The Impact of Predicted Earnings Surprises on Equity Prices

Cyrus A. Ramezani
California Polytechnic State University

Samuel J. Frame
California Polytechnic State University

In efficient markets, asset prices are expected to adjust rapidly when value relevant information is made public. In this paper we study the impact of "predicted earnings surprises" on short-term stock returns. Specifically, we collect earnings surprise forecasts for 807 firms from a free and publicly available source. These forecasts are produced by the top-rated analysts and are expected to be more accurate than the "consensus number", which is biased by analysts' conflicts of interests. Using standard regression analysis and an event study, we assess the impact of this information on equity prices. This impact appears to be asymmetrical, with extreme positive and negative forecasts being more significant drivers of returns. We quantify the risk-adjusted returns resulting from a trading strategy that exploits knowledge of these forecasts. Our results suggest that markets are efficient with respect to this publicly available information.

INTRODUCTION

A firm's earnings is an essential factor in determining its profitability, and therefore an important driver of its stock price. The efficient market hypothesis holds that value relevant information is quickly impounded into stock prices. In their seminal study, Ball and Brown (1968) showed that companies that exceed or fall short of analysts' earnings estimates experience abnormal returns over subsequent periods, a finding that appears to contradict the efficient market hypothesis.

A large body of academic and practitioner literature has subsequently investigated the impact of various measures of earnings on asset prices. In particular, researchers have been interested in how *unanticipated* or "surprise" changes in earnings impact stock prices. The rationale for this presumed effect is simple; an earnings surprise could be indicative of fundamental changes in the firm's business, and such information – good or bad – is expected to be quickly impounded in the firm's stock price as investors re-balance their portfolios.

An *ex post* estimate of earnings surprises widely used in the literature measures the deviation of realized earnings from the "consensus estimate". Under this intuitive formulation, the arithmetic mean (or median) of *available* earnings forecasts issued by the analysts covering a firm – the consensus – is viewed as an unbiased forecast of actual earnings. Using historical data, numerous studies have found that this measure of realized surprise earnings is useful in predicting subsequent abnormal stock returns. However, the use of consensus estimates as an unbiased forecast of actual earnings has been questioned on various grounds. For example, since analyst coverage varies across firms and industries, earnings forecasts may show little variation, particularly when few analysts cover a firm. Accordingly, the metrics for measuring surprise earnings have been enhanced in several directions. One proposed enhancement, the Standardized Unexpected Earnings (SUE), adjusts the realized earnings surprise by dispersion in analysts' forecasts.[1]

Standardized Unexpected Earnings is still premised on the assumption that the consensus number is an unbiased estimate of the market's expectation of a firm's actual earnings. However, it has been long recognized that conflicts of interest, even among a subset of analysts, could significantly bias their earnings forecasts. For example, as Chiang et al. (2016) point out, traditional earnings surprise measures, such as SUE, indicate that companies consistently beat consensus estimates by a sizable margins. As they demonstrate, this finding may be due to the fact that analysts systematically underpredict earnings, consequently lowering the consensus number. This tendency to underestimate may be due to managers' down- ward forecast guidance, which would lead analysts to underpredict earnings and therefore "surprise" the market. It may also be due to the fact that analysts that produce earnings estimates have other business relationships with the firms they cover, "incentivizing" them to strategically manipulate their earnings projections.

Hwang et al. (2014) empirically demonstrate that analysts with bullish or bearish recommendations are averse to subsequently being contradicted by bad earnings news. As a result, they tend to issue earnings forecasts that ensure the company will experience a positive earnings surprise. Moreover, they find that analysts' recommendations significantly and positively predict subsequent surprise earnings and show that this predictability is concentrated in situations where the motivation for such behavior is strong. These authors show that a long-short portfolio that exploits analysts' conflict of interest bias earns significant abnormal returns.

To summarize, researchers have found that analysts routinely report biased forecasts in order to generate investment banking business, stimulate trading in a company's stock (Hayes, 1998), enhance their access to the firms' management (Lim, 2001), or for a combination of these objectives. Chiang et al. (2016) forcefully argue that the prevalent conflict of interest results in biased earnings forecasts, consequently biasing consensus earnings and "earnings surprise" measures that use the consensus number as an unbiased forecast of a firm's earnings.

Given the prevalence of conflict of interest bias, is there a better method for estimating surprise earnings? Chiang et al. (2016) propose the use of the "fraction of forecasts that miss on the same side" as a measure of earnings surprise.[2] This measure essentially captures the overall accuracy of the analysts' forecast for a given firm. The objective of our study is to consider the influence of analysts' relative "rating," which is a direct measure of their forecast accuracy. We posit that the competition for achieving "top rating" can significantly reduce the conflict of interest bias.

The rationale for this assertion is provided in the literature. As Hong and Kubik (2003) have shown, analysts compete for ranking and prestige, and accurate forecasters are more likely to experience favorable career outcomes. Moreover, to generate investment banking business or trading commissions in the longer run, analysts need to gain a reputation as accurate forecasters. Hence, an analyst's credibility is determined by her forecast accuracy, which is likely to remove, or at least mitigate, her conflict of interest bias in the long run.

Given this kind of competition among the analysts, we utilize an *ex ante* measure of earning surprise, with the desired property of reducing the bias due to conflict of interest. In particular, we use surprise earnings per share, defined as, $E = \frac{(A-C)}{\sigma}$, where E is a weighted average of the most recent earnings forecasts by top-rated sell-side analysts and C is the consensus projection. Under this formulation, the earnings per share forecast, E, is a more accurate predictor of future earnings than the consensus number, C[3]. While the consensus remains biased, the earnings projection is based on the best available forecasts. Consequently, we posit that SEPS reduces the conflict of interest bias, offering an improved predication of future earnings surprise. How would predicted SEPS impact equity prices? The answer is somewhat ambiguous, depending upon the magnitude and the direction of the predicted SEPS, investors' risk aversion, as well as the confidence market participants place upon the analysts that provide such critical forecasts.

Considering the SEPS' magnitude, we find that relatively "small" predicted SEPS have minimal impact on prices. As Chiang et al. (2016) state, "it seems that a minor earnings surprise that would be breaking news on CNBC is actually not a surprise at all. If anything, investors should expect companies to systematically exceeded expectations." Our results confirm this conjecture, suggesting that investors discount predicted SEPS within the ±25% range as normal noise attributable to forecasting error and therefore not "value relevant" information.

Investors may view an "extreme" predicted SEPS as a strong indicator of the potential future performance of a stock and therefore trade on such information accordingly. Moreover, as Levis and Liodakis (2001) and others have pointed out, positive and negative earnings surprises are likely to have an asymmetrical effect on equity prices. We therefore study the impact of extreme predicted earnings surprises on equity prices. Interestingly we find the impact of extreme positive SEPS on prices is small, while extreme negative SEPS is significantly larger. A potential explanation for this finding may be investors' tendency to avert potential losses more readily than pursing potential gains, which is indicative of risk averse investor behavior.

The rest of the paper is organized as follows. In section 2, we describe the data and our methodology for collecting it from freely available public sources. In section 3, we present our analysis linking predicted SEPS to equity prices based on regression models that are standard in the literature. In section 4, we quantify the returns to a trading strategy that exploits the results from the regression analysis. In section (5), we undertake a formal event study to corroborate the results of our regression analysis. We conclude with a summary of our findings and potential directions for further research.

DATA

In this section we describe our methodology for collecting predicted earnings surprises, stock prices, and other relevant data for a large number of firms. These data will facilitate the test for the weak form of the efficient market hypothesis and hence the guiding principal for this exercise is to obtain the required data from freely available sources in the public domain. To this end, we use the The Day Ahead newsletter (TDA hereafter), which is freely available online every day after the markets close.[4]

The TDA provides a recap of the day's market activity, macroeconomic and firm-specific news, analysis and research, and information on companies scheduled to report their earnings in the following week. The TDA released on the first trading day of each week also contains the SEPS, which is defined as above and billed as a "leading indicator of future analyst revisions and actual earnings surprises".[5] Each week we record the date and the reported SEPS for firms that appear in TDA. Note that each SEPS, whether fresh or a revision to an existing SEPS, constitutes a new piece of information for the market.[6]

Our data spans the period 01-07-2014 through 06-01-2016. Following the standard practice in the literature, we *winsorize* the SEPS by dropping the outliers that appear in the top and bottom 1% of the data. As a consequence, a few very large SEPS (often in excess of ±400%) are removed. Table 1 shows the frequency of SEPS made public each month. It is apparent that the vast majority of SEPS are released during the first two months of each quarter, which corresponds to the peak in the earnings season. Figure 1 provides a weekly time series plot of the SEPS, again highlighting the peak arrivals during the earnings season. Note that despite the removal of the extreme outliers, the large variation in SEPS remains apparent, with many surprise earnings falling outside the ±50% range.

TABLE 1
FREQUENCY OF SEPS BY YEAR AND MONTH

	01	02	03	04	05	06	07	08	09	10	11	12
2014	46	41	11	40	23	19	47	31	26	47	25	8
2015	39	43	26	45	32	30	45	39	20	37	33	7
2016	42	57	33	44	36							

FIGURE 1
TIME SERIES PLOT OF SEPS OVER THE PERIOD 01-07-2014 TO 06-001-2016

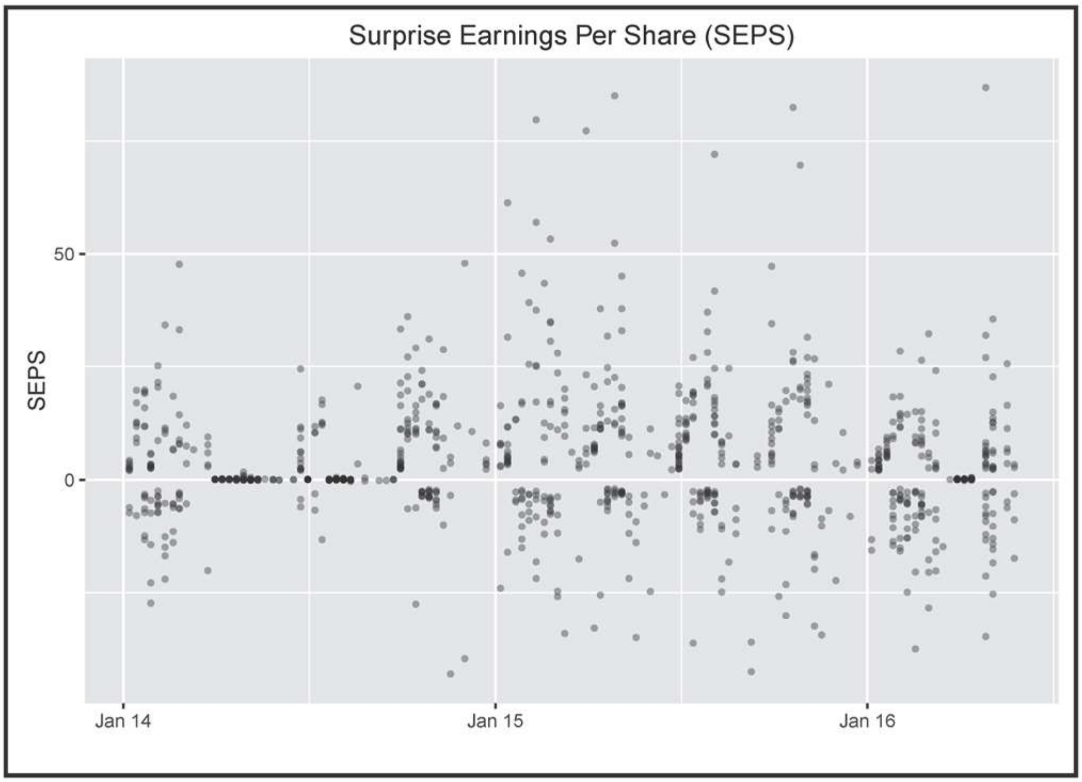


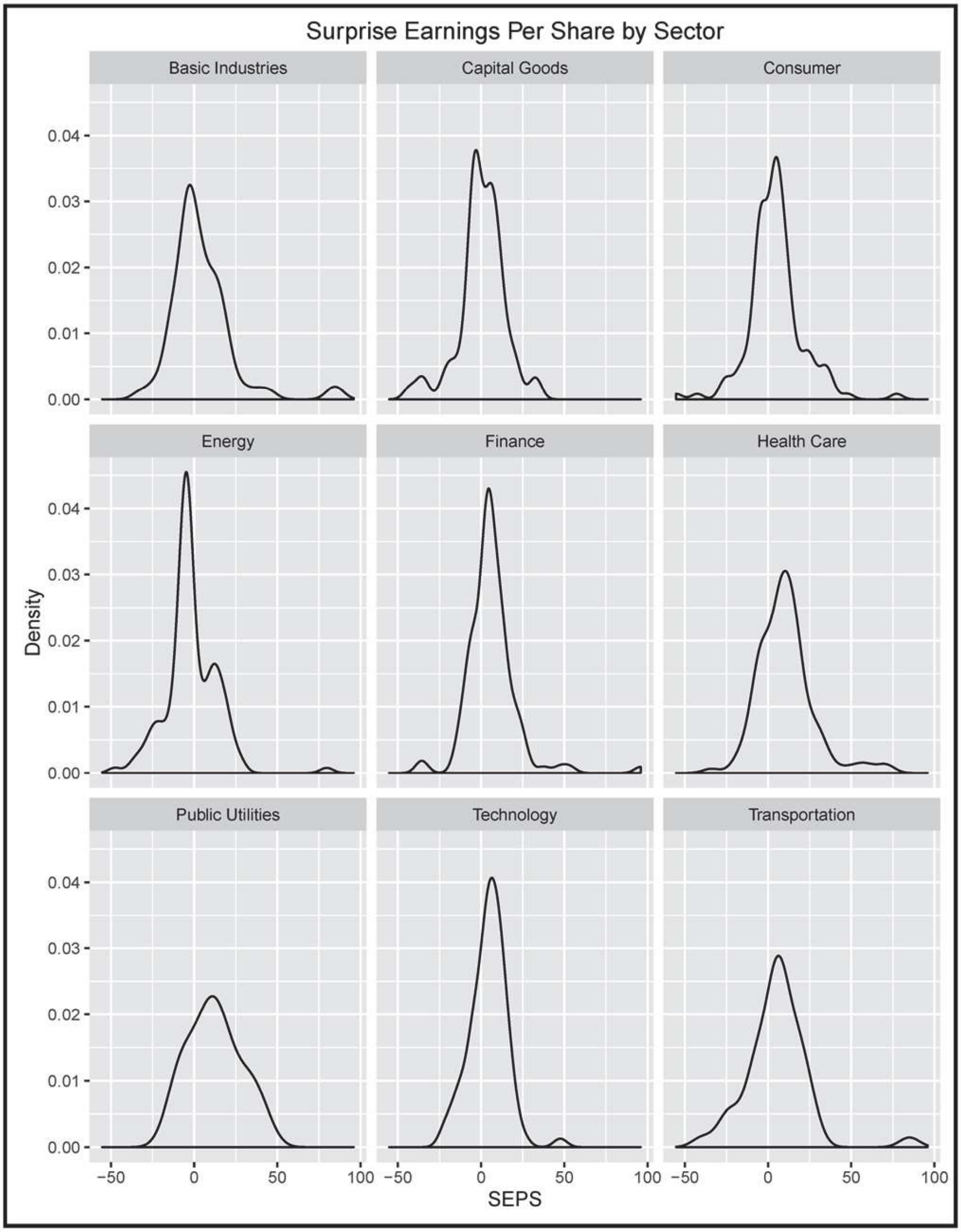
Table 2 shows the mean (%), the standard deviation, and the frequency of SEPS across broad industry groupings. For the period under consideration, the mean SEPS range from -1.26% (Energy) to 9.17% (Public Utilities), while the variation in SEPS across the sectors are similar in magnitude. The table also contains basic statistics on the firms' market capitalization, indicating that our sample is composed primarily of small and midsize companies. Figure 2 shows the distribution of SEPS by industry grouping. It appears that the modes (and means) are similar and the distribution of most SEPS, with the exception of the Energy sector, is skewed right, which is again reflective of the economic trends during the period under consideration.

TABLE 2
SEPS & MARKET CAPITALIZATION VS BROAD INDUSTRY GROUPS

	SEPS			Market Capitalization			
Sector	Mean	Median	StDev	Mean	Median	StDev	N
Basic Industries	4.14	2.17	18.74	4.99	2.03	7.67	80
Capital Goods	0.52	2.30	13.77	5.60	1.27	10.46	63
Consumer	4.35	3.65	16.16	5.66	2.01	8.73	133
Energy	-1.79	-3.65	15.44	15.12	3.38	44.35	132
Finance	6.13	4.36	15.06	6.20	2.06	12.27	114
Health Care	10.32	9.37	16.54	6.14	0.94	20.42	125
Public Utilities	12.18	12.19	15.85	12.78	3.71	37.20	36
Technology	4.27	4.39	11.06	11.54	1.75	61.62	78
Transportation	5.12	5.71	18.96	4.69	1.29	7.65	46

The Table 2 shows the mean (%), the standard deviation (StDev), and the frequency of SEPS, as well as the market capitalization ($ Billion) across broad industry groups spanning the period 01-07-2014 to 06-01-2016.

FIGURE 2
DENSITY ESTIMATES OF THE SEPS BY INDUSTRY GROUPS

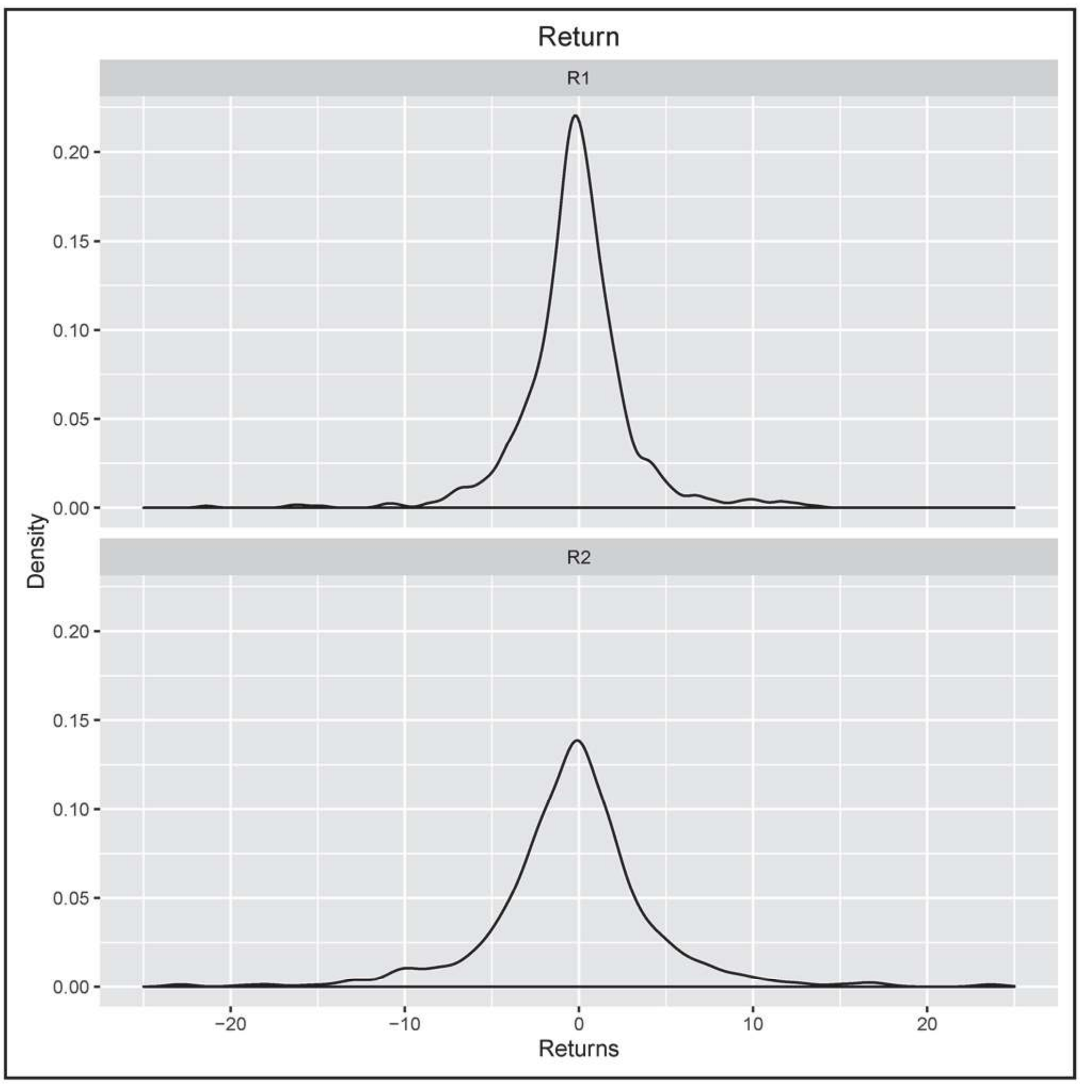


There exists a large body of literature that studies the impact of earnings news and earnings guidance on stock returns, though to our knowledge no previous study has used SEPS. Brown et al. (1996) and Brown (1997) form an *ex post* earnings surprise predictor based on factors including past surprises and firm size. They find that constructing a portfolio comprised of buying stocks with the 'best quarterly earnings news' and shorting stocks with the 'worst quarterly earnings news' yields positive abnormal returns.

Next we turn to calculating equity returns for firms in our sample. In keeping with our stated aim of relying on freely available data, we obtain daily prices for our firms from Yahoo! Finance. After careful matching and cross checking, we end up with 972 SEPS for 807 unique ticker symbols. It is important to note that 344 firms in our sample have only one SEPS, while the remainder of the firms have up to four SEPS during this period.[7] Using the daily price data, we compute *log-returns* over two time periods subsequent to the SEPS release date. Let R_1 be the return (open to close) the day after and R_2 be return (open to close) over two days after the SEPS release. Denote SR_1 and SR_2 as log-returns for the S&P 500 corresponding to the same time periods, respectively.

Each return specification will capture a different form of information dissemination among the market participants. Specifically, R_1 and R_2 are associated with trading strategies that use available public information about the SEPS, immediately after it has been published. Figure 3 provide density estimates for the two rates of return. The distributions are centered near zero and their variation grows with the length of the holding period, as expected.

FIGURE 3
DENSITY ESTIMATES OF THE RETURN DISTRIBUTIONS



REGRESSION ANALYSIS

Our regression modeling approach is similar to Jegadeesh and Livnat (2006), who find that earnings surprises result in significant post-announcement abnormal returns. Researchers have also considered the time required for markets to incorporate earnings predictions into asset prices. Jegadeesh and Livnat (2006), Stickel (1991) and others suggest that markets may be slow to incorporate earnings surprises. On the other hand, Barber et al. (2001) form portfolios based on analysts' recommendations with daily re-balancing that yield abnormal returns, and show that the returns decay with the length of holding period. Our returns regression follow this literature and is intended to capture the speed of information diffusion among the market participants.

We use the standard regression model from the extant literature to investigate the relationship between SEPS and short-term returns as follows:

$$R = \alpha + \beta \times \text{SEPS} + \sum_{i=1}^{k} \beta_i X_i + \epsilon, \tag{1}$$

where R is the one or two days return post the SEPS release, α is the intercept, β is the estimated impact of SEPS, X_is are control variables with their associated coefficients β_is, and $\epsilon \sim N(0, \sigma)$ is the regression residual. The set of explanatory variables we consider include the return on the S&P 500 over the corresponding periods (SR_i, $i = 1, 2$), and several indicator variables and interaction terms.

Specifically, we use a variety of proxies for firm size, including the logarithm of market capitalization, as well as indicator variables corresponding to small, mid, and large capital- ization. Following Chiang et al. (2016), we include the proportion of SEPS that are positive surprises as a proxy for the "fraction of forecasts that miss on the same side". We also include indicator variables for industry groups, and specific months and quarters. Finally, we included products of the explanatory variables as a proxy for the interactions between the explanatory variables. However, to save space, the control variables that were statistically insignificant are omitted from the regression results presented below.

Table 3 contains the regression result for R_1 and R_2. Each model includes SEPS and the S&P 500 return denoted by SR_i, corresponding to periods $i = 1, 2$. To delineate the effect of extreme SEPS, two indicator variables I_U and I_L are included. These assume a value of 1 when SEPS are above 20% (below -25%) at each date. We also include dummy variables for months so as to capture the peak earning season's effect. On a number of occasions, SEPS are reported on Tuesdays, following a Monday holiday, which implies trades would occur on a Wednesday. We include a dummy variable to capture this effect. We explored adding interaction terms involving the control variables but these were statistically insignificant and are omitted from the table. The F-test for all regression models are significant at the 99% confidence level. The reported adjusted R^2s, while low, are very similar to those reported in previous studies (e.g., Brown et al. (1996)).

TABLE 3
REGRESSION RESULTS

	R_1			R_2		
Variable	All	Positive	Negative	All	Positive	Negative
α	0.3725	-0.0496	1.242	-0.5281	-1.0873	1.3654
SEPS	-0.0301**	-0.0247	-0.0185	-0.0605**	-0.0637	0.0105
SR_i	0.8292**	0.4899**	1.2977**	0.1567	0.1527	0.3208
I_L	5.0004	-	5.8726	-2.8741	-	-0.7692
I_U	-0.5833	-0.3314	-	0.1994	0.135	-
February	-1.1076**	-0.5292	-1.9973**	-1.2606	0.2648	-3.0741**
March	-0.0961	-0.1665	-0.2515	1.2878	1.1689	1.9295
April	-0.3856	-0.223	-0.9921	0.957	0.9357	0.3491
May	-1.4717**	-0.7102	-2.8018**	-1.2228	0.1299	-3.2508**
June	-0.2738	-0.105	0.7445	1.2922	1.6504	2.4122
July	-0.4905	-0.2936	-1.0281	0.6375	0.7886	-0.1994
August	-1.0855**	-0.2131	-2.5903**	-1.0289	0.3646	-3.3689**
September	-1.1007**	-0.819	-0.1988	0.1268	0.1242	6.032**
October	0.0806	0.2583	-0.9013	0.4646	1.2622	-1.3755
November	-0.7326	-1.2503**	-0.5415	-0.125	-0.0811	-0.7568
December	-0.4545	0.8829	-4.9988**	-2.5989	-3.0319	0.9426
Wednesday	1.1346**	1.6958	0.1399	1.904**	2.7274**	0.4245
$SEP\ S \times I_L$	0.2078**	-	0.2261**	0.0076	-	0.0468
$SEP\ S \times I_U$	0.045**	0.0367	-	0.0893**	0.0902	-
Adjusted R^2	0.0885	0.0525	0.1668	0.0296	0.0259	0.0687

The table 3 shows the Regression results for one day (R_1) and two days returns (R_2) after the SEPS are released. The models are estimated for all data, positive SEPS and negative SEPS. The S&P 500 return corresponding to R_i, i = 1, 2 is denoted by SR_i. The models include indicator variables for months, Wednesdays, extreme SEPS, and their interaction with SEPS values. "**" indicate 95% confidence level. The F-test is significant at the 99% confidence level in all regressions.

Focusing on the regression results for R_1, we find that the SEPS coefficient is significant when the entire sample is used, but is insignificant when the sample is partitioned into positive and negative SEPS. Considering the negative and positive regression models, we find the regression results for the negative SEPS partition are more significant, suggesting that prices are more responsive to negative SEPS. This asymmetrical response is consistent with risk averse behavior that causes investors' to avert potential losses more readily than pursing potential gains. Turning to extreme SEPS values, we find that the indicator variables I_U and I_L are insignificant. However, the interaction terms, $SEPS \times I_L$ and $SEPS \times I_U$ are highly significant, suggesting that extreme SEPS have a large impact on returns. The asymmetrical effect of SEPS on returns is confirmed by these interaction terms, as the coefficient of negative extreme SEPS is larger than the positive extreme SEPS (.2078 versus .045). Overall, we find an inverse relationship between returns and SEPS, which is confirmed with the event study results reported later.

Turning to other control variables, the return on the S&P 500 is highly significant, as expected. The months' dummy variables are generally significant for the month immediately before the quarter's end. Interestingly, the coefficient for the month of May is negative and highly significant (where the baseline month is January), particularly for the negative SEPS partition, providing support to the old adage "sell in May and go away". Finally, the regression results for R_2 shows that the information content of SEPS quickly dissipates over time, as most explanatory variables become statistically insignificant.

PORTFOLIO ANALYSIS

We next construct portfolios guided by our regression results. In particular, at each date, we compute the median SEPS based on the data accumulated up to that point in time (no forward looking bias). Assuming there are no transactions costs or taxes, we then compose and dynamically rebalance two equally weighted portfolios. Portfolio 1 consists of stocks with SEPS above the calculated median and portfolio 2 consists of stocks with SEPS below the calculated median. There are two reasons we use the median SEPS for forming portfolios. First, the median ensures that the number of stocks in the portfolios are comparable. Second, as noted earlier, the SEPS are positively skewed, where the mean is larger than the median, suggesting that there is systematic upward bias in the predicted earnings surprises, despite reliance on the analysts' forecast accuracy.[8]

It is important to note that since the first opportunity to trade based upon SEPS is the next day's open to close rate of return (R_1), the assets in our hypothetical portfolios are held for one trading day. Suppose an investor takes a short position in portfolio 1 and a long position in portfolio 2. This would constitutes a simple contrarian strategy, where predicted earnings surprises above the median are viewed as "overly optimistic," and those below the median are viewed the opposite.

Figure 4 shows the cumulative return to portfolio 1 (short), portfolio 2 (long), and the combined portfolios over the period under consideration. It appears that over time the short portfolio generates consistent positive returns, the long portfolio's returns rises but falls abruptly, and the combined portfolio, while mostly positive, is dragged down by the long component. These results are confirmed in the first two rows of Table 4, which shows the average daily return and daily volatility for these portfolios. As the table shows, relative to S&P 500 returns over the same time period, these portfolios are highly volatile.

Given that the risk free rate is nearly constant during this period, we benchmark the performance of these portfolios against the S&P 500 using the market model. Table 4 shows the relative performance of these portfolios. The table also provides estimates of the Alpha and Beta associated with each portfolio. The test of significance for the Beta corresponds to $H_0 : \beta = 1$ since these diversified portfolios are expected to have a Beta close to 1. Overall, it appears that controlling for risk, these portfolios do not generate a statistically significant Alpha. It also appears that the short portfolio offers the highest Sharpe Ratio.

FIGURE 4
CUMULATIVE PORTFOLIO PERFORMANCES (BLUE) RELATIVE TO THE S&P 500 (RED)

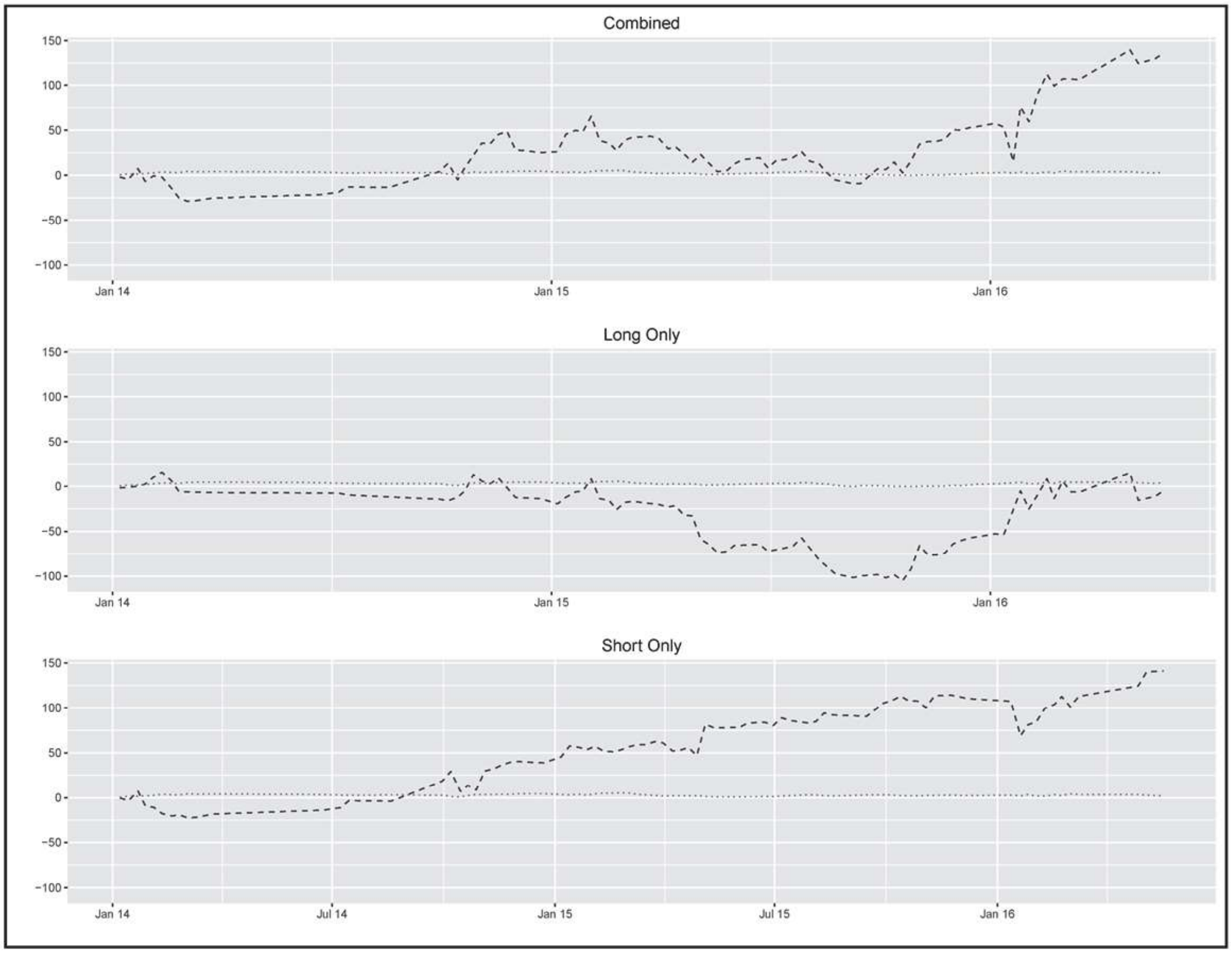


TABLE 4
PORTFOLIO PERFORMANCE SUMMARY

	Combined	Long	Short	S&P 500
Average daily return %	1.497	-0.0591	1.809	0.0396
Daily Volatility %	12.87	11.51	9.53	0.77
Sharpe Ratio	0.1160	-0.0051	0.1898	0.0512
CAPM Alpha	1.306	-0.424	1.870	-
CAPM Beta	4.811**	7.048**	-2.378**	-
Adjusted R^2	.0730	0.227	0.023	-
Number of Trades	807	401	406	-

In Table 4, at each date we compute the median SEPS based on the data accumulated up to that point in time. The Long (Short) portfolio consists of equally weighted stocks with SEPS below (above) the median SEPS. The Combined portfolio is simply the sum of the Long and Short portfolios. The portfolios are rebalanced dynamically at the market opening after the SEPS are released. The "**" indicate 95% confidence level. The F-test is significant at the 99% confidence level in all regressions.

MARKET REACTION TO SEPS

To evaluate whether predicted earning surprises are received as value-relevant news by in- vestors, we study the equity market's reaction around the dates when SEPS are released to the public. To this end, we perform an event study, using standard methods to measure abnormal returns (MacKinlay, 1997). For this exercise, we rely on Wharton Research Data Services' (WRDS) event study software. It is important to note that this application uses the Center for Research in Security Prices (CRSP) return data. We estimate four risk-adjusted models over a 60-day period, leaving a gap of 30 days prior to the release of SEPS. We measure abnormal returns over the window -15 to +15 days for each model, where t = 0 is the date when SEPS are actually published online.

Following Ball and Brown (1968), short-horizon event studies generally utilize either the capital asset pricing model (CAPM) or alternative models to estimate abnormal returns during the event window.[9]
The WRDS application estimates the following risk adjusted models:

- **The Market-Adjusted Model:** $AR_{MA} = R - R_{market}$, where R (R_{market}) is the firm's (the market's) actual return at each date during the event window.
- **The Market Model:** $AR_{MM} = R-(\alpha+\beta*R_{market})$, where α and β are the parameters that were estimated using data from the designated estimation period.
- **The Fama-French Model:** Denote SMB – "Small Minus Bi" – as the excess returns of small capitalization over big capitalization firms, and HML – "High Minus Low" – as the excess returns for value stocks (high book-to-market) over growth stocks (low book-to-market), then:
  $AR_{F\,F} = R - (R_f + \alpha + \beta_1 * (R_{market} - R_f) + \beta_2 * SMP + \beta_3 * HML,$
  where R_f is the risk free rate, and α and βs are the estimated Fama-French parameters.
- **The Fama-French-Carhart Model:** Denote MOM as the excess returns of "winner" over "loser" stocks associated with pursuing a "momentum strategy", then:
  $AR_{FFC} = R - (R_f + \alpha + \beta_1 * (R_{market} - R_f) + \beta_2 * SMP + \beta_3 * HML + \beta_4 * MOM$
  where α and βs are the estimated Fama-French-Carhart parameters.

We use three standard test statistics to assess whether the abnormal returns during each date in the event window are statistically different from zero (see MacKinlay (1997)). **S1** is the cross sectional T-test, which allows for event-induced changes in the variance of abnormal returns, but assumes that there is no cross-sectional dependence in abnormal returns. **S2** is the "standardized cross-sectional T-test", which controls for the possibility that events may cluster in calendar time, in turn violating the assumption of cross-sectional independence of abnormal returns. This test takes into account information from both the estimation and the event windows and allows for event-induced variance shifts. **S3** is the Patells Z, which standardizes abnormal returns by the standard deviation of the estimation period abnormal returns. This test assumes that the cross-sectional abnormal returns are independent and there is no event-induced change in the variance of the event-period abnormal returns.

Table 5 reports the result of the event study under the alternative risk models. Focusing on the three test statistics, we find evidence of statistically significant abnormal returns on days -6, -1, +12, and +14. This suggests that the SEPS were available to a subset of market participants on 1 and 6 days prior to their release to the general public via the TDA. The abnormal returns 12 and 14 days after the release of SEPS, are likely due to the actual earnings announcement that occurred after the SEPS were published. Consistent with our regression results, daily abnormal returns immediately after the SEPS release are negative and generally statistically insignificant. Finally, we also calculate the average cumulative abnormal returns (CAAR) over the event window for each risk model. The CAAR are statistically insignificant for all dates and are omitted to save space.

TABLE 5
EVENT STUDY RESULTS FOR RISK ADJUSTED MODELS

	Market-Adjusted				Market Model				Fama-French				Fama-French-Carhart			
Event Time	AAR	S1	S2	S3	AAR	S1	S2	S3	AAR	S1	S2	S3	AAR	S1	S2	S3
-10	-0.0002				-0.0004				-0.0011		**	**	-0.0010		**	**
-6	-0.0024	***	***	***	-0.0027	***	***	***	-0.0021	***	***	***	-0.0019	**	***	***
-1	-0.0024	**		**	-0.0025	***	***	**	-0.0025	***	**	***	-0.0025	**	**	***
t=0	0.0006				0.0006				-0.0003				-0.0004			
1	-0.0016			**	-0.0015			**	-0.0021			***	-0.0022			***
12	-0.0029	***	***	***	-0.0025	***	***	***	-0.0022	***	***	***	-0.0015		**	**
13	0.0028	***	***	***	0.0025	***	***	***	0.0013			**	0.0014			**
14	-0.0020	**	**	**	-0.0022	***	**	***	-0.0028	***	***	***	-0.0024	***	**	***
15	0.0019	**		**	0.0018			**	0.0011				0.0008			

In Table 5, AAR is the average abnormal return and S1, S2, and S3 are statistical test of the null hypothesis that AAR is zero. S1 is the Cross sectional T-test, S2 is the Standardized Cross Sectional T-test, and S3 is Patell's Z-test. The event window spans ±15 days. "***" indicates 99% confidence and "**" indicate 95% confidence level. The data for statistically insignificant days have been dropped to save space.

CONCLUSION

Market efficiency studies rely on *ex post* measures of earnings surprise that suffer from conflict of interest embedded in analysts earning forecasts. The traditional metrics measure the difference between realized earnings and the consensus number. In this paper we collect *ex ante* forecasts of the earning surprise from freely available public sources. Because this measure of earning surprise (SEPS) accounts for analysts' forecast accuracy, we hypothesize that it is less affected by the conflicts of interests biases. We then assess the impact of SEPS on equity prices over short horizons and determine if the SEPS can be used to form profitable trading strategies. Our analysis shows that while the SEPS have a statistically significant impact on prices, portfolio strategies based on SEPS do not generate risk-adjusted abnormal returns. Our detailed event study shows that the information content of SEPS have been revealed to market participants at least a week in advance their release in the public domain. Indeed, it is likely that SEPS represent "stale information" by the time an investor is able to access them on the day it is published online.

ACKNOWLEDGEMENT

Ramezani was supported by OCOB summer research grants. Frame acknowledges support from the COSAM Summer Undergraduate Research program. We are grateful to Herbert Hunt and participants at the South Western Finance Association meetings for their valuable comments. The authors retain full monopoly rights over any error or omission. Please direct comments to cramezan@calpoly.edu and sframe@calpoly.edu.

END NOTES

1. Standardized Unexpected Earnings is defined as $SUE = \frac{(A-C)}{\sigma}$ where A is actual earnings per share reported by the firm, C is consensus earnings per share, and σ is the standard deviation of earnings forecast across the analysts covering the firm.
2. Chiang et al. (2016) prove mathematically and show empirically that relative to SUE, their proposed measure is a more robust measure of surprise earnings.
3. In fact, Bradley et al. (2017) show that analysts with consistent forecast accuracy, have previous work experience in the industry they cover and are more likely to gain top ranking.
4. Thomson Reuters publishes the TDA. We last accessed TDA on June 2017 at: http://share.thomsonreuters.com/assets/newsletters/The Day Ahead/TDA_NAM.pdf.
5. The SEPS are created from the Thomson Reuters I/B/E/S data and are called SmartEstimates®. Thomson Reuters states: "SmartEstimates® aim to provide earnings forecasts that are more accurate than Consensus Estimates, by putting more weight on the recent forecasts of top-rated analysts". For further details see http://pyquants.thomsonreuters.com/News%20Sentiment.pdf and https://www.slideshare.net/ruzitakamis/star-mine-armwhitepaper.
6. We then match each firm's name to its ticker symbol, using the list of stocks traded on NYSE and NASDAQ. We obtain market capitalization and industry classifications data from this list as well. This list was last accessed on June 2017: http://www.nasdaq.com/screening/company-list.aspx.
7. The unmatched companies were private firms, had ambiguous names, or were not present in NAS-DAQ/NYSE lists, and were omitted from our analysis. We also exclude firms with SEPS in the range of ± 2%, as these range of values are likely to be noise rather than surprise.
8. We explored several trading strategies based on the extreme values of SPES but found none to be as effective as the median-based strategy reported in this section.
9. We note that an event study assumes that the parameters of the risk models are the same regardless of the time interval over which returns are measured. That is the regression βs from daily, weekly and monthly returns will be the same and time invariant.

REFERENCES

Ball, R. & P. R. Brown (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research 6* (2).

Barber, B., R. Lehavy, M. McNichols, & B. Trueman (2001). Can investors profit from the prophets? security analyst recommendations and stock returns. *Journal of Finance 56* (2).

Bradley, D., S. Gokkaya, & X. Liu (2017). Before an analyst becomes an analysts: Does industry experience matter? *Journal of Finance 72* (2).

Brown, L. (1997). Can esp yield abnormal returns? *Journal of Portfolio Managment 23* (4). Brown, L., J. Han, E. Keon, & W. Quinn (1996). Predicting analysts' earnings surprise. *Journal of Investing 5* (1).

Chiang, C.-H., W. Dai, J. Fan, H. G. Hong, & J. Tu (2016). Robust measures of earnings surprises. *Social Science Research Network* http://dx.doi.org/10.2139/ssrn.2473366.

Hayes, R. M. (1998). The impact of trading commission incentives on analysts stock coverage decisions and earnings forecasts. *Journal of Accounting Research 36*.

Hong, H. & J. D. Kubik (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance 58*.

Hwang, B.-H., B. Liu, & D. Lou (2014). 'consistent' earnings surprises. *Social Science Research Network* http://dx.doi.org/10.2139/ssrn.1571619.

Jegadeesh, N. & J. Livnat (2006). Revenue surprises and stock returns. *Journal of Ac- counting and Economics 41*.

Levis, M. & M. Liodakis (2001). Contrarian strategies and investor expectations: The u.k. evidence. *Financial Analysts Journal 57* (5).

Lim, T. (2001). Rationality and analysts forecast bias. *Journal of Finance 56*.

MacKinlay, C. (1997). Event studies in economics and finance. *Journal of Economic Liter- ature 35*.

Stickel, S. (1991).Common stock returns surronding earnings forecast revisions: More puzzling evidence. *The Accounting Review 66* (2).