International Journal of Accounting and Financial Reporting
ISSN 2162-3082
2020, Vol. 10, No. 4

Forecastability of Earnings Surprises

James G. Bulsiewicz

Department of Finance, Economics, and International Business

Silberman College of Business, Fairleigh Dickinson University

Box M-MS2-03, Madison, NJ 07940, USA

E-mail: jbulsiewicz@fdu.edu

Received: November 12, 2020 Accepted: December 18, 2020 Published: December 30, 2020

doi: 10.5296/ijafr.v10i4.17933 URL: https://doi.org/10.5296/ijafr.v10i4.17933

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:

$$E_{i,t} = \delta + E_{i,t-4} + \varphi(E_{i,t-1} - E_{i,t-5}) + \varepsilon_t, \tag{1}$$

where $E_{i,t}$ is earnings for firm i at time t, and δ and φ are estimated parameters. After forecasting earnings using equation (1), I plug forecasted earnings into the *SUE* equation to generate the predicted value of *SUE*, $\hat{SUE} = (\hat{E}_{i,q} - E_{i,q-4})/\sigma_{i,q}$. 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 $(E_{i,t}-E_{i,t-4})/\sigma(E_{i,t}-E_{i,t-4})_{i,t}$. 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

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:

$$Return_{i,t+1}= \alpha+\beta_1 *BEME_{i,t} +\beta_2 *Size_{i,t} +\beta_3 *Turn_{i,t} + \beta_4 *E_{i,t}/P_{i,t} + \beta_5 *SUE_{i,t}, \quad (2)$$

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						
	Constant	BEME	E/P	Size	Turn	Actual SUE
Coefficient	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						
	Constant	BEME	E/P	Size	Turn	Predicted SUE
Coefficient	0.020615	0.001826	0.000001	-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
-2	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%.

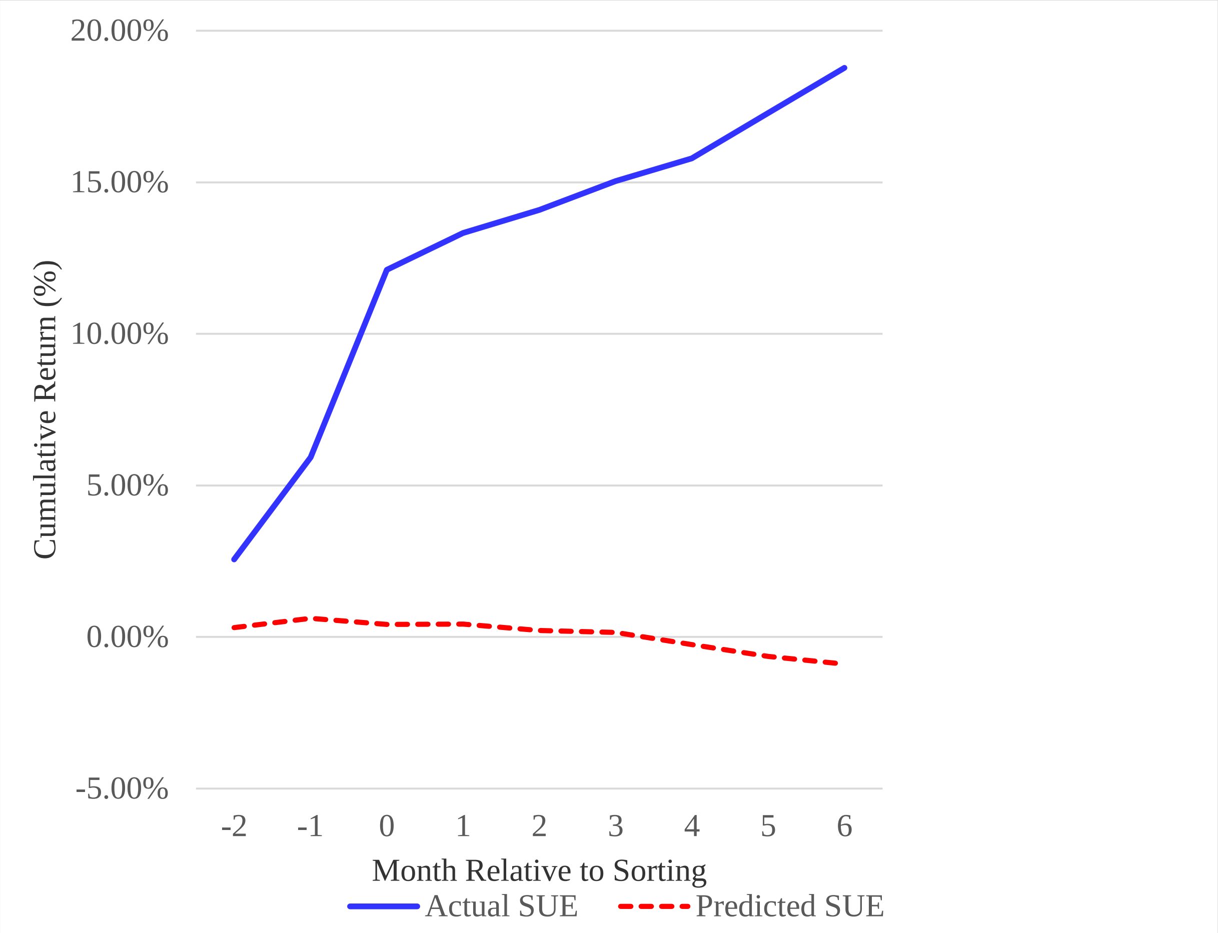

Figure 1. Cumulative average monthly return to high-low SUE portfolios in event time

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.

Acknowledgements

This paper is based on research completed at the University of Utah.

References

Akbas, F. (2016). The calm before the storm. *Journal of Finance, 71,* 225-266. https://doi.org/10.1111/jofi.12377

Ali, A., Chen, X., Yao, T., & Yu, T. (2020). Can mutual funds profit from post earnings announcement drift? The role of competition. *Journal of Banking and Finance, 114,* 1-19. https://doi.org/10.1016/j.jbankfin.2020.105774

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research, 6,* 159-177. https://doi.org/10.2307/2490232

Bartov, E., Faurel, L., & Mohanram, P. S. (2018). Can Twitter help predict firm-level earnings and stock returns?. *Accounting Review, 93,* 25-57. https://doi.org/10.2308/accr-51865

Beaver, W. H., McNichols, M. F., & Wang, Z. Z. (2018). The information content of earnings announcements: new insights from intertemporal and cross-sectional behavior. *Review of Accounting Studies, 23,* 95-135. https://doi.org/10.1007/s11142-017-9417-z

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings announcement drift: delayed price response or risk premium?. *Journal of Accounting Research, 27,* 1-48. https://doi.org/10.2307/2491062

Bernard, V. L., & Thomas, J. K. (1990). Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics, 13,* 305-340. https://doi.org/10.1016/0165-4101(90)90008-R

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52,* 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chiang, C.-H., Dai, W., Fan, J., Hong, H., & Tu, J. (2019). Robust measures of earnings surprises. *Journal of Finance, 74,* 943-983. https://doi.org/10.1111/jofi.12746

Chordia, T., & Shivakumar, L. (2006). Earnings and price momentum. *Journal of Financial Economics, 80,* 627-656. https://doi.org/10.1016/j.jfineco.2005.05.005

Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics, 59*, 3-32. https://doi.org/10.1016/S0304-405X(00)00080-5

Fama, E. F., & Macbeth, J. (1973). Risk and return: some empirical tests. *Journal of Political Economy, 81*, 607-636. https://doi.org/10.1086/260061

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *Journal of Finance, 63*, 1653-1678. https://doi.org/10.1111/j.1540-6261.2008.01371.x

Foster, G. (1977). Quarterly Accounting Data: Time-Series Properties and Predictive-Ability Results. *Accounting Review, 52*, 1-22.

Ham, C. G., Kaplan, Z. R., & Leary, M. T. (2020). Do dividends convey information about future earnings?. *Journal of Financial Economics, 136*, 547-570. https://doi.org/10.1016/j.jfineco.2019.10.006

He, S., & Narayanamoorthy, G. (2020). Earnings acceleration and stock returns. *Journal of Accounting and Economics, 69*, 1-22. https://doi.org/10.1016/j.jacceco.2019.101238

Kausar, A. (2020). Post-earnings-announcement drift and the return predictability of earnings levels: One effect or two?. *Management Science, 64*, 4877-4892. https://doi.org/10.1287/mnsc.2017.2838

Konchitchki, Y., Lou, X., Sadka, G., & Sadka, R. (2010). On the Predictability of analyst forecast errors and the Post-Earnings Announcement Drift. *Working paper.*

Li, Z., & Lytvynenko, I. P. (2020). Currency fluctuations and the post-earnings announcement drift. *Finance Research Letters,* in press, 1-8. https://doi.org/10.1016/j.frl.2020.101742

Livnat, J., & Mendenhall, R. R. (2006). Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research, 44*, 177-204. https://doi.org/10.1111/j.1475-679X.2006.00196.x

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55,* 703-708. https://doi.org/10.2307/1913610

Copyright Disclaimer