Earnings Announcement and Abnormal Return of S&P 500 Companies

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Abstract

In this paper, I investigate the extent and pattern of abnormal returns of S&P 500 companies around quarterly earnings announcements. I also explore the factors that influence the size of the abnormal return. My regression results show that abnormal returns are influenced by both the change of guidance and the magnitude of earnings surprises, and to a lesser degree, the number of analysts covering the stock. My findings suggest that Standardized Unexpected Earnings is a better variable for explaining abnormal returns than the previous variables used in the literature. My findings also indicate that it is important to divide companies into negative and positive earnings surprise groups, something which has not been done previously in the literature on abnormal returns and earnings surprises.

Acknowledgement

I would like to thank my thesis advisor, Professor Bruce Petersen, for his invaluable contribution and support. I would also like to thank Professor Dorothy Petersen for her insightful comments and for coordinating this honor’s conference.
I. Introduction

The stock market’s reaction to earnings surprises has long been an important topic among investors and companies. Prior research has found that companies have significant abnormal returns in a two-to three-day window around earnings announcements. These temporary abnormal returns suggest that, while stock markets are generally efficient, there may be information leakages right before the announcement, coupled with post-earnings drift. The study of such inefficiency in the stock market can help investors identify and capture the arbitrage opportunity associated with the earnings announcement. The study of factors that contribute to abnormal returns can also help companies understand the driving forces behind its stock market performance after the announcement, as it is an important indicator of investors’ confidence in the company.

There are a number of reasons to re-examine the stock market reaction to earnings surprises. First, nearly all of the related research was done in the late 1980s and 1990s, a time period when the only method of earnings announcements was through publishing in the Wall Street Journal. Since then, companies have shifted toward releasing their earnings digitally. This change in the method of release of information has arguably made stock markets more efficient. Information technology allows for a more effective, faster means to disseminate information, and electronic trading facilitates prices adjustments more quickly to news entering the market. There has been, however, little research on how markets react to earnings announcements in the modern period of digital earnings announcements.

A second reason for re-examining the stock market’s reaction to earnings surprises is that previous studies used unexpected earnings as the key indicators of surprises. However,
unexpected earnings measure only the actual earnings against the mean of analysts’ forecasts, disregarding information on the variation of analysts’ forecasts. A new measure of earnings surprises, Standardized Unexpected Earnings (SUE), remedies this shortcoming. To date this measure has not been employed in any study of the market’s reaction to earnings surprises.

A third reason for re-examining the stock market reaction to earnings announcements is that nearly all previous research has pooled companies with negative and positive earnings surprises when measuring the effect of earnings surprises on abnormal returns. These studies regress the absolute value of earnings surprise against the absolute value of abnormal return. There are, however, reasons to believe that stock markets may not react symmetrically to negative and positive earnings surprises. One reason is that analysts tend to underestimate companies’ earnings, resulting in a more severe market reaction. Therefore, a better research approach is to separate companies into a positive surprise group and a negative surprise group.

The final reason for a new study on the market reaction to earnings announcements is to test, with modern data, variables identified in previous studies that appear to have impact on abnormal return. Kothari and Ball (1991) theorize that an “unsophisticated investors” effect should influence the abnormal return because “unsophisticated investors” don’t fully understand the information provided by earnings reports. They use the size of the company as a proxy for such an effect, on the premise that unsophisticated investors have a larger impact on smaller companies because smaller companies have a greater proportion of unsophisticated investors trading in the stock compared to larger companies. One problem with size as a proxy is that smaller companies may exhibit greater abnormal returns due to liquidity problems rather than the “unsophisticated investors” effect. I therefore propose and test a new measure of the “unsophisticated investor” effect.
My study explores data for S&P 500 companies. I calculate abnormal returns using the Capital Asset Pricing Model (CAPM) used by Kothari and Ball (1989) and Cornell and Landsman (1991). I use an event study to identify the timing of abnormal returns and examine the days immediately before and after an earnings announcement to test whether there are information leakages and post-earnings drift. I then estimate regressions of abnormal returns on a number of explanatory variables including SUE, Number of Analysts and Change of Guidance. I find a strong impact of SUE and Change of Guidance on abnormal returns. I also find that SUE is a better measurement of earnings surprises than the measure commonly used in the literature. In addition, I find some evidence that the number of analysts impacts the magnitude of abnormal returns.

My study makes a number of contributions to the literature on stock market reactions to earnings announcements. First, it uses modern data to check whether the stock market is more efficient than two decades ago, and my findings suggest that, indeed, the stock market has become more efficient. In addition, my approach includes a number of improvements over the approach used in earlier studies. As I argue below, the number of analysts is a better proxy for the “unsophisticated investors” effect. In addition, my findings show that it is important to divide the data into negative and positive earnings surprises. Finally, my findings for Standardized Unexpected Earnings (SUE) and Unexpected Earnings (UE) indicate that SUE does a much better job of capturing earnings surprises, a finding that is new to the literature.

II. Literature Review

Falk and Levy (1989) test whether the stock market is efficient and whether abnormal returns exist in the period between 1962 and 1965 for 171 publicly traded companies. They use a
method called stochastic dominance instead of CAPM because of their concern that constructing a market portfolio of 171 companies was not sufficiently representative of the whole stock market\textsuperscript{1}. Falk and Levy find that, except for day -1, 0 and +1, the 171 companies do not have significant abnormal returns. The abnormal returns for day -1 indicates that there are information leakages in their sample before the earnings announcement. Similarly, abnormal returns for day +1 reveals that there are post-earnings announcement drift for the companies in their sample. Their findings show that the stock market may be inefficient in the days immediately surrounding the earnings announcement.

Kothari and Ball (1991) also test whether companies on the New York Stock Exchange display abnormal returns around the time of earnings announcements. They used the CAPM model to calculate abnormal returns and run an event study on all stocks in the NYSE and AMEX from day -11 to day 11 surrounding the earnings announcement date. Similar to Falk and Levy (1989), they find that there are significant abnormal returns for days -1, 0 and +1 but not for the other days in their study. The majority of their paper then focuses on the “unsophisticated investors” effect. Kothari and Ball state that “unsophisticated investors” are those who fail to correctly distinguish the valuation implications of components of reported earnings and thus their response to reported earnings is solely based on whether the surprise is positive or negative. As a result, their null hypothesis is that unsophisticated investors drive up the abnormal return around the announcement date. They use the size of the company as a proxy for such an effect because they believe unsophisticated investors tend to own larger fractions of smaller companies. Thus, they predict that smaller companies will exhibit greater excess returns in response to earnings

\textsuperscript{1} If CAPM is used, the beta of each stock, a critical measure in calculating abnormal return, is only measured against 171 companies as opposed to the stock market, which can result in an accurate measure of abnormal return. Stochastic dominance, however, can overcome this problem because it does not need to calculate the abnormal return itself.
surprises, other things held constant. Kothari and Ball create an independent variable that captures the relative size of companies (RSIZE)\(^2\). They estimate a regression of abnormal returns on earnings surprises and RSIZE and find that both explanatory variables have the expected sign and are statistically significant.

However, there is a potential problem with Kothari and Ball’s interpretation of their findings regarding smaller companies having bigger abnormal returns. While they interpret their findings as evidence of unsophisticated investors, an alternative interpretation is that small firms may have a larger abnormal return at the time of an earnings announcement because their stocks are less liquid, which leads to greater changes in stock prices. Thus size may not be the best proxy for the unsophisticated investor effect, and therefore I propose an alternative proxy in the next section.

Cornell and Landsman (1989) look at how earnings surprises and earnings forecast changes can impact abnormal return. They examine 330 companies’ quarterly announcements in the period between 1984 and 1987 and estimate a regression of abnormal returns on unexpected earnings and change of earnings forecasts. They find that during non-fourth-quarter announcements, unexpected earnings are not statistically significant while change of earnings forecasts are quantitatively important and statistically significant. Cornell and Landsman conclude that the market focuses more on future earnings compared to current surprises in quarterly earnings.

\(^2\) Their regression is: \(\text{RSIZE} = \frac{\log(\max \text{MV}) - \log(\text{MV}_i)}{\log(\max \text{MV}) - \log(\min \text{MV})}\), in which \(\text{MV}\) is the Market Capitalization of the stock.
III. Data and Abnormal Returns around Announcement Date

Data Source

All 500 companies and their industry classification come from the Capital IQ platform, which is run by Standard & Poor, the company that publishes the S&P 500 Index. My sample consists of 499 companies\(^3\). I select the latest non Q4 earnings for the 499 companies as of July 16, 2013. The reason I exclude Q4 earnings is because companies often publish year-end information along with fourth quarter earnings announcements. They may, for example, release their 10K. Since the 10K contains much more information (e.g. company risk analysis), it may contaminate a study exploring the impact of earnings surprises on abnormal stock returns. Data for my explanatory variables (discussed below) come from Thomson Reuter’s ThomsonOne database.

Day 0 and Construction of Abnormal Returns

The construction of abnormal returns is crucial to this research. Companies generally release their earnings either before the market opens (BMO) or after the market closes (AMC), with only a few exceptions where no time is specified (NTS). I identify day 0 by the following two rules. If the company releases its earnings any time before the market closes, then day 0 should be the same day as the announcement day. If the company releases its earnings after the market closes, then day 0 should be the first trading day after the announcement day. For my sample, all 499 companies fell into either the AMC or the BMO groups. I calculate the abnormal return using the CAPM model. It is typically calculated as following:

\[
\text{AR}_{it} = \text{R}_{it} - [\beta_i \times (\text{R}_{Mt} - \text{R}_f) + \text{R}_f]
\]

\(^3\) NewsCorp and its successor has only reported a 10-K after breaking up, therefore I omit the company from my sample
AR_{it}=the abnormal stock return for firm i associated with quarterly earnings announcements at time t. The abnormal return can be positive or negative.

R_{it}= Return for company i’s stock at time t

R_{M_t}= Return of the S&P 500 index at time t

\beta_i=5-year beta of company i’s stock against S&P 500

R_{f_t}= One month risk free rate at time t

However, since the one month risk-free rate is very close to 0 in 2013, I ignore R_{f_t} and thus equation (1) simplifies to AR_{it} = R_{it} - \beta_i * R_{M_t}.

Summary of Abnormal Returns from Day -9 to Day +10

I split the 499 companies into four groups based on their earnings surprise. The four groups have the following ranges of earnings surprises\(^4\): i) less than -3%, ii) -3% to 0%, iii) 0% to 3%, iv) larger than 3%. The groups have, respectively, 87, 59, 100 and 253 companies. I report the abnormal return (based on equation 1) for the earnings announcement day (day 0) and 10 days before and after the announcement day. The results appear in Table 1. For each group of firms, the first column of numbers are average abnormal returns while the numbers in parentheses are the standard deviations.

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\(^4\) The earnings surprise measured by the difference, in percentage, between the announced and analysts’ mean estimated earnings
From day -9 to day -1, all four groups show abnormal returns that are close to zero and not statistically significant. This indicates that in general there are little or no information leakages before the earnings announcements for these 499 companies. Likewise, between day +1 to day +10, all four groups also show trivial and insignificant abnormal returns. This indicates that on average there is no significant post-earnings drift in stock prices following the earnings announcement. In contrast, for day 0, three of the four groups have large abnormal returns compared to abnormal returns on the other days reported in Table 1. In addition, for these three groups, the average abnormal return is also statistically significant. The exception is the group
with earnings surprises between 0% and 3%, where the average abnormal return at event time equal to 0 is 0.17% and statistically insignificant. It is also noteworthy that the group with the largest negative earnings surprise (<-3%) has, on average, larger negative abnormal returns than the group with -3% to 0% earnings surprise. A similar statement applies to the two groups with positive earnings surprises.

There is one other interesting pattern of results in Table 1. Despite negative and positive earnings surprise groups being defined symmetrically, negative earnings surprise groups have larger (absolute value) abnormal returns compared to positive earnings surprise groups even though both positive groups have higher (absolute value) average earnings surprise than their negative group’s counterpart. Such effects might arise because analysts tend to underestimate companies’ earnings to be conservative. Thus, when a company falls short of the analysts’ earnings estimate, the market responds more severely. This asymmetry in earnings surprises is impetus to my approach of dividing companies into two groups and running regressions separately.

IV. The Econometric Model and Independent Variables

Econometric Model

I estimate the following regression for both positive and negative earnings surprise companies.

\[ AR_i = c + \alpha_1 SUE + \alpha_2 \text{ChangeGuidance} + \alpha_3 \text{RSIZE} + \alpha_4 \text{NumberAnalysts} + \alpha_4 SUE \times \text{NumberAnalysts} \]

(2)

The dependent variable in the regression, \( AR_i \) is the abnormal return for firm i at time equal zero, the day of the earnings announcement.
Independent Variables

SUE measures the number of standard deviations actual earnings differ from analysts’ mean estimates and shows the actual earnings position relative to the entire set of analysts’ forecasts. For example, a 2.0 SUE means the company’s earnings beat 97.5% of analysts’ forecasts, while a -2.0 SUE shows that the company’s earnings is below 97.5% of analysts’ forecasts. SUE should have a positive impact on abnormal returns. UE, on the other hand, measures the difference, expressed as a percentage, between the actual and estimated earnings. UE disregards the information on the variation of analysts’ forecasts. SUE, on the other hand, remedies this problem. In section V, I report regression results for both SUE and UE to explore differences in their performance.

When firms announce earnings, they frequently announce a change in guidance. Similar to Cornell and Landsman’s (1991) study, I use the change of guidance as a control variable. It is a dummy variable which takes the value -1 when change in guidance is negative, +1 when change in guidance is positive, and 0 when there is either no announcement or a reiteration of the existing forecast. The change of guidance should be positively correlated with the abnormal return.

I consider two different proxies for “unsophisticated investors”. The first is Kothari and Ball’s independent variable RSIZE, which measures a company’s relative size. The advantage of RSIZE is that it creates a near normal distribution of the size of companies, therefore preventing a skewed size distribution. If Kothari and Ball’s claim holds true, I expect to see a positive
coefficient on the RSIZE variable which, based on how RSIZE is constructed\(^5\), implies that smaller companies have higher abnormal return.

There are, however, reasons to believe that Kothari and Ball’s RSIZE measure is not a good proxy for the unsophisticated investor effect. The reason is that small firms may be less liquid and liquidity problems can accentuate abnormal returns at the time of the earnings announcement. Therefore I consider a different proxy for the unsophisticated investor effect, which is the number of analysts that contribute to the earnings forecast. I hypothesize that the greater the number of analysts covering a company the more likely “unsophisticated investors” are going to trade in response to an earnings announcement. The reason is that earnings announcements of companies with more analysts’ coverage receive more publicity, which draws the attention of unsophisticated investors, leading them to trade in response to the earnings announcement, resulting in greater abnormal returns.

Finally, I also create the interaction variables SUE*Number of Analysts and UE*Number of Analysts. Since I propose that unsophisticated investors (proxied by the number of analysts) will cause a stronger stock market reaction to the announcement of an earnings surprise, I therefore expect a positive coefficient on the interaction variable.

V. Regression Results

\[^5\text{RSIZE} = \log(\text{max MV}) - \log(\text{MV}_i))/[\log(\text{max MV}) - \log(\text{min MV})],\] therefore smaller companies have bigger RSIZE
Table 2 reports regression estimates for equation 2 for both positive (left side of the table) and negative group (right side of the table) earnings surprises. As indicated in equation 2, SUE is the measure of the earnings surprise. For both the positive and negative earnings surprise groups, the first regression includes RSIZE, the second regression replaces RSIZE with the number of analysts and the third regression adds SUE interacted with the number of analysts. In all six regressions, the point estimate for Change of Guidance is positive, quantitatively large, and highly statistically significant. RSIZE is never statistically significant. However, the number of analysts (which is my proxy for the unsophisticated investor effect) is significant, at least in the first set of regressions. I will return to this point below.

Of particular interest in my study are the results for SUE, a variable which has not been utilized in previous studies. In the first two regressions, for both the positive and the negative SUE groups, the estimate for SUE is positive, quantitatively large, and statistically significant. This changes in the third regression (for both groups of firms) when I add the interaction variable.
For the positive SUE group, the estimates for both SUE and the number of analysts is now small and statistically insignificant. However, the estimate for the interaction variable is positive and statistically significant. This implies that for any given level of SUE, the abnormal return increases (in absolute value) with the number of analysts. That is, the number of analysts enhances the SUE effect. For the negative SUE group, the estimate for the interaction variable is insignificant. It is noteworthy, however, that the point estimate for the interaction variable for the negative group is in fact larger than the point estimate for the positive SUE group. The point estimate for the negative group is simply not precisely estimated, which may be due to the small sample size for the negative SUE group.

As noted above, when RSIZE is included in regression 1 and regression 4, RSIZE is statistically insignificant in both groups. Thus, my results in Table 2 do not support Kothari and Ball’s (1991) findings of a significant RSIZE effect. One explanation for the difference is that Kothari and Ball’s RSIZE measure may not be a very good proxy for unsophisticated investors. Instead, it may be the proxy for a liquidity effect. As explained above, their sample contains many small firms, which arguably do face liquidity issues. In contrast, my sample consists entirely of S&P 500 firms that rarely face liquidity problems. Thus, it is not surprising that RSIZE is statistically insignificant in my sample if in fact RSIZE is mainly picking up a liquidity effect (which should be absent in my sample).

I argue above that the Number of Analysts may be a better proxy for the “unsophisticated investor” effect. In regressions 2 and 5, the point estimates for the Number of Analysts are very similar, although not statistically significant in the negative SUE group (which has comparatively few observations). Furthermore, the interaction of SUE and the Number of Analysts is statistically significant for the positive SUE group. Thus, my findings support using a
different measure of the “unsophisticated investor” effect than what has been used in the literature.

Finally, the significant intercept in the negative group also supports the idea that stock markets will react more severely to negative earnings. The significant intercept shows that once companies miss the earnings estimates, even by a little, their stock will tumble more than 2.5%. Under the efficient market theory, market price should reflect all available information in the stock market, therefore when all variables are close to zero, companies with negative earnings surprises theoretically should also have close to zero abnormal returns. Thus, the significantly negative intercept indicates that the stock market is not efficient for companies with negative earnings surprises.

One of the main contributions of my study is my use of SUE, which I believe is a superior measure of earnings surprises. Recall that previous studies have used UE instead of

<table>
<thead>
<tr>
<th>Regression</th>
<th>Positive UE Group</th>
<th>Negative UE Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.1220</td>
<td>0.2588</td>
</tr>
<tr>
<td>Change of Guidance</td>
<td>1.5648***</td>
<td>2.1270**</td>
</tr>
<tr>
<td>UE</td>
<td>0.0031</td>
<td>-0.0199</td>
</tr>
<tr>
<td># of Analysts</td>
<td>0.0441</td>
<td>0.0777</td>
</tr>
<tr>
<td>UE*# of Analysts</td>
<td>0.0014*</td>
<td>-0.0031</td>
</tr>
<tr>
<td>RSIZE</td>
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<td>-3.3393</td>
</tr>
<tr>
<td>R-Sqare</td>
<td>4.5765%</td>
<td>6.0318%</td>
</tr>
</tbody>
</table>

Note: *** significant at 1%; ** significant at 5%; * significant at 10%
SUE. To compare the performance of SUE to UE, in Table 3 I replace SUE (used in Table 2) with UE. In all regressions, the point estimate for UE is quantitatively small and is insignificant. Likewise, the estimated coefficient for the variable that interacts UE with the number of analysts is also statistically insignificant. In fact, Change of Guidance is the only variable that is consistently significant in all equations. Furthermore, all equations have considerably smaller R-Square than their counterpart in Table 2. Thus, results in Table 2 and Table 3 indicate that SUE is a better measure of earnings surprises than UE.

VI. Limitations and Conclusions

There are limitations in my study. Of the 499 companies I tested, only 142 companies have a negative earnings surprise, roughly one-third of the number in the positive group. The obvious solution to this limitation is to expand the size of my sample. I can greatly expand my sample size by exploring multiple quarters of earnings announcements for these 499 companies.

In this paper, I use an event study and find that there are sizable and significant abnormal returns on the day earnings are announced. In contrast, in the days immediately around the earnings announcement, abnormal returns are trivial and insignificant. This indicates that for S&P 500 companies, there are no significant information leakages before the earnings announcements and markets immediately adjust to the new information level after the announcement. These findings differ from those in Falk and Levy (1989) since they find abnormal returns in day -1 and day 1, as well as day 0. One interpretation is that the stock market is more efficient than three decades ago. I also find that both SUE and Change of Guidance have a significant impact on the abnormal return on the announcement day, with the latter variable having a larger impact. This supports the conclusion in Cornell and Landsman (1989) that the
market cares more about new information pertaining to the stream of future earnings, and cares comparatively less about earnings surprises in the current period. I did not find any evidence of a relative size effect on the abnormal return at the time of the earnings announcement and thus my findings do not support those of Kothari and Ball (1991) who did find a size effect. I do, however, find that in the positive surprise group, the number of analysts has a significant impact on the abnormal return, which I take as evidence of an “unsophisticated investor” effect. For the negative surprise group, the point estimate for the number of analysts is very similar to that for the positive earnings surprise group. The point estimate is, however, statistically insignificant, possibly due to the relatively small number of observations in the negative earnings surprise group. Finally, I find that when estimating abnormal returns, SUE is a better measure of an earnings surprise than UE, used by previous studies, as the point estimate for SUE is generally significant while for UE it is insignificant. The result suggests that, when estimating abnormal returns, the best measure of earnings surprises is the proportion of the entire set of analysts that the actual earnings beat (i.e., SUE) rather than the percentage size of the surprise itself (i.e., UE).
Reference


Appendix I. Summary of Abnormal Return when using SUE

<table>
<thead>
<tr>
<th>SUE</th>
<th>Day</th>
<th>&lt;-0.5</th>
<th>&gt;=-0.5,&lt;0</th>
<th>&gt;=0,&lt;=0.5</th>
<th>&gt;0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AR</td>
<td>AR</td>
<td>AR</td>
<td>AR</td>
</tr>
<tr>
<td>-9</td>
<td>0.03%</td>
<td>0.20%</td>
<td>-0.22%</td>
<td>0.07%</td>
<td></td>
</tr>
<tr>
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<td>-0.12%</td>
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<td>-0.01%</td>
<td>-0.05%</td>
<td></td>
</tr>
<tr>
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<tr>
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<td></td>
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<tr>
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<td>0.04%</td>
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<td></td>
</tr>
<tr>
<td>-3</td>
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<td>-0.26%</td>
<td>0.02%</td>
<td>-0.08%</td>
<td></td>
</tr>
<tr>
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<td>0.02%</td>
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<td></td>
</tr>
<tr>
<td>-1</td>
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<td></td>
</tr>
<tr>
<td>0</td>
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<td><strong>-1.02%</strong></td>
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<td><strong>1.05%</strong></td>
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</tr>
<tr>
<td>1</td>
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</tr>
<tr>
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<tr>
<td>7</td>
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<tr>
<td>10</td>
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<td>0.30%</td>
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</tbody>
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<table>
<thead>
<tr>
<th># of companies</th>
<th>100</th>
<th>46</th>
<th>54</th>
<th>299</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average SUE</td>
<td>-2.24</td>
<td>-0.26</td>
<td>0.25</td>
<td>2.92</td>
</tr>
</tbody>
</table>

Note: -0.5 SUE indicates the actual earnings beat roughly 30% of all analysts that cover the company, 0.5 SUE indicates the actual earnings beat roughly 60% of all analysts that cover the company.