Dispersion of Beliefs, Stock Prices and the Earnings Surprise Measures-A Generalized Approach

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Abstract

In this paper we address the issue of modelling the relation between the stock prices and accounting earnings in the presence of potential divergence of opinions regarding the earnings data generating process. In our model the market’s earnings expectation is defined as the weighted average of both the time-series and analysts’ forecasts, with weights being estimated directly from stock returns. No assumptions are made on functional form of the earnings surprise-stock returns relation, which makes our model flexible enough to incorporate a variety of models discussed in the previous literature. The model is estimated semiparametrically following Hardle et al. [Annals of Statistics, 1993]. Our key findings are as follows. First, we find that investors use both the time-series models and analysts’ forecasts to predict future earnings. Second, the proportion of investors using the random walk (analysts) forecasts is significantly higher (lower) for the stocks with low (high) proportion of institutional holdings. Third, we find the choice of a particular earnings forecasting model to be related to its’ forecast accuracy, effect which is less pronounced for the institutional investors. Finally, we show how accounting for the dispersion of earnings forecasts leads to a substantial increase in the magnitude of the post-earnings announcement drift.

1 Introduction

The relation between the accounting earnings and stock prices is, probably, one of the most widely discussed issues in the academic literature. Since Ball and Brown (1968) seminal work a plethora of studies which examine this topic were published in both the academic and practitioners journals. The reason for such ongoing interest is twofold. First, in terms of the asset pricing theory, the equilibrium stock price is the expected discounted stream of free cash flows. Therefore, studying the impact of the earnings news on stock prices provides important clues about how and to what extent the information regarding firm-specific "fundamentals" is impounded in securities prices. Second, the widely reported post-earnings announcement drift phenomenon, that is, the tendency of stock prices to rise (fall) when the good (bad) news is released challenges the notion of the semi-strong market
efficiency on the one hand, while for the same reason being of a particular interest for the
investors on the other hand.

Clearly, to address the questions discussed above one needs a proper definition of the
earnings news or, in other words, an appropriate measure of earnings expected by the mar-
ket. In this paper we propose a new approach of estimating the earnings news. In contrast
to previous studies, which choose *ex ante* a particular earnings model as a proxy for mar-
ket expectations, our approach explicitly allows for the dispersion in earnings expectations
among the investors. More specifically, in our model a market earnings surprise is defined as
a weighted average of the earnings surprises implied by both time-series and the analysts’
forecasts related models. No assumption on the functional form of the earnings-returns
relation is imposed which allows our model to incorporate both the linear and non-linear
earnings-returns models discussed in previous studies as special cases. Both weights and the
earnings-returns function are simultaneously estimated from the stock returns and earnings
data, which provides us with a direct way of testing which of the earnings models are used
by market participants.

This study contributes to the existing literature in a number of ways. First, we extend
the existing literature on the earnings forecasting and the earnings-returns relation. In
particular, this research can be viewed as a further and significant extension of studies
such as Ball and Bartov (1996), Walther (1997) and Livnat and Mendenhall (2006). As
we show in the following sections, our model nests these as well as other models as special
cases and, thus, provides a much broader perspective on the earnings surprise measure as
perceived by the market as well as on the earnings-returns relation. Second, by extracting
the earnings surprise measure directly from the stock prices our approach allows us to
directly address the question which earnings forecasting models discussed in the previous
studies and to what extent are used by market participants. This issue is of particular
importance for the finance practitioners as the means of identifying both the direction and
the magnitude of the earnings news *as perceived by the market* rather than assuming *ex ante*
a particular earnings model. Third, we propose a simple filter which allows to incorporate
the dispersion of investors’ earnings expectations in the post-announcement drift based
investment strategies.

Our major findings are as follows. First, we find that market participants use *both* the
time-series and analysts’ forecasts related models while forming their earnings expectations.
Both the time-series and analysts’ related measures of the earnings surprise have a statisti-
cally significant effect on the behavior of stock prices around and following the earnings
announcements. Second, we find the share of investors using less (more) "sophisticated"
earnings forecast models to decline (increase) with an increase in the proportion of firm
shares held by institutional investors. Third we find forecast accuracy to be a significant
factor affecting investors’ choice of the earnings forecasting model, effect which appears to
be less pronounced for the institutional investors. We interpret this finding as the evidence
of institutional investors facing lower costs of constructing forecasts from more sophisti-
cated models. Finally, we show that taking into account the dispersion of investors’ earnings
expectations leads to a substantial increase in the magnitude of the post-announcement drift,
a result, which emphasizes the economic significance of our findings.

Our findings have important methodological as well as practical implications. We show
that both the time-series and analysts’ forecasts based measures of the earnings news used
in the previous studies are misspecified. In light of our findings, using a weighted average of both the time-series and analysts’ related forecasts as the measure of market earnings expectations seems to be a more appropriate way to proceed. Also, since investors appear to rely on both the time-series and analysts’ forecasts, finance practitioners who seek to exploit the post-announcement drift may consider using both kinds of models to predict the future trends of stock prices.

2 Literature Review

While varying in their objectives and methodologies, all earnings-returns studies share a common element-a need to define the earnings surprise. Generally, the earnings surprise measure is calculated as actual earnings minus market earnings forecast proxy scaled by a deflator. The critical decision is the choice of market forecast, since choosing a wrong forecast will lead to a measurement error in the unexpected earnings and, consequently, may cause the model to be misspecified.

Though it is most likely that investors vary in their beliefs regarding the earnings data generating process, a vast majority of studies use a single earnings forecast, either the one based on a particular time-series model or the analysts’ forecasts to measure the unexpected earnings. The studies using time-series models include Kormendi and Lipe (1987), Ramakrishnan and Thomas (1992), Bartov, Radhakrishnan and Krinsky (2000), Collins and Hribar (2000) and Narayanamoorthy (2003). On the other hand, a substantial number of other studies view the analysts’ forecasts as a more appropriate measure of market earnings expectations. These studies, among others, include Imhoff and Lobo (1992), Freeman and Tse (1992), Mendenhall (2004) and Francis et al. (2004).

In light of different earnings expectation measures proposed in literature two questions arise. First: how does one evaluate these measures to choose the right earnings forecasting model or, at least, the closest proxy to the one used by the market? Second: Why should one limit himself to a choice of a single forecasting model? In his influential paper Brown (1993) discusses two ways of approaching the first question. He makes a distinction between the "accuracy approach" and the "association approach". The "accuracy approach" suggests to evaluate earnings expectations models based on their ability to forecast future earnings. On the other hand, the "association approach", introduced by Foster (1977) suggests to look at contemporaneous association between the abnormal stock returns and the earnings surprise, conditional on a particular earnings model. This approach is particularly appealing as it evaluates how well a particular earnings model captures the market’s expectation based on how strong security price responds to the earnings surprise and, thus, directly links a capital market research to the accounting research.

Our research focuses on the second question. While numerous studies evaluate and compare the performance of both the time-series based and analysts’ forecasts (see Kothari, 2001) only relatively recently have studies appeared that consider using more than one model to measure the market’s earnings expectations. Ball and Bartov (1996) find that investors are aware of serial correlation in the seasonally differenced quarterly earnings but tend to underestimate its’ magnitude. Walther (1997) reports the stock returns around the earnings announcement being associated with the earnings surprises calculated using both seasonal random walk model and the analysts’ forecasts as a proxy for the market’s
earnings expectations. Using various proxies for investors’ sophistication he concludes that the sophisticated investors place more weight on the analysts’ consensus forecasts as the earnings expectations relative to expectation implied by a naive random walk model. Taking a trade size as a proxy for investors’ sophistication, Bhattacharaya (2001) reports a positive correlation between the number of small trades around the earnings announcements and the magnitude of the random walk based earnings surprise controlling for the magnitude of the analysts’ forecast errors. Doyle, Lundholm and Soliman (2004) and Mendenhall and Livnat (2006) both find the magnitude of the post-earnings announcement drift to be more pronounced when the earnings surprises are calculated using analysts’ forecasts compared to the ones based on a random walk model. Furthermore, Mendenhall and Livnat (2006) document that the analysts based and the time-series based earnings surprises lead to a different stock return dynamics around the future earnings announcements, suggesting that the two measures of surprises may capture different forms of mispricing. Battalio and Mendenhall (2005) provide evidence that identifiable subsets of investors classified by their trade-size around the earnings announcements use different models to forecast future earnings.

A current study seeks to further extend the sparse literature on the earnings-returns relation in the presence of heterogeneous beliefs. Rather than conducting a pairwise comparison of stock return behavior conditional on different earning surprise measures our approach treats earnings forecasts implied by different models as potential components of the market’s earnings expectation. Our approach is closely related to the Foster (1977) "association approach", as instead of searching for the "best" model we "let the market speak for itself" by estimating the weights placed on each of these models directly from stock prices.

In terms of methodology we estimate a semiparametric single-index model following the approach suggested by Hardle et al. (1993). The unknown weights represent a parametric component of the model while the link function which determines the relation between the stock returns and unexpected earnings is estimated nonparametrically. The flexibility of a link function is particularly important in context of this study. The ongoing debates in the accounting literature on the functional form of the earnings-returns relation are far from reaching a consensus (see Brown, 1993; Kothari, 2001). Since both earnings forecast models weights and a link function are estimated simultaneously, a wrong choice of the link function may have a significant effect on the estimated weights (Li and Duan, 1989; Horowitz and Hardle, 1996). As we show later, our model nests a variety of the earnings-returns models developed in the previous studies and, thus, provides a useful framework for evaluation of these models.

3 Data

3.1 Sample Selection

Our sample consists of the earnings announcements for all the firms covered by Institutional Brokers Estimate System (I/B/E/S) over the years 1996-2003. Each firm-quarter observation includes actual earning per share, median analysts’ forecast for the last month before the month when the earnings announcement is made and the date when the announcement has been released. We use the earnings reported by the I/B/E/S (Street Earnings)
instead of those reported by the Compustat (GAAP) earnings. Compustat follows a policy of changing firms’ reported earnings to reflect restated values. This means that some of the Compustat earnings figures were not the ones seen by investors. As a result, these data errors may potentially lead to the misspecification of the earnings-returns relation (Livnat and Mendenhall, 2006).

We delete from our sample all firms with less than fifteen consecutive earnings announcements. The reason for doing so is to ensure that we have enough observations in order to estimate various earnings models, which will then be used to calculate the earnings surprises. These models will be described in the following subsection. After the earnings surprises are calculated, we exclude from our sample all the observations in the 0.5 tail of the earnings surprises variables. This is done in order to reduce the impact of the potential outliers caused by either earnings data input errors or "stale" share prices (Lim, 2001).

We also collect the data on institutional holdings for each firm-quarter meeting the first set of requirements from the Thomson Reuters (former CDA Spectrum) database. This database contains the total number of shares held by institutional investors at the end of each calendar quarter based on 13 (f) filings. We require that data on institutional holdings be available for the quarter immediately preceding the earnings announcement. Also, for each firm we collect the total number of shares outstanding at the end of the last calendar quarter before the earnings announcement was made. This data will be used to calculate proxies for investors’ sophistication, as it will be discussed in the following subsection.

Finally, for every firm-quarter observation we match the stock returns and the benchmark portfolio returns based on NYSE/AMEX market capitalization deciles over the [0,+60] trading days window around the announcement date. This data has been obtained from the Center for Research in Security Prices (CRSP).

3.2 Variable Definitions

For each firm-quarter observation we calculate the abnormal return (AR) and cumulative abnormal return (CAR) using a companion-portfolio approach. The daily abnormal return for firm \( i \) on day \( t \) is calculated as the difference between the holding return of firm \( i \) on day \( t, R_{i,t} \), and the return on equally weighted portfolio on day \( t \) for all NYSE/AMEX firms in the same size-decile based on January 1 market values, \( R_{s,i,t} \) (Bartov et al., 2000; Garfinkel and Sokobin, 2005)

\[
AR_{i,t} = R_{i,t} - R_{s,i,t}
\]

Similarly, cumulative abnormal return and the cumulative average abnormal return (CAAR) over the time window \([t, t + k]\) are calculated as

\[
CAR_{i,[t,t+k]} = \sum_{i=t}^{t+k} AR_{i}
\]

\[
CAAR_{[t,t+k]} = \frac{1}{N} \sum_{i=1}^{N} CAR_{i,[t,t+k]}
\]

where \( N \) is the number of firm-quarter observations.
The unexpected component of quarterly earnings, $UE$, is calculated using three earnings forecasting models most widely used in the previous literature. To set forth notations, let $e_{i,t}$ be actual earnings per share for a firm $i$ and period $t$, $c_{i,t}$ a median ("consensus") analysts' forecast from the last month before the month when the announcement has been released and $L$ a lag operator. These models are

- **Seasonal Random Walk**
  \[ UE_{i,t} = e_{i,t} - e_{i,t-4} - \alpha \]  
  (2)

- **AR(4)**
  \[ UE_{i,t} = (1 - \beta_1 L - \beta_2 L^2 - \beta_3 L^3 - \beta_4 L^4)(e_{i,t} - e_{i,t-4}) - \alpha \]  
  (3)

- **Analysts**
  \[ UE_{i,t} = e_{i,t} - c_{i,t} \]  
  (4)

The first model is a "naive" seasonal random walk model with drift, which suggests that the "best" forecast of the future quarterly earnings would be past earnings for the same quarter from a previous year plus a constant drift term. This model, among others, was used by Bartov et al. (2000) and Collins and Hribar (2000). On the contrary, a second model takes into account a serial correlation between seasonal changes in the earnings, reported by many studies (see Ball and Bartov, 1996 among others). In a third model the analysts' "consensus" forecast is believed to be the "best" earnings forecast. Among all the models discussed in this paper, this model is the most widely used in finance and accounting literature (see, for instance, Lo and MacKinlay, 1997; Della Vigna and Pollet, 2005 among others).

The earnings surprises implied by the random walk and AR(4) models are estimated as follows. First, we divide the total number of observations available for each firm into the "estimation" and "testing" periods. All but the last observations are used to estimate the models while the last observation is used to calculate the earnings surprise. For instance, if we have at our disposal 20 consecutive firm-quarter observations for company $i$ over the period of Q1,1996 up to Q4,2000 then the first 19 observations from the period Q1,1996 up to Q3,2000 will be used to estimate the parameters of the models, while the observation of Q4,2000 will be used to estimate the earnings surprises implied by each of these models. All models are estimated by using least squares. Following Livnat and Mendenhal (2006) we scale firms' unexpected earnings implied by each model by it's share price from the last trading day of a quarter preceding the earnings announcement.

Finally, for each firm-quarter observation we calculate the proportion of firm shares held by institutional investors, $IH$, as follows

\[ IH = \frac{\text{number of shares held by institutional investors}}{\text{total number of outstanding shares}} \]

We follow previous studies which use this variable to proxy for investors' sophistication (see El-Gazzar, 1998 and Bartov, 2000, among others).
3.3 Descriptive Statistics

Selected descriptive statistics are reported in Table I. The abnormal returns at the announcement date ($AR_0$) are slightly skewed to the right as evident by the difference between the mean (0.08%) and median (-0.06%). On the other hand, the analysts’ consensus ($UE_{AN}$), as well as the random walk ($UE_{RW}$) and AR(4) unexpected earnings variables, appear to be skewed to the left. The mean institutional holdings proportion (IH) is 0.48 and median is 0.52. The distribution seems to be approximately symmetric around the mean.

The CAR$_{1,60}$ series contains outliers, as evidenced by the sample minimum (-305.6%) and maximum (150.8%). To alleviate the problem we delete 0.5 percent of each tail (Bartov et al., 2000). Trimming outlying abnormal return observation is also motivated by the results reported by Knez and Ready (1997). They find that the risk premium on size disappears when the 1 percent most extreme observations are trimmed each month.

4 A Model

Consider a situation when investors have heterogenous beliefs regarding the data generating process of the company’s earnings. Then, each investor will form his earnings expectation based on his beliefs and, consequently, as the actual earnings are released, the earnings news (hereafter, the earnings surprise) will be the difference between the actual and forecasted earnings. Next, let us assume that investors use the three earnings surprise measures discussed in this paper. We model the market’s earnings surprise for company $i$, $UE_i$, and the earnings-returns relation as follows

$$AR_{i,0} = F(UE_i) + \epsilon_i$$

$$E(\epsilon_i | UE_i) = 0$$

$$UE_i = \omega_{RW} UE_{RW,i} + \omega_{AN} UE_{AN,i} + \omega_{AR(4)} UE_{AR(4),i}$$

Here $UE_{RW,i}$, $UE_{AN,i}$, and $UE_{AR(4),i}$ are the earnings surprises implied by the random walk, analysts’ consensus, and AR(4) models, respectively, and $\omega$’s are the weights which measure the relative importance of each forecast in the aggregate stock market’s earnings expectation. For instance, setting $\omega_{AN}$ equal to unity and rest of the weights equal to zero would suggest that all the investors rely solely on the analysts’ consensus forecast while forming their earnings expectations. $AR_{i,0}$ is the size-adjusted abnormal return on the day when the earnings announcement is released and $F(\cdot)$ is the earnings-response function which determines a causal relation between the abnormal returns around the earnings announcement and the market earnings surprise.

Two issues regarding formulation of our model should be clarified. The first question concerns formulation of the market’s earnings expectation as weighted average of the individual forecasts. A theoretical justification comes from Kandel and Pearson (1995) and Hirshleifer and Teoh (2003). They show that equilibrium prices determined through the market-clearing conditions reflect a weighted average of the beliefs of different traders.

Second question concerns the choice of the earnings-response function $F(\cdot)$. Though it is the $\omega$’s which constitute the focus of our study, both $\omega$’s and $F(\cdot)$ must be estimated.
simultaneously. Clearly, a misspecification of \( F(\cdot) \) may lead to inconsistent estimates of the market earnings surprise weights. Taking this consideration into account, we proceed with the nonparametric estimation of the earnings-response function. More specifically we apply a Nadaraya-Watson kernel estimate (see Pagan and Ullah, 1994 and Yatchew, 2003)

\[
\hat{F}(x) = \frac{\sum_{i=1}^{N} AR_{i,0}K((x - UE_i)h^{-1})}{K((x - UE_i)h^{-1})} \tag{6}
\]

Here, \( K(\cdot) \) is a kernel function and \( h \) is a smoothing parameter, or bandwidth, which will be estimated simultaneously with other parameters. It can be shown that under mild conditions \( \hat{F}(\cdot) \) is a (pointwise) consistent estimator of a true function \( F(\cdot) \). Throughout this paper we use a Gaussian (normal) kernel.

We should also consider an identification issue, since the weights are identified up to multiplication by a scalar (Yatchew, 2003). Therefore, as the identification condition we set sum of the parameters equal to unity. Under this restriction the model parameters can be naturally interpreted as the earnings forecast models weights. To find the estimates of \( \omega \)'s and \( h \) the following minimization problem is solved

\[
\omega_n, h_n = \arg \min_{\omega, h} \frac{1}{N} \sum_{i=1}^{N} (AR_{i,0} - \hat{F}(UE_i))^2
\]

This approach has been proposed by Hardle et al. (1993). They show that while the link function \( F(\cdot) \) is estimated nonparametrically the index parameters are still estimated with the same degree of accuracy as if some assumptions on the functional form of \( F(\cdot) \) were made and are also normally distributed in large samples. This virtue is of particular importance for our study since it allows us to estimate the parameters of interest with a reasonable degree of accuracy which are also robust to various specifications of the earnings-returns models. In particular, among other models our model nests a number of the following important cases

a) Freeman and Tse (1992). \( F(x) = \alpha + \beta \arctan(\gamma x), \omega_{RW} = \omega_{AR(4)} = 0 \)
b) Ball and Bartov (1996). \( F(x) = \alpha + \beta x, \omega_{AN} = 0 \)
c) Walther (1997). \( F(x) = \alpha + \beta x, \alpha + \beta x, \omega_{AR(4)} = 0 \)

5 Earnings Expectations and Investors’ Sophistication

The model estimates are reported in Table II. The estimated weights of each earnings forecasting model (random walk, AR(4) and the analysts’ consensus forecast) are reported in separate columns under corresponding headings. Asymptotic standard errors calculated following Yatchew (2003) are reported below each estimate in parentheses. **(*) denotes statistical significance at 5(10)% level.\(^1\)

We begin with estimating the model using the full sample. The estimated weights and the corresponding standard errors are reported under the "Full sample" heading. A

\(^1\) All models were estimated using Matlab R2009a. The data and Matlab code are available upon request.
number of interesting findings should be mentioned. First, when using full sample, we find
no statistical evidence of investors using the analysts' consensus forecasts to predict future
earnings. The estimated weight of the analysts' consensus model ($\omega_{AN}$) is 0.17, which
implies that only 17 percent of investors rely on the analysts' forecasts, and is statistically
insignificant. On the other hand, we find strong evidence of market participants using the
random walk model to forecast corporate earnings. The estimated weight of the random
walk earnings surprise ($\omega_{RW}$) is 0.489 and is highly statistically significant. In other words,
it appears that about 50% investors believe current quarterly earnings figure to be the best
forecast of the future earnings. Also, we find that a significant proportion of investors uses
a more sophisticated AR(4) model to forecast future earnings. The estimated weight of
the AR(4) model ($\omega_{AR(4)}$) is 0.34 and is statistically significant. This finding suggest that
overall about one third of market participants are aware of a serial correlation in seasonally
differenced quarterly earnings.

A relatively low and statistically insignificant estimate of the $\omega_{AN}$ seems to be quite
surprising in light of findings in Doyle, Lundholm and Soliman (2004) and Mendenhall
and Livnat (2006) who both find stock prices to be more associated with the unexpected
earnings based on the analysts' forecasts rather than a random walk model. Previous studies
(Walther, 1997; Bhattacharaya, 2001) suggest that the choice of the earnings forecasting
model may be related to investors’ sophistication. In particular, Battalio and Mendenhall
(2005) suggest that "...the magnitudes of both the costs and the benefits associated with
obtaining different types of forecasts are obviously different" for different groups of investors.
While it takes a minimum effort to construct a forecast based on a random walk model,
it would require both time and efforts, as well as some analytical skills to construct the
earnings forecast based on more sophisticated models." Thus, we would expect the less
sophisticated investors to place more weight on the earnings forecasts generated by the
"naive" random walk model relative to those generated by the more sophisticated models,
such as the AR(4) model or models. To test this conjecture we re-estimate our model while
controlling for the institutional holdings which we use as a proxy for investors' sophistication.
More specifically, we divide our full sample into five sub-samples based on the proportion
of shares held by the institutional investors. Next, we estimate our model using the data
from each sub-sample, respectively.

The estimated weights along with the corresponding standard errors are reported in
Table II under the "IH1" to "IH5" headings where IH1 (IH5) denote lower (upper) quantile
of the IH variable. Starting with the estimated weights of the random walk model, we find
that the proportion of investors relying on the random walk forecasts seems to decline as
the proportion of firm shares held by the institutional investors increases. For instance, the
estimates of the $\omega_{RW}$ for the firms in the first and second IH quantiles are 0.36 and 0.7,
respectively. On the other hand, the estimated weight of the random walk is only 0.18, i.e.,
for the firms with high institutional holdings a random walk model is used by less than 20
percent of investors. Turning to the estimated weights of the analysts’ consensus forecast
model, we find the estimates of the $\omega_{AN}$ to increase as we move from the firms with low to
the firms with high proportion of institutional holdings. For instance, for the firms in the
lower IH quantile the estimated weight of the analysts’ consensus model is equal to 0.197
and is statistically insignificant. On the other hand, for the firms in the upper IH quantile
the estimate of the $\omega_{AN}$ is 0.31 and is highly statistically significant.
Turning to the estimated weights of the $AR(4)$ model we find the estimates of the $\omega_{AR(4)}$ to be both statistically and economically significant for all five sub-samples. However, compared to the analysts’ consensus model, the relation between the investors’ sophistication and the proportion of investors using the $AR(4)$ model appears to be less pronounced. The estimate of the $\omega_{AR(4)}$ is equal to 0.447 for the firms in the lower $IH$ quantile and is statistically significant, a finding which suggests that even amongst the least sophisticated investors about 45 percent of them are aware of and take into account the serial correlation in the seasonally differenced quarterly earnings. On the contrary, it appears that less than 30 percent of investors rely on the $AR(4)$ model for the firms in the $IH_4$ sub-sample.

We formally test the conjecture that more sophisticated investors place less weight on the random walk model forecasts compared to the "more sophisticated" or time-consuming models such as the analysts’ consensus forecast or the $AR(4)$ by testing the following hypothesis

$$H_0: \omega_{RW,i} = \omega_{AN,i} + \omega_{AR(4),i} \text{ for } i = IH_1, ..., IH_5$$

The $p$-values of the corresponding $t$-statistics are reported in the last column of Table II. For all but one sub-sample the null hypothesis is strongly rejected. The only exception is the $IH_1$ sub-sample where the null could not be rejected due to large standard errors of the model estimates. Overall, we find strong evidence of market participants using all three models to construct earnings forecasts. Also, institutional investors appear to rely more on the sophisticated (analysts’ consensus or the $AR(4)$) models compared to the individual investors who seem to form their forecasts based on the seasonal random walk model.

6 Earnings Expectations and Investors’ Sophistication: Controlling for the Forecast Accuracy

As suggested by Battalio and Mendenhall (2005), a choice of the earnings forecasting models involves a comparison between the benefits associated with using this model and the costs of estimating it. A natural way to compare the benefits associated with using different forecasting models is to evaluate their forecasting performance.

Let $RMSE_{RW}$, $RMSE_{AN}$, and $RMSE_{AR(4)}$ be the root mean squared errors of the random walk, analysts’ consensus, and the $AR(4)$ models, respectively. Next, for each firm and each earnings forecasting model we calculate a relative root mean squared error, $RRMSE$, as the root mean squared error of that particular model scaled by the root mean squared error of the random walk model. That is, for the firm $i$ $RRMSE_{AN,i} = \frac{RMSE_{AN,i}}{RMSE_{RW,i}}$, and $RRMSE_{AR(4),i} = \frac{RMSE_{AR(4),i}}{RMSE_{RW,i}}$. The interpretation of these measures is quite straightforward—the lower these ratios become the more substantial the gains from using analysts’ related earnings forecasts are compared to the "naive" forecasts of the random walk model.

We hypothesize that while making a choice between different earnings forecasting models investors take into account their forecasting performance. If so, we would expect the weights of the analysts’ consensus and $AR(4)$ models to be negatively related to the corresponding relative mean squared errors. Also, since for the institutional investors the costs of estimating sophisticated earnings forecasting models are negligible compared to those of
the individual investors, impact of the forecast accuracy on the models weights is likely to be more pronounced for the firms with small proportion of institutional holdings.

To take into account forecast accuracy we estimate the following model:

$$ AR_{i,0} = F(UE_i) + \epsilon_i $$

$$ E(\epsilon_i | UE_i) = 0 $$

$$ UE_i = \omega_{RW,i} UE_{RW,i} + \omega_{AN,i} UE_{AN,i} + \omega_{AR,4(i)} UE_{AR,4} + \omega_{ANAR,4(i)} UE_{ANAR,4,i} $$

A key distinction between this model and the one estimated in a previous section is that here we allow for the firm-specific component in the earnings surprise weights. More specifically, we assume that the weights of the analysts’ consensus and $AR(4)$ models are linearly related to the corresponding relative root mean squared errors, $RRMSE$'s

$$ \omega_{j,i} = \alpha_j + \beta_j RRMSE_{j,i} $$

where $j = AN, AR(4)$ and $\alpha'$s and $\beta'$ are the parameters to be estimated. This model encompasses the following important cases:

a) Investors’ decision which forecasting model to use is not related to the forecasts’ accuracy. In this case all $\beta$’s are equal to zero and the weights, $\omega$’s, are constant for all the firms in the IH quantile.

b) Investors take into account the forecast accuracy. The impact of the forecast accuracy is the same for both institutional and individual investors. In this case for a particular forecasting model all $\beta$’s are negative and equal for all firms regardless the proportion of firm shares held by the institutional investors.

The estimation results are reported in Table III. For each sub-sample (IH$_1$ to IH$_5$) we report the estimates of the augmented single-index model as formulated in eq. (7). As in the previous sections, we set the sum of the weights being equal to unity for the identification purposes. The corresponding asymptotic standard errors are reported below each estimate in parentheses.

The key aspect of interest is the link between the models’ weights and the forecasts accuracy, measured by the $\beta$’s. More specifically, if market participants take into account accuracy of the forecasts we would expect the weights of the analysts’ consensus and $AR(4)$ models to be decreasing in the corresponding $RRMSE$. In other words, we would expect the estimates of $\beta$’s to be negative and statistically significant.

Starting with firms in the lower IH quantile (IH$_1$) we find strong evidence of investors’ choice of the forecasting model being dependent on its’ forecast accuracy. The estimated $\beta$’s are negative and statistically significant for both the analysts’ consensus and $AR(4)$ models. The impact of the forecast accuracy on model weights for these firms is economically significant as well. For instance, when the relative mean squared error of the analysts’ consensus model is 0.232 (lower RRMSE decile), the estimated $\omega_{AN}$ is about 0.16. In other words, when the analysts’ consensus model substantially outperforms the random
walk benchmark model, about 16% of investors use the analysts’ forecasts to form their earnings expectations. On the other hand, when the relative root mean squared error of the analysts’ consensus model is equal to 0.99 (upper RRMSE decile) the estimated weight of the analysts’ consensus model plummets to almost zero. Similarly, the estimated weight of the AR(4) model is equal to 0.41 (0.2) when the corresponding RRMSE is in the lower (upper) decile. The impact of the forecast accuracy on model weights remains both statistically and economically significant for the firms in the second and third IH quantile as well.

However, our findings seem to change as we move to the firms with high proportion of the institutional holdings (IH4 and IH5). Negative sign of the estimated β’s is still consistent with the notion of investors relying on the forecasting performance of models while forming their earnings expectations. However, the magnitude of the estimated β’s seems to substantially decline and for the firms in the fourth IH quantile the estimates also lack statistical significance. This observation provides some preliminary support to our second conjecture that the trade-off between the costs and the benefits of the earnings forecasting models will be more pronounced for the individual rather than institutional investors.

We formally test this conjecture by testing the following hypothesis

\[ H_0 : \beta_{j,IH_1} = \ldots = \beta_{j,IH_5} \]

where \( j = AN, AR(4) \) using Wald test. The p-values of the corresponding Wald statistics for the analysts’ consensus and AR(4) models are reported in the last two rows of Table III. Based on our findings we conclude that the null hypothesis is strongly rejected both for the analysts’ consensus and AR(4) models.

Overall, we find forecast accuracy to be an important factor affecting investors choice of the earnings forecasting model. The estimated proportion of investors relying on a particular earnings forecasting model is decreasing in the root mean squared error of the model. Moreover, we find the impact of the forecast accuracy to be more pronounced for the individual rather than institutional investors. These results are consistent with the notion of individual investors facing higher costs of obtaining forecasts based on more sophisticated earnings forecasting models.

7 Earnings Expectations and the Post-Earnings Announcement Drift

Until now we studied the link between various earnings forecasting models and at-the-announcement returns. However, a question of a particular interest for the finance practitioners is which of these models is mostly associated with the Post-Earnings Announcement Drift or, in other words, which of the three earnings surprise measures has predictive power in explaining the dynamics of stock prices after the earnings news is released. To address this issue, we estimate a single-index model with the post-announcement abnormal returns. More specifically, for each IH quantile we estimate the following model

\[ CAR_{i,[+1,+60]} = F(UE_i) + \epsilon_i \]

\[ E(\epsilon_i | UE_i ) = 0 \]
As in the previous sections, $F(\cdot)$ denotes a link function estimated nonparametrically using kernel method. The definition of the unexpected earnings, $UE$, also remains the same, that is, the weighted average of the unexpected earnings implied by the random walk, analysts’ consensus and $AR(4)$ models. The distinction between this and the model estimated in Section..is that the dependent variable is now the cumulative abnormal return over the $[1,+60]$ trading days window. That is, we study the relation between different measures of earnings surprise and the post-announcement returns over the period of approximately one quarter following the earnings announcement.

Our findings are reported in Table IV. Overall, it appears that the random walk model dominates the analysts’ consensus or $AR(4)$ models in explaining the post-announcement dynamics of stock returns. The estimated weights of the random walk model are statistically significant for all but one sub-sample. Also, for the firms in the IH$1$ to IH$3$ quantiles the estimates of the $\omega_{RW}$ are significantly larger than the weights of the analysts’ consensus and $AR(4)$ models put together, as suggested by the corresponding $p$-values reported in the last column of the Table. The only exception are the firms in the upper IH quantile where the estimate of the $\omega_{AR}$ is statistically insignificant. The estimated weights of the random walk model also seem to decline as we move from the firms with low to the firms with high proportion of institutional holdings, an observation which is consistent with the results reported in Section..

Turning to the estimates of the analysts’ consensus model we find it to be statistically significant for all sub-samples. Also, the estimates of the $\omega_{AN}$ seem to increase as we move to the firms with higher proportion of shares held by the institutional investors. For the firms in the upper decile the analysts’ consensus forecast dominate those of the random walk and $AR(4)$ models.

The estimates of the $AR(4)$ model weights are of particular interest. As suggested by previous literature (Bernard and Thomas, 1989; Ball and Bartov, 1996) the post-earnings announcement drift is a manifestation of investors not taking into account serial correlation in the seasonally differenced quarterly earnings. Furthermore, Bartov et al. (2000) reports the drift to be more pronounced for firms with smaller proportion of institutional holdings, which would suggest using Bernard and Thomas (1989) argument that institutional investors asses correctly the earnings data-generating process. Consequently, we would expect the estimated weights of the $AR(4)$ model to be larger for the firms in the upper IH quantiles. Indeed, we find the estimated $\omega_{AR}$ to be higher for the firms with larger proportion of institutional holdings. Using Wald test we conclude that the difference is statistically significant as well.

Table IV approximately here

Overall, we find strong statistical evidence in favor of all three models having incremental power of explaining the post-earnings announcement drift. A next step will be to evaluate economic significance of the dispersion of the earnings expectations among market participants. Let $Cons_i$ be a consensus dummy variable defined as follows

$$
Cons_i = \begin{cases} 
1 & \text{if } \text{sign}(UE_{RW,i}) = \text{sign}(UE_{AN,i}) = \text{sign}(UE_{AR(4),i}) \\
0 & \text{otherwise}
\end{cases}
$$

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Next, we estimate cumulative average abnormal returns over the [1, 60] trading days window following the announcement for the following scenarios

a) $\text{Cons} = 1, \text{UE}_AN > 0$

b) $\text{Cons} = 0, \text{UE}_AN > 0$

c) $\text{Cons} = 1, \text{UE}_AN < 0$

d) $\text{Cons} = 0, \text{UE}_AN < 0$

Here we compare the post-announcement returns when all market participants interpret the earnings news in the same fashion (scenarios a. and c.) with those when investors disagree about the sign of the earnings surprise (scenarios b. and d.). Since all three models seem to explain the post-announcement dynamics of stock prices, we would expect the post-announcement drift to be more pronounced when investors agree about the sign of the earnings news. More specifically, we would expect the abnormal returns to be higher when all investors perceive the earnings announcement as good news compared to the case when at least one subset of investors views the earnings news as a negative shock. Similarly, we would expect the abnormal returns around the earnings announcement to be lower when the earnings information is viewed by all investors as bad news.

The estimated cumulative average abnormal returns are plotted in Figure 1. Post-announcement returns for scenarios a. and b. (c. and d.) are depicted in the upper (lower) plots, respectively and denoted by the dotted (solid) lines for the "consensus" ($\text{Cons}= 1$) and "no consensus" ($\text{Cons}= 0$) scenarios. As a benchmark we also plot cumulative average abnormal returns conditional on the analysts’ earnings surprise sign but without decomposing it into "consensus" and "no consensus" scenarios. These benchmark returns are denoted by dashed lines.

The results plotted in Figure 1 strongly suggest the importance of taking into account the dispersion of earnings expectations among market participants. Starting with the "good" news scenario when the analysts’ consensus earnings surprise is positive, we find the average 60-days post-announcement return to be about 4.4% when investors agree about the sign of the earnings news ($\text{Cons}= 1$). On the contrary, when market participants disagree about the sign of the earnings surprise the post-announcement return is only 1.8%. The benchmark post-announcement return is about 3%. These observations are consistent with our conjecture that the drift will be more pronounced when there is consensus among investors regarding the sign of the earnings surprise.

The difference between the "consensus" and "no consensus" scenarios is even more pronounced when we inspect the post-announcement returns for the "bad" news scenario ($\text{UE}_AN > 0$). When earnings news are perceived by all market participants as negative ($\text{Cons}= 1$) the 60-days average abnormal return is -6.9%. On the other hand, when investors disagree about the sign of the earnings surprise, the 60-days average return is about 0.3%. The benchmark average abnormal return is -0.63%.

To further assess the economic significance of the dispersion of beliefs, let us consider three zero-investment portfolios. The first one involves buying shares of all the firms with positive earnings news, as suggested by the analysts’ earnings surprise and selling short shares of all companies with negative analysts' earnings surprise. This can be viewed as
a benchmark post-announcement drift investment strategy. Second investment strategy involves going long on shares with positive analysts' earnings surprises and selling short stocks with negative analysts' earnings news conditional on Cons=1. That is, we invest in the post-announcement drift only in those stocks, for which investors agree about the sign of the earnings news. Similarly, the last zero-investment portfolio will have the same long-short positions conditional on Cons = 0. Our results suggest that taking into account our dispersion of beliefs measure does provide a substantial improvement over the benchmark post-announcement investment strategy. The 60-days abnormal return on the first zero-investment portfolio, which does not take into account a dispersion of beliefs measure is about 3.6%. On the other hand, the return on second zero-investment portfolio over the same holding period, which includes firms with "no dispersion" earnings announcements is 11.3%. Finally, the return on a zero-investment portfolio which includes firms with the "dispersion of beliefs" announcements is about 1.5%.

In Table V we assess statistical significance of our findings. We start with a simple pairwise comparison by regressing the 60-days post-announcement returns on the unity vector and "consensus" dummy. The estimates of the Cons loadings are positive (negative) for the "good" ("bad") news scenario and also statistically significant at 5 percent level.

Next, we conduct the same analysis controlling for additional factors mentioned in previous literature. More specifically, we include the institutional holdings variable (IH) to control for investors' sophistication (Bartov et al., 2000) and changes in the systematic and idiosyncratic risk measures, $\Delta \beta$ and $\Delta \sigma$ (Garfinkel and Sokobin, 2005). We calculate $\Delta \beta$ variable as the difference between the pre-and-post announcement stock betas estimated using [-54,-5] and [+5,+54] trading days windows, respectively. Similarly, $\Delta \sigma$ is calculated as the difference between the pre-and-post announcement abnormal return volatilities estimated using [-54,-5] and [+5,+54] trading days windows. Finally, we include analysts' consensus earnings surprise ($SUE_{AN}$) scaled between 0 and 1 (Livnat and Mendenhal, 2006) to control for the magnitude of the earnings news.

The estimates are reported in the last two columns of Table V. The estimates of the Cons loadings remain positive (negative) for the "good" ("bad") news scenarios. For the "good" news scenario the estimate also remains statistically significant. Also, for the "bad" news scenario the magnitude of the drift appears to be negatively correlated with the institutional holdings variable, a finding which is consistent with the results reported in Bartov et al. (2000). Also, consistent with findings in Garfinkel and Sokobin (2005) we find the standard deviation of abnormal returns to positively affect post-announcement returns, possibly suggesting that the idiosyncratic risk does matter.

8 Summary and Conclusions

In this paper we examine the link between the earnings news and the dispersion of beliefs regarding future earnings among the investors. Clearly, if investors use different models to forecast future earnings using a particular model chosen ex ante to calculate the earnings
surprise may potentially lead to severe model misspecification and wrong conclusions. To address this issue we propose a new approach which explicitly takes into account a divergence in opinions among market participants regarding future earnings. More specifically, we consider various earnings forecasting models discussed in the previous studies. The earnings surprise, as defined in our model, is a weighted average of the earnings surprises implied by each of these models where the weights are the parameters to be estimated from the data. No functional form is imposed on the earnings-returns relation, which is estimated nonparametrically. This model encompasses a variety of the earnings-returns models, both the linear and non linear, discussed in the accounting literature.

Our major findings are as follows. First, we find significant evidence of market participants using both the time-series models and the analysts’ forecasts to predict future earnings. Moreover, we find a substantial share of investors being aware of the serial correlations in the seasonally differenced earnings and exploit this knowledge while forming their earnings expectations. Interestingly enough, the share of investors using "naive" random walk model forecasts seems to be smaller for the firms with large proportion of institutional holdings, which proxies for investors’ sophistication. Furthermore, we find forecast accuracy to be a significant factor affecting the choice of the earnings forecasting model, effect which also appears to be more pronounced among the individual investors. Finally, we show that taking into account the divergence in opinions regarding future earnings substantially improves the profitability of the post-announcement drift based investment strategies.

Overall, our results emphasize the importance of accounting for the dispersion of investors beliefs while modelling the earnings-returns relation. A failure to do so, for instance, by using an ex ante chosen earnings forecasting model may lead to severe model misspecification and, as a result, to the wrong conclusions. Moreover, our results may be of a particular interest to the finance practitioners by proposing a new measure of the earnings surprise as the indicator of how the earnings news is perceived by the market which, therefore, may serve as a useful tool in predicting the post-announcement trends of stock prices.

Finally, we consider a number of possible directions for further research. First, it may be interesting to study how the earnings surprise weights of different forecasting models evolved over time. In particular, if investors learned about the serial correlation of the seasonally differenced earnings one would expect the share of investors using a "naive" random walk model to decline gradually. Also, one may consider conducting a similar study for the non-US markets to examine whether and how different market regulations and information environment affect the conclusions of this study. For instance, a limited accessibility to the analysts’ forecasts data outside the US markets may potentially cause the investors to rely more on the time-series models.
## Table I

### Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>$N$</th>
<th>Mean</th>
<th>St.Dev.</th>
<th>10th Pctl.</th>
<th>25th. Pctl.</th>
<th>Median</th>
<th>75th. Pctl</th>
<th>90th. Pctl</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR$_0$</td>
<td>2790</td>
<td>0.03</td>
<td>6.76</td>
<td>-5.49</td>
<td>-2.09</td>
<td>-0.07</td>
<td>1.97</td>
<td>5.37</td>
</tr>
<tr>
<td>CAR$_{1,60}$</td>
<td>2790</td>
<td>1.96</td>
<td>27.2</td>
<td>-22.8</td>
<td>-8.6</td>
<td>1.73</td>
<td>14</td>
<td>27.9</td>
</tr>
<tr>
<td>UE, Random walk</td>
<td>2726</td>
<td>-0.0008</td>
<td>0.106</td>
<td>-0.022</td>
<td>-0.0035</td>
<td>0.0005</td>
<td>0.0047</td>
<td>0.017</td>
</tr>
<tr>
<td>UE, AR(4)</td>
<td>2726</td>
<td>0.0003</td>
<td>0.168</td>
<td>-0.032</td>
<td>0.0005</td>
<td>0.009</td>
<td>0.0015</td>
<td>0.0193</td>
</tr>
<tr>
<td>UE, Analysts</td>
<td>2726</td>
<td>-0.012</td>
<td>0.099</td>
<td>-0.011</td>
<td>-0.0008</td>
<td>0.0002</td>
<td>0.0016</td>
<td>0.0051</td>
</tr>
<tr>
<td>INST</td>
<td>2656</td>
<td>0.479</td>
<td>0.283</td>
<td>0.002</td>
<td>0.26</td>
<td>0.522</td>
<td>0.712</td>
<td>0.827</td>
</tr>
<tr>
<td>Book Value$_{t-1}$</td>
<td>2769</td>
<td>1609.6</td>
<td>5317.1</td>
<td>47.9</td>
<td>118.8</td>
<td>323.3</td>
<td>989.5</td>
<td>3469.8</td>
</tr>
<tr>
<td>Market Value$_{t-1}$</td>
<td>2790</td>
<td>4446.3</td>
<td>17214</td>
<td>68.9</td>
<td>197.2</td>
<td>687.7</td>
<td>2289.9</td>
<td>8224.7</td>
</tr>
<tr>
<td>Total Assets$_{t-1}$</td>
<td>2770</td>
<td>9420.5</td>
<td>52347</td>
<td>96.5</td>
<td>264.5</td>
<td>866.1</td>
<td>3188.9</td>
<td>13849.5</td>
</tr>
</tbody>
</table>

In this Table we report selected descriptive statistics of the firms and announcements included in our sample. AR$_0$ denotes size-adjusted return on the announcement day. Descriptive statistics of the unexpected earnings series are reported under the "Random walk", "AR(4)" and "Analysts" headings, respectively. Book (Market) Value$_{t-1}$ denote book (market) value of equity at the end of a last fiscal year before the earnings announcement was released (in millions of dollars). This date was obtained from COMPUSTAT and CRSP. Total Assets$_{t-1}$ denote book value of total assets at the end of a last fiscal year before the earnings announcement was released (in millions of dollars). This data was collected from COMPUSTAT/CRSP merged database.
Table II
Estimates of a single-index model

<table>
<thead>
<tr>
<th></th>
<th>$\omega_{RW}$</th>
<th>$\omega_{AN}$</th>
<th>$\omega_{AR(4)}$</th>
<th>$h$</th>
<th>$R^2$</th>
<th>$H_0 : \omega_{RW} = \omega_{AN} + \omega_{AR(4)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All sample</td>
<td>0.489**</td>
<td>0.17</td>
<td>0.34**</td>
<td>0.013</td>
<td>0.02</td>
<td>$p$-value=0.92</td>
</tr>
<tr>
<td>IH1</td>
<td>0.356**</td>
<td>0.197</td>
<td>0.447**</td>
<td>0.019</td>
<td>0.014</td>
<td>$p$-value=0.36</td>
</tr>
<tr>
<td>IH2</td>
<td>0.701**</td>
<td>0.071**</td>
<td>0.228**</td>
<td>0.0007</td>
<td>0.057</td>
<td>$p$-value&lt;0.01</td>
</tr>
<tr>
<td>IH3</td>
<td>0.292**</td>
<td>0.203**</td>
<td>0.505**</td>
<td>0.0017</td>
<td>0.173</td>
<td>$p$-value&lt;0.01</td>
</tr>
<tr>
<td>IH4</td>
<td>0.358**</td>
<td>0.347**</td>
<td>0.295**</td>
<td>0.0003</td>
<td>0.09</td>
<td>$p$-value&lt;0.01</td>
</tr>
<tr>
<td>IH5</td>
<td>0.182**</td>
<td>0.31**</td>
<td>0.508**</td>
<td>0.0009</td>
<td>0.059</td>
<td>$p$-value&lt;0.01</td>
</tr>
</tbody>
</table>

In this Table we present the estimates of a single-index model (Section 4, eq. 5 and 6) for each of the five sub-samples sorted based on the institutional holdings variable (IH). Each firm is assigned to one of the five sub-samples based on proportion of firm shares held by institutional investors out of total number of the outstanding shares. The estimated weights for each sub-sample are reported under the corresponding headings with asymptotic standard errors being reported below each estimate. The numbers in the last column are the $p$-values corresponding to the null hypothesis that for a given institutional holdings sub-sample the weights of the random walk and more "sophisticated" models (analysts’ consensus and AR(4)) are equal.
### Table III

**Estimates of a single-index model with forecasts’ accuracy**

<table>
<thead>
<tr>
<th>IH</th>
<th>$\alpha_{AN}$</th>
<th>$\beta_{AN}$</th>
<th>$\alpha_{AR(4)}$</th>
<th>$\beta_{AR(4)}$</th>
<th>$h$</th>
<th>$R^2$</th>
<th>$H_0 : \beta_{AN} = \beta_{AR(4)} = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>IH1</td>
<td>0.204**</td>
<td>-0.186**</td>
<td>0.486**</td>
<td>-0.34**</td>
<td>0.0012</td>
<td>0.03</td>
<td>p-value &lt; 0.01</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.035)</td>
<td>(0.0084)</td>
<td>(0.014)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IH2</td>
<td>0.08**</td>
<td>-0.394**</td>
<td>0.494**</td>
<td>-0.226**</td>
<td>0.0005</td>
<td>0.106</td>
<td>p-value &lt; 0.01</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IH3</td>
<td>0.598**</td>
<td>-0.252**</td>
<td>0.562**</td>
<td>-0.131*</td>
<td>0.0013</td>
<td>0.226</td>
<td>p-value &lt; 0.01</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.048)</td>
<td>(0.041)</td>
<td>(0.066)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IH4</td>
<td>0.111**</td>
<td>-0.101</td>
<td>0.406**</td>
<td>-0.046</td>
<td>0.0006</td>
<td>0.112</td>
<td>p-value = 0.24</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.14)</td>
<td>(0.03)</td>
<td>(0.039)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IH5</td>
<td>0.208**</td>
<td>-0.105**</td>
<td>0.244**</td>
<td>-0.05**</td>
<td>0.0001</td>
<td>0.086</td>
<td>p-value &lt; 0.01</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.02)</td>
<td>(0.005)</td>
<td>(0.007)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$p$-values corresponding to the null hypothesis that all $\beta$’s are jointly equal to zero (Section 6, scenario a). The number in the last two rows are the $p$-value corresponding to the null hypothesis that for a given earnings forecasting model (analysts’ consensus or AR(4)) all $\beta$’s are equal (Section 6, scenario b).
### Table IV

Estimates of a single-index model with post-announcement returns

<table>
<thead>
<tr>
<th></th>
<th>$\omega_{RW}$</th>
<th>$\omega_{AN}$</th>
<th>$\omega_{AR(4)}$</th>
<th>$h$</th>
<th>$R^2$</th>
<th>$H_0 : \omega_{RW} = \omega_{AN} + \omega_{AR(4)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>IH$_1$</td>
<td>0.668** (0.019)</td>
<td>0.196** (0.021)</td>
<td>0.136** (0.004)</td>
<td>0.0025</td>
<td>0.035</td>
<td>p-value&lt;0.01</td>
</tr>
<tr>
<td>IH$_2$</td>
<td>0.826** (0.005)</td>
<td>0.053** (0.004)</td>
<td>0.121** (0.003)</td>
<td>0.0006</td>
<td>0.024</td>
<td>p-value&lt;0.01</td>
</tr>
<tr>
<td>IH$_3$</td>
<td>0.61** (0.056)</td>
<td>0.217** (0.065)</td>
<td>0.173** (0.017)</td>
<td>0.0017</td>
<td>0.082</td>
<td>p-value=0.049</td>
</tr>
<tr>
<td>IH$_4$</td>
<td>0.551** (0.04)</td>
<td>0.298** (0.047)</td>
<td>0.152** (0.014)</td>
<td>0.001</td>
<td>0.047</td>
<td>p-value=0.202</td>
</tr>
<tr>
<td>IH$_5$</td>
<td>0.035 (0.031)</td>
<td>0.727** (0.041)</td>
<td>0.238** (0.019)</td>
<td>0.0008</td>
<td>0.048</td>
<td>p-value&lt;0.01</td>
</tr>
</tbody>
</table>

In this Table we report the estimation results of a single-index model applied to the post-announcement abnormal stock returns, as described in Section 7, eq. (9). The dependent variable is the cumulative abnormal stock return over the period of 60 trading days following the earnings announcement. The numbers in the last column are the $p-$values corresponding to the null hypothesis that for a given institutional holdings sub-sample the weights of the random walk and more "sophisticated" models (analysts’ consensus and AR(4)) are equal.
Table V

PEAD and the dispersion of earnings expectations

<table>
<thead>
<tr>
<th></th>
<th>Pairwise analysis</th>
<th>Regression analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$UE_{AN} &gt; 0$</td>
<td>$UE_{AN} &lt; 0$</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.018</td>
<td>0.0029</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Cons</td>
<td>0.026**</td>
<td>0.072**</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>$\Delta \sigma_{AR}$</td>
<td>0.507</td>
<td>1.572**</td>
</tr>
<tr>
<td></td>
<td>(0.486)</td>
<td>(0.65)</td>
</tr>
<tr>
<td>$\Delta \beta$</td>
<td>0.018*</td>
<td>0.027*</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>IH</td>
<td>-0.0002</td>
<td>0.074**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>$SUE_{AN}$</td>
<td>0.026</td>
<td>0.144</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.0024</td>
<td>0.0038</td>
</tr>
</tbody>
</table>

In this Table we report the estimates of the Post-Earnings Announcement Drift (PEAD). We regress CAR’s over the [1,60] trading days following the announcement on the Consensus dummy (Cons) and control variables. Each regression is estimated separately for the firms with positive ($UE_{AN} > 0$) and negative ($UE_{AN}$) analysts’ consensus unexpected earnings. Hubert-White standard errors are reported in parentheses. *(***) denotes significance at 10 (5)% level.
Figure 1: In this Figure we plot the 60-days average cumulative abnormal returns following the earnings announcement for the "consensus" and "no consensus" scenarios, as described in Section 7. Returns are depicted separately for the cases when the analysts’ consensus earnings surprise is positive (upper plot) and negative (lower plot).
References


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