Evidence of a Positive Trend in Positive Quarterly Earnings Surprise over the Past Two Decades

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ABSTRACT
This paper confirms our prediction of a sustained positive trend in positive quarterly earnings surprise (ES) over the past two decades for reported and forecasted quarterly "Street" earnings. The time-series distribution of Street ES has not shifted symmetrically to the right, however. Specifically, the shift is the result of fewer small ES in the bins at or just below zero and more and larger positive ES in the bins further away from zero. This descriptive evidence supports two explanations: of (i) increasingly upwardly biased Street earnings and/or increasingly downwardly biased forecasts of Street earnings and (ii) of greater use by analysts of adjustments to bias Street earnings to exceed GAAP earnings, especially in the fourth quarter. An analysis of ES based on the difference between GAAP earnings and time-series forecasts of GAAP earnings (GAAP ES) does not show the same trends, however, implying that the positive trend in Street ES would more likely stem from analysts' efforts to bias ES rather than firms' actions to manage GAAP earnings to achieve the same result. We also document that, whereas forecast accuracy improves for shorter forecast horizons, analysts' Street ES bias increases for shorter forecast horizons. These results are robust to firm size and the earnings surprise shocks of the Sarbanes Oxley legislation and the 2007–2008 global financial crisis.

KEYWORDS
Earnings surprise distribution, I/B/E/S forecasts, Street earnings, temporal change, forecast bias, non-GAAP

JEL Classification G10, G14, M41, M48.

1 INTRODUCTION

We identify in this paper a sustained upward trend over the past two decades in positive earnings surprise (ES) defined as the difference between reported and forecasted quarterly "Street" earnings, specifically, the quarterly earnings per share numbers produced and disseminated by Thompson Reuter I/B/E/S based on the estimates and actuals of the analysts who contribute to that service. I/B/E/S protocols (Thomson Reuters 2009) guide contributing analysts to forecast earnings per share by normalizing their estimates for discontinued operations, extraordinary charges, and other non-operating items as decided by a majority of contributing analysts. I/B/E/S protocols also adjust reported GAAP earnings on a majority basis using actual amounts of the same adjustments used for normalization.[1] I/B/E/S premises its use of adjustments on the theory that normalized earnings are a better reflection of performance for valuation and better gauge of firms' results versus expectations.[2] I/B/E/S's forecasts and actuals are also subject to strict quality controls, which apply to the contributing analysts, their institutions and forecasts, and the firms' actual results. The outcome is that I/B/E/S produces and distributes what it promotes as high-quality forecasted and actual earnings per share aligned to a majority-based definition of earnings considered useful for valuation (i.e., Street earnings). Asset markets agree with this assessment. Most studies show significant stock market reactions to positive Street ES (Bradshaw and Sloan 2002; Bhattacharya, Black, Christensen, and Larson 2003; Brown and Sivakumar 2003; Collins, Li, and Xie 2009; Hand, Laurion, Lawrence, and Martin 2018). These and other studies also find that Street ES is more informative for stock price discovery than equivalent ES measures based on unexpected GAAP earnings despite evidence that investors can recognize the tendency for optimism in Street earnings and Street ES.[3]

What if the extant market reactions to positive Street ES were to induce I/B/E/S analysts to produce even higher Street ES in search of generating an even stronger stock market response? Does our evidence of a sustained upward trend in positive Street ES raise this possibility? Relatedly, it would be interesting to know what factors might be driving this upward trend? For example, it may be that I/B/E/S analysts increasingly produce higher Street ES because they asymmetrically back out more negative than positive transitory items to generate actual results on a normalized basis. I/B/E/S analysts may also be increasingly generating Street ES guided by firms' actions to manage earnings

[1] For U.S. companies, normalized earnings per share are also measured on a diluted basis after considering convertible securities, except if a loss is reported, then no dilution is assumed to reflect a more conservative measure (Thomson Reuters 2009).

[2] Thomson Reuters (2009) states that its goal is to "present actuals on an operating basis, whereby a corporation's reported earnings are adjusted to reflect the basis that the majority of contributors use to value the stock. … The majority accounting basis is determined on a quarter-by-quarter basis." (p. 6).

[3] Abarbanell and Lehavy (2007) raise questions about the generalizability of this finding, pointing out that some results depend on samples that overweight large positive differences in I/B/E/S minus GAAP earnings. For further discussion on Abarbanell and Lehavy (2007), see Bradshaw and Soliman (2007) and Christensen (2007).

or promote non-GAAP measures of earnings.[4] These are important questions because I/B/E/S performance metrics are deeply embedded in market pricing behavior as credible and high-quality information for investors. Moreover, they are generated by an organization (i.e., Thomson Reuters) whose value depends critically on the reputation and quality of its information products. That reputation could be eroded, however, should the sustained trends we document in this study continue. To examine the overall time-series trend in Street ES, we first predict the following.

P1: Street ES in the bins above zero has shown a steady upward trend over the past two decades.

One explanation of this trend builds on the notion that Street forecasts and earnings adjustments occur due to imitative behavior, such as analyst herding (Hong, Kubik, and Soliman 2000; Clement and Tse 2005; Jegadeesh and Kim 2010), contagion (Chiu et al. 2013), the effects of social networks (Cohen, Frazzini, and Malloy 2010; Mande and Son 2012), and consensus behavior within organizations. Indeed, I/B/E/S's emphasis on the majority views of its contributing analysts (Thomson Reuters 2009) and willingness to consider firms' non-GAAP earnings (Bentley, Christensen, Joo, and Whipple 2018) may encourage this. Also supporting this view are studies documenting that I/B/E/S analysts collectively trim their optimistic forecasts close to earnings announcement in response to guidance by the firm to promote a positive ES (Matsumoto 2002; Bartov, Givoly, and Hayn 2002; Richardson, Teoh, and Wysocki 2004; Bradshaw, Lee, and Peterson 2016).[5] Analysts who trim their forecasts face a trade-off, however. While positive Street ES may curry favor with firm managers and shareholders due to a stock price increase or the avoidance of a

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[4] Throughout our study, when we refer to Street earnings or Street ES, we are specifically referring to the work product of the contributing analysts to Thomson Reuters I/B/E/S, a service provider that sells work product to investors and others after subjecting it to stringent quality controls. We also acknowledge the existence of other definitions of Street earnings, for example, earnings estimates generated by firms as management guidance forecasts and managers' measures of non-GAAP earnings. While they may differ from a firm's original guidance estimate, Thomson Reuters I/B/E/S archives management guidance forecasts and lists guidance forecasts and contributing analysts' estimates measured on a consistent basis in its Guidance data feed product (Thomson Reuters 2009, p. 19). Thus, much of the guidance information available to investors is computed on the same basis as I/B/E/S earnings. Yet, as shown by Bentley et al. (2018) and others, while there is much overlap, the two are not the same. "In particular, we find that I/B/E/S captures managers' more informative non-GAAP disclosures, while it excludes their more aggressive reporting. In addition, I/B/E/S sometimes contains high-quality non-GAAP performance measures in periods when managers do not explicitly disclose non-GAAP metrics." (Bentley et al. 2018, p. 1).

[5] Late forecasts may also emanate from more pessimistic I/B/E/S analysts (Barron, Byard, and Liang 2013).

stock price drop (which could also bring more business to the analyst's firm), more positive ES could also increase forecast error, which if sufficiently large and growing could adversely affect analysts' reputations (Stickel 1992; Ke and Yu 2006; Meng 2015; Lu, Hou, Oppenheimer, and Zhang 2016; He and Lu 2017). Still, that tradeoff might not occur because a more positive ES need not always produce a less accurate forecast (see Section 3.3).

A second theoretical view attributes the trend of increasingly upwardly biased Street ES to earnings management (EM) defined broadly (infra note 6), which could occur if analysts do not correct for upwardly biased GAAP or non-GAAP earnings (Keung, Lin, and Shih 2010; Doyle, Jennings, Soliman 2013) or bad news (Xu, Jiang, Chan, and Wu 2017) from the EM activities of firm managers.[6] However, detection probability increases in the duration of some forms of EM (Schrand and Zechman 2012; Chu, Dechow, Hui, and Wang 2017), and targeted firms may eventually pay a steep price for this behavior (Karpoff, Lee, and Martin 2008; Beneish, Marshall, and Yang 2017). Nevertheless, undetected or acceptable EM to produce positive Street ES could be beneficial for manager compensation and firm value in the short run and, hence, a motivation for this activity (Bolton, Scheinkman, and Xiong 2006). A finding of a declining proportion of firms in the Street ES bin at or just below zero would support this view, as several studies conclude that the discontinuity of those bins in the ES distribution is evidence of EM (Abarbanell 1991; Burgstahler and Dichev 1997). A declining proportion of firms in the Street ES bins at or just below zero could also signal an increasing proportion of firms in the Street ES bins above zero. This leads to our second prediction.

P2: Street ES in the bins at or just below zero has shown a steady downward trend over the past two decades.

Street ES, however, may misrepresent the impact of accrual or real activities EM because I/B/E/S adjusts its estimates and actuals for discontinued operations, extraordinary charges, and other

[6] Throughout this study, we view EM as a tool of firm managers whose goal is to produce positive Street ES through the strategic use of accrual earnings management, real activities management, and non-GAAP earnings management to influence I/B/E/S estimates and actuals by contributing analysts. Black, Christensen, Joo, and Schmardebeck (2017) document tradeoffs among these EM tools. Street ES may, therefore, differ systematically from non-GAAP ES since the latter is the difference between a Street expectation and non-GAAP earnings as defined by the firm.

non-operating items (as decided by a majority of contributing analysts). These adjustments, moreover, could be the very places where influential accrual or real activities EM reside. Therefore, in addition to our analysis of Street ES, we repeat our design for GAAP ES, defined as the difference between GAAP earnings and expected GAAP earnings based on a model independent of I/B/E/S. This difference should be mostly unadjusted for the contribution of accrual or real activities EM to Street ES. However, if the trends of increasingly upwardly biased Street ES relate predominantly to accrual or real activities EM, we should observe similar trends for GAAP ES. Our third prediction is:

P3: GAAP ES in the bins close to or above zero has not shown a steady upward trend over the past two decades.

We also predict that the trend in Street ES above zero should be more positive for activities in the fourth quarter and for S&P 500 firms. The first case occurs because annual earnings are settled up in the fourth quarter conditional on the sum of earnings in the first three quarters. Fourth quarter earnings may also reflect more potential for higher Street ES because of end-of-fiscal-year accounting adjustments required by the outside auditor. In short, given the higher frequency, we predict that I/B/E/S analysts will exploit more opportunity for positive ES in the fourth quarter. Building on prior work (Huang, Pereira, and Wang 2017), we also predict that S&P 500 firms are driven by a stronger need to generate positive ES. This need could also be intensified by the imitative behavior of the much larger pool of analysts who follow S&P 500 firms.[7] Our fourth and fifth predictions are:

P4: Street ES in the bins above zero has increased more in the fourth quarter over the past two decades.

P5: Street ES in the bins above zero has increased more for S&P 500 firms over the past two decades.

We test these predictions by examining the time-series behavior of the probability density function (hereafter, distribution) of quarterly Street ES. We do this by tracking the changing proportion of firms with positive quarterly ES on average for distribution bins at or just below zero,

[7] For example, Table 2 supra shows that not only do more analysts cover S&P 500 firms than non-S&P 500 firms but, also, that the average S&P 500 analyst issues more forecasts per firm.

and for distribution bins further away from zero. The bins close to zero have been shown to associate with accrual or real activities earnings management (EM), whereas the latter bins have not. In addition to the time-series patterns, we examine the temporal change in the Street ES distribution by examining changes in the proportions of firms in each bin from a pre- to a post-period and test whether the shape of the distribution change reflects a symmetric or asymmetric shift to the right. We focus on Street ES bins based on dollars and cents rather than bins scaled by market capitalization because investors and the media have more interest in the former (Bissessur and Veenman 2016). Scaling, however, should not affect our results, as the relative magnitude of ES does not change (Degeorge, Patel, and Zeckhauser 1999; Cheong and Thomas 2017).[8]

Our paper documents the following key findings. We first observe a significantly positive trend for positive Street ES greater than zero (*P1*) and a significantly negative trend for ES just below zero (*P2*). An analysis of ES based on GAAP earnings and time-series forecasts of GAAP earnings (GAAP ES), by contrast, does not confirm the same trends, which is our third finding (*P3*). This third finding suggests that firms' actions to manage GAAP ES to achieve the first two findings may play a less pivotal role. Fourth, we extend results from prior research by showing that while I/B/E/S analysts increasingly adjust GAAP earnings in all quarters, those actions are amplified in the fourth quarter, arguably, because fourth-quarter GAAP earnings contain more one-time adjustments to bring annual earnings in line with the previous three quarters (*P4*). Fifth, we show that the trends of positive Street ES are more prominent for S&P 500 firms (*P5*). This last result is disquieting because given their focus on strong corporate governance practices and accounting controls, one might predict that S&P 500 firms as a group should be the least likely to reflect an increasing trend in positive Street ES driven by a growing gap in Street earnings and Street expectations. Apparently, S&P 500 firms are driven by a stronger need to generate positive ES than are other firms.

[8] While scaling could be a more stringent test, as the trend in market capitalization has also been positive over time, scaling introduces other design considerations. According to Burgstahler and Chuk (2017, p. 730), "research designs that correct for these flaws reveal highly significant discontinuities that cannot be attributed to scaling, selection, and the relation between earnings and price. Thus, these are not plausible alternative explanations for discontinuities in earnings distributions."

These trends in Street ES also raise interesting questions about the role of I/B/E/S. Given that these trends reflect the activities of that organization, why do they occur in the first place? This is important because left unabated they spotlight concerns that could conflict with I/B/E/S's strict focus on quality control and analysts' penchant for reputation. Our evidence is also important because the positive Street ES trends we document are contrary to indications that managers prefer small positive ES over large positive ES (Graham, Harvey, and Rajgopal 2005) and that the propensity for positive ES over negative ES has stabilized in recent years (Abarbanell and Park 2017).

Our findings, however, only have practical meaning if they are not already embedded in the contemporaneous expectations of the market. While we cannot observe that knowledge directly, as a proxy, we can examine the prior literature on quarterly ES. This is extensive and dates back to the early studies on the measurement of and reactions to quarterly earnings (e.g., Foster 1977; Brown et al. 1987). Much of that prior work, however, is cross-sectional, examining common models and average market reactions to shocks and events. By contrast, relatively few studies examine temporal changes in market reactions or sensitivities to earnings announcements (e.g., Landsman and Maydew 2002; Francis, Schipper, and Vincent 2002; Collins, Li, and Xie 2009; Beaver, McNichols, and Wang 2017, 2018; Shao, Stoumbos, and Zhang. 2018).

Another strand of the literature studies the probability density function of quarterly ES and what might drive ES discontinuities around prominent benchmarks such as zero. Stemming from the early work of Abarbanell (1991) and Burgstahler and Dichev (1997), other representative studies include Degeorge et al. (1999), Abarbanell and Lehavy (2003), Brown and Caylor (2005), Keung et al. (2010), Li (2014), and Burgstahler and Chuk (2017). Matsumoto (2002) and Bartov et al. (2002) suggest that analyst walk-downs explain the higher proportions of small positive ES. Contrariwise, Abarbanell and Park (2017) posit that analyst walk-downs to produce positive ES could be fruitless if investors anticipate the changing bias and, thus, embed it in market prices, which could also exist in equilibrium (Beyer 2008). Nonetheless, some managers express that the goal of meeting or beating analyst forecasts is a priority at earnings announcement (Graham et al. 2005), possibly achievable by using firm-based non-GAAP earnings.

Despite this literature, we know surprisingly little about the time series of the distribution of quarterly Street ES and whether it might have shifted, especially in recent years. Brown and Caylor (2005) document that, since the 1990s, investors have rewarded firms more for positive ES than for avoiding small quarterly earnings decreases. If the payoff to positive quarterly ES has increased temporally, this suggests a stronger motivation for this activity. However, their study period ends in 2002, so it is an open question whether their results are robust to subsequent years. Chen, Lin, Wang, and Lu. (2010) also report an increase in EM to meet forecasted earnings, but this trend reverses after 2002, and their data period ends in 2004. Abarbanell and Park (2017) report different results, showing no time trend over 1996–2012 in the propensity for positively biased quarterly ES, suggesting "that overall incentives to bias surprises and the market reactions to such biases vary in the cross section over time rather than following a monotonic trend." (p. 1075).

In related work, Koh, Matsumoto, and Rajgopal (2008) and Gilliam, Heflin, and Patterson (2015) conclude that the discontinuity of annual earnings just below zero has vanished since the passage of SOX. They attribute this to stronger governance and better accounting practices. However, Koh et al. (2008) end their study period in Q2:2006 and Gilliam et al. (2015) examine the trend of annual earnings above and below zero and not quarterly ES, and their study period ends in 2012. Both of these studies may not reflect current conditions. In addition, while the discontinuity of annual (or quarterly) earnings around zero may have disappeared since SOX, it is also possible that the discontinuity of earnings or Street ES around zero has not truly disappeared but, instead, has shifted asymmetrically to the right, spread over a wider range of positive bins of the ES distribution, consistent with a shift in the higher moments of the ES distribution. A related explanation lies in the Brown and Caylor (2005) result, which we interpret as suggesting less investor interest in the use of EM to avoid small losses and more investor interest in actions encouraging I/B/E/S to produce greater positive quarterly Street ES.[9]

[9] Longitudinal studies of the excess of Street or firm-originated non-GAAP earnings over GAAP earnings, which may partially explain Street ES trends, also do not reflect current conditions. For example, Abarbanell and Lehavy (2007) examine observations over 1985–1998; Bentley et al. (2018) study 2003–2012; and Leung and Veenman (2018) cover the 2006–2014 period.

Our paper continues as follows. Section 3 describes the sample, data, and research metrics. Section 3 summarizes the results. Section 4 concludes.

2 SAMPLE, DATA, METRICS

To establish our sample, we merge the I/B/E/S and Compustat datasets as of June 30, 2017 with the requirement that each firm-quarter have (i) at least one date-stamped I/B/E/S analyst estimate within 90 days of quarterly earnings announcement (to avoid stale forecasts), (ii) I/B/E/S earnings per share, and (iii) the I/B/E/S-indicated Compustat equivalent of I/B/E/S earnings per share, namely Compustat diluted earnings per share. For each firm-quarter, we also identify a firm's membership in the S&P 500 stock index. This identification allows us to identify the time-series patterns of the largest firms in the U.S. economy, those with more analyst coverage, and those with shorter reporting lags due to accelerated filing rules.[10] Similar to others, S&P 500 firms generally adopt strong governance practices (Ayers, Ramalingegowda, and Yeung 2011), are mostly held by institutional investors, and have more accurate earnings forecasts (Malloy 2005; Yu 2008). We also know that S&P 500 firms cluster mostly in the urban Northeastern U.S. (Barker and Loughran 2007), which is also the predominant location of the analysts who cover them. This suggests that these firms' equities and disclosures are well studied by informed asset managers who understand the potential for ES bias. Still, some contend that S&P 500 firms have more incentives to generate positively biased Street ES (Huang et al. 2017).

To focus on the most up-to-date time period and to avoid the smaller sample sizes in Q1:2017 and Q2:2017 (and the years prior to 2000), we analyze I/B/E/S and Compustat variables for firms with fiscal quarter ends from Q1:2000 to Q4:2016. Table 1 shows the composition of firms across 11 industry sectors and S&P 500 membership using 2016 as the representative year. The largest sectors by firm count are financials, information technology, health care, and industrials (each

[10] As of June 30, 2017, institutions held an average of 82.39% of the common shares of S&P 500 firms. S&P 500 firms are also of interest in their own right as they comprise more than 80% of total American stock market capitalization (S&P Capital IQ).

contains over 500 firms). Note, also, that the number of non-S&P 500 firms in the sample far exceeds those in the S&P 500.

Concentrating on the medians to avoid the effects of outliers, the firms in the sample appear to be mostly profitable (*ROE*), earn positive margins (*PRETAX/REV*), have substantial leverage (*TA/CE* or *LEV*), and generate positive operating cash flow (*OANCF*) and negative investing cash flow (*IVNCF*). As expected, S&P 500 firms are larger than non-S&P 500 firms based on total assets (*AT*). Table 2 summarizes the descriptive statistics for the I/B/E/S forecasts. The number of firms and analysts per year are reasonably stable over 2000–2016. In addition, even though similar numbers of I/B/E/S analysts cover S&P 500 and non-S&P 500 firms, the analysts covering S&P 500 firms are much more active in generating ES, that is, they produce far more forecasts per firm over the forecast horizon we study (≤90 days before quarterly earnings announcement). The number of forecasts at ≤30 days and, hence, the number of ≤30-day ES, however, for S&P 500 and non-S&P 500 firms are reasonably similar because of the larger number of non-S&P 500 firms. On balance, we have a large sample representative of the entire I/B/E/S data set of U.S. firms. For example, in terms of analyst-firm-quarter observations of forecasts ≤30 days before quarterly earnings announcement, we analyze 444,171 individual data items relating to 891 analysts covering 8,682 different firms over 17 years (2000–2016).

For all firm-quarters in the dataset, we calculate Street quarterly earnings surprise (ES) in dollars and cents as the excess of I/B/E/S quarterly earnings per share over estimated earnings per share for each analyst-firm-quarter forecast made from ≤90 days before quarterly earnings announcement. To assess the time-series distribution of Street ES, we then analyze the trend of the proportion of analyst-firm ES in a particular bin to the total number of analyst-firm ES in each quarter. If we observe a negative trend for a smaller bin and a positive trend for a larger bin, this suggests a right shift in the ES distribution over time. The changing shapes of the proportions from the small to the large bins also allows us to assess whether the shift in ES distribution is from the first or a higher moment. To examine ES differences by quarter, we partition the sample observations on quarter (Q1, Q2, and Q3 versus Q4). Greater Street ES should occur in the fourth quarter. We also partition by S&P 500 based on a firm's membership contemporaneous with each firm-quarter. In addition to trend analysis, we split the study period into pre- and post-intervals and conduct difference-in-difference regression tests, for example, a test of whether the trend in Street ES increases more for S&P 500 firms versus non-S&P 500 firms from the earlier years to the later years in the study period.

3 RESULTS

3.1 Bins Analysis

We first examine the proportion of Street ES in the -.01≤ES<0 and .05≤ES<.15 bins for a particular subsample with I/B/E/S forecasts of quarterly earnings per share of all forecasts made within 30 days of a quarterly earnings announcement. The subsamples are S&P 500, non-S&P 500, Q1–Q3 forecasts, and Q4 forecasts. We focus on these two ES bins because prior research suggests that the former more likely associates with EM behavior (Abarbanell 1991; Burgstahler and Dichev 1997; Roychowdhury 2006; Gilliam et al. 2014) whereas the latter does not (i.e., prior research advances no reasons why managers would want to shift to or from the .05≤ES<.15 bin, or any bin substantially greater than zero, using EM). Figure 1 plots the proportions of quarterly Street ES averaged over the quarters in each year. We aggregate the analyst-quarter-firm Street ES observations over each fiscal year to remove seasonality from the quarterly time-series. In addition, Table 3 shows the results of regressing the ES proportions for each partition on time.[11] We observe two key results. First, the regressions document that the proportions of firms in the -.01≤ES<0 bin have declined substantially since 2000 for all partitions of the sample. For example, for the non-S&P 500 and S&P 500 -.01≤ES<.01 bins, the *t*-statistics for the coefficients on time are -6.46 and -6.98, respectively. By contrast, the proportions of firms with ES in the .05≤ES<.15 bins have all increased significantly. For example, for the non-S&P 500 and S&P 500 .05≤ES<.15 bins, the *t*-statistics on time are 6.70 and 8.74, respectively. These patterns together imply a right shift in the ES distribution. The graphs in Figure 1 also illustrate visually that the right shift in Street ES is not explained by SOX

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[11] We estimate the following time series regression. $ES\_PROP = \alpha + \beta T + \varepsilon$, where *ES_PROP* is the proportion of Street ES observations for forecasts within 30 days of earnings announcement in a particular bin to the total ES observations for a particular sample or sub-sample, T is time (in years from 2000 to 2016), and ε is random error.

in 2002 or the GFC in 2007–2008 and persists in quarters subsequent to these events. Untabulated analysis shows very similar linear regression trends in the proportion of Street ES in a bin with and without SOX or the GFC years.

We also regress the difference in proportions for each partition on time. Untabulated analysis shows a significantly negative trend for the S&P 500 less non-S&P 500 $-.01 \leq ES < .01$ bin proportions (t stat.= -5.60, $p<.0001$) and a significantly positive trend for the S&P 500 less non-S&P 500 $.05 \leq ES < .15$ bin proportions (t stat.= 1.91, $p=0.07$).[12] The trends for the differences in ES bins for Q4 versus Q123 are not significant, however. Our result of a sustained and significant decline in the proportion of ES in the $-.01 \leq ES < .01$ bin after 2002 differs from the conclusion of Gilliam et al. (2014), who state that the zero-earnings discontinuity from EM has disappeared following SOX, although they base their results on the discontinuity from an under-representation of small losses (Compustat item *NI*) rather than small negative Street ES.

A second way to check for a right shift in the distribution of Street ES is to examine changes in the proportions in each one cent bin of the entire ES distribution from a pre-period to a post-period. We split the years evenly into 2000–2008 and 2009–2016 as the two subperiods. We then calculate the difference in each bin proportion (the later less the earlier proportion) and test whether it differs from zero based on a variant of the BD test (Burgstahler and Dichev 1997), where the estimated standard deviation of the difference considers all bin differences from $-.15 \leq ES < -.14$ to $.15 \leq ES < .16$) except the five closest to zero (which are the most expected to change). Figure 2 plots these differences. As expected, we observe significantly negative differences in the bins just below or above zero ($-.01 \leq ES < 0$, $0 \leq ES < .01$, and $.01 \leq ES < .02$) and mostly significantly positive differences in the bins further to the right, whose proportions generally decline as the bin level increases. For example, for the S&P 500 sub-sample (Figure 2a), the differences in the positive ES bins

[12] We also show a significantly more positive trend in Street ES for S&P 500 firms versus non-S&P 500 firms by estimating the following regression: $ES = \alpha + \beta T + \chi SP500 + \delta SP500 \times T + \varepsilon$, where ES = Street ES, T is time (in years from 2000 to 2016), *SP500* is dummy variable for an S&P 500 firm = 1 otherwise 0, and *SP500* x T is the interaction of time x S&P membership for all Street ES within 30 days of earnings announcement. Untabulated tests show that the δ coefficient for the interaction is significantly positive, indicating that on average for the entire ES distribution the time trend in ES over 2000–2016 is more positive for S&P 500 firms.

from .04≤ES<.05 to .09≤ES<.10 are all significantly positive at less than five percent. By contrast, the differences in the bins below zero (other than the -.01≤ES<0 bin) are all insignificantly different from zero. The results for the non-S&P 500 sample (Figure 2b) are similar but less significant. While we observe significantly negative differences in the bins just below or above zero (-.01≤ES<0, 0≤ES<.01, and .01≤ES<.02), we find positive but mostly insignificant differences in most of the bins further to the right. In untabulated analysis, we also obtain similar results when we run the same tests for ES observations over 2000–2006 and 2010–2016, which exclude three years before and after the GFC.

Another way to view the results in Figure 2 is to consider the shape shift of the ES distribution if all ES were to receive the same placebo injection of one or two cents a share, either from positive EM or the same amount induced by more negatively biased forecasts or positively biased Street earnings.[13] In theory, for a bell-shaped distribution, if the counterfactual shift in the ES distribution were symmetric but for the mean, the proportions in the negative and small positive bins (bins less than the mean shift) would reflect a negative bell-shaped curve and the proportions in the larger positive bins would reflect an equivalent positive bell-shaped curve (the probability densities would sum to zero). Figure 2 does not show these expected shapes. While proportions in the -.01≤ES<0, 0≤ES<0.01, and .01≤ES<0.02 bins decrease as expected, the proportions in the negative ES bins increase rather than decrease, and the proportions in the larger positive ES bins (to .09≤ES<.10) increase significantly from the pre- to the post-years. However, if only a uniform mean shift had occurred as the counterfactual, the proportions in these larger positive would be much more bell-shaped than shown in Figure 2. Further, if the placebo mean shift in the ES distribution were to have included an increase in the standard deviation of ES, then we would expect the change in proportions

[13] This placebo-shift approach follows in the spirit of Dickens and Manning (2004) and Stewart (2012), who compare the percentiles of the U.K. wage distribution before and after the introduction of a higher minimum wage with the percentiles of a counterfactual distribution of wages had the minimum wage increase not occurred. Rather than assuming a fixed counterfactual change to wages had the higher minimum wage not occurred, as do Dickens and Manning (2004) and Stewart (2012), we adjust all bins in the ES distribution up by a counterfactual fixed amount of one or two cents. We anchor on this arbitrary amount of increase in ES to make the ES just above and below zero disappear (i.e., the ES most likely due to EM as per Gilliam et al. 2014) but not necessarily disappear in the higher bins, which is the focus of our test.

to drop for a wider range of positive bins than shown in Figure 2 and increase for the more extreme negative bins. We do not observe these shapes in Figure 2. Thus, this placebo-shift approach confirms our earlier analysis that the distribution of Street ES has shifted asymmetrically to the right, with significantly fewer ES in the smaller bins around zero ES and significantly more ES in the larger bins above zero.

3.2 GAAP analysis

While the results in the previous section suggest that since 2000 the Street ES distribution has moved asymmetrically to the right, this does not necessarily imply the same shift in the distribution of GAAP ES, defined as the excess of GAAP earnings over expected GAAP earnings, even though for many analyst-firm-quarters Street earnings are the same as GAAP earnings (Abarbanell and Lehavy 2007; also, supra Section 3.4). This means that for the same firms Street ES would be equal to the excess of GAAP earnings over Street expected earnings. To conduct our analysis on a GAAP-only basis, we use a time-series model to predict GAAP quarterly earnings, defined as net income before extraordinary items on a fully-diluted basis (QE_t). We assume this series evolves as seasonal random walk (RW) in four-quarter differences; that is, $QE_t - QE_{t-4} = QE_{t-1} - QE_{t-5} + \varepsilon$, where ε is uncorrelated random error. Much prior work suggests that this common seasonal RW model captures the underlying earnings process parsimoniously for quarterly earnings before extraordinary items (e.g., Foster 1977, Brown and Rozeff 1978, Brown, Griffin, Hagerman, and Zmijewski 1987).[14] A definition of GAAP ES based on this RW model should also be largely unrelated to the efforts of I/B/E/S analysts to influence Street ES, yet include the efforts of firm managers to influence GAAP ES from EM other than EM through the use of non-GAAP measures.[15]

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[14] This RW model is equivalent to TS2 in Brown et al. (1987) with the adjacent and seasonal autoregressive parameters equal to one and TS3 in Brown et al. (1987) with the adjacent and seasonal moving average parameters equal to zero.

[15] GAAP ES may not be completely immune to the efforts of I/B/E/S analysts because the relation between Street and GAAP ES may not be completely exogenous; for example, managers may use the flexibility allowed by GAAP rules to produce an expected GAAP ES in line with an expected Street ES.

Table 4 and Figure 3 show the patterns of the proportions of RW ES for the $-.01 \le ES < 0$ and $.05 \le ES < .15$ bins from 2000 to 2016 for the different sub-samples. First, as shown in column 3 of Table 4 (and in Figure 3a), we observe that S&P 500 firms are the only sub-group showing a negative trend in the $-.01 \le ES < 0$ bin, with a time-series slope coefficient (β) of -6.5, significant at $p < .0001$.[16] The other trends for the $-.01 \le ES < 0$ bin for the other subgroups are not significant. Thus, the proportion of small negative GAAP ES continues to decline for S&P 500 firms, arguably for reasons less to do with the activities of Street analysts and more to do with the right shift in the ES distribution from EM to produce a small positive GAAP ES.[17] The second finding from Table 4 (and in Figure 3b) is that, contrary to Table 3, none of the $.05 \le ES < .15$ bins shows a positive trend. The *t*-statistics for the slope coefficient are either insignificant or negative. Thus, when ES is calculated independently of I/B/E/S actuals or estimates, the positive trends shown in Table 3 largely disappear. In short, the proportion of positive GAAP ES in the $.05 \le ES < .15$ bin does not increase for any of the subsamples, ostensibly for reasons less to do with a right shift in the ES distribution from EM and more to do with an absence in GAAP ES of adjustments to produce positive Street ES through the activities of I/B/E/S analysts.[18]

3.3 Forecast error analysis

The tables and figures so far show that, for the representative I/B/E/S firm, analysts' forecasts increasingly under-estimate actual EPS, thus, producing what we document as a growing trend in Street ES. Increasingly positive ES could also generate increasingly inaccurate forecasts, which could erode analysts' and I/B/E/S's reputations. To examine this contention, we calculate the

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[16] We estimate the following time series regression. $ES\_PROP = \alpha + \beta T + \varepsilon$, where ES_PROP is the proportion of RW ES observations in a particular bin to the total RW ES observations for a particular sample or sub-sample, T is time (in years from 2000 to 2016), and ε is random error. We aggregate the analyst-quarter-firm Street ES observations over each fiscal year to remove seasonality from the quarterly time-series.

[17] Untabulated analysis also shows a significantly negative trend for the difference of the S&P 500 proportion less non-S&P 500 proportion in the $-.01 \le ES < .01$ bin (*t* stat.= -5.60, $p < .0001$).

[18] Interestingly, with an undifferenced seasonal random walk model, that is, $QE_t = QE_{t-1} + \varepsilon$, or $QE_t = QE_{t-4} + \varepsilon$, where ε is uncorrelated random error, we are able to reproduce the results in Table 3. However, undifferenced seasonal random walk models mechanically introduce a growth component into the forecast error that produces temporal ES growth because undifferenced seasonal random walk models do not recognize the potential for earnings growth in a prior quarter to carry over to the current and future quarters.

absolute forecast error (*AFE*) for each analyst-firm-quarter, defined as the absolute value of FE (Street EPS less analysts' forecast of Street EPS divided by the absolute value of Street EPS. We then estimate the trend of *AFE* based on regressions of mean quarterly forecast error (*MAFE*) on time averaged over S&P 500 or non-S&P 500 firms and the Q1–Q3 or Q4 quarters in each year for all forecasts made within 30 days of quarterly earnings announcement. Figure 4 plots these series and indicates that there is no discernable trend in *MAFE* for any of the subsamples, except that *MAFE* is smaller for S&P 500 firms–hovering around 10 percent–than for non-S&P 500 firms, which is in the 15–20 percent range. When we regress *MAFE* on time, we also find no discernable positive or negative slope (β) coefficients for any of the subgroups.[19] This result is of interest because it differs from prior work showing a temporal *decrease* in earnings *AFE* over 1993–2005 (Givoly et al. 2009, p. 1891), although that prior work does not consider the temporal effects of one-year-ahead earnings *AFE* on analyst walk-downs. The patterns in Figure 3 also run counter to Malloy (2005, p. 735), who states that the EPS forecast accuracy of closely-monitored firms (e.g., the S&P 500) strengthened over 1985–2002.

The *AFE* results in Figure 4 are also potentially of interest because Figure 1 shows mostly increasingly *positive* Street ES; that is, we observe an increase in Street ES bias, yet we find no discernable increase in Street *MAFE*. To understand this result better, we condition Street ES on forecast horizon to show possible countervailing effects. On the one hand, if I/B/E/S analysts use walk-downs prior to earnings announcement, we should observe that Street ES increases for shorter forecast horizons versus longer horizons. On the other hand, with shorter horizons, analysts should be more accurate. Figure 5 plots the results of this analysis applied to all analyst-firm-quarters over 2000–2016 for horizons of 61–90, 31–60, and 0–30 days prior to earnings announcement. The plots show that whereas *MAFE* decreases as the horizon decreases (error decreases), the mean Street ES increases as the horizon decreases (the positive bias increases). The dotted line in each plot is the

[19] The regression is $MAFE = \alpha + \beta T + \varepsilon$, where *MAFE* is the mean absolute forecast error for forecasts within 30 days of earnings announcement, T is time (in years from 2000 to 2016), and ε is random error.

line of best fit for *MAFE*. Thus, we show that I/B/E/S analyst forecasting behavior reflects two offsetting effects–a decrease in forecast error for shorter horizons and an increase in positive bias (and positive Street ES) for the same forecast horizons. This offsetting effect of increasing Street ES may explain why we do not continue to observe a steady temporal decrease in earnings *AFE*, as suggested in prior work (Malloy 2005; Givoly et al. 2009).

3.4 Street versus GAAP earnings

Another way to examine the trends in Street ES is to anchor those trends on a related one, namely, the trend in the difference between GAAP and Street earnings. This is important because Street ES may mirror the trend in GAAP earnings less non-GAAP earnings as reported by firm managers. Considerable work has detailed these differences, their components, and their differential market effects in terms of announcement reactions or response coefficients (Abarbanell and Lehavy 2007; Bradshaw and Soliman 2007; Brown and Larocque 2013). If I/B/E/S earnings were to mimic mostly firms' non-GAAP earnings or, relatedly, if most firms were to simply conform their non-GAAP earnings to I/B/E/S's definition of operating earnings, then one source of our documented trends in Street ES would relate to analysts' use of firms' non-GAAP measures of earnings. As shown by Bentley et al. (2018), there are, however, differences in the two series stemming mainly from firms' greater exclusion of transitory losses and certain recurring items, leading to the conclusion that I/B/E/S earnings reflect higher quality.

To consider this literature in the context of our study, Table 5 and Figure 6 examine the trends over 2000–2016 in the difference between GAAP earnings as defined by Compustat *EPSFXQ* and Street earnings as reported by I/B/E/S. This table confirms most of the same trends documented in the literature for the earlier years. Perhaps the most striking result from Table 5 is that all positive *EPSFXQ* subgroups show a positive trend in Street EPS-*EPSFXQ*, whereas no negative *EPSFXQ* subgroup shows a negative (or positive) trend. Yet each negative *EPSFXQ* subgroup still shows consistently positive differences in Street EPS-*EPSFXQ*. That is, even the loss firms on a GAAP basis tend to show a smaller Street loss (or a larger Street profit). The gap for loss firms is not growing, however.[20]

The last two columns of Table 5 also show that the trend in Street less GAAP earnings (plotted in Figure 6a) is significantly more positive for Q4 versus Q123 earnings, consistent with earlier results in Bradshaw and Sloan (2002), and for S&P 500 versus non-S&P 500 firms (Figure 6b).[21] The latter result for S&P 500 firms, not in the literature to our knowledge, is disquieting because despite their insistence on strong corporate governance practices and accounting controls some of the largest companies in the world by market capitalization have steadily increasing Street ES driven in part by an increasing gap between GAAP earnings and Street earnings. In untabulated analysis, we also show that the percentage of zero Street less GAAP earnings differences is considerably lower for S&P 500 firms (34.1%) versus non-S&P 500 firms (43.5%), and much lower than the percentages reported in earlier work (e.g., Abarbanell and Lehavy 2007, Table 2). While worrisome, this latter result might also be expected given that prior work (Huang et al. 2017) confirms that larger firms (with greater coverage) more than smaller firms have stronger equity market incentives to pressure analysts to produce a positive ES (and a positive Street less GAAP earnings difference).[22]

3.5 Sales Revenue Surprises

Because sales revenue surprise (SS) has been shown to generate stock price reactions incremental to ES (Jegadeesh and Livnat 2006), firm managers and I/B/E/S analysts may be subject to the same or similar motivations and incentives to produce a positive SS. We, therefore, test for a

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[20] Even though we do not find an increasing trend for the excess of non-GAAP earnings for loss firms over GAAP earnings for loss firms over 2000–2017, Leung and Veenman (2018) find that compared to the non-GAAP earnings of profitable firms, loss firm's non-GAAP earnings are significantly more informative than profit firms' non-GAAP earnings and loss firms' GAAP earnings.

[21] We regress Street EPS-*EPSFXQ* for S&P 500 firms (or Q4) less Street EPS-*EPSFXQ* for non-S&P 500 (or Q123) on time. The slope coefficients for the difference-in-difference variables are positive and significant. The *t*-statistics are 2.61** for Q4 vs Q123 and 6.82*** for S&P 500 vs non-S&P 500.

[22] Our trend results in this section also relate to the Abarbanell and Lehavy (2007) conclusion that the trend is mechanically generated because of changes in the asymmetric treatment by managers of large transitory losses and large transitory gains. This phenomenon, however, is not supported by our results in Figure 6c because the trends in Table 5 and Figure 6c are only positive for profit firms, that is, firms with *EPSFXQ*>0.

temporal right shift in the distribution of SS for the same reasons as before.[23] However, we also expect that managers may curb the potential right shift in SS because, arguably, they may have less proclivity to manage top-line sales compared with bottom-line EPS (Ertimur et al. 2003). To investigate these possibilities, we apply the same ES analyses to SS. To align our SS metric with investor and media analysis of missed sales forecasts, we define an SS in percentage terms as actual quarterly sales revenue less analysts' forecasts of sales revenue within 30 days of earnings announcement scaled by actual quarterly sales.

We summarize the results of an untabulated analyses of SS as follows. Specifically, we first track the proportion of SS in the 0%>SS≤2% bin and find that it has increased over time more than the proportion of SS in the -2%>SS≤0% bin. Moreover, when we regress the *difference* in these proportions on time over 2000–2016, the slope coefficient for the difference is positive and significant. Hence, SS on average has increased temporally for a significant proportion of our sample. Second, we track the change in the proportion of SS in the fixed-interval bins close to zero. Consistent with the regression analysis of SS, when we split the study period into two equal sub-periods, the proportions in the 0%>SS≤1% and 1%>SS≤2% bins increase *more* than the proportions in the -2%>SS≤-1% and -1%>SS≤0% bins, and the proportions outside of these bins decrease. These changes are significant based on a chi-square test. We would expect the proportions for the outside bins to decrease, however, if sales forecast accuracy had increased over time. On this point, a regression of the mean sales forecast error (SFE) (defined as the absolute value of ((actual minus forecast) ÷ actual) from 2000–2016 on time (in years) shows a significant decline in the mean SFE.

We also partition firms into four groups based on the sign of SS and ES and test the notion that Group A firms (SS<0 and ES>0) are more likely to reflect a temporal right shift in ES due to EM compared with Group B firms (SS>0 and ES>0) (Ertimur et al. 2003, p. 206). Thus, our test examines whether the difference in the ES bins just above zero for the pre- versus the post-period (equal

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[23] With the exception of Zhao (2017), a review of the prior literature on SS (Ertimur et al. 2003; Jegadeesh and Livnat 2006) reveals an absence of temporal analysis of SS.

quarters within 2000–2016 differs for Group A (EM more likely) versus B (EM less likely). We observe a large negative difference-in-difference (A-B post-period less A-B pre-period) in the 0<ES≤.01 bin, mostly large positive difference-in-differences in the .01<ES≤.02 to .04<ES≤.05 bins, and mostly small negative difference-in-differences in the bins above .04<ES≤.05. A binomial test rejects the possibility that these differences could have arisen by chance, assuming a 50-50 chance of a positive or negative difference-in-difference. This reinforces our view that the right shift in ES stems from a temporal increase in EM practices rather than increased analyst forecast pessimism or error.

To summarize, we find three results of interest when we repeat our analysis for SS. First, we find evidence of a modest right shift in the distribution of SS, which is clustered mostly in the bins just above zero, in particular, SS with positive surprises of up to two percent. Second, unlike ES, no right shift occurs for SS above two percent. We show that this occurs, in part, because of a temporal increase in sales forecast accuracy, so that fewer observations fall into the extreme bins. Third, we find a stronger right shift from the pre-period (2000–2008) to the post-period (2009–2016) in SS for firms with a higher propensity for EM, namely, firms with SS<0 and ES>0. This suggests that the potential right shift in SS for bins close to zero relates more to EM than to analyst activities, in much the same way as the potential right shift in Street ES in the bins close to zero also relates to EM (as it relates to a changes in the discontinuity of the distribution around a zero benchmark).

3.6 Explanations of the ES Trend

A positive trend or right shift in the Street ES distribution could occur for at least two reasons. The first is that analysts increasingly bias their Street expectations downwards to generate a more positive market response for their clients, that is, they engage in strategic pessimism. This reason has merit if the reporting firms reward analysts with more business or more access to firm information as a result of helping firms create a positive ES. Although if the gap is too wide, and increasingly lacks credibility with asset managers, analysts could eventually suffer a loss of reputation (even though the wider gap could still be predictable by some investors). This view is, nonetheless, supported by research suggesting that analysts walk down their quarterly forecasts close to earnings announcement and engage in strategic pessimism (Matsumoto 2002; Bartov et al. 2002; Richardson et al. 2004; Bradshaw et al. 2016; Veenman and Verwijmeren 2017). Our results summarized in Section 3.3 comport with this behavior. However, as a behavior attributed to analysts as a group, this shift in pessimistic forecast bias should not apply asymmetrically to the ES distribution. That is, unless there is cooperation or near-perfect foresight of EM adjustments, we would not expect analysts as a group to bias their forecasts down with regard to a particular bin of the mostly positive ES distribution. Put differently, as an ex post measure, a Street ES bin is conditional on announced GAAP and Street earnings and/or post-forecast adjustments by firm managers, which an analyst could only forecast at the earlier earnings forecast date. We denote this as the *managed forecast* explanation.

A second reason for the right shift in the Street ES distribution relates to EM, defined broadly to include accrual, real activities, and non-GAAP adjustments to pre-managed or actual earnings. While non-EM explanations have been advanced to explain the Street ES discontinuity, one view posits that some firms make changes not revealed to or anticipated by analysts to pre-managed earnings to generate higher GAAP EPS and/or adjust GAAP earnings to generate higher Street EPS. If this second view has merit, then relative to the *managed forecast* explanation, we should at least observe a shift in the discontinuity of Street ES in the bins close to zero, as that is where some EM arguably takes place. Much research supports the view that the discontinuity of ES around zero is evidence of accrual or real activities EM. However, in subsection 3.1, we show a drop in the discontinuity of Street ES just below zero in favor of an increase in the discontinuity of Street ES for bins much greater than zero. Thus, if the right shift in the Street ES distribution relates to EM, it potentially must be of a different form and, possibly, one more acceptable to shareholders' agents such as auditors, directors, and regulators. Non-GAAP earnings management is one such form. If those monitors had focused on small changes around zero earnings or zero earnings surprise as evidence of accrual or real activities EM, then one would expect managers to refrain from this form of EM and produce positive ES in different ways. Consistent with this view, Koh et al. (2008) and Gilliam et al. (2015) conclude that the discontinuity of annual earnings just below zero has disappeared since the passage of SOX, attributing this to stronger governance and accounting practices. Also, Brown and Caylor (2005) identify a systematic negative trend in Street ES bins close to zero, attributing this trend to firms having less interest in avoiding losses or earnings decreases and more interest in reporting positive (or avoiding negative) ES. In short, if non-accrual EM is the primary driver of the positive ES trend, to the extent that a smaller positive Street ES could be construed as relating to detectable and costly EM, then we would expect to observe fewer small positive ES (just below or at zero) and more large positive ES (to the right of zero). We denote this as the *managed actual* explanation. Compared to the first explanation, the key difference is that the shift from fewer negative Street ES to more positive Street ES is being achieved more by efforts to increase Street earnings rather than decrease Street expectations.

There is no reason these two explanations should be mutually exclusive, however. We, thus, offer a third explanation as a combination of the two, essentially requiring that I/B/E/S forecasts and firms' actuals and, potentially, investors' response, are determined endogenously. One variant posits that firms' and I/B/E/S's efforts to generate increasing Street ES occur due to incentives in common. Both agents may prefer a higher stock price conditional on earnings announcement (Kasznik and McNichols 2002; Lopez and Rees 2002), and both may prefer to avoid a negative Street ES to avoid a stock price drop on announcement. A second variant involves some form of linkage between firm managers and I/B/E/S contributing analysts. One notion is that I/B/E/S analysts wish to curry favor with firm managers who engage in non-GAAP EM to generate positive Street ES by adjusting their quarterly earnings for known or anticipated non-GAAP forms of EM. The plausibility of this idea, however, requires a mechanism whereby managers reveal their non-GAAP policies or adjustments to analysts as a group (not just one or two analysts). However, to generate positive ES from forecast bias, the transmission would have to precede actual earnings or non-GAAP earnings, which both managers and analysts would not know until several weeks after the end of a quarter. Still, managers could generate positive ES by communicating EM practices contemporaneous with earnings announcement (e.g., through the mechanism of a conference call), such as those that increase GAAP or non-GAAP EPS through greater use of real activities (e.g., reduction in discretionary expenses) or non-GAAP earnings management (e.g., the exclusion of transitory losses). This third explanation aligns well with evidence that accrual EM practices to affect Street ES have fallen in recent years in favor of a significant rise in real activities EM (Cohen et al. 2008; Coates and Srinivasan 2014) and clear indications of greater use of non-GAAP earnings management (Doyle et al. 2013; Black et al. 2017; Black et al. 2018).

4 CONCLUSION

It used to be that a significant number of firms reported earnings that either met or just exceeded Street expectations, suggesting that, to accomplish this result, managers would either make small late changes to pre-managed earnings or that analysts would intentionally under-forecast reported earnings by similar amounts. The common incentives of analysts and managers, such as the desire to increase firms' stock price or avoid a stock price drop, could also mean that they unsuspectingly produced the outcome in tandem. However, the evidence since the passage of the SOX in 2002 and the additional regulatory supervision following the GFC indicates that this behavior has mostly died out. If firms no longer report earnings to just meet or exceed Street forecasts, then what do they do now? We answer this question by providing robust evidence that since 2000, the distribution of Street earnings surprise (Street ES) has moved steadily and significantly to the right for a large proportion of the I/B/E/S population. The right shift in Street ES is also especially prominent for S&P 500 firms, the firms for which we might not expect this to occur due to their emphasis on strong corporate governance and accounting controls.

We devise tests based on the shape of the shift in the ES distribution to determine whether it arises primarily from (i) efforts to generate earnings surprises that just meet or exceed expectations or (ii) efforts to produce increasingly positive earnings surprises. Taking the view that I/B/E/S analysts' focus on Street earnings and that non-GAAP metrics is a form of earnings and expectations management, we find that the latter view is the more likely explanation of the ES shape shift. Should I/B/E/S's (and analysts') efforts to generate increasingly positive Street ES with non-GAAP adjustments continue, this shape shift could undermine its reputation as a source of high-quality market information. The participation of firm managers in guiding I/B/E/S analysts to a majority view of Street earnings could further amplify those effects. There are those, nonetheless, who might claim that so far this century the U.S. economy has experienced such an unusual period of economic growth and success that it has taken I/B/E/S analysts and investors increasingly by surprise each quarter with better-than-expected earnings performance for almost two-decades. This view strains credulity, however.

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FIGURE 1
Temporal Analysis of Quarterly Street Earnings Surprise from 2000 to 2016

Figure 1a: Proportion of Street ES in the -.01≤ES<0 Bin for S&P 500 and Non-S&P 500

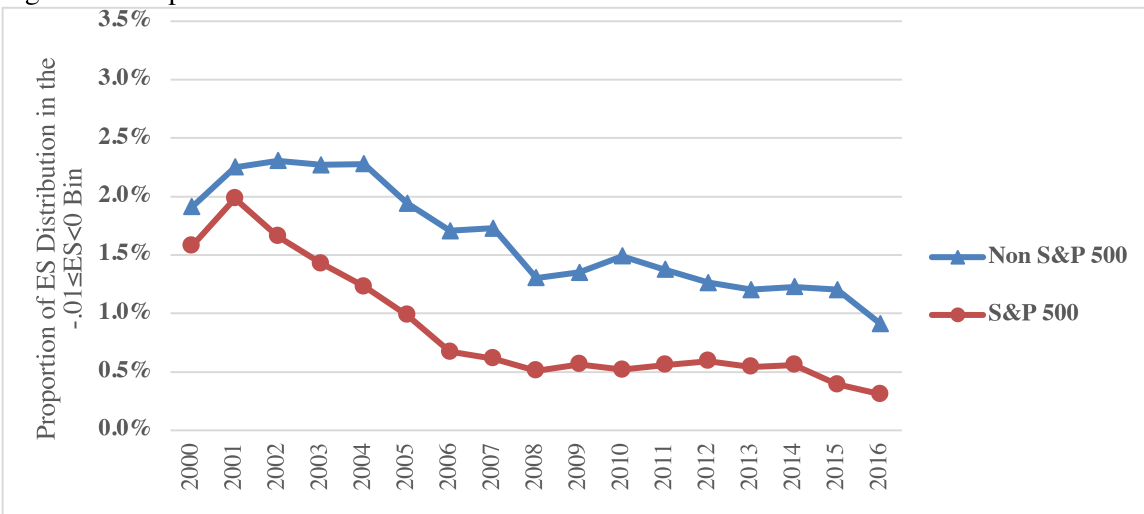
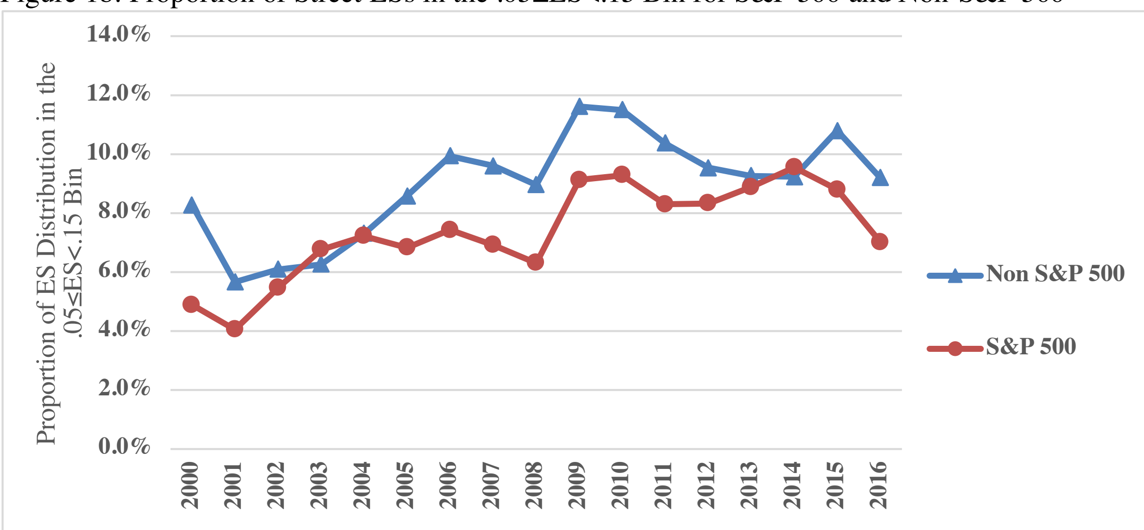


Figure 1b: Proportion of Street ESs in the .05≤ES<.15 Bin for S&P 500 and Non-S&P 500



This figure plots the proportion of firms with quarterly ES in the bin just below zero (-.01≤ES<0) (Panel A) and the larger bin above zero (.05≤ES<.15) (Panel B). Street ES for each year equals I/B/E/S actual quarterly earnings per share less I/B/E/S estimated quarterly earnings per share averaged over the four quarters in each year for all forecasts made within one month of a quarterly earnings announcement.

FIGURE 2
Right Shift in Street Quarterly Earnings Surprise from 2000 to 2016

Figure 2a. S&P 500

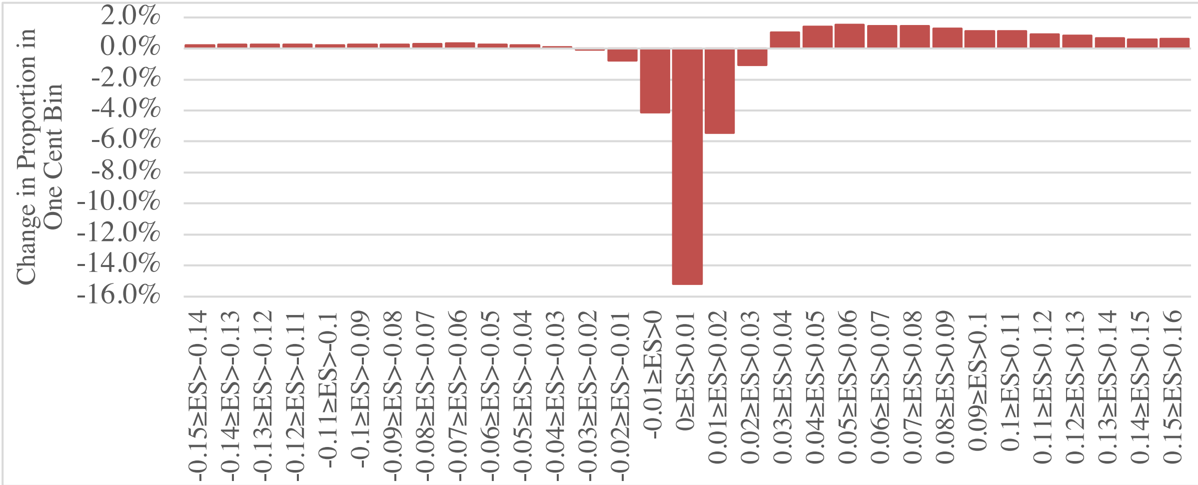
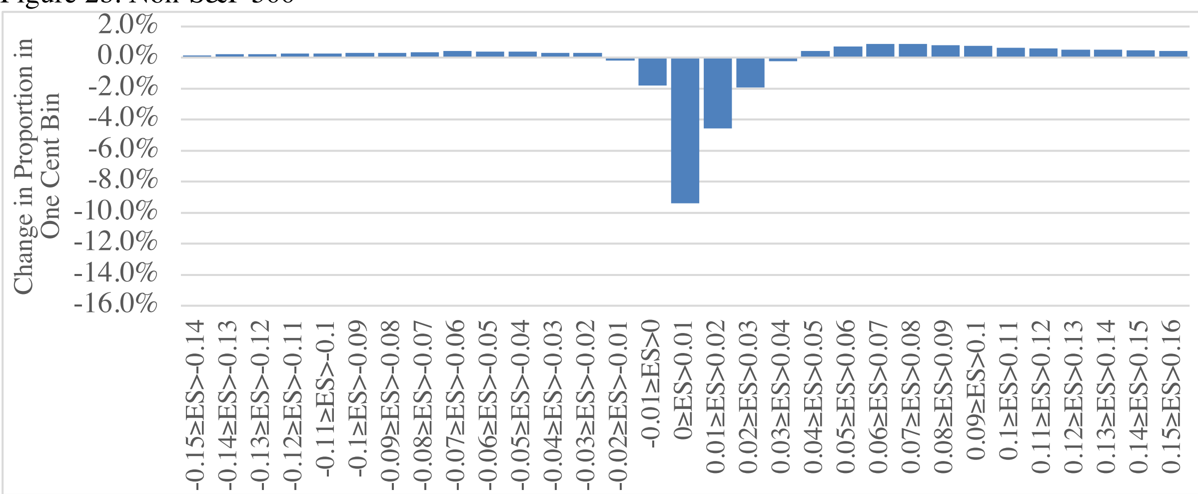


Figure 2b. Non-S&P 500



Panel A (Panel B) plots the difference in the proportion of observations in each one cent bin of the distribution of quarterly Street ES from the pre-subperiod (2000-2008) to the post-subperiod (2009-2016) for S&P 500 firms (non-S&P 500 firms) in the sample. A positive (negative) column means indicates more (fewer) ES in that bin in the post-period compared to the pre-period. By definition, the sum of the differences across all ES bins in each distribution is zero.

FIGURE 3
Temporal Analysis of Quarterly Random Walk Earnings Surprise from 2000 to 2016

Figure 3a: Proportion of RW ES in the -.01≤ES<0 Bin for S&P 500 and Non-S&P 500

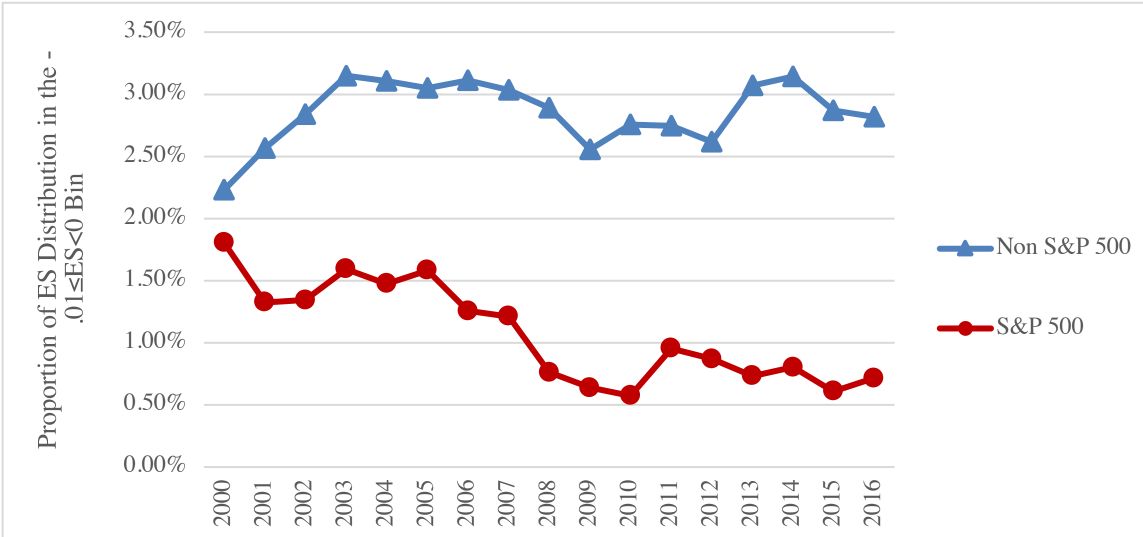
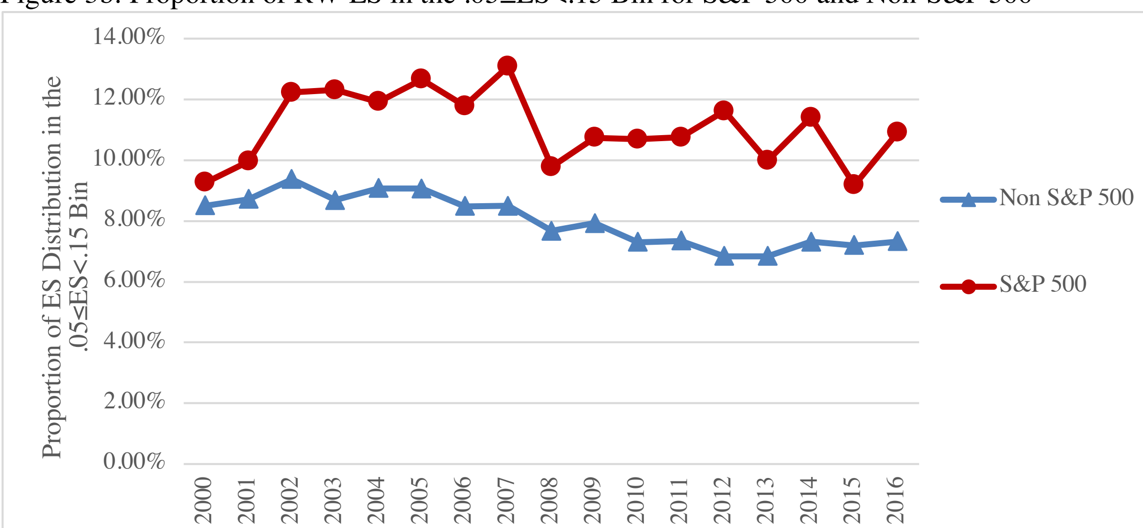
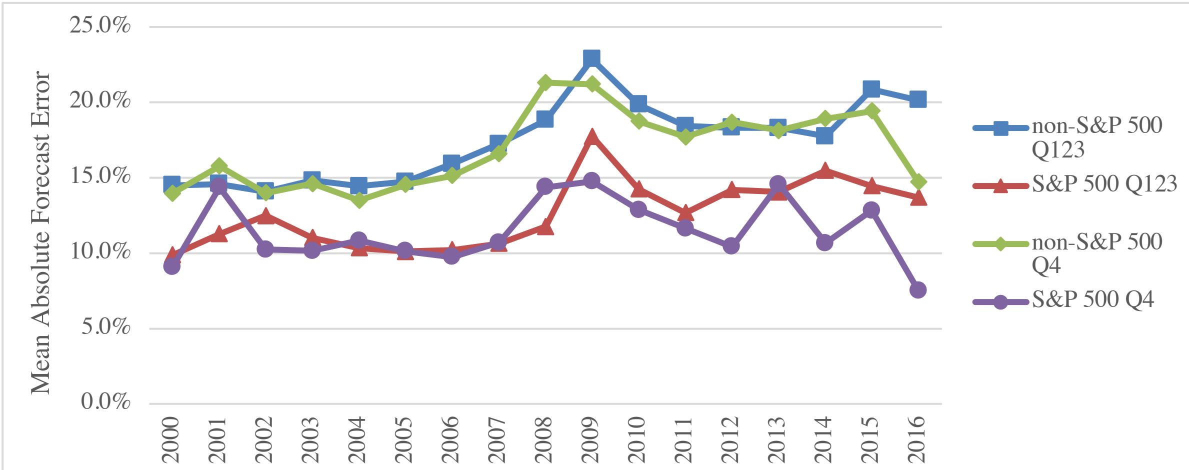


Figure 3b: Proportion of RW ES in the .05≤ES<.15 Bin for S&P 500 and Non-S&P 500



These figures plot the proportion of firms with quarterly RW ES in the bin just below zero (-.01≤ES<0) (Panel A) and the larger bin above zero (.05≤ES<.15) (Panel B). A RW ES for quarter *t* is defined as $QE_t - E(QE_t)$, where $E(QE_t) = QE_{t-4} - (QE_{t-1} - QE_{t-5})$ averaged over the four quarters in each year for all forecasts with Compustat *EPSFXQ* quarterly earnings per share.

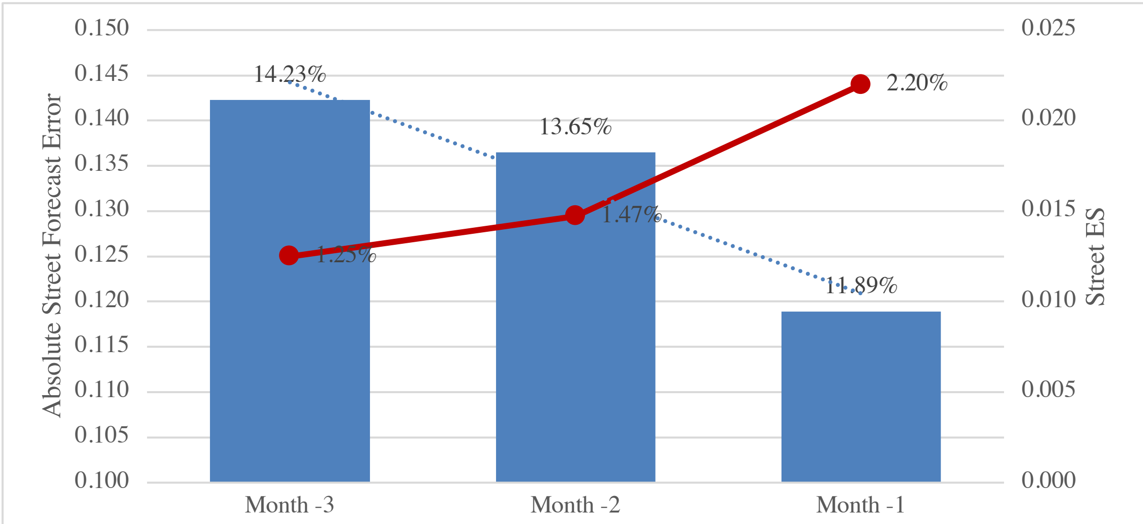
FIGURE 4
Temporal Analysis of Street Forecast Error from 2000 to 2016



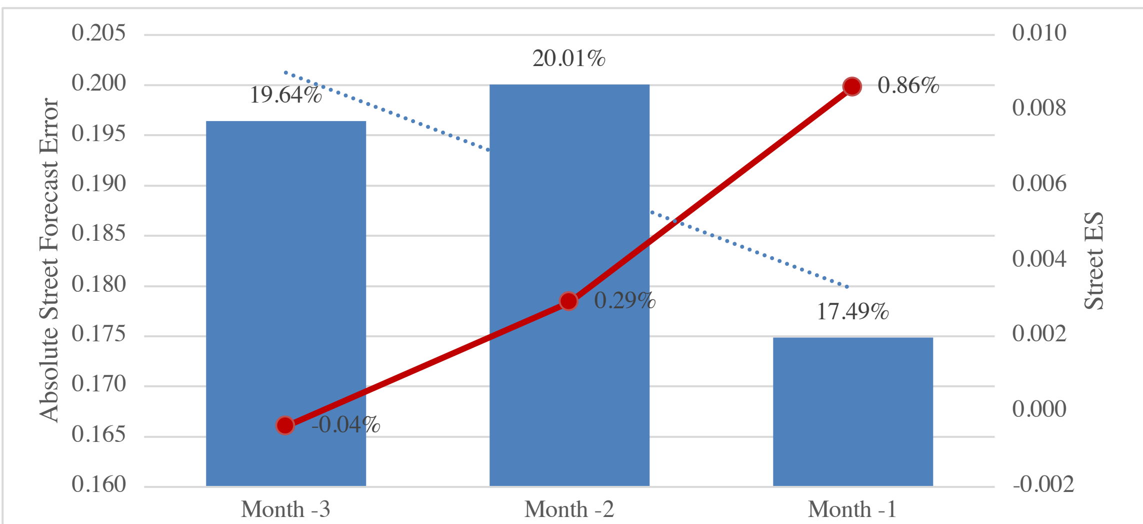
This figure plots the mean absolute forecast error (MAFE) for S&P 500 and non-S&P 500 firms defined as |A-F|÷|A|, where A = I/B/E/S actual quarterly earnings per share and F = I/B/E/S estimated quarterly earnings per share averaged over the Q1–Q3 or Q4 quarters in each year for all forecasts made within 30 days of a quarterly earnings announcement. This figure shows that there is no significant difference or trend in MAFE for Q1–Q3 versus Q4 over 2000–2016, except that MAFE is smaller for S&P 500 firms (larger on the average) than for non-S&P 500 firms (smaller on the average).

FIGURE 5
Street Forecast Error vs. Street Earnings Surprise: Effects of Horizon

Panel 5a: S&P 500



Panel 5b Non-S&P 500



These figures plot the mean absolute Street quarterly earnings forecast error (*MAFE*) against the mean Street ES for the same firms averaged over 2000–2016. *MAFE* is defined as |A-F|÷|A|, where A = I/B/E/S actual quarterly earnings per share and F = I/B/E/S estimated quarterly earnings per share averaged over the Q1–Q4 quarters in each year for all forecasts made within 30, 60, or 90 days of a quarterly earnings announcement. The plots show that, whereas *MAFE* decreases as the horizon decreases (error decreases), ES increases as the horizon decreases (positive bias increases). The dotted line is the line of best fit for *MAFE*.

FIGURE 6
Temporal Analysis of Street EPS and GAAP EPS from 2000 to 2016

Figure 6a: Street EPS less *EPSFXQ* for Q123 versus Q4 quarters

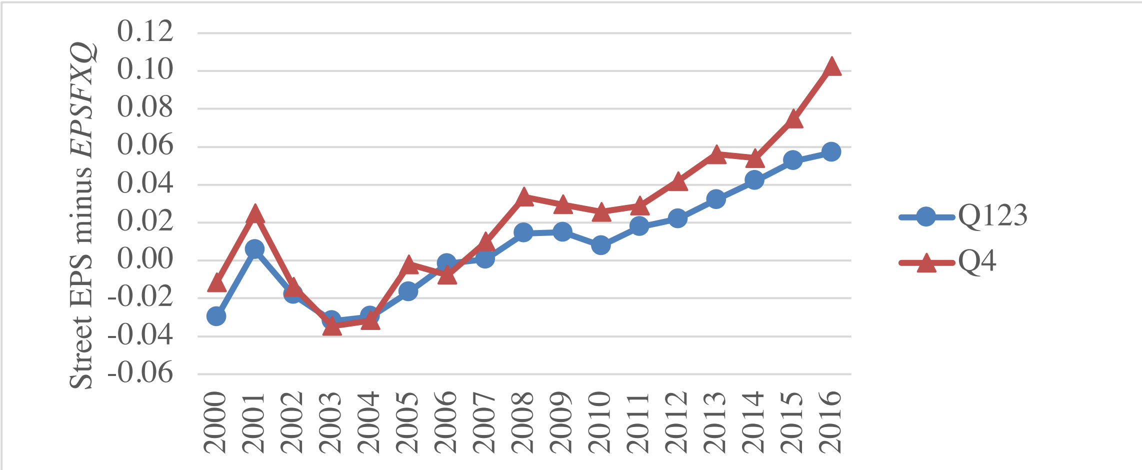


Figure 6b: Street EPS less *EPSFXQ* for S&P 500 versus non-S&P 500 firms

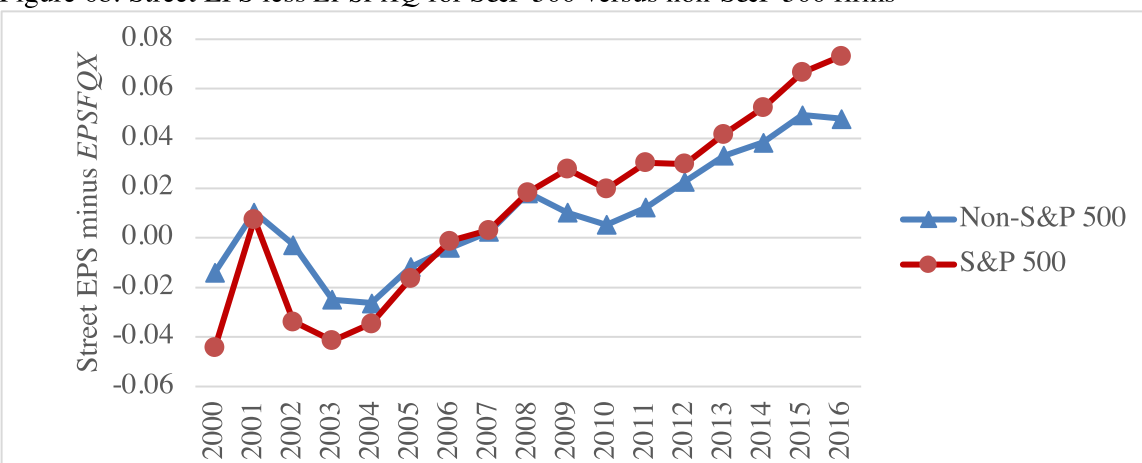


Figure 6c: Street EPS less *EPSFXQ* for Q4 for *EPSFXQ* < 0, 0>*EPSFXQ*≤0.25, and *EPSFXQ*>0.25

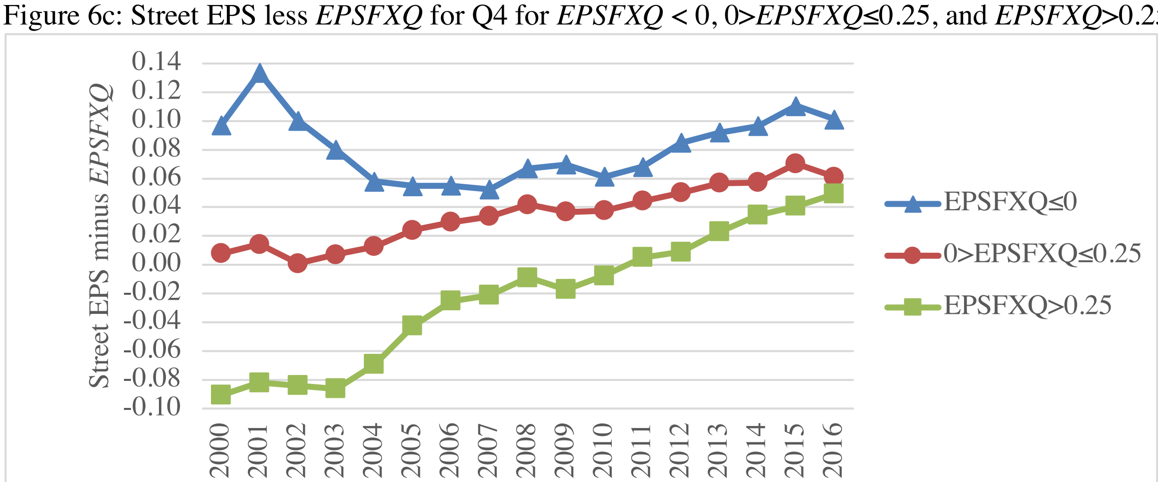


TABLE 1
Descriptive Statistics for the I/B/E/S Sample of Firms

Sector		Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecommunications	Utilities	Real Estate	Non-S&P 500	S&P 500
Ratio (Fiscal 2016 data)		10	15	20	25	30	35	40	45	50	55	60		
ROE	Mean	-0.059	-0.096	0.064	0.079	0.123	-0.283	0.064	-0.010	-0.014	0.025	0.093	-0.021	-0.008
	Quantile75	0.104	0.119	0.186	0.211	0.217	0.167	0.113	0.168	0.146	0.105	0.107	0.149	0.132
	Median	-0.034	-0.034	0.083	0.097	0.109	-0.172	0.083	0.049	0.057	0.091	0.060	0.060	0.071
	Quantile25	-0.240	-0.221	-0.029	-0.020	0.005	-0.730	0.049	-0.143	-0.073	0.050	0.012	-0.113	-0.061
PRETAX/	Mean	-0.339	-0.113	-0.058	-0.032	-0.034	-0.696	0.239	-0.144	-0.114	0.077	0.124	-0.087	0.002
REV	Quantile75	0.067	0.117	0.101	0.108	0.118	0.091	0.334	0.099	0.129	0.196	0.328	0.176	0.213
	Median	-0.111	0.043	0.041	0.054	0.049	-0.068	0.238	0.009	0.062	0.139	0.177	0.059	0.078
	Quantile25	-0.583	-0.067	-0.024	-0.016	0.004	-0.989	0.116	-0.155	0.003	0.078	0.037	-0.070	-0.024
REV/AT	Mean	0.401	0.324	1.075	1.145	1.290	0.458	0.164	0.892	0.533	0.341	0.189	0.593	0.651
	Quantile75	0.445	0.539	1.451	1.582	1.763	0.688	0.122	1.136	0.605	0.340	0.178	0.865	0.978
	Median	0.213	0.000	0.902	1.029	1.029	0.213	0.047	0.738	0.486	0.258	0.118	0.337	0.399
	Quantile25	0.104	0.000	0.539	0.530	0.571	0.001	0.040	0.467	0.367	0.201	0.088	0.047	0.080
AT/CE	Mean	2.365	1.952	2.839	2.992	2.767	1.820	8.068	2.406	3.409	3.668	2.885	3.367	3.701
	Quantile75	2.565	2.124	3.195	3.431	3.116	2.157	10.824	2.443	4.431	3.852	3.111	3.636	4.036
	Median	1.720	1.260	2.172	2.074	2.182	1.400	8.370	1.630	2.683	3.279	2.284	1.981	2.119
	Quantile25	1.164	1.037	1.512	1.405	1.392	1.083	3.399	1.199	1.939	2.780	1.811	1.229	1.322
LEV	Mean	1.270	1.011	1.244	1.346	1.311	1.015	1.498	0.886	1.684	2.460	1.643	1.233	1.308
	Quantile75	1.255	1.029	1.284	1.527	1.427	0.969	1.343	0.896	2.128	2.509	1.744	1.275	1.242
	Median	0.663	0.434	0.676	0.696	0.628	0.431	0.502	0.363	1.045	1.257	1.116	0.600	0.619
	Quantile25	0.312	0.137	0.275	0.280	0.225	0.120	0.230	0.120	0.476	0.742	0.753	0.230	0.238
AT	Mean	8,279.53	2,369.94	5,016.26	6,583.33	9,077.76	2,963.07	61,592.60	3,670.66	27,945.72	15,761.5	4,038.27	13,512.58	21,508.01
	Quantile75	3,012.40	616.10	2,655.62	2,855.68	4,870.48	316.06	8,740.45	1,254.85	25,420.44	17,070.6	4,904.08	2,725.79	4,464.74
	Median	570.27	36.84	653.75	694.27	633.54	63.44	1,553.13	194.78	3,774.75	6,300.00	2,073.98	427.24	846.08
	Quantile25	52.59	4.29	68.86	120.99	41.14	12.90	521.99	22.94	344.29	2,040.31	518.49	36.84	63.04
OANCF	Mean	618.31	203.38	396.81	525.01	888.66	248.71	990.63	443.11	3,248.52	1,069.25	210.81	536.97	702.91
	Quantile75	235.31	44.87	250.06	301.60	515.71	6.07	176.33	115.34	3,436.70	1,072.50	263.98	173.33	271.77
	Median	23.98	-0.24	48.15	54.29	55.29	-4.51	24.30	7.55	531.98	387.68	96.13	13.17	32.89
	Quantile25	-0.48	-1.65	0.36	2.27	1.10	-24.45	4.21	-1.07	24.32	147.76	14.92	-0.95	-0.43
IVNCF	Mean	-579.82	-144.71	-201.34	-456.68	-661.81	-178.97	-451.58	-402.97	-2,408.57	-	-125.53	-368.85	-759.52
	Quantile75	-0.02	0.00	-0.51	-0.73	-0.45	0.00	-0.01	-0.04	-21.84	-123.39	0.06	-0.02	-0.05
	Median	-14.26	-0.96	-21.08	-26.01	-22.83	-0.56	-48.50	-4.40	-420.96	-436.80	-49.36	-11.41	-18.74
	Quantile25	-191.79	-33.83	-146.47	-174.40	-318.41	-25.28	-276.90	-66.58	-2,072.73	-	-215.48	-143.00	-187.80
N Obs.		393	345	510	474	143	642	1171	609	55	95	307	4,244	500

This table summarizes the sample based on fiscal 2016 data. *AT*=total assets, *REV*=revenue, *NI*=net income, *PRETAX*=pretax net income, *CE*=common equity, *LEV*=total debt to *CE*, *AT*=total assets, *OANCF*=operating cash flow, *IVNCF*=investing cash flow. Source: Compustat.

TABLE 2
Descriptive Statistics for the I/B/E/S Sample of Forecasts

	No. Firms		No. Analysts		No. of forecasts < 30 days		Coverage per analyst		Forecasts per firm	
	S&P 500	non-S&P 500	S&P 500	non-S&P 500	S&P 500	non-S&P 500	S&P 500	non-S&P 500	S&P 500	non-S&P 500
2000	431	3,297	169	275	5,651	7,550	14	12	13.1	2.3
2001	429	2,915	175	272	9,166	10,528	13	10	21.4	3.6
2002	443	2,843	175	287	8,714	9,557	13	9	19.7	3.4
2003	446	2,861	211	348	9,082	9,994	14	9	20.4	3.5
2004	457	3,157	216	367	9,671	11,183	14	10	21.2	3.5
2005	463	3,310	224	366	9,374	12,182	14	11	20.2	3.7
2006	459	3,384	211	345	9,213	12,494	13	11	20.1	3.7
2007	459	3,526	232	350	9,723	13,583	13	12	21.2	3.9
2008	461	3,309	233	351	12,898	16,465	12	10	28.0	5.0
2009	454	3,354	234	371	12,535	15,193	14	10	27.6	4.5
2010	462	3,494	265	403	14,745	16,522	16	12	31.9	4.7
2011	470	3,466	240	378	15,385	17,865	17	12	32.7	5.2
2012	479	3,513	220	372	19,347	19,057	17	10	40.4	5.4
2013	490	3,679	233	383	21,688	19,334	18	10	44.3	5.3
2014	490	3,899	231	372	23,425	20,094	17	9	47.8	5.2
2015	500	4,024	218	367	20,632	21,254	18	11	41.3	5.3
2016	500	4,244	187	341	18,928	20,964	20	13	37.9	4.9

This table summarizes the sample of I/B/E/S forecasts of quarterly earnings per share averaged over the four quarters in each year for all forecasts made within 30 days of a quarterly earnings announcement.

TABLE 3
Proportion of Street ES in the -.01≤ES<0 and .05≤ES<.15 Bins

ES Bin	-.01≤ES<0		.05≤ES<.15		-.01≤ES<0		.05≤ES<.15	
Year	Non-S&P500	S&P 500	Non-S&P500	S&P 500	Q123	Q4	Q123	Q4
2000	0.0372	0.0319	0.1305	0.1210	0.0333	0.0417	0.1308	0.1081
2001	0.0390	0.0471	0.0998	0.1156	0.0440	0.0373	0.1067	0.1095
2002	0.0449	0.0364	0.0909	0.1190	0.0398	0.0447	0.1030	0.1092
2003	0.0423	0.0296	0.0996	0.1416	0.0350	0.0412	0.1177	0.1268
2004	0.0408	0.0320	0.1117	0.1630	0.0375	0.0336	0.1331	0.1445
2005	0.0369	0.0273	0.1356	0.1764	0.0341	0.0273	0.1542	0.1498
2006	0.0276	0.0190	0.1581	0.1886	0.0224	0.0298	0.1743	0.1591
2007	0.0292	0.0161	0.1500	0.1880	0.0234	0.0250	0.1677	0.1595
2008	0.0199	0.0116	0.1507	0.1679	0.0163	0.0160	0.1607	0.1491
2009	0.0254	0.0155	0.1794	0.2162	0.0215	0.0187	0.1971	0.1919
2010	0.0279	0.0128	0.1759	0.2187	0.0212	0.0194	0.1995	0.1845
2011	0.0245	0.0147	0.1683	0.2026	0.0213	0.0152	0.1866	0.1751
2012	0.0253	0.0127	0.1684	0.1837	0.0192	0.0180	0.1763	0.1752
2013	0.0249	0.0142	0.1607	0.2011	0.0190	0.0201	0.1849	0.1710
2014	0.0242	0.0096	0.1645	0.2218	0.0173	0.0126	0.1970	0.1886
2015	0.0205	0.0102	0.1843	0.2263	0.0162	0.0122	0.2052	0.2038
2016	0.0214	0.0120	0.1913	0.2553	0.0173	0.0152	0.2171	0.2902
Intercept	2.835	3.872	-10.750	-14.639	3.245	4.017	-12.776	-15.074
Slope coeff.	-0.001	-0.002	0.005	0.007	-0.002	-0.002	0.006	0.008
Slope *t*-stat.	-6.46***	-6.98***	6.70***	8.74***	-6.99***	-8.96***	8.51***	6.88***
Regr. R^2	73.58%	81.03%	80.29%	83.25%	69.45%	80.34%	82.88%	77.10%

This table summarizes the proportion of Street ES in the -.01≤ES<0 and .05≤ES<.15 bins for a particular subsample with I/B/E/S forecasts of quarterly earnings per share averaged over the four quarters in each year of all forecasts made within 30 days of a quarterly earnings announcement. The subsamples are S&P 500, non-S&P 500, Q1, Q2, and Q3 forecasts, and Q4 forecasts. The intercept and slope coefficients are for the time-series regressions of the proportion of Street ES in a bin on time over 2000–2016. *** = $p < 0.01$, ** = $p < 0.05$. * = $p < 0.10$.

TABLE 4
Proportion of Random Walk ES in the -.01≤ES<0 and .05≤ES<.15 Bins

ES Bin	-.01≤ES<0		.05≤ES<.15		-.01≤ES<0		.05≤ES<.15	
Year	Non-S&P500	S&P 500	Non-S&P500	S&P 500	Q123	Q4	Q123	Q4
2000	0.0223	0.0180	0.0850	0.0926	0.0235	0.0172	0.0864	0.0828
2001	0.0257	0.0133	0.0872	0.0996	0.0258	0.0217	0.0869	0.0914
2002	0.0284	0.0134	0.0937	0.1222	0.0288	0.0228	0.0954	0.0965
2003	0.0315	0.0159	0.0868	0.1231	0.0306	0.0296	0.0875	0.0953
2004	0.0311	0.0147	0.0907	0.1192	0.0311	0.0261	0.0919	0.0955
2005	0.0305	0.0158	0.0906	0.1266	0.0309	0.0249	0.0926	0.0950
2006	0.0311	0.0126	0.0849	0.1179	0.0309	0.0265	0.0862	0.0903
2007	0.0303	0.0121	0.0850	0.1309	0.0300	0.0260	0.0885	0.0872
2008	0.0289	0.0076	0.0767	0.0977	0.0291	0.0223	0.0830	0.0628
2009	0.0255	0.0064	0.0793	0.1074	0.0249	0.0221	0.0814	0.0807
2010	0.0276	0.0057	0.0731	0.1069	0.0266	0.0246	0.0745	0.0781
2011	0.0275	0.0096	0.0734	0.1075	0.0277	0.0221	0.0766	0.0729
2012	0.0262	0.0087	0.0684	0.1161	0.0264	0.0212	0.0712	0.0715
2013	0.0307	0.0073	0.0684	0.0998	0.0294	0.0289	0.0717	0.0659
2014	0.0314	0.0080	0.0731	0.1140	0.0315	0.0253	0.0754	0.0761
2015	0.0287	0.0061	0.0720	0.0918	0.0281	0.0248	0.0730	0.0737
2016	0.0282	0.0071	0.0732	0.1091	0.0277	0.0246	0.0767	0.0713
Intercept	-0.1772	1.3646	2.9666	1.1123	-0.0592	-0.2549	2.7163	3.4209
Slope coeff.	0.0001	-0.0007	-0.0014	-0.0005	0.0000	0.0001	-0.0013	-0.0017
Slope *t*-stat.	0.80	-6.5***	-7.0***	-0.94	0.36	0.93	-6.1***	-4.8***
Regr. R^2	4.08%	73.11%	75.53%	4.56%	0.78%	5.57%	71.40%	57.14%

This table summarizes the proportion of random walk (RW) ES in the -.01≤ES<0 and .05≤ES<.15 bins in a particular subsample of firms with Compustat *EPSFXQ* quarterly earnings per share averaged over the four quarters in each year of all forecasts. A RW ES for quarter t is defined as $QE_t - E(QE_t)$, where $E(QE_t) = QE_{t-4} - (QE_{t-1} - QE_{t-5})$. The subsamples are S&P 500, non-S&P 500, Q1–Q3 forecasts, and Q4 forecasts. The intercept and slope coefficients are for the time-series regressions of the proportion of RW ES in a bin on time over 2000–2016. *** = $p < 0.01$, ** = $p < 0.05$. * = $p < 0.10$.

TABLE 5
Mean Difference Between Quarterly Street EPS and *EPSFXQ* Split on S&P 500 vs. Non-S&P 500 and Q123 vs. Q4

Year	Non-S&P 500	S&P 500	Q123	Q4	Non-S&P 500	S&P 500	Non-S&P 500	S&P 500	Q123	Q123	Q4	Q4	Q4-Q123	S&P 500–Non-S&P 500
					NEG EPSFXQ	*NEG EPSFXQ*	*POS EPSFXQ*	*POS EPSFXQ*	*NEG EPSFXQ*	*POS EPSFXQ*	*NEG EPSFXQ*	*POS EPSFXQ*		
2000	-0.01399	-0.04432	-0.02993	-0.01151	0.08441	0.15948	-0.05167	-0.06472	0.08950	-0.06067	0.11891	-0.04526	0.01841	-0.01305
2001	0.01021	0.00743	0.00551	0.02484	0.11796	0.19327	-0.04403	-0.03962	0.12477	-0.04451	0.15629	-0.03445	0.01932	0.00441
2002	-0.00286	-0.03382	-0.01813	-0.01392	0.09910	0.10994	-0.04454	-0.05612	0.09029	-0.05100	0.13502	-0.04855	0.00420	-0.01159
2003	-0.02502	-0.04151	-0.03199	-0.03463	0.06419	0.11751	-0.04890	-0.06112	0.07618	-0.05125	0.09256	-0.04900	-0.00263	-0.01222
2004	-0.02631	-0.03464	-0.02957	-0.03152	0.04563	0.09529	-0.04423	-0.04233	0.05559	-0.03984	0.06489	-0.04217	-0.00195	0.00190
2005	-0.01181	-0.01649	-0.01663	-0.00197	0.04270	0.07656	-0.02628	-0.02143	0.05261	-0.02350	0.06105	-0.01515	0.01466	0.00485
2006	-0.00411	-0.00131	-0.00174	-0.00753	0.04751	0.08837	-0.01522	-0.00519	0.05035	-0.00615	0.06860	-0.01363	-0.00579	0.01003
2007	0.00234	0.00305	0.00067	0.00996	0.04504	0.10677	-0.00818	-0.00507	0.05055	-0.00560	0.05727	-0.00073	0.00929	0.00311
2008	0.01801	0.01830	0.01439	0.03357	0.06877	0.07349	0.00169	0.01191	0.05604	0.00643	0.09042	0.00994	0.01918	0.01021
2009	0.01015	0.02766	0.01493	0.02957	0.06433	0.09185	-0.00964	0.01466	0.06444	0.00127	0.08609	0.00678	0.01463	0.02429
2010	0.00529	0.01964	0.00776	0.02560	0.05000	0.10531	-0.00536	0.01314	0.05118	0.00490	0.09190	0.01450	0.01784	0.01850
2011	0.01224	0.03026	0.01774	0.02884	0.05482	0.11571	0.00187	0.02413	0.06180	0.01358	0.08469	0.02515	0.01110	0.02226
2012	0.02268	0.02978	0.02199	0.04184	0.07477	0.16565	0.00950	0.01978	0.08064	0.01620	0.09683	0.03242	0.01984	0.01028
2013	0.03308	0.04169	0.03212	0.05607	0.08621	0.14750	0.01941	0.03754	0.08754	0.02701	0.10499	0.04634	0.02395	0.01813
2014	0.03832	0.05244	0.04202	0.05399	0.09506	0.14534	0.02354	0.04859	0.09436	0.03840	0.10228	0.04550	0.01197	0.02506
2015	0.04948	0.06669	0.05257	0.07477	0.09744	0.22092	0.03137	0.05208	0.10733	0.04579	0.12017	0.05721	0.02220	0.02071
2016	0.04788	0.07325	0.05698	0.10272	0.08692	0.16736	0.03170	0.05674	0.09835	0.04993	0.15716	0.08149	0.04574	0.02504
Intercept	-7.875	-13.539	-10.075	-12.754	-0.614	-4.974	-11.145	-15.635	-0.777	-13.829	-0.850	-15.645	-2.67929	-5.66395
Slope coeff.	0.00393	0.00675	0.00502	0.00636	0.00034	0.00254	0.00554	0.00779	0.00042	0.00688	0.00047	0.00779	0.00134	0.00224
t-stat.	6.40***	9.53***	8.55***	6.60***	0.29	1.23	17.18***	16.27***	0.37	20.36***	0.31	17.00***	2.61**	6.82***
Regr. R^2	73.2%	85.8%	83.0%	74.4%	0.6%	9.2%	95.2%	94.6%	0.9%	96.5%	0.6%	95.1%	31.2%	75.4%

This table summarizes the mean difference between quarterly Street EPS and *EPSFXQ* averaged over the particular quarters in a given year. The subsamples are S&P 500, non-S&P 500, Q1–Q3 forecasts, and Q4 forecasts. The intercept and slope coefficients are for the time-series regressions of the mean Street EPS–*EPSFXQ* difference on time over 2000–2016. Cols. 14 and 15 regress the difference in Q4 minus Q123 and S&P 500 minus non-S&P 500 on time over 2000–2016. A positive slope coefficient means that the series is increasing in time. *** = $p < 0.01$, ** = $p < 0.05$. * = $p < 0.10$.