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The value of publicly available predicted earnings surprises[☆]

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Abstract

This paper demonstrates how to collect and manage free predicted earnings surprises available in the public domain. The predicted earnings surprises we collect are expected to be more accurate than the corresponding consensus estimates and other predicted earnings, but have not been studied in the academic literature until very recently. We find a number of unexpected and problematic idiosyncrasies with the source of the data and the predicted earnings surprises themselves. The data are hard to work with, perhaps by design, and contain both big and small extreme values that are unexpected given their origin. It is unclear how these observations are selected for public release. After the data science exercise of managing and merging the predicted earnings surprises with other freely available public information (specifically ticker symbols and return data), we examine the predicted earnings surprises and investigate how the predicted earnings surprises affect short-term stock prices. We find evidence of a linear association between the predicted earnings surprises and subsequent short-term returns, although the significance is driven by extreme outliers. Most importantly, we use the predicted earnings surprises to form short-term trading strategies. The most profitable trading strategy that exploits the predicted earnings surprises is a contrarian trading strategy.

Keywords: Data science; Data management; Exploratory data analysis; Regression analysis; Pre-dicted earnings surprises; Quantitative finance; Trading

1. Introduction

Publicly traded companies report their performances through quarterly earnings reports. These reports contain various layers of detailed performance information, and one of the most closely watched metrics is the earnings per

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share (EPS): the ratio of the earnings to the shares outstanding. Investors and analysts closely monitor EPSs to gauge profitability and financial health, and most importantly to make investment decisions. As such, earnings can impact stock prices.

Earnings estimates of a given firm come from both sell- and buy-side analysts that follow the firm. The consensus estimate is a numerical summary (either the mean or median) of all available analyst estimates, and can be interpreted as a forecasted or predicted earnings. The number of analysts following each firm can vary greatly, and[7] points out that analysts systematically underpredict earnings consequently lowering the consensus estimate. The reasons for analysts to manipulate and underpredict earnings has been well-studied,[3,7–9] and occurs because analysts don't want to be wrong about their earnings estimates, would like to receive high rankings, want to stimulate trading, and/or may have business relationships with the firms they cover.

An earnings surprise is when a firm's actual earnings are significantly above or below the predicted earnings given by the consensus estimate. There is an enormous body of literature devoted to the impact of actual earnings and earnings surprises on asset prices. For example,[1] find that companies with actual earnings that exceed or fall short of earnings estimates experience abnormal returns over subsequent periods. The consensus estimate is not the only predictor of future earnings or the only way to define an earnings surprise.[5] And[4] form an 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 returns (for firms in the IBES International Inc database).[6] Extend this work using the same method to select firms in the S&P 500 that "outperform" or "underperform" the market yielding similar portfolio results. In this paper, we study predicted earnings and predicted earnings surprises developed by StarMine.

StarMine is a subsidiary of Thomson Reuters specializing in quantitative analytics, and one of their metrics is the StarMine SmartEstimate which is StarMine's predicted earnings per share (PEPS). For a given company, the StarMine predicted surprise is their Surprise Earnings Per Share (SEPS) defined as:

$$SEPS = \frac{PEPS - CONS}{CONS}$$

where *PEPS* is the StarMine SmartEstimate and *CONS* is the current consensus estimate (note that SEPS is reported as a percentage). The Starmine SmartEstimate, PEPS, is a weighted average of the most recent earnings forecasts by top-rated sell-side analysts, reduces any conflict-of-interest bias, and is a more accurate predictor of future earnings than the consensus number. The Starmine SmartEstimates are billed as a "leading indicator of future analyst revisions and actual earnings surprises." 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."

StarMine is a subsidiary of Thomson Reuters specializing in quantitative analytics. Access to the entire universe of StarMine products, including 35,000 PEPS (and corresponding SEPS) annually, requires a subscription. However, after the NYSE and NASDAQ exchanges close every day, Thomson Reuters publishes *The Day Ahead* newsletter. *The Day Ahead* newsletter (hereafter 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 during the next week. More importantly for our consideration, the TDA released on the first trading day of each week also contains the SmartEstimates for selected companies with scheduled earnings reports that are at least one week away. Although access to all of Starmine and their analytics requires a subscription, the TDA can be obtained for free by filling out a short subscription form at the Thomson Reuters website.

The objectives of this research fall into the body of literature that study the impact of earnings news on stock returns, and more specifically how predicted earnings surprises impact short-term returns.[13] Have recently extended and built on the work presented here. In many ways, this paper is a *prequel* to their paper. There are substantial differences between [13] and the work presented here. First,[13] do not describe the data in any detail. We first devote an entire section to the data collection and management process, which is fundamentally a data science exercise. Furthermore,[13] further subset the data described in this paper. Lastly,[13] consider a very different regression analysis, construct very different portfolios, and include a formal event study described by[1] and.[12] Each of these distinctions will be detailed further in their relevant sections. The remainder of the paper is organized as follows. Section 2 details the data science exercise of collecting the StarMine SmartEstimates from the TDA and merging this information with other freely available public data. An exploratory data analysis is provided in Section 3 along with a regression analysis in Section 4. Section 5 details the trading portfolios and their performances in comparison to the S&P 500. We conclude the paper with comments and suggestions for future research.

2. Data collection

Since the TDA is publicly available, a guiding principal for this research is to obtain data from freely available sources in the public domain. Counter to our own expectations, the data management process proved to be a challenging data science exercise. Each source of data has its own idiosyncrasies that complicates the process. A list of the data steps is below.

1. Extract the SmartEstimate information from the TDA
2. Match the company names to a list of official company names and identify their ticker symbols
3. Obtain prices and create returns for the companies with SmartEstimates

Extracting the SEPS information from the TDA is straight-forward and not at all novel. Because the company names in the TDA are not standardized or consistent, we carefully match company names to a list of company names in order to obtain the company ticker symbols. The ticker symbols for each of the companies are required to obtain price data.

Each week, we create an Excel file that records the company names, SEPSs, PEPSs, predicted revenues and industries (which are really subsectors of the standard S&P 500 sectors). This is the first source of data. It is possible to parse/read the TDA files each week (which are PDF files), but the time required to copy/paste this information is minimal (we open and read the TDA anyhow). Parsing the TDA PDF files is an area of current research. To be clear, the TDA does not publish all of the SmartEstimates for every company followed by StarMine. The SmartEstimates released in the TDA are a very small subset of this population and there is no indication of how the information is selected for release. Our EDA might provide some insights, however, about what they are not making publicly available.

In order to obtain price information, the company names are matched to ticker symbols. This is the second set of data, and is the most complex and critical component of the data management tasks. We scrapped a list of the companies and their ticker symbols traded on the NYSE and NASDAQ.[1] The challenge is to match the company names in the TDA to the company names in NYSE/NASDAQ lists so that we can identify their ticker symbols (and subsequently obtain price information to create returns).

We suspect the StarMine information in the TDA are not computer generated because there are many inconsistent spellings of the same company name(s) (e.g. different abbreviations) and common generic company words (e.g. company). For example, Pacific Biosciences of California has four different spellings or four different character strings. The character strings for the industries are even more disparate. For example, there are twelve different character strings representing the semiconductor equipment industry. Lastly, many of the spellings and use of common company words in the TDA are not consistent with those found on our NYSE/NASDAQ list.

To match the names, we explored a number of text mining and pattern recognition methods found in existing R packages. Many methods returned matches for mostly all the companies, but the error rate was too high (above 20% in some cases). We implemented our own matching methodology. The first phase of matching attempts to match the character strings directly (very low match rates). When either no or multiple matches occur, we separate the character strings using the space between words and then create a strength of association score based on the percentage of the substrings that match target substrings. Some matches were not available because they are private firms or not traded on the NYSE/NASDAQ, had ambiguous names (for example First Bancorp exists on both exchanges), or were not present in NASDAQ/NYSE lists. For each firm, we obtain the market capitalization and sector from the NYSE/NASDAQ information.

The third source of data is the price data obtained from Yahoo! Finance that are used to create log-returns. Some of the companies were not available from Yahoo! Finance and were also removed. Using this price data, we compute four different log-returns over times visualized in Fig. 1. The first two returns, R_0 and R_1 capture price movements before the SEPS information is released in the TDA. The actionable returns, R_2 and R_3, capture price movements after the

[1] http://www.nasdaq.com/screening/company-list.aspx

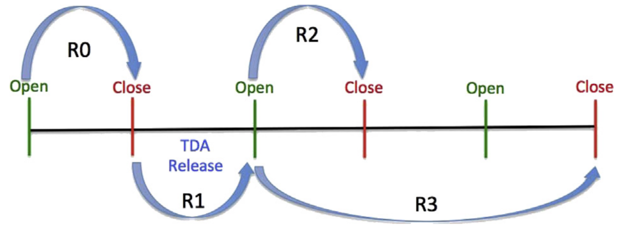

Fig. 1. Return specifications relative to TDA release.

information is released. Note that the same returns are computed for the S&P 500 and are denoted SR_i for $i = 0, 1, 2, 3$. To be clear, the SEPSs reported in the TDA occur at least one week prior to the corresponding actual earnings reports. So the returns we compute do not capture the effects of the actual earnings news itself rather only the SEPS predictions released in the TDA.

We started with 1690 observations on 744 unique companies and we ended with 1605 observations on 718 companies. Our data spans the period from 01–07–2014 to 06-01-2016. In June 2016, the TDA stopped publishing the Starmine predicted earnings surprise information for several weeks. The TDA started to include the predicted earnings information once again but it was structurally very different and contained different information. We are currently processing the data from June 2016 to present. After doing so, will compare the data (and analysis results) before and after June 2016.[13] Do not articulate these details of the data collection and management process.

3. Exploratory data analysis

Our exploratory analysis investigates (1) the distribution of the SEPSs that are released in the TDA and (2) the relationship between the SEPSs and short-term returns. Recall that the SEPSs released in the TDA are free and publicly available, chosen from the population of SEPSs which paying StarMine subscribers would have access to. Therefore, the distribution of the SEPSs released in the TDA is of particular interest.

Our analysis reveals some very interesting features of the SEPSs, and suggests they are likely not randomly sampled. First, some companies have multiple SEPS reports within a given quarter and/or across multiple quarters. There are also extreme (both positive, negative, and small) SEPSs made public in the TDA. This is particularly interesting since StarMine claims to have removed extreme values prior to computing their improved PEPS estimates. We have also found two “slices” of SEPSs that are strangely not included in the TDA. The SEPSs themselves and their frequencies vary dramatically across the different market sectors. Lastly, the relationship between the SEPSs and the R_2 returns is strongly influenced by extreme values.

Quarterly earnings are seasonal happening four times per year. Peak earnings season happens when the majority of firms report earnings, and there are times in between the peaks where relatively few firms report earnings. Table 1 shows the frequency of SEPSs made public each month. Typically the vast majority of SEPSs are released during the first two months of each quarter, which corresponds to predictions made prior to the peak of the actual earnings seasons. Fig. 2 is a weekly time-series plot of the SEPSs, again highlighting the peak arrivals during the earnings season. The presence of both extreme SEPSs should be clear; 19 values are outside the interval [-100%, 100%] and a few are even larger than 250%!

We have 1605 SEPS observations on 718 unique firms. This occurs because some firms have multiple SEPS reports within the same quarter and/or across different quarters. Fig. 3 shows the distribution of the number of SEPS reports per company. While a large number of firms have only one SEPS report, the majority of firms have two or more SEPS reports. Instances of multiple SEPS reports are realized in a number of different ways as various combinations of

Table 1
Frequency of observations by month and year.

	01	02	03	04	05	06	07	08	09	10	11	12
2014	77	81	20	97	34	22	94	37	46	82	44	11
2015	71	79	48	86	40	38	87	47	27	82	44	11
2016	70	94	51	60	52	0	0	0	0	0	0	0

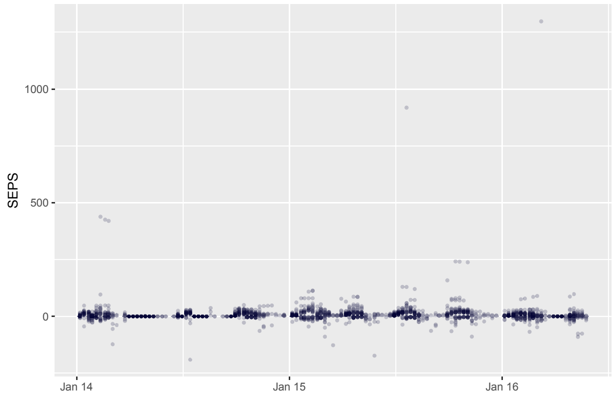

Fig. 2. Time series plot of SEPS.

SEPS released within the same quarter or across different quarters. For example, a firm with two SEPS reports could have two reports - consecutive or otherwise - within the same quarter and when the reports are not consecutive they could be separated by as many as six weeks. On the other hand, the two reports could be for two different quarters which, again, do not have to be consecutive quarters and the separation can be highly irregular. This introduces potential autocorrelation, however irregular and hard to assess, that may adversely impact the standard errors of the regression coefficients.

These data are not standard panel data, and are best described as irregularly spaced and sparsely populated panel data. It is possible for firms to have multiple SEPS reports within the same quarter because of revisions to either the

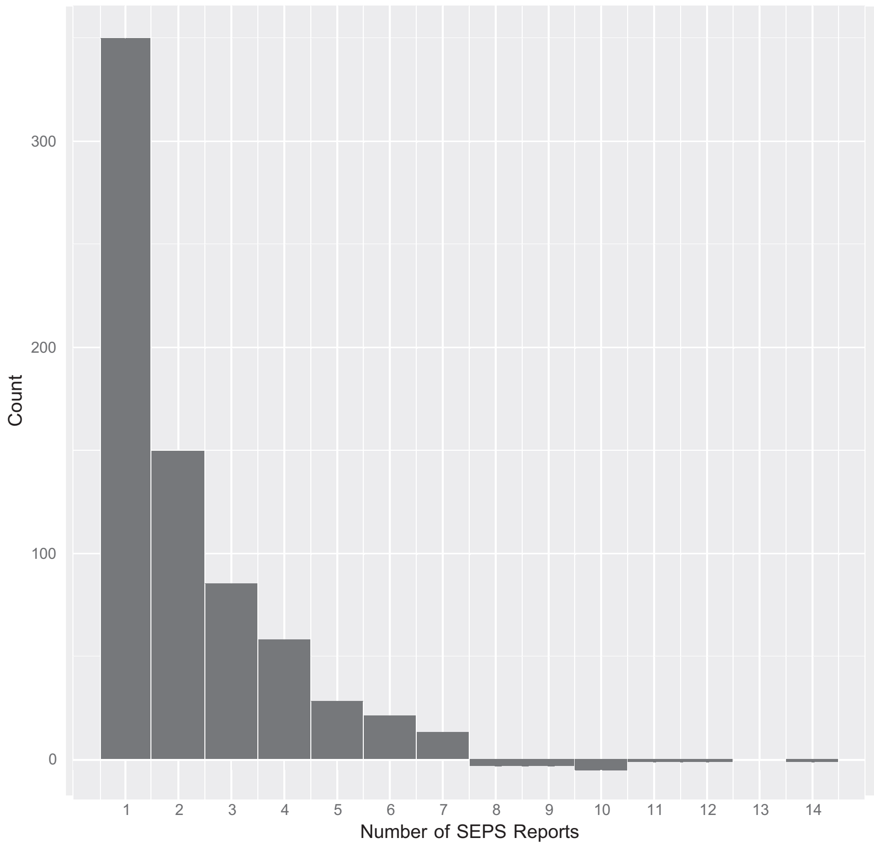

Fig. 3. Distribution of the number of SEPS reports per company.

PEPS or the consensus estimate. We have found that the PEPSs are rarely revised whereas the consensus estimates can vary dramatically at times. The SEPSs do not always change consistently, sometimes they increase and sometimes decrease. To account for this, we create a subset of the data that only contains one SEPS report per firm per quarter. For a firm with multiple SEPS reports within a quarter, we retain and use only the last report that is generated for the given quarter. Being closest to the actual report, this final SEPS is likely the best information. After doing so, the subset has 996 observations on 718 unique companies. We use this subset for the rest of the EDA and regression analysis in Section 4 as do.[13]

However, the portfolios discussed in Section 5 rely on all of the SEPSs each week, which is a more realistic trading situation. This is a significant point of distinction from [13] who build portfolios only using the last SEPS reported for a firm in a given quarter. This restriction is not realistic, because one does not know when the last SEPS for a firm in a given quarter will actually occur.[13] also further subset the SEPS data developed here by not including SEPSs that are exactly 0%, between −2% and 2%, or more extreme than −62% and 97%. Our analysis here does not exclude any of these extreme values.

Fig. 4 shows density estimates for the SEPSs by sector. The axis has been restricted to remove the scaling effects of the values above 100% (and below −100%). The density estimates should be examined in conjunction with the SEPS summary statistics shown in Table 2. All sectors contain small modes in the tails of the distributions, contributing to the large kurtosis shown in Table 2. With the exception of the energy sector, the SEPS distributions are all skewed. Most of the sectors have positively skewed distributions, however the capital goods and transportation sectors are negatively skewed. These also show that the majority of the SEPSs are positive (about 61%). The shapes of the estimated distributions are similar for the basic industries, health care, public utilities and transportation sectors which all have the highest standard deviations. The consumer sector has the second largest standard deviation, but the shape of the distribution is more similar to the capital goods, energy, finance and technologies sectors which are the least varied.

Including extreme SEPSs results in highly variable means that may not be expected. Table 2 shows that the public utilities sector (with a maximum SEPS of 419.79%) has a mean SEPS about three times higher than that of the technology sector (with a maximum SEPS of 120.15%). This may seem counter intuitive since we might expect that firms in the technology sector to have higher predicted earnings surprises than those in the public utilities sector. We find the mean SEPS is the highest for the basic industries, health care and pubic utilities sectors, and the lowest for the energy and capital good and the transportation sectors. The findings don't have to be consistent with the expected statistics for each sector since our data are not a random sample of SEPSs from each sector. Furthermore, we don't know how the data was actually selected for publication in the TDA.

Due to the nature of density estimates and scaling, Fig. 4 does not reveal an interesting characteristic of the SEPS reported in the TDA. The StarMine trading literature claims that SEPSs between 2% are the most accurate. Fig. 5 shows the SEPSs (aggregated across sector) focusing on values between −3% and 3%. The slice of SEPSs concentrated at 0% is interesting given what StarMine claims, and it is unclear why these values have been selected for release in the TDA. Similarly, it is unclear why they have also reported SEPSs that are extremely high above 100%. Given the superior nature of the StarMine method and data, we do not remove any of the extreme large or small SEPSs that are reported in the TDA as[13] do. After all, they are reported in the TDA. Note that these values have been double-checked to ensure they are not data processing errors.

Fig. 6 shows the returns each week for the companies with SEPS reports in the TDA. To be clear, this is not a traditional time-series plot (which would be for the same subject observed over time). This plot shows the various returns each week which are likely not for the same companies and the number of firms with SEPS reports does change each week. However, as we might expect, the variation in the returns increases as the asset holding time increases shown in the progression from R_0 to R_2 to R_3. The variation in the close to open return, R_1, is also smaller than the variation in the open to close returns. These points are confirmed by the statistics in Table 3 and the density estimates show in Fig. 7.

Scatterplots of the SEPS and the R_2 returns are shown in Fig. 8. These include regression fits that correspond to a linear model for each sector. Most of the slopes are close to zero, and those that are not close to zero are the result of extreme positive SEPS values. Based on the figure, it is not clear that there is a (significant) linear relationship between the SEPS and the R_2 returns. We also consider the relationship between the SEPS and the R_3 returns.

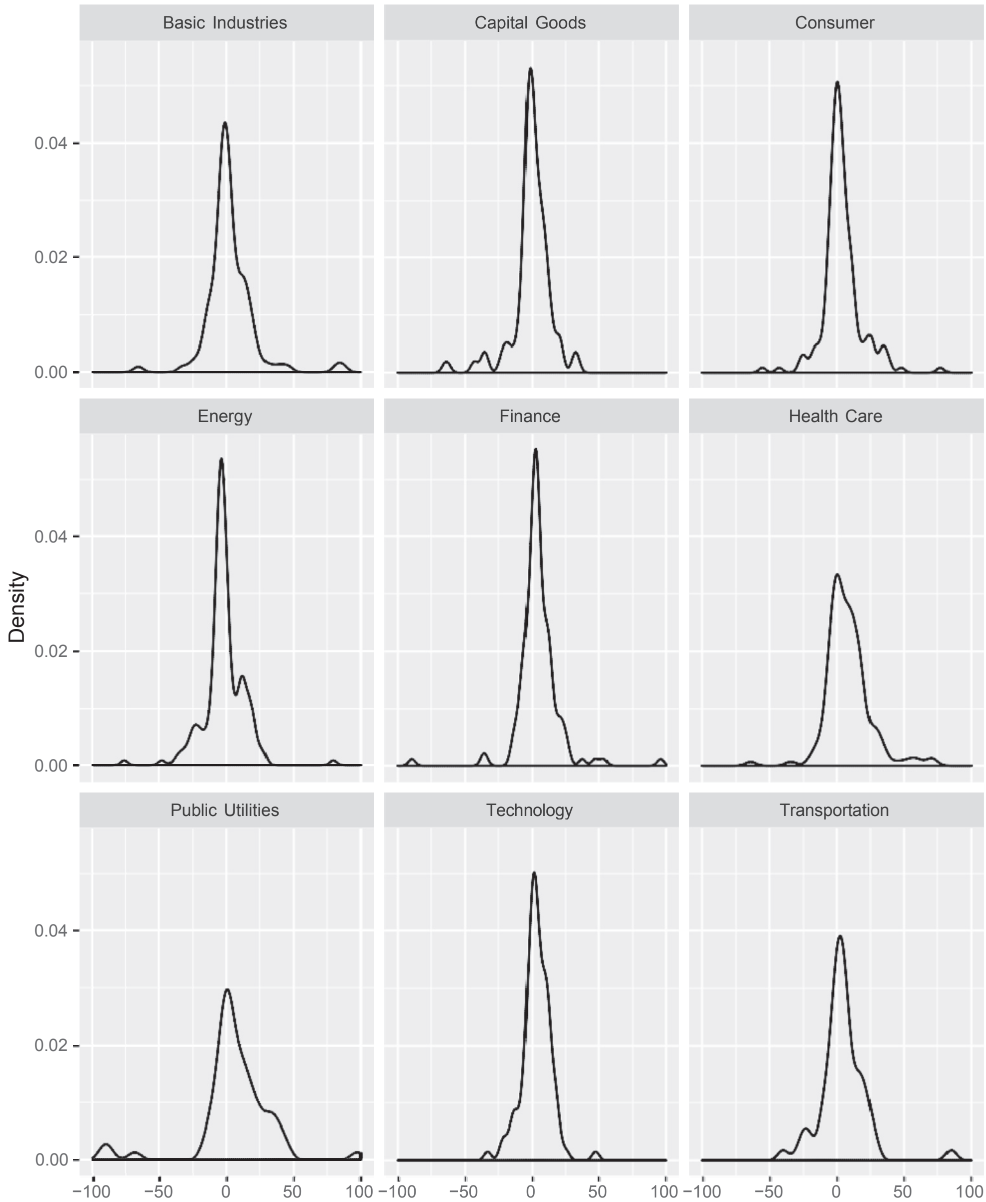

Fig. 4. Density estimates of the SEPS distributions by sector with x-axis restricted to −100% to 100%.

4. Regression analysis

Our regression modeling approach is similar to[10]; 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.[10,14] and others suggest that markets may be slow to incorporate earnings surprises. On the other hand,[2] form portfolios based on analysts' recommendations with daily rebalancing that yield abnormal returns, and show that the returns decay with the length of holding period. Our regressions for the R_2 and R_3 returns follow this literature.

Recall that the analysis in this section is based on the subset consisting of only one SEPS report per firm per quarter. However, 65% of firms have more than one SEPS report for different quarters which are, again, highly irregularly spaced. This might introduce potentially problematic autocorrelation, however irregular, that may adversely impact

Table 2
SEPS mean, median, minimum, maximum, standard deviation, skewness, kurtosis and sample size by sector.

Sector	Mean	Median	Minimum	Maximum	Skewness	Kurtosis	SD	N
Basic Industries	17.17	0.06	−65.33	1297.50	9.42	89.58	130.86	101
Capital Goods	−0.39	−0.03	−63.79	33.33	−1.44	5.16	14.34	78
Consumer	8.97	2.08	−55.28	918.00	12.07	149.87	72.02	168
Energy	−2.06	−2.92	−75.97	79.69	0.03	7.13	15.66	151
Finance	5.26	3.14	−89.41	113.07	1.43	15.84	18.50	138
Health Care	10.39	6.67	−64.07	237.92	4.77	37.27	26.26	152
Public Utilities	13.41	5.29	−90.32	419.79	4.88	29.82	63.72	53
Technology	4.34	2.88	−32.99	120.15	3.91	27.24	15.99	97
Transportation	1.88	3.41	−126.75	85.00	−2.03	14.23	24.15	58

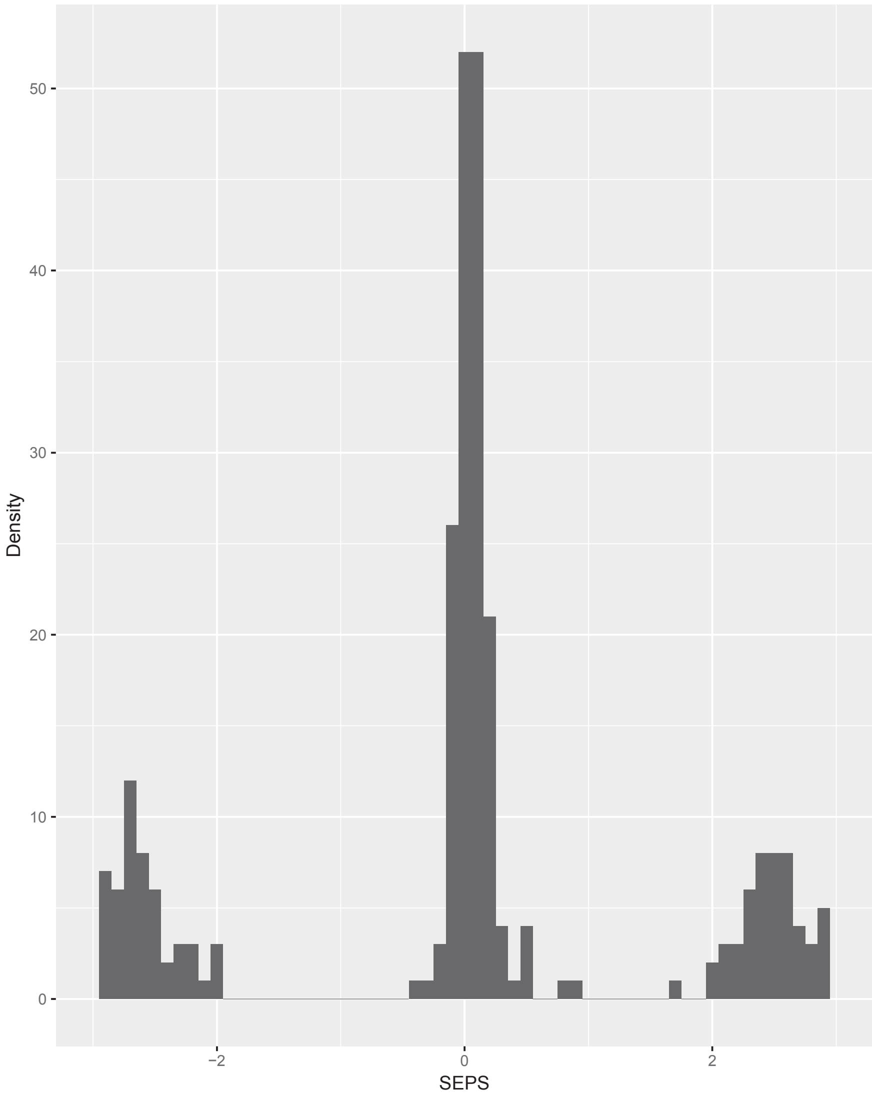

Fig. 5. Histogram of SEPS values between −3% and 3%.

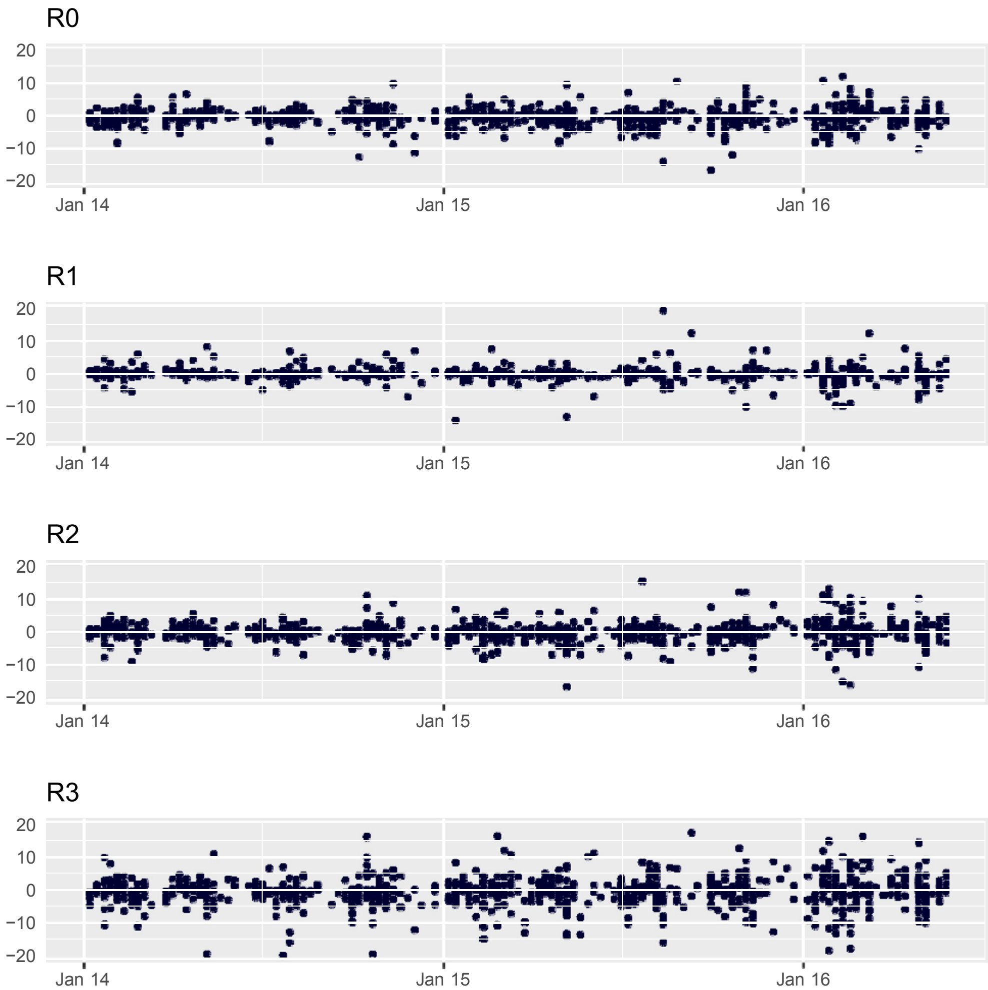

Fig. 6. Returns over time.

the standard errors of the regression coefficients. It is both unclear how and if this sporadic and irregular autocorrelation will bias the standard errors of the regression coefficients, and most importantly, how to correct or adjust for it. This is an area of future research.

The R_0 and R_1 returns are not tradable returns based on the SEPS information. Unless, of course, one had access to that information prior to the information release in the TDA. It might be possible to obtain this information by purchasing a subscription to StarMine. Since our focus is on free and publicly available information, results for these returns are not material to the regression analysis or the subsequent trading portfolios. The regression analysis focuses only on the R_2 and R_3 returns.

Based on Fig. 8, the slopes between the SEPSs and the R_2 returns depend on sector although this seems to be driven by extreme values. The sector information and their interactions turned out to be insignificant and have been omitted here. We focus on a simple model given by

$$\begin{aligned} R_2 = \beta_0 + \beta_1 SEPS + \beta_2 SR_2 + \beta_3 Feb + \beta_4 March + \beta_5 May + \beta_6 June + \beta_7 July + \beta_8 Aug + \beta_9 Sept + \beta_{10} Oct \\ + \beta_{11} Nov + \beta_{12} Dec + \beta_{13} Wed + \beta_{14} 2015 + \beta_{15} 2016 + E \end{aligned}$$

where the reference month is January and the reference year is 2014. Note that *Feb, . . ., Dec* are month indicators, and 2015 and 2016 are year indicators. On a number occasions, SEPSs are reported on Tuesdays, following a Monday holiday, which implies trades would occur on a Wednesday and this is captured with the *Wed* dummy variable.

Table 3
Return statistics: mean, median, minimum, maximum, standard deviation, skewness and kurtosis.

Return	Mean	Median	Minimum	Maximum	Skewness	Kurtosis	SD
RO	−0.30	−0.18	−16.43	12.06	−0.37	4.58	2.66
R1	0.09	0.00	−13.94	33.51	4.70	65.02	2.38
R2	−0.06	−0.10	−21.38	15.92	−0.13	7.45	3.02
R3	−0.33	−0.17	−65.92	28.64	−2.25	28.38	5.38

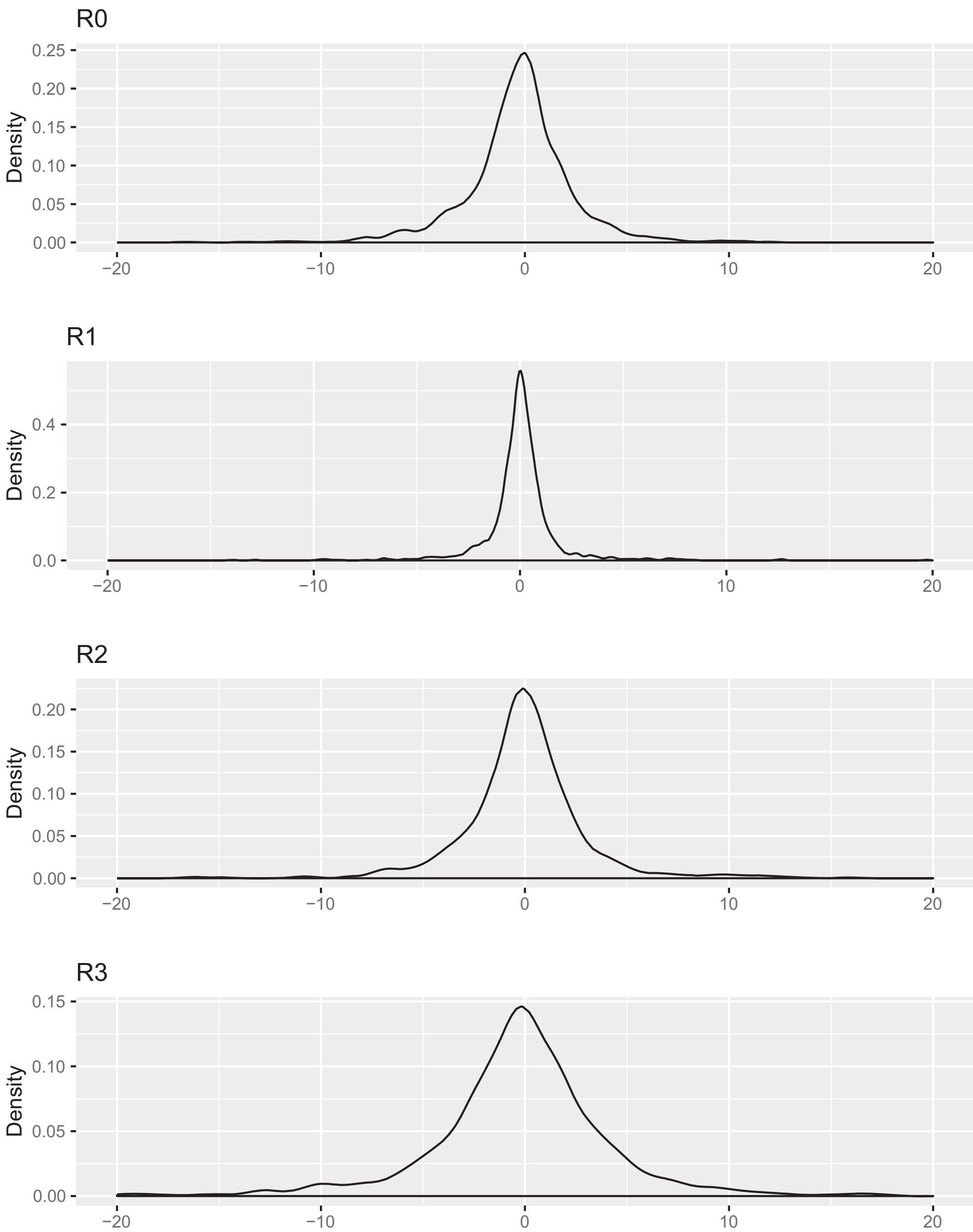

Fig. 7. Estimated return distributions.

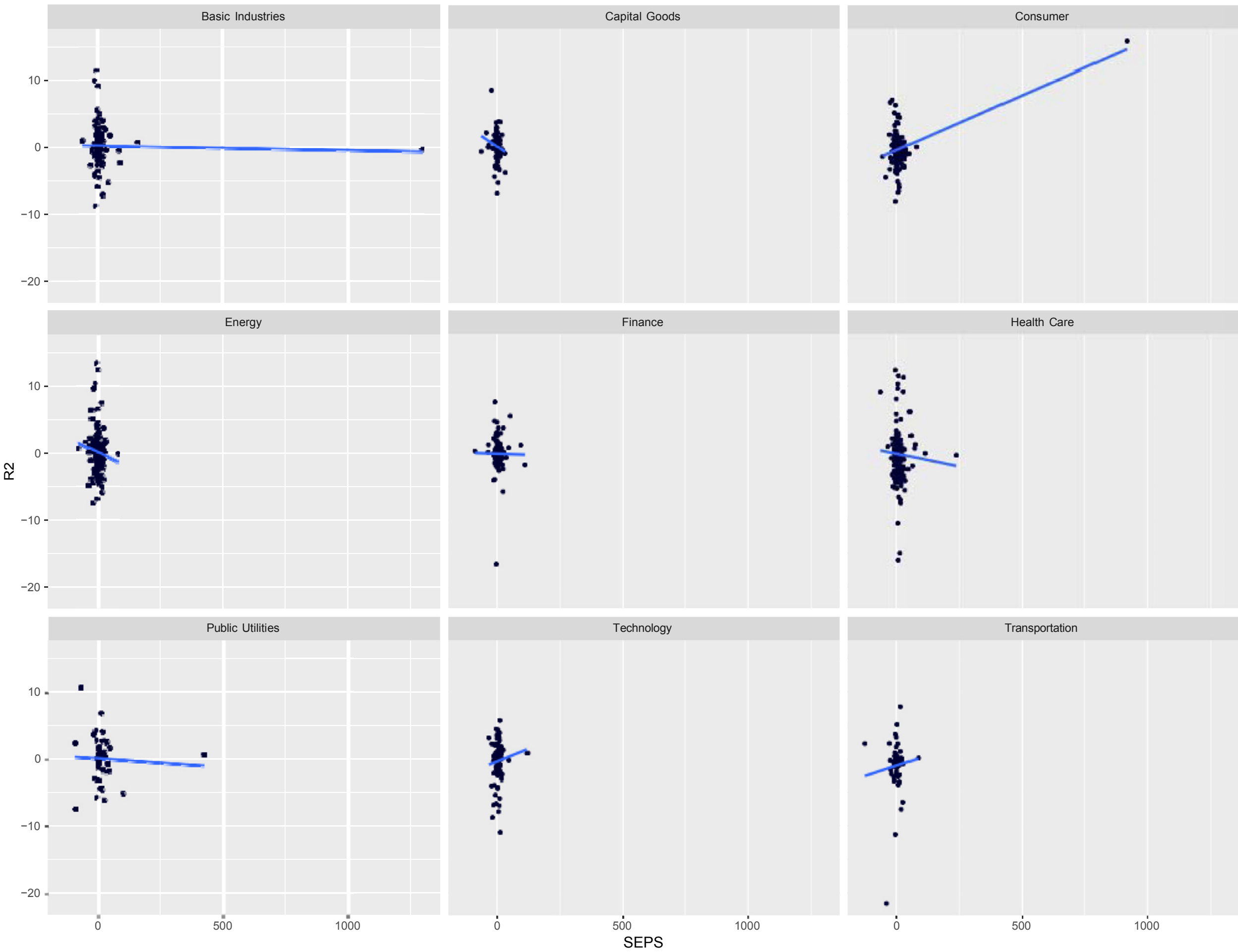

Fig. 8. SEPS vs R2 returns with regression fits by sector.

We have also considered firm size (including the logarithm of market capitalization) as well as indicator variables corresponding to small (55% of firms), mid (30%), and large (15%) capitalizations, sector indicators and interactions, and revenue estimates. However, to save space, the control variables that were statistically insignificant are omitted from the regression results.[13] consider a very different regression model that includes indicators of extreme values, interactions with these indicators and SEPSs, and do not include the year indicator variables. Furthermore, their regression analysis is based a subset of the data without the extreme values. The regression analysis done here precedes the regression analysis in their paper.

Table 4 shows the regression for the R_2 returns. The adjusted R^2s, while low, are very similar to those reported in previous studies such as[5] and.[13] For the combined data, the SEPS is significant but this is likely due to a few specific sectors with extreme outliers. We also find negative effects for the months of February and May (relative to the baseline month of January) providing support to the old adage "sell in May and go away" and fairly significant positive effect for Wednesday (relative to Tuesday).

Moreover, as[11] and others have pointed out, positive and negative earnings surprises are likely to have asymmetrical effects on equity prices. We therefore fit the regression model for two subsets of the data: observations with only positive SEPSs and only negative SEPSs. These correspond to the positive and negative columns in Table 4. The asymmetric effects are confirmed by these regressions. The SEPS coefficient is positive for the positive subset (and significant due the influential observations) but negative for the negative subset. The most convincing piece of

Table 4
R2 regression model for all the data, positive SEPS only, and negative SEPS only.

	All	Positive	Negative
(Intercept)	0.1269	−0.2188	0.9966
SEPS	0.0042*	0.0056*	-5e-04
SR2	0.8823*	0.6176*	1.2292*
Month 02	−1.0331*	−0.6296	−2.1449*
Month 03	0.0147	0.2989	−0.8118
Month 04	−0.2099	0.2291	−1.1755
Month 05	−1.3218*	−0.7536	−2.5501*
Month 06	−0.0651	0.0283	1.0061
Month 07	−0.0981	0.0644	−0.6942
Month 08	−0.3502	0.0442	−1.277
Month 09	−0.9771	−0.7153	−1.0052
Month 10	0.2476	0.2216	−0.5609
Month 11	−0.5989	−1.3231*	−0.4089
Month 12	−0.3837	0.9522	−5.35*
Day Wednesday	1.0757*	1.5806*	0.2451
Year 2015	−0.0649	−0.1655	0.0584
Year 2016	0.5985*	0.0669	1.3293*
R-Sq Adjusted	0.0913	0.08	0.153
Number of Observations	996	609	387

Note that coefficients with a * are significant at the 5 percent level.

information is that the adjusted R^2 is actually higher for the negative subset than the positive subset, which support our proposed contrarian trading strategy.

Model diagnostics actually indicate that there are only two influential observations with SEPSs of 918% and 1297%. After removing these extreme values, the SEPS coefficient is still statistically significant. However if SEPSs greater than 100% (or less than 100%) are removed, the SEPS coefficient becomes insignificant. This confirms that the significant relationship is driven by extreme SEPSs, and that without these extreme values there does not exist evidence of a statistical relationship between the SEPSs and the R_2 returns. We also performed the regression using the entire sample of 1605 observations. Interestingly, the regression results are nearly identical to the regression results reported in Table 4. This would suggest having multiple reports for the same firm has little impact on the regressions especially the standard errors. However, these standard errors still might be biased because of the irregular autocorrelation.

Researchers have also considered the time required for analysts and markets to incorporate earnings predictions and reports.[6] and[10] both suggest that analysts and markets are slow to incorporate earnings information, and[14] finds that the impact of earnings information is slow and hard to distinguish from other factors. However,[2] form portfolios shorting stocks with unfavorable recommendations with daily rebalancing that yield abnormal positive returns, and the returns diminish as the delay in rebalancing increases. Table 5 shows the regression for the R_3 returns. The statistical significance of the predictors is comparable to those found in Table 5, but what is noticeable is the reduction to the adjusted R^2s in particular for the negative SEPS subset. This demonstrates that the information content of SEPS quickly dissipates over time, and as such we only consider portfolios based on R_2.

5. Portfolio analysis

The portfolios we consider are forwardlooking weekly dynamic portfolios. After the TDA is released each week, an investor will form a portfolio based on the SEPSs contained in the TDA. We benchmark the performance of this portfolio against the S&P 500 over the same asset holding horizon. While having multiple SEPS reports for the same company is problematic for our regression analysis, this is not material to our trading strategy.[13] build portfolios only using the last SEPS reported for a firm in a given quarter. This restriction is not realistic, because one does not know when the last SEPS for a firm in a given quarter will actually occur. Recall that[13] further subset the data removing extreme SEPS values. Our portfolios trade on all of the SEPS information released each week. Furthermore,[13] consider an entirely different trading strategy where they compute the median SEPS of the accumulated data up to

Table 5
R3 regression model for all the data, positive SEPS only, and negative SEPS only.

	All	Positive	Negative
(Intercept)	−0.2207	−0.512	0.9189
SEPS	−0.0096*	−0.0097*	0.0198
SR3	0.9907*	1.0544*	0.9*
Month 02	−1.4555*	0.2027	−3.8779*
Month 03	1.0801	1.6313	0.4524
Month 04	0.2498	0.6313	−0.97
Month 05	−1.1563	0.24	−3.4811*
Month 06	0.4718	0.6297	2.0086
Month 07	−0.6172	−0.1093	−2.0382
Month 08	−0.4535	0.3211	−2.1573
Month 09	−0.469	−0.2884	0.4442
Month 10	0.0397	0.6097	−1.4863
Month 11	−0.6353	−0.6537	−1.2034
Month 12	−3.1752*	−3.6008*	−0.4756
DayWednesday	1.4697*	2.1453*	0.7112
Year 2015	0.0484	−0.37	0.782
Year 2016	0.6852	−0.2647	2.3742*
R-Sq Adjusted	0.0632	0.0693	0.0795
Number of Observations	996	609	387

Note that coefficients with a * are significant at the 5 percent level.

a certain point and short companies with SEPS greater that the median and long companies below the median. To calculate Sharpe ratios, we use LIBOR obtained from the Federal Reserve which[13] do not use. We also assume no taxes or trading costs. The number of shares purchased is not material to this analysis. The return from purchasing one share is the same as purchasing 100 shares. What we assume, however, is that in a given week the assets purchased are equally weighted.

Following[5] and[4]; the first trading strategy is a *conformist* approach. Companies with positive SEPSs (good news) should experience short-term gains after the release of the information (and the opposite should be true of companies with negative SEPSs or bad news). This is also consistent with the asymmetric effects of SEPSs on short-terms returns, and we might expect the average short-term returns to differ between companies with positive SEPSs and companies with negative SEPSs. Our conformist trading strategy has two components defined below and are not dependent on the SEPS magnitude or any other statistics.

1. Long component: long stocks with positive SEPS
2. Short component: short stocks with negative SEPS

The overall portfolio combines the two components into a single trading strategy which shorts and longs stocks each week. Table 6 shows the average daily return and daily volatility for the portfolio. As the table shows, relative to S&P 500 returns over the same time period, these portfolios are highly volatile and not profitable both with negative average returns. The table also provides estimates of the Alpha and Beta, and the test of significance for the Beta corresponds to H_0: $\beta = 1$ which is a test to determine if the portfolio/component risk differs from the market risk. Overall, it appears that the portfolios are highly risky and do not generate statistically significant positive Alpha. The cumulative performance is shown in Fig. 9.

Given these results, it makes sense to consider a completely *contrarian* trading strategy which does the opposite of the *conformist* trading strategy. The contrarian trading strategy is supported by our regression analysis findings.

1. Long component: long stocks with negative SEPS
2. Short component: short stocks with positive SEPS

Table 6
Dynamic conformist portfolio performance summary: average return, volatility and Sharpe ratio; CAPM alpha, beta, adjusted R-squared and p-value for the regression F-test; number of trades.

	Combined	Long	Short	SP
Return	−1.109	−0.2093	−1.117	0.0133
Volatility	14.99	14.54	11.22	0.7795
Sharpe	−0.07398	−0.01439	−0.09955	0.01707
Alpha	−1.126	−0.3021	−1.118	–
Beta	1.209	6.517*	−5.947*	–
R-Sq Adjusted	−0.004491	0.1157	0.1811	–
F Test P-value	0.4953	9.111e-05	8.267e-06	–
Number of Trades	1632	1172	460	–

Note that coefficients with a * are significantly different from 1 at the 5 percent level.

Fig. 9 shows the cumulative return using the contrarian trading strategy. Over most of the entire period, the long component of the portfolio generally has a positive return. The short component however, does not experience positive returns until the end of the sample. During the first half of our sample period, the long only portfolio does generate positive returns while the short only generates negative returns. However, during the second half of our sample period both components consistently lose money. Table 7 shows that the average daily return of the two components and the overall portfolio are positive and, even when riskadjusted in the presence of massive volatility, perform at least as good at the S&P 500. The cumulative performance is shown in Fig. 9. The Beta coefficients suggest that the two components are highly risky in comparison to market risk, but unfortunately do not generate significantly positive Alpha. The asymmetric effects of the positive and negative SEPS on the R_2 are also highly apparent given the large different between the average daily returns of the long and short components.

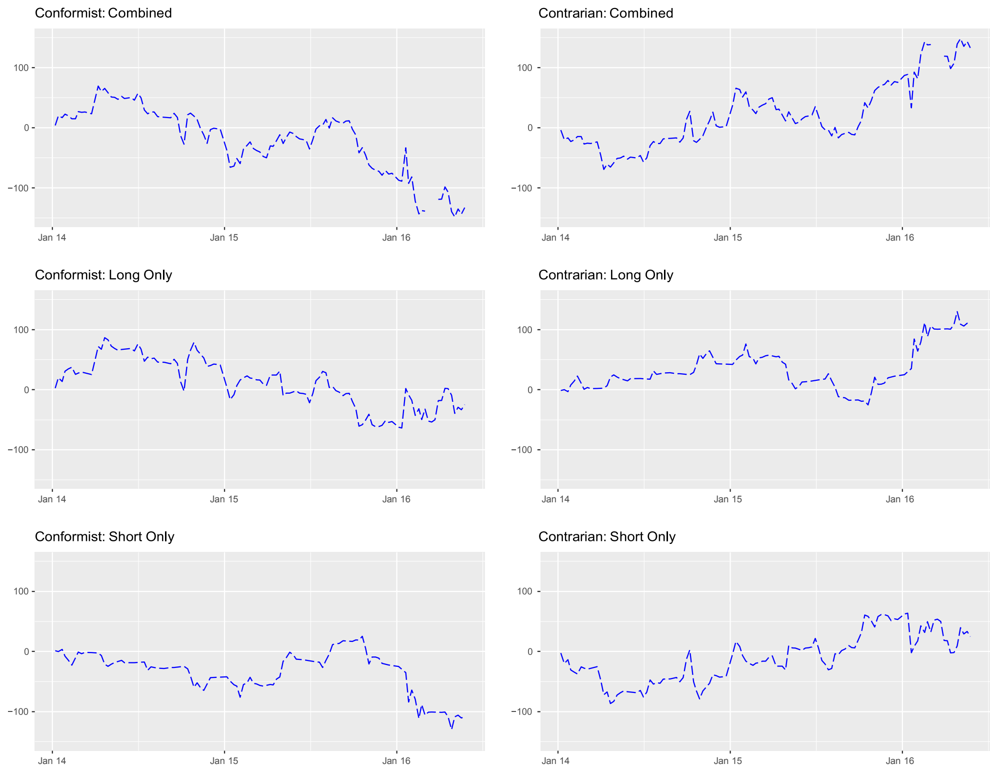

Fig. 9. Cumulative performance of the portfolios.

Table 7
Dynamic contrarian portfolio performance summary: average return, volatility and Sharpe ratio; CAPM alpha, beta, adjusted R-squared and p-value for the regression F-test; number of trades.

	Combined	Long	Short	SP
Return	1.106	1.114	0.2061	0.0133
Volatility	14.99	11.22	14.54	0.7795
Sharpe	0.07377	0.09927	0.01418	0.01707
Alpha	1.126	1.118	0.3021	−
Beta	−1.209*	5.947*	−6.517*	−
R-Sq Adjusted	−0.004491	0.1811	0.1157	−
F Test P-value	0.4953	8.267e-06	9.111e-05	−
Number of Trades	1632	460	1172	−

Note that coefficients with a * are significantly different from 1 at the 5 percent level.

6. Conclusions

We have obtained predicted earnings surprises from freely available public sources. Using data science techniques, we have managed and merged these data with other free and publicly available resources. A summary of our finding are as follows. The data are hard to work with perhaps by design, and contain both extreme values that are unexpected given their source. It is unclear how these observations are selected for publication, but there is little evidence to suggest that they are selected at random. Given this, our results are specific to the SEPSs contained in the TDA and not the larger StarMine population the public releases are chosen from. We find evidence of a linear association between the predicted earnings surprises and subsequent short-term returns, although the significance is driven by extreme outliers. The only profitable trading strategy that exploits the predicted earnings surprises is a contrarian trading strategy rather than conformist. Lastly, we find that positive and negative predicted earnings surprises have asymmetric effects on subsequent short-term returns.

Still, many questions remain to be answer that future research efforts will address. First, the end of our time period to study was deliberately chosen. After 06-01-2016, the TDA stopped publishing the StarMine information for six weeks and then resumed publication. Once the publication resumed, the format StarMine content visually looked different and seemed to consist of fewer reports. We hypothesize that the data post 06-01-2016 is notably different from the sample studied in this paper[13] We are currently analyzing the new data and comparing the results to those presented here.

As pointed out in Sections 3 and 4, the majority of companies have more than one report in some combination of multiple reports for the same quarter (possibly not consecutive) and/or across multiple quarters (inconsistently separated). It is both unclear how and if this sporadic and irregular autocorrelation will bias the standard errors of the regression coefficients, and most importantly, how to correct or adjust for it within a single model. We are currently exploring segmentation and advanced panel regression models to better understand any potential negative effects.

References

1. Ball R, Brown PR. An empirical evaluation of accounting income numbers. *J Account Res*. 1968;6(2).
2. Barber B, Lehavy R, McNichols M, Trueman B. Can investors profit from the prophets? security analyst recommendations and stock returns. *J Finance*. 2001;56(2).
3. Bradley D, Gokkaya S, Liu X. Before an analyst becomes an analysts: does industry experience matter? *J Finance*. 2017;72(2).
4. Brown L. Can esp yield abnormal returns? *J Portfolio Manag*. 1997;23(4).
5. Brown L, Han J, Keon E, Quinn W. Predicting analysts' earnings surprise. *J Invest*. 1996;5(1).
6. Brown L, Jeong S. Profiting from predicting earnings surprise. *J Financ Statement Anal*. 1998;3(2).
7. Chiang C-H, Dai W, Fan J, Hong HG, Tu J. Robust measures of earnings surprises. *Soc Sci Res Netw*; 2016. https://doi.org/10.2139/ssrn.2473366.
8. Hayes RM. The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. *J Account Res*. 1998;36.
9. Hwang B-H, Liu B, Lou D. consistent' earnings surprises. *Soc Sci Res Netw*; 2014. https://doi.org/10.2139/ssrn.1571619.
10. Jegadeesh N, Livnat J. Revenue surprises and stock returns. *J Account Econ*. 2006;41.
11. Levis M, Liodakis M. Contrarian strategies and investor expectations: the U.K. evidence. *Finance Anal J*. 2001;57(5).
12. MacKinlay C. Event studies in economics and finance. *J Econ Lit*. 1997;35.
13. Ramezani C, Frame SJ. The impact of predicted earnings surprises on equity returns. *J Account Finance*. 2018;18(7).
14. Stickel S. Common stock returns surrounding earnings forecast revisions: more puzzling evidence. *Account Rev*. 1991;66(2).