}^2}) & \text{if } \ s_{t+1}=-1 \end{cases} \tag{4}$$

Here $\mathbf{1}_{\Delta f_{t+1}=0}$ is an indicator function that equals one if $\Delta f_{t+1} = 0$ and otherwise is zero. We consider two specifications of the conditional mean in the two non-zero states, namely

$$\mu_{1,t} = \begin{cases} \mu_1 \\ \beta_{1,1} + \beta_{2,1}x_t \end{cases},$$
$$\mu_{-1,t} = \begin{cases} \mu_{-1} \\ \beta_{1,-1} + \beta_{2,-1}x_t \end{cases}, \tag{5}$$

where the first specification assumes a constant mean, while the second assumes a time-varying mean that is a linear function of the pre-dated covariates, x_t.

To complete the model, we need to characterize transitions between the three states, representing positive, zero and negative revisions to earnings expectations. We consider two models. The simplest model assumes that state transition probabilities $p_{i,k} = P(s_{t+1} = k|s_t = i)$ are constant:

$$\mathbf{P} = \begin{pmatrix} p_{1,1} & 1-p_{1,-1}-p_{1,1} & p_{1,-1} \\ 0.5(1-p_{0,0}) & p_{0,0} & 0.5(1-p_{0,0}) \\ p_{-1,1} & 1-p_{-1,1}-p_{-1,-1} & p_{-1,-1} \end{pmatrix}. \tag{6}$$

State transitions are parameterized so there are only five free parameters, namely $p_{1,1}$ (the probability of continued positive revisions), $p_{0,0}$ (the probability of continued zero revisions), $p_{-1,-1}$ (the probability of continued negative revisions), $p_{1,-1}$ (the probability of switching from a positive to a negative revision) and $p_{-1,1}$ (the probability of switching from a negative to a positive revision). Probabilities must add to one across columns so the only constraint is that the probabilities of moving from the 'zero' state to the negative and positive earnings revision states are identical, which is a natural symmetry restriction and is supported by the data.

This model captures the possibility that earnings revisions of the same sign persist− a feature which we shall see holds for most firms. Moreover, the persistence of negative revisions is greater than that of positive revisions when $p_{11} > p_{-1,-1}$. The model is also consistent with persistence in the mean of the revisions−this occurs when $\mu_1 \neq \mu_{-1}$ and $p_{1,1} \neq p_{-1,1}$ or $p_{-1,-1} \neq p_{1,-1}$−or in their volatility (assuming $\sigma_1^2 \neq \sigma_{-1}^2$).

We are also interested in establishing which economic variables help explain analysts' behavior. Our second model therefore lets the diagonal elements of the state transitions (the 'stayer' probabilities) vary as a function of a set of economic state or predictor variables, x_{t-1}, which along with data on revisions to earnings expectations are collected in the information set $\Omega_{t-1} = \{\Delta f_{t-1}, x_{t-1}\}$. Transitions between states s_{t-1} and s_t are thus allowed to depend on x_{t-1}: $p_{i,k,t-1} = P(s_t = k|s_{t-1} = i, x_{t-1})$. More specifically, we use a logit specification

$$p_{i,k,t-1} \equiv \frac{\exp(\delta_{1,i,k} + \delta_{2,i,k} x_{t-1})}{1 + \exp(\delta_{1,i,k} + \delta_{2,i,k} x_{t-1})}. \tag{7}$$

This gives rise to the following time-varying transition probability matrix

$$\mathbf{P}_{t-1} = \begin{pmatrix} p_{1,1,t-1} & 1 - p_{1,-1,t-1} - p_{1,1,t-1} & p_{1,-1,t-1} \\ 0.5(1 - p_{0,0,t-1}) & p_{0,0,t-1} & 0.5(1 - p_{0,0,t-1}) \\ p_{-1,1,t-1} & 1 - p_{-1,1,t-1} - p_{-1,-1,t-1} & p_{-1,-1,t-1} \end{pmatrix}. \tag{8}$$

This extended model allows us to analyze which variables drive revisions to analysts' earnings forecasts.

3.1 Estimation

Because all variables, including the underlying state, are observed, we can estimate our model by maximum likelihood methods. At time t, the log-likelihood conditional on the information set Ω_{t-1} (which includes knowledge of s_{t-1}), takes the form of a mixture distribution:

$$LL_t = ln\left[p_{s_{t-1},1} \times g\left(\Delta f_t | s_t = 1, \Omega_{t-1}\right) + p_{s_{t-1},0} \times \mathbf{1}_{\Delta f_t = 0} + p_{s_{t-1},-1} \times g\left(-\Delta f_t | s_t = -1, \Omega_{t-1}\right)\right], \tag{9}$$

where the densities $g()$ are given by (4). Summing across all time periods, $t = 1, .., T$ and across the three values that s_{t-1} can take $\{-1, 0, 1\}$, we get the full sample log-likelihood function:

$$LL = \sum_{t=1}^{T} \sum_{s_{t-1}=-1}^{1} \mathbf{1}_{s_{t-1}} LL_{t|\Omega_{t-1}}. \tag{10}$$

The chief complication is the highly non-linear functional form of the log-likelihood in (10), which means that numerical optimization methods have to be used. Estimation proceeds by choosing parameters $\{\mu_1, \mu_{-1}, \sigma_1^2, \sigma_{-1}^2, p_{1,1}, p_{0,0}, p_{-1,-1}, p_{1,-1}, p_{-1,1}\}$, using Quasi-Newton methods with a mixed quadratic and cubic line search procedure.

3.2 Persistence and Asymmetries in Revisions to Analysts' Earnings Expectations

Having introduced our formal model, we next turn to the sign mixture model (4) with constant transition probabilities (6). Parameter estimates for this model are reported in Table 4.[8] The first column of the table reports the ratio of the mean parameter in the negative revision state to its value in the positive revision state (exponentiated since we used logs). Consistent with Table 2, the magnitude of negative revisions to earnings expectations are up to 170% higher than their positive counterparts. Similarly, the ratio of the volatility estimates in the negative and positive revision states, shown in the second column, exceeds unity for two-thirds of the firms and are significantly above unity for around half of the firms. This corresponds to a significantly higher volatility for negative than for positive revisions to analysts' earnings expectations.

The asymmetry properties of the earnings revisions may be linked to the fact that firms treat positive and negative news differently due to the conservatism or verifiability principle of accounting. This principle holds that firms are more conservative in declaring positive news until they can be verified, whereas negative news is immediately stated. If positive news is smoothed out over time, this will lower the magnitude and volatility of the revisions associated with positive earnings news.

Turning to the sign of revisions in analysts' earnings expectations, columns three through seven show that these are highly persistent for many of the firms. For example, for Pfizer (PFE) the probability that a positive revision follows a previous positive revision is 45% while the probability that a negative revision follows a previous negative revision is 49%. Whenever the probability of observing a positive revision is greater if the previous revision was positive ($p_{1,1}$) than if it was negative ($p_{1,-1}$), positive revisions to earnings expectations are persistent. This condition holds for all but one of the firms, the exception being Kraft Foods which has a very limited sample. Similarly, negative revisions to earnings expectations are persistent when $p_{-1,-1}$ exceeds $p_{-1,1}$. This holds for every single firm for which estimates of both parameters are available.

We next conduct a likelihood ratio test of the null hypothesis of no sign persistence ($p_{1,1} = p_{1,-1}$ and $p_{-1,1} = p_{-1,-1}$). Column eight in Table 4 shows that this hypothesis is soundly rejected for all the firms in our sample. Interestingly, for around two-thirds of the firms, the probability of continued negative revisions to the earnings estimates exceeds that of continued positive revisions. Although negative revisions to earnings expectations tend to be greater than positive ones.[9]

The last three columns in Table 4 report the steady-state (or average) probabilities of positive, negative and zero revisions. These estimates can be compared to the observed frequencies reported in columns two through four in Table 2, all of which are closely matched by the model. For example, for 3M and Pfizer the probability of a zero state is 32% and 48%, matching the steady-state probabilities implied by our estimates. Comparing our estimates of $p_{0,0}$ to the steady-state probability $\bar{p}_0$, it is clear that the probability of observing a small (less than one cent per share) change in earnings expectations is in many cases raised by 5-10% if the previous change was small. This suggests volatility clustering (with clusters of zero revisions) in the revision process for analysts' earnings expectations.

3.3 Sources of Persistence in Revisions to Earnings Expectations

We conclude from tables 2 and 4 that revisions to analysts' earnings expectations are persistent with negative values that are greater in magnitude, more frequent and more persistent than positive values. To better understand what gives rise to such effects, it is interesting to link revisions in earnings expectations to economic state variables. To this end we next consider a variety of state variables, some of which have previously been studied in the accounting and finance literature, while others are new.

As our first measure we consider past returns, a variable that has been considered in many previous studies of analyst expectations, e.g., Brown, Foster and Noreen (1985), Klein (1990), Stickel (1991), Liu and Thomas (2000) and Park and Stice (2000). Asymmetric information models such as Diamond and Verrecchia (1981) and Glosten and Milgrom (1985) imply that price changes may contain information about fundamentals and so forecast revisions could be positively correlated with prior price changes when private information gradually gets incorporated into stock prices.

Building on these results, we compute the lagged cumulated return using daily data on stock returns obtained from CRSP. More precisely, let P_τ^j be the closing stock price for firm j on day τ, so the continuously compounded single-day stock return is given by $r_\tau^j = log(P_\tau^j/P_{\tau-1}^j)$. The cumulated return between time t and $t+1$ (typically one month apart) is then given by

$$r_{t:t+1}^j = \sum_{t<\tau\leq t+1} r_\tau^j = log(P_{t+1}^j) - log(P_t^j). \tag{11}$$

To see whether analysts' earnings expectations adjust gradually to news, we also use past revisions as a predictor of future revisions.

Another strand of the literature studies the effect that uncertainty has on earnings forecasts. Measuring such uncertainty directly is complicated since earnings data is not available at high frequency. To the extent that greater earnings uncertainty is reflected in more volatile stock returns, it is reasonable to consider a measure of return volatility. We adopt a measure that builds on the literature on realized volatility (see Andersen, Bollerslev and Diebold (2006)) and compute the realized volatility in stock returns between time t and $t+1$ as

$$vol_{t:t+1}^j = \sum_{t<\tau\leq t+1} \left(r_\tau^j\right)^2. \tag{12}$$

Finally, to explore the possibility that macroeconomic information predicts revisions to earnings expectations, we use the lagged 3-month T-bill rate ($Tbill$) as a predictor variable. This variable has been used extensively in the finance literature as a way of capturing variations in the state of the economy and tracking risk premia. Most studies find a negative association between stock returns and past interest rates (see, e.g., Fama and French (1988) and Ferson and Harvey (1991)).[10]

In summary, at a given point in time, t, we use the revision, Δf_t^j, the cumulated stock return $r_{t-1:t}^j$, its volatility, $vol_{t-1:t}^j$, and the 3-month T-bill rate, $Tbill_t$, to predict the earnings revision between time t and $t+1$. Our timing convention ensures that all variables are known to the analysts when the consensus forecast at time t was computed.

3.4 Empirical Results

Table 5 reports summary statistics for the estimates of the slope coefficients, $\delta_{2,i,k}$, using the logit specification (7) with different explanatory variables. For one-third of the firms, the short interest rate is significant in predicting a higher probability of continued positive revisions, while the corresponding numbers are 4, 13 and zero for past returns, past revisions and past volatility, respectively. The only variable to significantly affect the probability of continued negative revisions is past revisions themselves. Past revisions and the lagged T-bill rate are thus best at forecasting future revisions to analysts' earnings expectations.

The finding that past interest rates help predict future earnings revisions appears to be new. To better see how the probability of a negative, zero or positive state is affected by the lagged interest rate, Figure 2 plots the time-series of the estimated transition probabilities for 3M and Pfizer. Variations in the short interest rate give rise to substantial changes in the probability of staying in the current state for Pfizer, but not for 3M. For Pfizer, the stayer probabilities decline in both the positive revision and the negative revision state as interest rates decline, while the opposite happens in the zero state. Conversely, lower interest rates increase the probability of switching between the positive and negative revision states. Changes in these probabilities can be very large in magnitude for Pfizer for which variations of up to 60% in $p_{1,1}$ or $p_{-1,-1}$ are observed during our sample. In sharp contrast, the state transition probabilities are essentially time-invariant for 3M.

So far we have assumed that the predictor variables, x_t, only affect the state transitions but not the mean of the revision to earnings expectations within each state. It is natural, however, to consider whether the predictor variables directly affect the mean earnings revision within each state. We do so by considering the more general model

$$\Delta f_{t+1} = \beta_{1,s_{t+1}} + \beta_{2,s_{t+1}} x_t + \epsilon_{t+1}, \quad \epsilon_{t+1} \sim N\left(0, \sigma^2_{s_{t+1}}\right). \tag{13}$$

Evidence in support of this model is strongest for the short interest rate (Tb) which, when included in this model, is significant for almost every single firm. We therefore confine our discussion to this model, summary results for which are displayed in Table 6.

Higher interest rates appear to have two separate effects on how analysts revise their earnings expectations: A magnitude (level) and a persistence effect. Higher interest rates lead to smaller expected future revisions in the consensus estimate as most estimates of $\beta_{2,1}$ are negative in both the positive and negative revision state. Higher interest rates also increase the probability of staying in the positive revision state or, equivalently, reduce the probability of transitioning to the negative revision state or staying there if past revisions were negative.

4 Predictability of Actual and Expected Earnings

We next address whether the apparent evidence of 'in-sample' predictability extends to 'real-time' or out-of-sample predictability of revisions in analysts' earnings expectations and whether such predictability carries information about the actual earnings figures announced by the firms.

4.1 Forecasting Results

Our contiguous time series of earnings revisions is ideally suited to test for (out-of-sample) predictability. In our forecasting experiment, for each firm we use the first 120 monthly observations to estimate the parameters of the forecasting model. This is all done in 'real time' in order to simulate the forecasts that an analyst with access only to the historical data could have computed without the benefit of hindsight. The remainder of the sample is then used for out-of-sample evaluation. Suppose, for example, that in December 1995 we are interested in forecasting the revision to earnings expectations for January 1996. Then we only use data up to December 1995 to estimate the parameters of our model and predict the revision to the earnings estimate for January 1996. The next month we add one monthly observation and re-estimate the model so that the forecast for February 1996 only incorporates data known in January 1996 and so forth.

This approach has the advantage that it takes the effect of parameter estimation error and model misspecification into account: if our three-state model fits the revisions data poorly or its parameters are imprecisely estimated, this will be reflected in imprecise forecasts.

As a benchmark for evaluating our model's forecasting performance, we also report predictions generated by more traditional time-series models that use revisions to earnings expectations as the dependent variable and include the lagged revision in addition to other predictor variables (x):

$$\Delta f_{t+1} = \beta_0 + \beta_1 \Delta f_t + \beta_2 x_t + \varepsilon_{t+1}. \tag{14}$$

Here x_t is selected from the set of covariates used in the three-state model, i.e. the lagged T-bill rate, past stock returns or past volatility.

Before presenting the empirical results, it is worth pointing out that even the simple model with constant transition probabilities (6) and constant mean and variance parameters within each state can capture time-variations in revisions to analysts' earnings expectations. This seemingly surprising property arises because the state probabilities vary over time. To see this, note that the predicted value of the earnings revision as a function of the current state, s_t, is given by

$$\Delta \hat{f}_{t+1} = \begin{cases} p_{1,1} \exp(\mu_1 + 0.5\sigma_1^2) - p_{1,-1} \exp(\mu_{-1} + 0.5\sigma_{-1}^2) & \text{if } s_t = 1 \\ (1 - \frac{p_{0,0}}{2})(\exp(\mu_1 + 0.5\sigma_1^2) - \exp(\mu_{-1} + 0.5\sigma_{-1}^2)) & \text{if } s_t = 0 \\ p_{-1,1} \exp(\mu_1 + 0.5\sigma_1^2) - p_{-1,-1} \exp(\mu_{-1} + 0.5\sigma_{-1}^2) & \text{if } s_t = -1 \end{cases} \tag{15}$$

Clearly the predicted earnings revision will vary as a function of the current state, s_t, whenever $\mu_1 \neq \mu_{-1}$ or $\sigma_1 \neq \sigma_{-1}$. If state transitions are allowed to vary through time, this gives rise to further variation in the predicted consensus revisions.

The most common measure of forecasting performance is the correlation between the actual revision to earnings expectations and the predicted value. Summary values of this measure, computed out-of-sample, are reported in panel A of Table 7. We show results for the three-state model with constant transition probabilities ('constant') in addition to the models that allow for time-varying state transitions and predictions from the extended first-order autoregressive model (14). The three-state models generate average correlations around 0.23. These values are substantially higher than those observed for the linear model. We conclude that the forecasts from the three-state models generate substantially higher correlations with analysts' revisions than the forecasts from the extended autoregressive models accomplish.

Panel B of Table 7 reports the proportion of correctly predicted positive, zero and negative values of the revisions to earnings expectations−a statistic commonly referred to as the "hit rate."[11] Across firms, the average hit rate for the three-state models is 52%.[12] The autoregressive model generates average hit rates around 45 percent. This again indicates a clear advantage from separately modeling positive, negative and zero revisions.

Panel C of Table 7 is based on a more conventional measure of forecasting performance, namely root mean squared error. Again we present results for the three-state model as well as for the first-order autoregressive model. For more than two-thirds of the firms, the three-state model generates a lower root mean squared error value than the linear model. The root mean squared error averaged across all 30 firms is lower for the three-state model than for the linear model for all of the specifications and there is very little variation in root mean squared error values across the various specifications.

Panel D of Table 7 shows t-statistics associated with the Giacomini and White (2006) test for conditional forecast evaluation. Negative test values indicate that the three-state model generates the lowest root mean squared error while positive values suggest the reverse. While most values are not statistically significant, for a little less than one quarter of the firms, we find that the root mean squared error produced by the three-state model is significantly lower than that of the linear model. In particular, viewed across all firms and the four specifications with a time-varying covariate, the three-state model produced significantly lower squared errors than the linear model in 27 cases, while the converse holds only in a single case.

4.2 Predicted Revisions and Actual Earnings Per Share

So far our analysis has focused on modeling the process by which analysts revise their earnings expectations. This allowed us to uncover some of the factors that determine the updates in analysts' beliefs. A question of separate interest is whether our findings of predictability in revisions to analysts' earnings expectations translate into an ability to forecast the 'actuals', i.e. the realized earnings figure announced by firms once a year. If analysts' earnings estimates are systematically biased with a bias that itself is predictable, we would expect that the forecast error (i.e., the actual minus the predicted value) should be predictable. Moreover, this should translate into an ability to improve upon analysts' forecasts.

To see if this is the case, we estimate the following model for the actual earnings announced at time T, A_T, scaled by the past stock price:

$$\frac{A_T}{p_{T-1}} = \beta_0 + \beta_1 f_{T,T-1} + \beta_2 \Delta \hat{f}^{3s}_{T,T-1} + \varepsilon_T, \tag{16}$$

where $f_{T,T-1}$ is the consensus earnings forecast of A_T/p_{T-1} produced the month prior to the earnings announcement (i.e. at time $T-1$) and $\Delta \hat{f}^{3s}_{T,T-1}$ is the revision to the consensus earnings estimate that our three-state model predicts will occur between period $T-1$ and T. To conduct the test, for each firm we use data on the realized earnings per share for the fiscal year since this is the variable targeted by financial analysts. For each fiscal year, I/B/E/S reports actual earnings as soon as they are released to the market. These earnings figures are then adjusted for comparability with analysts' forecasts.[13]

Panel A in Table 8 reports summary results from applying (16) to our data. Each of the four predictor variables corresponds to a different value of $\Delta \hat{f}^{3s}_{T,T-1}$, so the table shows four sets of results. As expected, analysts' estimates of the earnings figure that is announced the following month are very precise with slope coefficients, β_1, near one and R^2-values (not shown to preserve space) that typically exceed 0.97.

Because we only have 22 annual observations on the actual earnings for each firm, we should not expect to have much power in detecting predictability from $\Delta \hat{f}^{3s}_{T,T-1}$. Interestingly, however, for around a quarter of the firms at least one of the explanatory variables−most often past revisions of volatility−leads to a coefficient on $\Delta\hat{f}^{3s}_{T,T-1}$ that is statistically significant at the 10% level. At the more stringent 5% level used in the table, we find significance for around one-sixth of the cases.

The forecast error in analysts' earnings estimate, $(A_T - f_{T,T-1})/p_{T-1}$, can alternatively be viewed as the predicted revision to the consensus earnings estimate, $\Delta\hat{f}^{3s}_{T,T-1}$, plus a forecast error. This follows because the earnings estimate will be identical to the actual earnings figure once this has been released and becomes known. It is therefore natural to conjecture that the predicted revision in the consensus earnings forecast may be correlated with the forecast error, $(A_T - f_{T,T-1})/p_{T-1}$. This suggests a regression closely related to (16):

$$\frac{A_T - f_{T,T-1}}{p_{T-1}} = \beta_0 + \beta_1 \Delta\hat{f}^{3s}_{T,T-1} + \varepsilon_T. \tag{17}$$

This regression is also interesting in view of the empirical findings that analysts' earnings forecasts are superior to those generated by traditional time series models, see e.g. Elton and Gruber (1972) and Brown and Rozeff (1978).

Panel B in Table 8 reports the outcome of applying this regression to our data. Errors in analysts' forecasts, $(A_T - f_{T,T-1})/p_{T-1}$, are often explained by the predicted revision to the earnings estimate generated by the three-state models based on the short interest rate or past revisions. Furthermore, the coefficients mostly have the sign one would expect. Of 16 estimates of β_1 that are significant at the 5% level using the four separate state variables, 11 are positive. Thus, a forecast of a positive earnings revision one month prior to the earnings announcement tends to translate into the actual earnings figure coming in higher than the consensus estimate.

The consensus forecast is widely regarded to be difficult to beat and we should not expect to find much predictability in the consensus forecast error, $A_T - f_{T,T-1}$. Indeed, the R^2-values reported by Abarbanell and Bernard (1992) and Easterwood and Nutt (1999) from regressions of forecast errors on prior-year earnings changes lie in the range of 0.01-0.02. While the explanatory power of our prediction of the consensus revision, $\Delta\hat{f}^{3s}_{T,T-1}$, is quite low in many cases, for around forty percent of the firms the three-state model generates an R^2 that exceeds 10%. This confirms that the predictability of earnings revisions has important implications for predictability of the actual earnings figures.

4.3 Predictability of Returns and Volatility

One could argue that, ultimately, the reason we are interested in predictability of earnings revisions is because they may affect stock returns, for which lack of predictability is linked to the efficient market hypothesis. To explore if our earnings forecasts help predict stock returns, we estimated simple regressions of the type

$$r_{T:T+1} = \beta_0 + \beta_1 \Delta f_{T+1} + \beta_2 \Delta \hat{f}^{3s}_{T+1,T} + \varepsilon_{T+1}, \tag{18}$$

where $r_{T:T+1}$ is the cumulated daily return during month $T+1$. Since the predicted earnings revision from the three-state model, $\Delta \hat{f}^{3s}_{T+1,T}$, is known at time T, if all information is efficiently incorporated in stock prices at time T, β_2 should not be significantly different from zero. Panel A of Table 9 shows that in fact for around 20% of all firms, the predicted forecast revision is statistically significant, with the forecasts based on past revisions delivering the strongest evidence.

We also tested if future realized volatility of stock returns is predictable by means of the predicted earnings revisions from the three-state model by estimating the following model

$$vol_{T:T+1} = \beta_0 + \beta_1 vol_{T:T-1} + \beta_2 \Delta \hat{f}^{3s}_{T+1,T} + \varepsilon_{T+1}, \tag{19}$$

where $vol_{T:T+1}$ is the realized volatility during month $T+1$ based on the corresponding daily observations. We include a lag of the realized volatility in the model due to the strong evidence of persistence in this variable. Panel B of Table 9 shows that for around one-sixth of the sample of firms there is evidence that the predicted earnings revision from the three-state model has predictive power over future return volatility. Once again the state variable for which the evidence is strongest is past revisions. Thus while there is some evidence that volatility can be predicted by means of the predicted earnings revisions, the evidence is weaker than that found for the return regressions.

5 Conclusion

If agents have squared loss and use information efficiently, revisions to forecast errors should follow a martingale difference process and thus be unpredictable with respect to all publicly available information. Although this is a well-known result, relatively little work has been undertaken on modeling the process underlying forecast revisions, let alone testing if the zero bias condition holds.

In this paper we proposed a new dynamic mixture of log-normals model for capturing the pronounced asymmetries, persistence and predictability that we found in revisions to analysts' earnings expectations. Such patterns are in part related to the magnitude of past revisions: small revisions are more likely to follow small revisions. They are also related to the sign of the revision to analysts' earnings expectations: continuation of revisions of the same sign are more likely than sign reversals. Variables such as past revisions and the lagged interest rate were found to predict future revisions in analysts' earnings expectations. These variables contain information that is relevant not only for the revisions to analysts' earnings forecasts but also for the actual earnings figure which is what ultimately matters to investors and financial analysts.

The methodology presented in this paper is more broadly applicable and should find use in areas such as finance with transactions data where zero price changes are commonly observed but sometimes ignored rather than modeled as part of the underlying data generating process.

Notes

[1]Papers that study the link between revisions in analysts' earnings estimates and movements in stock prices include Brown, Foster and Noreen (1985), Klein (1990), Stickel (1991), Park and Stice (2000), Liu and Thomas (2000) and Chen, Francis and Jiang (2005).

[2]See, e.g., Fried and Gilvoy (1982), O'Brien (1988), Butler and Lang (1991), Brous (1992), Kang, O'Brien and Sivaramakrishnan (1994), Easterwood and Nutt (1999), Lim (2001) and Hong and Kubik (2003).

[3]We are grateful to an anonymous referee for bringing these issues to our attention.

[4]This is in part due to herding among analysts, see, e.g., Hong, Kubik and Solomon (2000).

[5]Without risk of confusion we have omitted the horizon subscript, $T-h$, since it is not needed here.

[6]To make forecasts in adjacent months comparable, we adjust f_t^j and P_t^j using an adjustment factor which accounts for stock splits. One could could be more precise and let f_t^{j*} and P_t^{j*} denote split adjusted values, in which case the revision can be computed as $\Delta f_{t+1}^j = 100 \times \left(\frac{f_{t+1}^j - f_t^{j*}}{P_t^{j*}} \right)$. However, in order to avoid cumbersome notation we leave the notation as it stands, and remind the reader that adjustments were made whenever splits occurred.

[7]For simplicity, and without risk of confusion, we have omitted the firm superscript, j. We follow this convention in the subsequent analysis.

[8]Estimates were found to be robust to different starting values. Standard errors are obtained using the delta method.

[9]Our findings on asymmetries and persistence in revisions to the consensus earnings estimate bear an interesting relation to recent findings by Conrad et al (2006) that whereas analysts are equally likely to upgrade or downgrade a stock following a large increase in the stock price, they are more likely to issue a downgrade following a large negative movement in the stock price. Consistent with our findings of persistence in the direction of earnings forecasts, they also find that analysts recommendations are "sticky" and that analysts appear reluctant to issue a downgrade−a finding confirmed by Clarke et al (2006).

[10]Aiolfi and Rodriguez (2006) investigate how financial analysts incorporate macroeconomic information into their earnings forecasts for different industries and find that macroeconomic information helps explain revisions to the average analyst's forecast.

[11]To be consistent with our treatment of the consensus earnings estimate in the three-state model, we categorize forecast revisions from the autoregressive model as zero whenever the predicted earnings revision is smaller than one cent per share.

[12]We also computed predictions for the three-state models extended to incorporate time-varying mean earnings revisions within each state (using (13)). The forecasts implied by these models are given by

$$\Delta \hat{f}_{t+1} = \begin{cases} p_{1,1,t} \exp(\beta_{11} + \beta_{21} x_t + 0.5\sigma_1^2) - p_{1,-1,t} \exp(\beta_{1,-1} + \beta_{2,-1} x_t + 0.5\sigma_{-1}^2) & \text{if } s_t = 1 \\ (1 - \frac{p_{0,0,t}}{2})(\exp(\beta_{11} + \beta_{21} x_t + 0.5\sigma_1^2) - \exp(\beta_{1,-1} + \beta_{2,-1} x_t + 0.5\sigma_{-1}^2)) & \text{if } s_t = 0 \\ p_{-1,1,t} \exp(\beta_{11} + \beta_{21} x_t + 0.5\sigma_1^2) - p_{-1,-1,t} \exp(\beta_{1,-1} + \beta_{2,-1} x_t + 0.5\sigma_{-1}^2) & \text{if } s_t = -1 \end{cases}.$$

The forecasting performance produced by these models was very similar to that of the simpler models and we therefore do not report these results separately. Results are available on request.

[13]I/B/E/S does not require analysts to forecast earnings per share in the basic or diluted format, but instead lets the majority rule. In cases where an analyst follows a firm on a basis that is different from the

consensus, I/B/E/S adjusts the corresponding estimates to conform with the majority.

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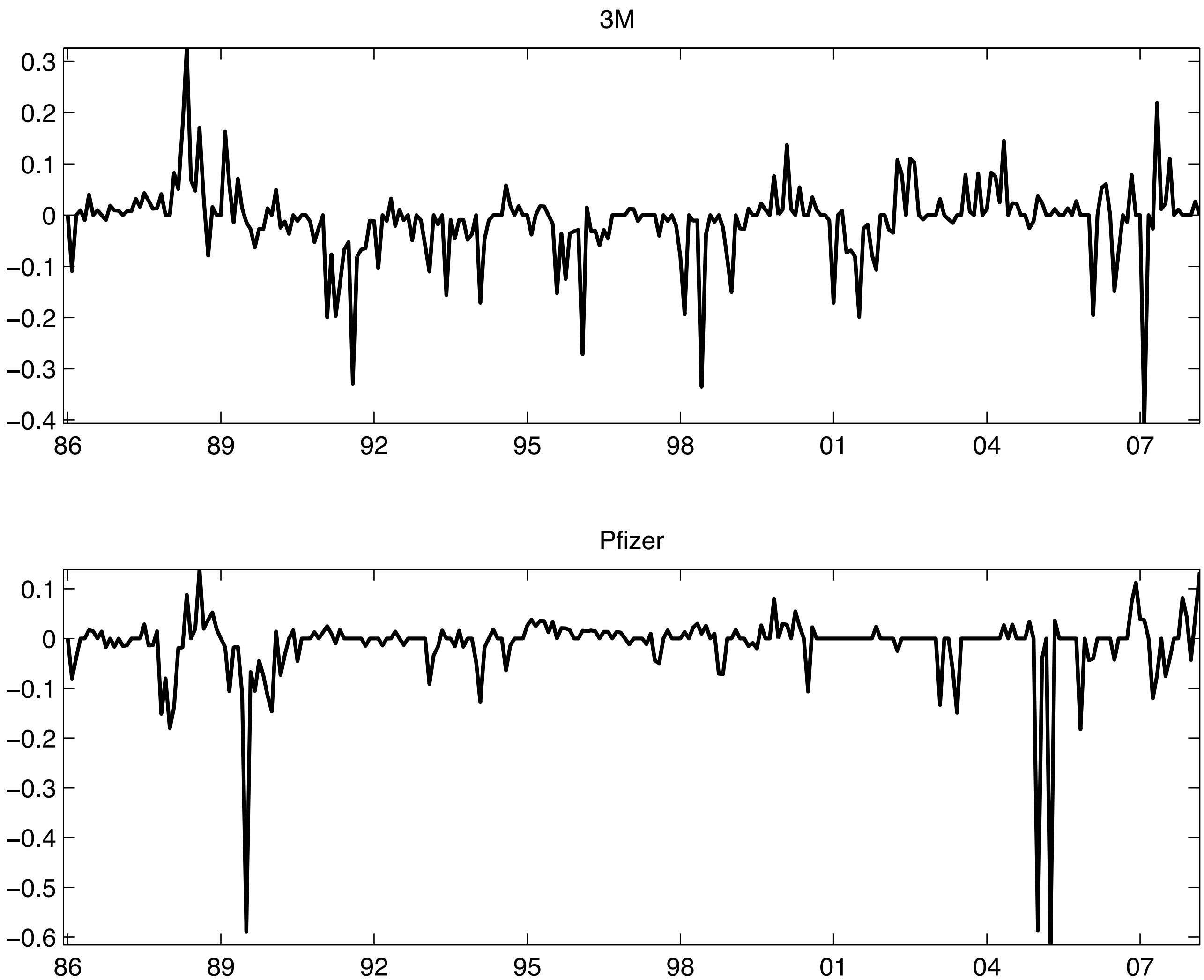
Figure 1:


3M
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
86
89
92
95
98
01
04
07
Pfizer
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.6
86
89
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04
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Figure 2:

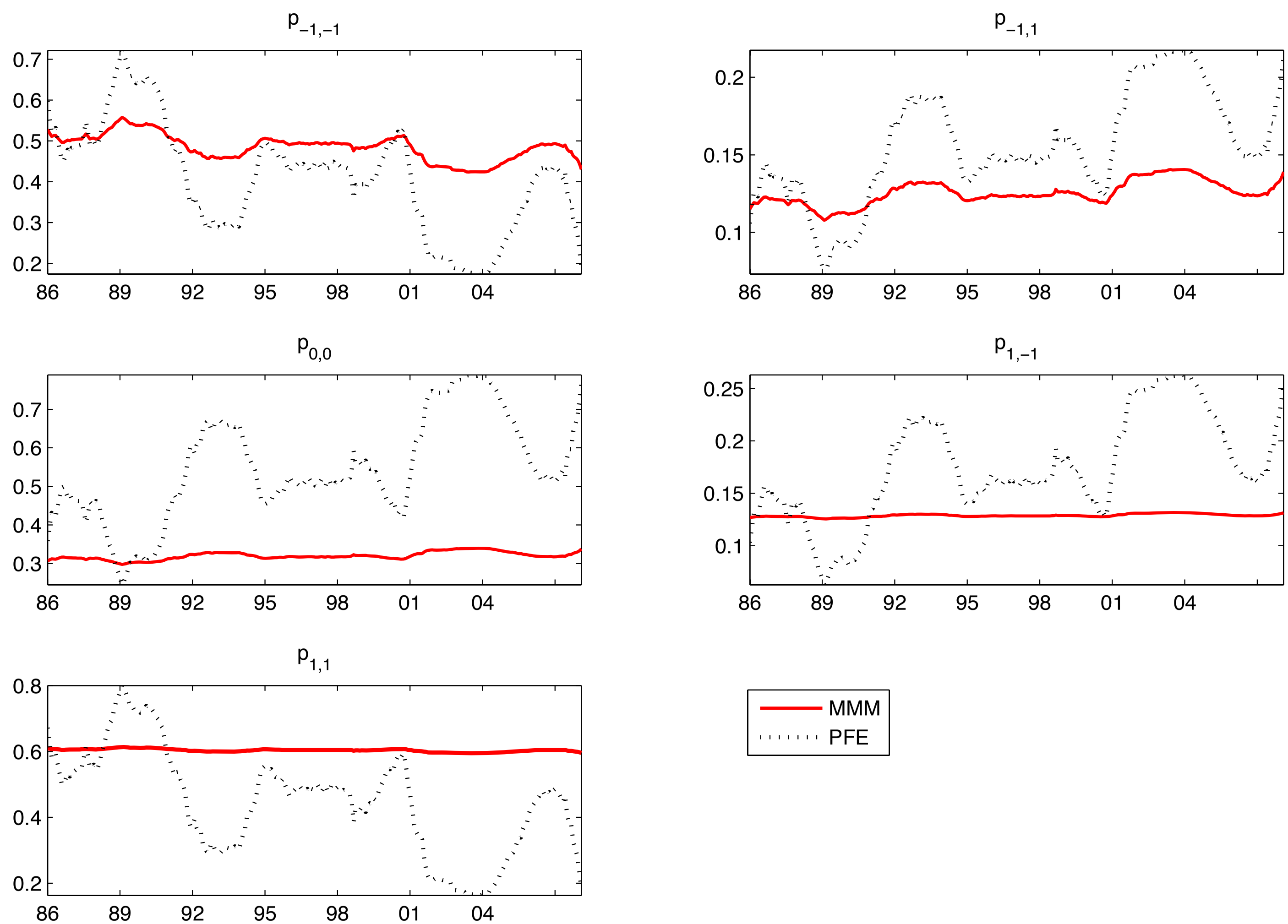

Figure 1: Time-series plot of monthly revisions in the consensus earnings forecast (scaled by the initial stock price) for 3M and Pfizer over the sample Jan 1986 - Mar 2008.

Figure 2: Time-varying transition probabilities for 3M (MMM) and Pfizer(PFE) obtained from a three-state model with time-varying transition probabilities that depend on the lagged T-bill rate. State 1 captures positive earnings revisions, state 0 captures zero revisions and state -1 captures negative earnings revisions.

Table 1: Analyst Coverage by Firm

Company Name	Ticker	Median	Min	Max
Alcoa Inc	AA	22	8	33
American Express Company	AXP	21	11	27
Boeing Co.	BA	26	13	37
Bank of America Corporation	BAC	31	10	44
Citigroup, Inc.	C	17	3	33
Caterpillar Inc.	CAT	23	12	33
Chevron Corp	CVX	33	17	43
E.I. du Pont de Nemours and Company	DD	23	10	32
Walt Disney Company	DIS	27	17	36
General Electric Company	GE	23	12	30
General Motors Corporation	GM	23	2	30
The Home Depot, Inc.	HD	25	15	41
Hewlett-Packard Co.	HPQ	29	15	45
International Business Machines	IBM	27	13	45
Intel Corporation	INTC	36	22	43
Johnson & Johnson	JNJ	30	11	38
JP Morgan & Chase & Co	JPM	24	8	30
Kraft Foods Inc.	KFT	17	13	20
The Coca-Cola Company	KO	24	13	31
McDonald's Corporation	MCD	27	9	35
3m Co	MMM	18	11	28
Merck & Co., Inc.	MRK	38	10	51
Microsoft Corporation	MSFT	32	8	44
Pfizer Inc	PFE	37	16	47
The Procter & Gamble Company	PG	21	9	26
AT&T Inc.	T	29	19	38
United Technologies Corporation	UTX	21	16	31
Verizon Communications	VZ	31	15	42
Wal-Mart Stores, Inc.	WMT	30	18	47
Exxon Mobil Corp	XOM	35	18	47

This table reports company names and ticker legends for the 30 Dow Jones firms in addition to the median, minimum and maximum number of analysts covering the firms during 1986-2008.

Table 2: Size and Frequency of Positive and Negative Revisions to Analysts' Earnings Forecasts

	# Obs	$\Delta f > 0$	$\Delta f = 0$	$\Delta f < 0$	Δf					$\Delta f > 0$		$\Delta f < 0$	
					Mean	Std	AR(1)	Skew	Kurt	Mean	Std	Mean	Std
AA	267	32.6%	5.2%	62.2%	-0.079	0.505	0.368	1.831	14.109	0.352	0.547	-0.311	0.320
AXP	267	30.0%	33.7%	36.3%	-0.112	0.471	0.411	-6.048	46.341	0.068	0.122	-0.364	0.706
BA	267	37.5%	18.4%	44.2%	-0.060	0.303	0.287	-3.829	28.162	0.109	0.139	-0.227	0.372
BAC	267	40.8%	21.3%	37.8%	-0.070	0.780	-0.109	-3.814	58.848	0.168	0.575	-0.366	1.054
C	253	51.8%	17.0%	31.2%	-0.037	0.409	0.439	-5.788	46.017	0.121	0.116	-0.318	0.628
CAT	267	47.2%	11.2%	41.6%	-0.078	0.472	0.277	-2.583	16.382	0.184	0.241	-0.396	0.540
CVX	267	52.8%	4.5%	42.7%	0.052	0.312	0.570	-0.056	6.928	0.246	0.243	-0.182	0.229
DD	267	35.2%	18.4%	46.4%	-0.028	0.184	0.468	-1.253	10.220	0.113	0.128	-0.147	0.175
DIS	267	41.6%	24.3%	34.1%	-0.003	0.104	0.389	-0.614	5.633	0.076	0.067	-0.102	0.094
GE	267	27.0%	52.1%	21.0%	-0.003	0.047	0.064	-7.294	84.478	0.025	0.023	-0.049	0.084
GM	267	43.4%	4.5%	52.1%	-0.262	1.545	0.237	-2.121	22.976	0.571	1.006	-0.979	1.628
HD	267	38.6%	41.6%	19.9%	0.003	0.124	0.185	-4.946	64.543	0.067	0.088	-0.113	0.203
HPQ	267	36.0%	23.2%	40.8%	-0.023	0.242	0.166	-0.388	13.016	0.137	0.212	-0.177	0.240
IBM	267	34.8%	18.7%	46.4%	-0.077	0.443	0.412	-1.344	18.048	0.146	0.369	-0.275	0.493
INTC	267	50.6%	12.4%	37.1%	-0.000	0.335	0.364	-0.036	9.150	0.187	0.265	-0.256	0.306
JNJ	267	35.6%	47.9%	16.5%	0.004	0.079	0.090	-7.535	120.008	0.038	0.060	-0.060	0.156
JPM	267	38.6%	13.1%	48.3%	-0.507	3.378	0.153	-9.943	107.793	0.204	0.297	-1.211	4.761
KFT	80	13.8%	58.8%	27.5%	-0.007	0.199	0.042	6.744	57.059	0.184	0.476	-0.117	0.097
KO	267	28.1%	49.8%	22.1%	0.001	0.036	0.220	-1.979	16.206	0.035	0.024	-0.041	0.045
MCD	267	24.0%	47.6%	28.5%	-0.002	0.071	0.272	-0.297	15.418	0.065	0.073	-0.062	0.077
MMM	267	30.0%	32.2%	37.8%	-0.010	0.073	0.301	-1.156	10.884	0.049	0.055	-0.066	0.076
MRK	267	41.6%	43.1%	15.4%	0.004	0.102	0.019	-7.355	96.807	0.042	0.065	-0.084	0.215
MSFT	259	54.1%	30.9%	15.1%	0.030	0.108	0.167	2.852	24.453	0.078	0.114	-0.083	0.089
PFE	267	26.2%	47.9%	25.8%	-0.013	0.075	0.182	-5.475	42.366	0.031	0.027	-0.080	0.120
PG	267	33.7%	40.1%	26.2%	-0.002	0.059	0.247	-1.991	16.598	0.041	0.040	-0.060	0.075
T	267	34.5%	33.7%	31.8%	-0.001	0.115	0.098	-2.052	37.623	0.069	0.108	-0.078	0.134
UTX	267	40.8%	29.6%	29.6%	-0.047	0.268	0.577	-6.803	70.706	0.054	0.086	-0.233	0.429
VZ	267	22.8%	44.2%	33.0%	-0.020	0.420	-0.454	-0.045	118.337	0.111	0.596	-0.137	0.517
WMT	267	28.8%	43.1%	28.1%	-0.003	0.038	0.356	-1.902	13.888	0.033	0.020	-0.045	0.040
XOM	267	56.2%	4.5%	39.3%	0.035	0.189	0.587	-0.548	9.187	0.143	0.141	-0.114	0.151
Average	260	36.9%	29.1%	34.0%	-0.044	0.383	0.246	-2.526	40.073	0.125	0.211	-0.224	0.468

This table reports descriptive statistics for revisions in the IBES consensus earnings forecast for each of the 30 firms in the Dow Jones index over the sample January 1986 - March 2008. The revision in the consensus earnings forecast between two consecutive months is reported as a percent of the initial month's stock price and is denoted by Δf.

Table 3: Asymmetry, Persistence and Conservatism in Earnings Statements

	Mean		Std Dev		Persistence	
θ	negative obs.	positive obs.	negative obs.	positive obs.	negative obs.	positive obs.
0	0.752	0.451	0.586	0.584	0.500	0.300
0.1	0.752	0.468	0.585	0.524	0.500	0.311
0.2	0.752	0.486	0.585	0.473	0.500	0.323
0.3	0.753	0.508	0.585	0.437	0.501	0.337
0.4	0.755	0.533	0.585	0.416	0.500	0.353
0.5	0.757	0.562	0.586	0.414	0.500	0.371
0.6	0.762	0.597	0.587	0.429	0.500	0.392
0.7	0.767	0.637	0.589	0.460	0.500	0.415
0.8	0.775	0.683	0.593	0.502	0.500	0.441
0.9	0.785	0.737	0.597	0.551	0.500	0.470
1	0.798	0.798	0.603	0.603	0.500	0.500

This table reports the effect on negative and positive values of earnings news when firms fully announce negative news but smooth positive earnings news, consistent with the model in Section 2.3.

Table 4: Parameter Estimates for the Sign Mixture Model with Constant Transition Probabilities

	$\frac{exp(\beta_{1,-1})}{exp(\beta_{1,1})}$	$\frac{\sigma_{-1}}{\sigma_1}$	$p_{1,1}$	$p_{1,-1}$	$p_{0,0}$	$p_{-1,1}$	$p_{-1,-1}$	*No Persist.*	$\overline{p}_{1,1}$	$\overline{p}_{0,0}$	$\overline{p}_{-1,-1}$
AA	1.03	0.99	0.70 (0.05)	0.24 (0.05)	— ()	0.12 (0.03)	0.83 (0.03)	81.82**	0.33	0.05	0.62
AXP	3.46**	1.52**	0.35 (0.05)	0.23 (0.05)	0.43 (0.05)	0.19 (0.04)	0.63 (0.05)	22.21**	0.26	0.33	0.41
BA	1.64**	1.17*	0.54 (0.05)	0.22 (0.04)	0.23 (0.06)	0.21 (0.04)	0.67 (0.04)	37.12**	0.36	0.18	0.45
BAC	1.42*	1.25**	0.56 (0.05)	0.21 (0.04)	0.26 (0.06)	0.23 (0.04)	0.60 (0.05)	30.57**	0.39	0.21	0.40
C	1.39*	1.42**	0.76 (0.04)	0.13 (0.03)	0.21 (0.06)	0.15 (0.04)	0.60 (0.06)	62.93**	0.49	0.17	0.33
CAT	2.14**	1.07	0.74 (0.04)	0.17 (0.03)	0.21 (0.08)	0.21 (0.04)	0.68 (0.04)	62.49**	0.49	0.11	0.39
CVX	0.68**	0.99	0.75 (0.04)	0.20 (0.03)	— ()	0.28 (0.04)	0.69 (0.04)	56.63**	0.55	0.04	0.41
DD	1.30*	1.00	0.54 (0.05)	0.23 (0.04)	0.17 (0.05)	0.18 (0.03)	0.66 (0.04)	40.24**	0.35	0.18	0.47
DIS	1.17	1.25**	0.65 (0.05)	0.12 (0.03)	0.30 (0.06)	0.13 (0.04)	0.66 (0.05)	57.47**	0.38	0.24	0.38
GE	1.44**	1.42**	0.32 (0.05)	0.19 (0.05)	0.55 (0.04)	0.18 (0.05)	0.31 (0.06)	3.92	0.24	0.53	0.24
GM	1.37*	1.26**	0.70 (0.04)	0.25 (0.04)	— ()	0.24 (0.04)	0.72 (0.04)	52.39**	0.46	0.04	0.49
HD	1.59**	0.65**	0.48 (0.05)	0.09 (0.03)	0.45 (0.05)	0.12 (0.05)	0.57 (0.07)	34.18**	0.28	0.40	0.31
HPQ	1.38**	0.98	0.55 (0.05)	0.18 (0.04)	0.21 (0.05)	0.14 (0.03)	0.66 (0.05)	46.59**	0.33	0.23	0.44
IBM	1.95**	1.18*	0.57 (0.05)	0.23 (0.04)	0.33 (0.07)	0.18 (0.03)	0.71 (0.04)	46.09**	0.34	0.18	0.48
INTC	1.40**	1.01	0.74 (0.04)	0.16 (0.03)	0.18 (0.07)	0.20 (0.04)	0.67 (0.05)	64.52**	0.49	0.13	0.39
JNJ	1.17	1.17	0.54 (0.05)	0.06 (0.02)	0.54 (0.04)	0.09 (0.04)	0.43 (0.07)	32.61**	0.29	0.49	0.23
JPM	2.35**	1.32**	0.62 (0.05)	0.28 (0.04)	0.23 (0.07)	0.20 (0.04)	0.67 (0.04)	41.43**	0.39	0.13	0.48
KFT	1.63	0.72	0.09 (0.09)	0.00 (0.00)	0.52 (0.07)	0.14 (0.07)	0.32 (0.10)	1.51	0.19	0.60	0.21
KO	0.97	1.35**	0.29 (0.05)	0.13 (0.04)	0.49 (0.04)	0.15 (0.05)	0.42 (0.06)	11.17**	0.24	0.49	0.27
MCD	0.93	0.93	0.59 (0.06)	0.06 (0.03)	0.55 (0.04)	0.07 (0.03)	0.49 (0.06)	35.50**	0.29	0.47	0.24
MMM	1.25	1.07	0.49 (0.06)	0.13 (0.04)	0.32 (0.05)	0.13 (0.03)	0.60 (0.05)	40.44**	0.31	0.32	0.37
MRK	1.23	1.27*	0.62 (0.05)	0.06 (0.02)	0.52 (0.05)	0.18 (0.06)	0.33 (0.07)	34.50**	0.37	0.44	0.19
MSFT	1.17	0.97	0.60 (0.04)	0.11 (0.03)	0.35 (0.05)	0.46 (0.08)	0.26 (0.07)	40.09**	0.49	0.31	0.20
PFE	1.83**	1.62**	0.45 (0.06)	0.14 (0.04)	0.59 (0.04)	0.16 (0.04)	0.49 (0.06)	20.25**	0.26	0.48	0.27
PG	1.10	1.30**	0.49 (0.05)	0.14 (0.04)	0.49 (0.05)	0.17 (0.05)	0.51 (0.06)	25.11**	0.30	0.40	0.30
T	1.18	0.97	0.38 (0.05)	0.16 (0.04)	0.28 (0.05)	0.25 (0.05)	0.49 (0.05)	13.74**	0.33	0.33	0.34
UTX	2.67**	1.53**	0.39 (0.05)	0.20 (0.04)	0.32 (0.05)	0.27 (0.05)	0.63 (0.05)	17.16**	0.32	0.26	0.42
VZ	1.63**	1.16	0.26 (0.06)	0.23 (0.05)	0.50 (0.05)	0.22 (0.04)	0.45 (0.05)	6.74**	0.24	0.45	0.31
WMT	1.26**	1.30**	0.51 (0.06)	0.17 (0.04)	0.49 (0.05)	0.15 (0.04)	0.41 (0.06)	19.90**	0.30	0.43	0.27
XOM	0.80*	0.88	0.78 (0.03)	0.16 (0.03)	— ()	0.27 (0.04)	0.70 (0.04)	67.96**	0.57	0.05	0.38

For each of the DJ30 firms a sign mixture model was estimated to revisions in the consensus earnings forecast between consecutive months, Δf_t: $log(|\Delta f_t|) = \beta_{1,s_t} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \sigma^2_{s_t}\right)$ with state transition probabilities $p_{i,k} = P\left(s_t = i | s_{t-1} = k\right)$ and $i, k = 1, 0, -1$. States 1,0,-1 capture positive, zero and negative earnings revisions, respectively. Standard errors appear in parentheses to the right of the parameter estimates. The first and second columns report the ratio of the means and volatilities in the negative versus the positive states. The column *No Persist.* reports the Wald test for the joint restrictions $p_{1,1} = p_{1,-1}$ and $p_{-1,1} = p_{-1,-1}$ and is a test of no persistence in the signs of the earnings revisions. (-) indicates too few transitions between states to allow estimation of the parameters. ** and * denote significance at 5% and 10% level respectively. $\overline{p}_{i,k}$ are the steady state probabilities.

Table 5: Parameter Estimates for the Sign Mixture Model with Time-Varying Transition Probabilities

	Tb			Ret			Rev		Vol		
	$\delta_{2,1,1}$	$\delta_{2,0,0}$	$\delta_{2,-1,-1}$	$\delta_{2,1,1}$	$\delta_{2,0,0}$	$\delta_{2,-1,-1}$	$\delta_{2,1,1}$	$\delta_{2,-1,-1}$	$\delta_{2,1,1}$	$\delta_{2,0,0}$	$\delta_{2,-1,-1}$
Number of positive coeff	21	10	19	25	15	6	26	28	14	14	21
Number of positive coeff at 5%	10	1	3	4	1	0	13	15	0	0	3
Number of negative coeff	9	16	11	5	11	24	3	1	16	12	9
Number of negative coeff at 5%	2	4	0	0	0	8	0	0	1	0	0

A sign mixture model was estimated for revisions to the consensus earnings forecasts of each of the DJ30 firms: $log(|\Delta f_t|) = \beta_{1,s_t} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \sigma^2_{s_t}\right)$ with state transition probabilities $p_{i,k} = P\left(s_t = i | s_{t-1} = k\right) = \Phi\left(\delta_{1,i,k} + \delta_{2,i,k} x_{t-1}\right)$ where x_{t-1} is the lagged value of the 3-month T-bill rate (Tb), past revisions (Rev), past returns (Ret) and past volatility (Vol) and $i, k = 1, 0, -1$. The table summarizes this information by reporting the sign of the coefficients as well as the number of coefficients that were statistically significant.

Table 6: Estimates for the Mixture Model with Time-Varying Mean and Transition Probabilities

	$\beta_{2,1}$	$\beta_{2,-1}$	$p_{1,1}$		$p_{1,-1}$	$p_{0,0}$		$p_{-1,1}$	$p_{-1,-1}$	
			δ_1	δ_2	δ_1	δ_1	δ_2	δ_1	δ_1	δ_2
Number of positive coeff	12	13	13	21	10	10	10	14	23	19
Number of positive coeff at 5%	4	2	9	10	5	2	1	5	7	3
Number of negative coeff	18	17	17	9	20	16	16	16	7	11
Number of negative coeff at 5%	6	5	3	2	15	1	4	10	1	0

A sign mixture model was estimated for revisions in the consensus earnings forecast for each of the DJ30 firms: $log(|\Delta f_t|) = \beta_{1,s_t} + \beta_{2,s_t} Tb_{t-1} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \sigma^2_{s_t}\right)$ where Tb_{t-1} is the lagged value of the 3-month T-bill rate and $p_{i,k} = P\left(s_t = i | s_{t-1} = k\right) = \Phi\left(\delta_{1,i,k} + \delta_{2,i,k} Tb_{t-1}\right)$ are the state transition probabilities between states $i, k = 1, 0, -1$. State 1,0,-1 capture positive, zero and negative earnings revisions, respectively. The table summarizes this information by reporting the sign of the coefficients as well as the number of coefficients that were statistically significant.

Table 7: Out-of-sample Predictability of Revisions in Analysts Earnings Expectations

	Three-State Model						Linear AR(1) Model				
	Const	Tb	Ret	Rev	Vol	Ew	Tb	Ret	Rev	Vol	Ew
Panel A: Correlations											
Number of positive correlations	27	26	27	26	25	27	21	25	23	24	24
Significantly positive correlations	23	20	21	22	23	20	15	18	16	18	17
Number of negative correlations	2	3	2	2	3	2	8	4	6	5	5
Significantly negative correlations	0	0	0	0	0	0	2	1	2	1	1
Average	0.23	0.22	0.24	0.24	0.23	0.25	0.13	0.17	0.14	0.17	0.17
Panel B: Percentage of correctly predicted signs											
Three-state model outperforms AR(1)		25	23	23	22	24					
Average	0.52	0.53	0.52	0.52	0.52	0.52	0.42	0.44	0.45	0.45	0.44
Panel C: Root mean squared error											
Three-state model outperforms AR(1)		24	26	21	21	23					
Average	0.0264	0.0264	0.0264	0.0255	0.0259	0.0262	0.0284	0.0285	0.0282	0.0282	0.0279
Panel D: Giacomini-White test statistic											
Number of Gw stat < 0		24	25	20	20	22					
Number of Gw stat > 0		5	4	8	9	6					

This table reports different measures of forecasting performance for the predicted values from the three-state model using a constant (Const), a constant and the lagged 3-month T-bill rate (Tb), a constant and the lagged holding period return (Ret), a constant and the past revision (Rev), and a constant and the lagged return volatility (Vol). (Ew) is the equal weighted combination of the forecasts generated by the four univariate forecasts. We also report results based on a first-order autoregressive (AR(1)) model extended to include the predictor variables. All forecasts are computed recursively out-of-sample. Panel A reports the total number of cases with positive and negative correlation estimates as well as the number of cases with positive and negative correlation significant at the 5% level, for the three-state model and the first-order autoregressive (AR(1)) model respectively. Average denotes the average (across firms) correlation coefficient between revisions to consensus earnings estimates and the predicted values. Panel B reports the number of cases where the three-state model has a higher percentage of correctly predicted states compared to the first-order autoregressive model. Average denotes the average (across firms) percentage of correctly predicted states from the three-state model and the first-order autoregressive model. Panel C reports the number of cases where the three-state model has a lower root mean squared error compared to the first-order autoregressive model. Average denotes the average (across firms) root mean squared error from the three-state model and the first-order autoregressive model. Panel D reports the number of cases where the Giacomini-White (2006) test statistic has positive and negative sign.

Table 8: Forecasts of Actual Earnings

Panel A: Earnings regression					
	Tb	Ret	Rev	Vol	Ew
No. significant $\beta_1 \neq 1$	5	6	6	6	6
No. significant $\beta_2 > 0$	2	3	4	2	4
No. significant $\beta_2 < 0$	0	2	3	5	5
Panel B: Forecast error regression					
	Tb	Ret	Rev	Vol	Ew
Average R-squared	0.11	0.14	0.13	0.13	0.14
No. significant $\beta_1 > 0$	2	3	3	3	3
No. significant $\beta_1 < 0$	0	1	2	2	2

Panel A reports the results of the regression $\left(\frac{A_t}{p_{t-1}}\right) = \beta_0 + \beta_1 f_{t,t-1} + \beta_2 \Delta \widehat{f}^{3s}_{t,t-1} + \epsilon_t$, where A_t is the actual earnings figure (published annually), $f_{t,t-1}$ is the previous month's consensus estimate of earnings and $\Delta \widehat{f}^{3s}_{t,t-1}$ is the predicted consensus revision (scaled by the stock price p_{t-1}) obtained from the three-state models. These models are based on covariates such as the lagged 3-month T-bill rate (Tb), the lagged holding period return (Ret), the lagged revision to the earnings forecast (Rev), and the lagged return volatility (Vol). (Ew) is the equal weighted combination of the forecasts generated by the four univariate forecasts. Panel B reports the results of the regression $\left(\frac{A_t - f_{t,t-1}}{p_{t-1}}\right) = \beta_0 + \beta_1 \Delta \widehat{f}^{3s}_{t,t-1} + \epsilon_t$. All forecasts are computed recursively out-of-sample. Significance is measured at the 5% level.

Table 9: Return and Volatility Predictability

Panel A: Return regression					
	Tb	Ret	Rev	Vol	Ew
Average R-squared	0.07	0.07	0.07	0.07	0.07
No. significant $\beta_2 > 0$	1	1	1	1	1
No. significant $\beta_2 < 0$	5	5	7	3	4
Panel B: Volatility regression					
	Tb	Ret	Rev	Vol	Ew
Average R-squared	0.24	0.24	0.24	0.23	0.23
No. significant $\beta_2 > 0$	1	0	1	1	1
No. significant $\beta_2 < 0$	2	4	5	4	4

Panel A reports the results of the regression $r_{t:t+1} = \beta_0 + \beta_1 \Delta f_{t+1} + \beta_2 \Delta \widehat{f}^{3s}_{t+1,t} + \epsilon_t$, where $r_{t:t+1}$ is the cumulated return between t and t+1, $\Delta \widehat{f}^{3s}_{t+1,t}$ is the predicted consensus revision (scaled by the stock price) obtained from the three-state models at time t. Panel B reports the results of the regression $vol_{t:t+1} = \beta_0 + \beta_1 vol_{t-1:t} + \beta_2 \Delta \widehat{f}^{3s}_{t+1,t} + \epsilon_t$, where $vol_{t:t+1}$ is the realized volatility in stock returns between t and t+1, $\Delta \widehat{f}^{3s}_{t+1,t}$ is the predicted consensus revision (scaled by the stock price) obtained from the three-state models at time t. These models are based on covariates such as the lagged 3-month T-bill rate (Tb), the lagged holding period return (Ret), the lagged revision to the earnings forecast (Rev), and the lagged return volatility (Vol). (Ew) is the equal weighted combination of the forecasts generated by the four univariate forecasts. All forecasts are computed recursively out-of-sample. The table summarizes the information by reporting the average R-squared as well as the number of cases with positive and negative β_2 that are significant at the 5% level.