Forecastability of Earnings Surprises

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Abstract

I investigate whether it is possible to profitably trade on predicted earnings surprises, forecasted using the Foster (1977) model. Unlike the extant literature, which documents a strong positive relation between actual earnings surprises and returns, I find that trading on predicted earnings surprises, generated by the Foster (1977) model, has earned a small negative, but statistically indistinguishable from zero, return. This result highlights the difficulty in forecasting earnings surprises.

Keywords: Anomalies, Earnings surprises, Forecasting, Market efficiency, Post-earnings announcement drift

JEL codes: G10, G12, G14, G17

1. Introduction

It has been shown in the capital markets literature that stocks of firms announcing earnings surprises experience large returns at the time of the announcement. Following the earnings announcement, firms with positive earnings news (surprises) continue to experience positive returns and firms with negative earnings news continue to experience negative returns. (Ball and Brown, 1968; Bernard and Thomas, 1989) This pattern in the data is referred to as post-earnings announcement drift (PEAD). I investigate whether it is possible to predict which stocks are going to have positive or negative earnings announcements and whether it is possible to profitability trade on those predictions. Post-earnings announcement drift is measured using Standardized Unexpected Earnings (SUE), defined by Bernard and Thomas (1990) as the forecast error from a first-order autoregressive earnings expectations model (in seasonal differences) scaled by its estimation period standard deviation. Specifically, I investigate whether it is possible to predict which stocks will be in the high and low SUE
portfolios. I also investigate how much this strategy deviates from a perfect forecast strategy, the strategy that is reported in the literature. Based on Fama MacBeth (1973) regression results, I find that predicted SUE values are not able to explain returns one month after the earnings announcement date. Additionally, a strategy that invests in a long-short portfolio formed on predicted SUE 2 months before the announcement and held for nine months yields a cumulative average return of -0.89%. On the other hand, the traditional long-short SUE strategy, formed on actual earnings surprises, yields a cumulative average return 18.77%.

2. Literature Review

Ball and Brown (1968) showed that the stocks of firms with positive (negative) earnings news experienced positive (negative) returns after the announcement. Bernard and Thomas (1989) confirmed this result using SUE. Bernard and Thomas (1990) find that the price reaction of earnings for quarters $t+1$ through $t+4$ is predictable based on the earnings of quarter $t$. Livnat and Mendenhall (2006) find that PEAD is stronger when analyst forecasts are used to calculate earnings surprises.

One theme in the literature is to look at earnings surprises calculated using the difference between actual and expected earnings or to look at the relation between earnings from the prior period and returns over the subsequent period(s). Bernard and Thomas (1990) find that the returns around the announcement of the current period can be predicted using the earnings surprise over the prior quarter, while, in Konchitchki et al. (2010) the authors calculate earnings surprises using the difference between actual earnings and forecasted earnings. Akbas (2016) finds that trading volume in the week prior to an earnings announcement is correlated with earnings surprises. Froot et al (2017) find that proxies for real-time sales are related to earnings surprises and returns. Chiang et al. (2019) propose a measure of earnings surprises that corrects for bias in analysts’ forecasts and provide evidence that their measure is related to returns.

Recent earnings and earnings surprises research has investigated a variety of topics. Ali et al. (2020) find that in order to outperform other mutual funds, funds trading on post-earnings announcement drift leverage their informational advantage by trading mispriced illiquid stocks. Bartov, Faurel, and Mohanram (2018) find that Twitter posts contain information about future earnings and returns. Beaver, McNichols, and Wang (2018) investigate the information content of earnings announcements. In Ham, Kaplan, and Leary (2020), the authors find that dividends contain information about future earnings. He and Narayanamoorthy (2020) provide evidence that earnings accelerations, i.e. changes in quarterly earnings growth, predict returns. Kausar (2017) finds that anomalies based on earnings levels, e.g. gross profitability, do not earn abnormal returns after controlling for earnings changes. Li and Lytvynenko (2020) find currency fluctuations can partially explain post-earnings announcement drift.

In this paper, I expand on the capital markets literature by assessing whether it is possible to profitably trade on predicted SUE values rather than realized values. If it is possible to predict earnings surprises, investors could take advantage of this information by trading in advance of earnings announcements, instead of waiting until after these announcements.
3. Methodology

I use the SUE measure proposed by Chordia and Shivakumar (2006). They define SUE for firm i at time t as \((E_{i,t} - E_{i,t-4})/\sigma_{i,t}\) where \(\sigma_{i,t}\) is the standard deviation of \((E_{i,q} - E_{i,q-4})\) over the previous eight quarters. I forecast the earnings for quarter t using the Foster (1977) model. The Foster (1977) model was found to be a good predictor of quarterly earnings and is defined as:

\[
E_{i,t} = \delta + E_{i,t-4} + \varphi(E_{i,t-1} - E_{i,t-5}) + \epsilon_t, \tag{1}
\]

where \(E_{i,t}\) is earnings for firm i at time t, and \(\delta\) and \(\varphi\) are estimated parameters. After forecasting earnings using equation (1), I plug forecasted earnings into the SUE equation to generate the predicted value of SUE, \(^\wedge\)SUE = \((E_{i,q} - E_{i,q-4})/\sigma_{i,q}\). I allocate stocks to decile portfolios based on predicted SUE. I track the returns of these portfolios from \(t-2\) until \(t+6\), i.e. from two months prior to the announcement until six months after the announcement. I also form portfolios using the Chordia and Shivakumar (2006) measure of actual SUE, where actual SUE is defined as \((E_{i,t} - E_{i,t-4})/\sigma(E_{i,t} - E_{i,t-4})\). Actual earnings are adjusted for stock splits and dividends while predicted earnings are not adjusted. Predicted earnings are calculated using all historical earnings information available prior to the earnings announcement at time \(t\).

For the Fama MacBeth cross-section (1973) regressions, I calculate book-to-market ratio, firm size, and earnings-to-price ratio following the definitions presented in Fama and French (2008) and share turnover following the definition given in Chordia, Subrahmanyam, and Anshuman (2001). Book-to-market is defined as the logarithm of book value divided by market value where book value is calculated as: total assets – total liabilities – preferred stock + tax and deferred investment tax credit, market value is equal to price times common shares outstanding, firm size is defined as the logarithm of price times common shares outstanding, earnings-to-price is defined as earnings before extraordinary items divided by price, and share turnover is defined as shares traded monthly divided by common shares outstanding. These variables are calculated using the most recently reported accounting information from the Compustat database.

4. Data Description

I downloaded stock return data and company accounting information from the CRSP Compustat Merged Database (CCM) via WRDS (Wharton Research Data Services). Analyst forecasts and summary statistics for these forecasts were collected from the Institutional Brokers Estimates System (IBES) unadjusted forecasts database via WRDS. The overall data set was constructed by merging the analyst data to the firm financial and accounting data. Data is for all years from 1987 to 2010. I use the earnings report dates given in Compustat, but fill in missing report dates with dates given in the IBES database when available.
5. Results

First I calculate summary statistics for actual and predicted \( SUE \). These statistics are reported in Table 1. I have 127,286 firm observations with both predicted and actual \( SUE \) values. Both variables have high dispersion, but predicted \( SUE \) has a lower standard deviation than actual \( SUE \).

Table 1. Summary statistics for actual \( SUE \) and predicted \( SUE \)

| Measure       | Number | Mean | Median | Standard Deviation | 10th Percentile | 90th Percentile |
|---------------|--------|------|--------|--------------------|-----------------|-----------------|
| Actual        | 127286 | 0.33 | 0.22   | 3.89               | -1.53           | 2.70            |
| Predicted     | 127286 | 0.24 | 0.12   | 2.09               | -0.87           | 1.40            |

Note. This table presents summary statistics for actual and predicted Standardized Unexpected Earnings (\( SUE \)). Predicted \( SUE \) is calculated using earnings forecasted using the Foster (1977) model in place of actual earnings.

Next, I investigate whether actual and predicted \( SUE \) can predict returns the month after the earnings announcement date. I estimate Fama and MacBeth (1973) regressions of monthly returns on lagged financial variables. Using all firms that reported earnings during the prior month, I estimate the following model:

\[
\text{Return}_{i,t+1} = \alpha + \beta_1 \text{BEME}_{i,t} + \beta_2 \text{Size}_{i,t} + \beta_3 \text{Turn}_{i,t} + \beta_4 \frac{\text{E}_{i,t}}{\text{P}_{i,t}} + \beta_5 \text{SUE}_{i,t},
\]

where BEME is book-to-market ratio, size is firm size, turn is share turnover, E/P is earnings to price, and SUE is either actual or predicted standardized unexpected earnings.

Table 2. Fama MacBeth firm level cross-sectional regression results

| Panel A: Regression Results Using Actual SUE |
|---------------------------------------------|
| Coefficient | Constant 0.02035 0.00185 -0.00001 -0.00112 0.00717 0.00076 |
| t-statistic | 3.25 1.44 -0.27 -1.40 0.78 2.47 |

| Panel B: Regression Results Using Predicted SUE |
|-----------------------------------------------|
| Coefficient | Constant 0.020615 0.001826 0.000000 0.001121 0.003421 0.000596 |
| t-statistic | 3.33 1.42 0.03 -1.42 0.37 0.94 |

Note. This table reports estimated coefficients from Fama and MacBeth (1973) regressions of monthly returns on lagged variables.

Table 2 presents the estimates of these regressions. The results indicate that actual (realized) \( SUE \) predicts returns but predicted \( SUE \) does not.
Next I form decile portfolios by sorting firms on predicted SUE. I track the returns of these portfolios from t-2 until t+6, i.e. 2 months before the earnings announcement until 6 months after the earnings announcement. I present the average monthly raw returns and Carhart (1997) alphas to the high-low actual and predicted SUE portfolios in Table 3.

The high-low predicted SUE decile portfolio does not earn a statistically significant return during any of the months before or after the actual earnings announcement date. However, consistent with the extant literature, the high-low portfolio formed on actual SUE earns large and statistically significant returns, especially during the earnings announcement month. These results indicate that forecasts generated using the Foster (1977) model do not do an adequate job of predicting earnings surprises. Thus, historically, it has not been profitable to trade on forecasts of SUE generated by the Foster (1977) model.

Table 3. Average monthly return to actual and predicted SUE in event time

| Month Relative to Sorting | Average Raw Returns | Carhart Alphas |
|---------------------------|---------------------|----------------|
|                           | Actual SUE          | Predicted SUE  | Actual SUE          | Predicted SUE  |
|                           | 0.0255              | 0.0031         | 0.0250              | 0.0038        |
|                           | (8.26)              | (1.08)         | (7.31)              | (1.25)        |
| -1                        | 0.0329              | 0.0031         | 0.0323              | 0.0022        |
|                           | (9.38)              | (0.90)         | (9.83)              | (0.68)        |
| 0                         | 0.0584              | -0.0021        | 0.0574              | -0.0018       |
|                           | (13.88)             | (-0.69)        | (12.45)             | (-0.62)       |
| 1                         | 0.0108              | 0.0002         | 0.0090              | 0.0004        |
|                           | (3.94)              | (0.07)         | (3.44)              | (0.13)        |
| 2                         | 0.0067              | -0.0022        | 0.0048              | -0.0015       |
|                           | (1.61)              | (-0.81)        | (1.42)              | (-0.57)       |
| 3                         | 0.0084              | -0.0006        | 0.0064              | 0.0001        |
|                           | (2.46)              | (-0.18)        | (2.26)              | (0.04)        |
| 4                         | 0.0065              | -0.0040        | 0.0055              | -0.0025       |
|                           | (1.74)              | (-1.30)        | (1.65)              | (-0.89)       |
| 5                         | 0.0129              | -0.0040        | 0.0114              | -0.0033       |
|                           | (3.50)              | (-1.24)        | (3.23)              | (-0.95)       |
| 6                         | 0.0127              | -0.0025        | 0.0118              | -0.0007       |
|                           | (3.28)              | (-0.67)        | (3.58)              | (-0.23)       |

Note. This table presents average monthly returns in event time to high-low decile portfolios formed on actual and predicted standardized unexpected earnings (SUE). Reported t-statistics are in parentheses and are adjusted for autocorrelation using Newey-West (1987) standard errors.
I plot the cumulative average return to the long-short predicted and actual SUE strategies in Figure 1. The evidence presented in this figure shows that historically an investor that was able to accurately forecast SUE would have earned a cumulative average return of approximately 19%.

Figure 1. Cumulative average monthly return to high-low SUE portfolios in event time

Note. This figure shows the cumulative average monthly return to the long-short predicted and actual SUE portfolios in event time.

An investor that forecasted SUE using the Foster (1977) model and traded on these predictions would have lost close to one percent. Thus, an investor would have not earned a large return by trading on forecasted earnings surprises, generated by the Foster (1977) model.

6. Conclusion

I test whether an investor can accurately predict earnings surprises, i.e. SUE, using the Foster (1977) model and find that a long-short strategy that invests based on these predictions has not been profitable. The strategy that uses actual SUE values is highly profitable during the month of the earnings announcement but this return decreases dramatically afterwards. These results highlight the challenge of forecasting earnings surprises. Forecasting earnings surprises likely requires a broad information set and a sophisticated method of processing this.
information. Even if investors are able to forecast earnings surprises in advance these results suggest that investors can still trade on realized earnings surprises. However, trading on realized earnings surprises probably yields a lower return than trading in advance of the surprise since prices can adjust to the new earnings information prior to an investor acting on that information. Collectively, these results indicate that while it is possible with perfect foresight to determine earnings surprise stocks, in practice it is difficult to accurately identify and profitably trade these stocks. Thus, the returns to trading on post-earnings announcement drift are likely lower than the perfect foresight trading strategy reported in the literature.

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