Do Earnings Have Information Content in the Era of Alternative Data?

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Abstract

Is earnings obsolete in a world of abundant third-party alternative data? We provide evidence relevant to this question by examining how the information content of earnings news changes following the introduction of satellite imagery data on retail firms' parking lot traffic. Using the staggered rollout of this data as a shock to alternative data availability, we find that the market response to unexpected earnings increases more for treated firms around the onset of coverage, relative to control firms that receive no such coverage. This result suggests earnings news becomes more informative when satellite data becomes available. Additionally, our findings suggest that satellite imagery enhances the information content of earnings news by (1) strengthening investor oversight and thereby improving reporting quality, and (2) reducing investor uncertainty about earnings. Together, these findings suggest the effect of alternative data is more nuanced, as it also plays a complementary role alongside earnings.

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1. Introduction

In the past decade, advances in information technology have driven the rapid growth of alternative data, which are typically defined as timely, relevant, non-financial data produced by independent third parties. Examples of such data include web traffic, app usage, geolocation, and satellite imagery. These data stand out for their granularity and real-time availability, fundamentally transforming how investors and information intermediaries gather and process information. Recent studies demonstrate that alternative data provides valuable insights into firms' underlying economic performance and shapes market participants' decisions (e.g., Froot et al. 2017; Zhu 2019; Kang et al. 2021; Chang and Da 2022; Kang 2023; Katona et al. 2023). These findings raise an important question: Is alternative data a substitute for accounting information, potentially diminishing the role of earnings as a source of new information (Ball and Shivakumar 2008)? In this paper, we instead explore whether alternative data complements financial reports by enhancing their informativeness about firms' underlying fundamentals. Specifically, we examine how the availability of alternative data affects the information content of earnings, measured by stock price reactions to unexpected earnings.

In this paper, we focus on satellite imagery data—a key type of alternative data that captures customer traffic in and out of retail firms' parking lots. Satellite imagery data serves as an objective measure of performance, immune to personal beliefs or managerial manipulation. Several recent studies find that satellite imagery data provides real-time insights into firm performance (Kang et al. 2022; Kang 2023; Katona et al. 2023). Key stakeholders, including management, hedge funds, asset management firms, government entities, and nonprofit organizations, subscribe to these data sources.[1] Due to its relevance, objectivity, and independence,

[1] We thank R.S. Metrics for sharing the insights regarding data users.

satellite imagery data can be used by stakeholders to scrutinize firms' reporting choices. Specifically, satellite imagery data provide information about customer traffic that investors can use to evaluate the plausibility of reported sales and earnings. For example, in the Luckin Coffee fraud case, the Wall Street Journal (2020) reported that BCC Global used customer traffic and sales data to uncover discrepancies in Luckin's reported figures.

We posit that satellite data improves the informativeness of earnings news through two channels: the *disciplining channel* and the *information mosaic channel*. First, the availability of satellite imagery provides stakeholders with an externally generated benchmark of firm performance that is not subject to managerial discretion. Although satellite data provides an imperfect signal of firm performance, it helps investors evaluate the plausibility of reported sales and earnings and increases the expected cost of biasing earnings. As a result, managers are less likely to engage in opportunistic reporting, leading to less biased earnings reports and a stronger market reaction to unexpected earnings (Fischer and Verrecchia 2000). We refer to this effect as the *disciplining channel*.

Second, in addition to disciplining reporting quality, satellite imagery expands the information mosaic investors use to interpret earnings news. Because satellite data is generated by a third party, captures real economic activity necessary for sales (i.e., foot traffic), and is quantitative in nature, it provides an independent and economically grounded signal that investors can use to benchmark and verify reported performance. At earnings announcements, investors combine the fundamentals implied by this external signal with other information, such as historical financial statements, analyst forecasts, and management disclosures, to interpret earnings news. This helps them isolate its fundamental component and assess the extent to which it reflects potential managerial reporting bias. This reduction in uncertainty about potential reporting biases enhances investors' interpretation of earnings news and leads to stronger stock price responses. We refer to this effect as the *information mosaic channel*. Together, the *disciplining* and *information mosaic channels* suggest that the market's reaction to earnings news will be stronger after alternative data becomes available.

There is, however, an alternative hypothesis. Prior theory suggests investors react less to new information when they have more precise private information (Holthausen and Verrecchia 1988, Kim and Verrecchia 1991). Prior studies provide evidence that sophisticated investors trade on fundamental information contained in satellite imagery data (Zhu 2019; Katona et al. 2024). These studies suggest satellite imagery data is informative, thereby increasing the precision of investors' private information about sales and earnings. All else equal, theory suggests that the availability of alternative data may result in a smaller market reaction to earnings news by increasing the precision of investors' private information about sales and earnings. Given these competing predictions, the effect of alternative data on the information content of earnings remains an open empirical question.

We obtain satellite imagery data on the store-level parking lots of U.S. retail firms from R.S. Metrics, which contains intraday information about the capacity, traffic, and utilization of retail firms' parking lots. R.S. Metrics staggered the release of this data for 46 major U.S. retailers from 2011 to 2018. This data feature allows us to employ a stacked difference-in-differences (DID) research design by exploiting the staggered release of satellite imagery data for these retail firms. Based on quarterly earnings announcements, our stacked DID research design compares changes in the earnings response coefficients (ERCs) of treatment firms—firms for which satellite imagery data becomes available—to those of control firms in the same four-digit SIC industry that did not have coverage in either the pre- or post-treatment period.[2] We employ entropy balancing to neutralize observable differences between our treatment and control samples (Hainmueller 2012; McMullin and Schonberger 2020). We find a statistically and economically significant increase in ERCs for treatment firms relative to control firms of 0.009, corresponding to a 29% increase over the pre-coverage level of 0.031. Our results suggest that the availability of satellite imagery data improves the informativeness of earnings news.[3]

In addition, we examine pre-treatment trends in ERCs for treatment and control firms to provide evidence on the plausibility of the parallel trends assumption (Roberts and Whited 2013). Specifically, we rerun our ERC specification each year relative to the initiation year when satellite imagery data becomes available. We plot ERCs over the years from t-3 to t+3 for both treated and control firms, respectively. We do not find a significant difference in the ERC trend between our treatment and control samples before the availability of satellite imagery data.[4] However, there is a significant difference between the ERCs of our treatment and control samples in the post-period, suggesting that alternative data increases the informativeness of earnings. This analysis ameliorates concerns that unobservable differences between our treatment and control samples drive our difference-in-differences result.

Next, we explore the channels through which satellite data improves the informativeness of earnings news. First, if satellite data improves the informativeness of earnings news through the *disciplining channel*, we expect an improvement in earnings quality – i.e., the mapping between accruals and cash flows. We construct two measures of financial reporting quality based on

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[2] Orbital Insight's data became commercially available in Q3 2015, which does not coincide with the staggered releases of R.S. Metrics. Thus, it is unlikely that Orbital Insight coverage drives our results.
[3] Our results are statistically significant, and the economic magnitudes are similar when we do not employ entropy balancing.
[4] Hribar, McInnis, and Wang (2025) suggest that short pre-treatment windows often have low power to detect violations of the parallel trends assumption. Accordingly, in untabulated analyses, we extend the pre-window to five years and continue to find no significant differences in ERC trends, alleviating this concern.

Dechow and Dichev's (2002) accrual model modified by McNichols (2002). Consistent with our prediction, we find a significant increase in financial reporting quality for treated firms relative to control firms after satellite imagery data becomes available. Additionally, using revenue-related restatements from Audit Analytics as an alternative measure of revenue misreporting, we find that the likelihood of such restatements declines after satellite data becomes available.

Second, we explore the *information mosaic channel*. We posit that investors' uncertainty after earnings announcements should decrease when satellite data becomes available, as it helps investors estimate the reporting bias in earnings news and, thus, better understand the implications of reported earnings for future cash flows. We find investors are relatively less uncertain about earnings news, as evidenced by a greater reduction in implied volatility after earnings announcements for treatment firms relative to control firms from the pre- to the post-period. In addition, we examine investors' information gathering using web traffic on the SEC's EDGAR servers. The log files of the EDGAR server track user access statistics for all regulatory filings mandated by the SEC. We conjecture that when investors have less uncertainty about reporting biases due to the availability of satellite data, they are less likely to download historical filings to assess the accounting discretion exercised by managers (Drake et al., 2015). We find a greater downtick in downloads of historical filings following earnings announcements for treatment firms after satellite imagery data becomes available, relative to control firms that do not receive such data. Collectively, these results are consistent with the idea that investors better understand the implications of earnings news for future cash flows, leading to less uncertainty about earnings news after satellite data becomes available.

Finally, we conduct several cross-sectional tests to better understand when the availability of satellite data matters more. First, we explore whether the effect of satellite data on the informativeness of earnings news varies with the relevance of satellite data. Specifically, we follow Kang (2023) and use the correlation between the parking lot fill rate and sales growth as a proxy for the relevance of the real-time parking lot data. Additionally, we use the number of business segments as another proxy, as satellite data is likely more relevant for firms concentrated in the retail sector only. We predict and find that the availability of satellite data strengthens the market reaction to earnings news when satellite data maps better into sales growth and when firms have only one segment. This finding is consistent with satellite data providing value when it maps well into the firm's underlying economic performance.

Second, we examine whether the effect of satellite data varies with the demand for such data, as captured by auditor quality and ex ante uncertainty about reporting biases. Satellite data should play a more important role when investors face greater uncertainty about the reliability of earnings, such as when firms are audited by lower-quality auditors or when managers have greater reporting discretion. To examine this, we use a non-Big 4 indicator as a proxy for auditor quality and Hribar et al.'s (2022) measure that captures the GAAP's limits on managerial reporting discretion. We find that satellite data has a stronger effect on price reactions to earnings news in settings with lower audit quality and where GAAP affords managers greater reporting discretion, consistent with third-party alternative data mitigating investors' uncertainty about the reporting bias in earnings.

Our study contributes to prior literature in several ways. First, our study contributes to the literature on the usefulness of financial statement information, a central question in capital markets research (Kothari 2001). Prior studies find that the usefulness of financial statement information, as measured by earnings response coefficients, varies with firm characteristics and external forces such as audit quality, regulatory oversight, and disclosure requirements (Teoh and Wong 1993;

Kothari 2001; Francis and Ke 2006; Gipper et al. 2020; Ferri et al. 2018). We add to this literature by providing evidence that timely, relevant alternative data complements financial reports by making earnings news more informative about underlying fundamentals through two mechanisms: improving reporting quality and reducing investors' uncertainty about earnings news. Our evidence suggests that earnings remain decision useful for valuation in the era of independent, timely, and informative alternative data. In particular, we find that such data complements earnings by increasing the information content of earnings news. This enhanced decision usefulness may also have implications for the role of earnings in contracting, which we leave for future research.

Second, we contribute to the growing literature on the implications of alternative data. Prior research emphasizes the informativeness of alternative data and focuses on the incorporation of such information into prices. For example, Zhu (2019) finds that because satellite data is informative, its availability lowers investors' information acquisition costs, improves price informativeness, and disciplines insider trading. Katona et al. (2025) find that some institutional investors trade on satellite-based signals ahead of earnings announcements. Our study contributes to these studies by examining a distinct and fundamental accounting question—how the presence of alternative data affects the information content of earnings news and investors' ability to process it. Our evidence suggests alternative data also complements earnings, as earnings news become more informative, reporting quality improves, and investor uncertainty about earnings news declines. This evidence is consistent with alternative data both disciplining managers financial reporting decisions and helping investors better assess the implications of earnings for future cash flows. We note that while Zhu (2019) also frames big data as a governance mechanism, her findings do not directly imply those in our paper. Zhu's (2019) findings on improved price informativeness suggest that alternative data may weaken market reactions during the announcement period by pre-empting earnings news. By contrast, we expect that alternative data may increase market reactions due to improved credibility and interpretability of reported earnings. Importantly, Zhu (2019) abstracts from changes in reporting quality, whereas we show that alternative data improves financial reporting quality and reduces investor uncertainty about earnings. Taken together, although alternative data may serve as a more timely substitute for certain information in financial reports, our findings highlight that satellite data also plays an important complementary role by both improving reporting quality and helping investors understand the implications of earnings news.

Third, our study extends the findings of Blankespoor et al. (2022), who examine how managers disclose private information about real-time abnormal revenue, derived from credit and debit card sales. Their findings suggest that managers are less likely to disclose negative news early in the quarter and benefit from doing so through more profitable insider sales. These patterns weaken as earnings announcements approach, consistent with scheduled disclosure acting as a disciplining mechanism. In contrast, our evidence highlights the disciplining role of public, third-party alternative data—specifically, satellite-based measures of parking lot traffic, which is a different mechanism. Together, the two studies suggest that the public or private nature of alternative data plays a central role in shaping the firm's information environment.

2. Hypotheses development

Countervailing theories suggest alternative data could either increase or decrease the information content of earnings news. On the one hand, the disciplining and information mosaic channels suggest that the introduction of alternative data will increase the informativeness of earnings news. The *disciplining channel* is grounded in Fischer and Verrecchia (2000), which predicts a stronger relation between unexpected earnings and earnings announcement returns when the cost of biasing earnings is higher. Satellite data provides timely, independent, and relevant information about customer traffic in and out of retail firms' parking lots, which can be used by various stakeholders to independently verify sales and earnings ex post, thereby disciplining managers' financial reporting choices. Several recent studies document that traffic patterns of retail firms' parking lots map well to consumer transactions in retail stores, and aggregated signals across store-level parking lots provide timely information about firms' underlying performance (e.g., Kang et al. 2021; Gerken and Painter 2022; Katona et al. 2023). Further, anecdotal evidence suggests that customer traffic data can be used to identify discrepancies in financial reporting figures (Wall Street Journal 2020). Given this, it seems plausible that investors can use satellite imagery data to assess the validity of reported sales or earnings figures. Hence, investors will be better positioned to evaluate management's reported numbers and discipline managers when they engage in opportunistic reporting, thereby increasing the cost of biasing earnings. Accordingly, the introduction of satellite data should strengthen the relation between unexpected earnings and earnings announcement returns because it increases the cost of biasing earnings.

The *information mosaic channel* also predicts that satellite data can strengthen the relation between unexpected earnings and earnings announcement returns. The idea is that investors assemble an incremental information mosaic by combining signals from different information sources when interpreting firm news (Cheynel and Levine 2020). Satellite data provides valuable information about customer traffic in retail stores' parking lots, serving as a plausibly objective indicator of firms' underlying economic performance (Kang 2023). Specifically, Kang (2023) finds that parking lot fill rates are positively correlated with sales growth. By integrating signals from satellite data and other available information sources (e.g., historical financial reports, analyst reports, and management disclosures), investors assemble a more complete information mosaic about the firm and use it to better evaluate the plausibility of reported performance and assess the extent to which such performance reflects potential managerial reporting bias. As a result, investors face less uncertainty in interpreting earnings and respond more strongly to unexpected earnings. Overall, the *disciplining* and *information mosaic channels* lead to the following hypotheses.

H1: The market reaction to unexpected earnings will be greater after the release of satellite imagery data.

H2: Earnings quality will improve after the release of satellite imagery data.

H3: Investors will be less uncertain about earnings information after the release of satellite imagery data.

Alternatively, the introduction of satellite imagery data may be associated with a decrease in the market reaction to unexpected earnings because it improves the precision of investors' private information about firms' underlying economic performance. Consistent with this view, Zhu (2019) and Katona et al. (2024) provide evidence that satellite imagery data is informative and that sophisticated investors trade on fundamental information contained in satellite imagery data. Holding all else constant, because satellite data increases the precision of investors' private information about sales and earnings before earnings announcements, investors may have a smaller belief revision when new information is released, leading to a muted market response to unexpected earnings (Holthausen and Verrecchia 1988; Kim and Verrecchia 1991). These arguments lead to a countervailing prediction that the introduction of alternative data may lead to a weaker market reaction to unexpected earnings.

3. Data and sample

3.1 Satellite imagery data from R.S. Metrics

We obtain satellite imagery data from R.S. Metrics from 2011 to 2018. R.S. Metrics is the first U.S. data vendor to release real-time satellite imagery data that captures parking lot traffic for 46 listed U.S. retail firms starting from the first quarter of 2011.[5] The data consists of daily store-level information about parking lot capacity and utilization. R.S. Metrics partners with satellite data providers to obtain high-resolution retail parking lot location images. These images are sourced from commercial satellites that can capture detailed views of the Earth's surface. R.S. Metrics counts the number of cars and spaces in each parking lot by using advanced machine learning algorithms and computer vision techniques to enhance the accuracy of the car counts. In particular, geofences (i.e., virtual boundaries) are used to identify which sections of each parking lot correspond to each store. These procedures help delineate which parts of the parking lot are most likely used by customers of specific stores. In addition, if multiple stores share the same parking lot, R.S. Metrics uses detailed geospatial data to map out the exact boundaries of the shared parking lot and the individual stores within a shopping center or mall.

We also obtain detailed information from the data vendors on the exact time each retail firm's satellite imagery data was first released to its clients. R.S. Metrics discloses that its clients include public companies, asset management firms, government entities, and nonprofit organizations.

During our sample period, R.S. Metrics provides rich coverage of satellite imagery data at the daily level across stores in the U.S. for 46 publicly listed retail firms in different years.

[5] We also obtain parking lot traffic satellite imagery data from another data vendor, Orbital Insight, which also tracks the number of cars in parking lots for a subset of publicly listed U.S. firms. Orbital Insight commercially released the parking lot image data in the third quarter of 2015. However, store-level coverage expands gradually over three years for a typical firm, and thus, the timing of when investors gain access to satellite imagery data at the firm level is ambiguous. Because our study focuses on the verification role of satellite data in assessing earnings news, the timing of investors' access to such data is critical. Given this, Orbital Insight's setting is not ideal for a difference-in-differences design because its adoption is not staggered. That said, our results remain statistically significant, and the economic magnitude of our results is similar when we employ the Orbital Insights data.

Appendix 1 lists company names and their coverage dates by R.S. Metrics in the U.S. The R.S. Metrics not only covers the largest and most influential retailers in the U.S., such as Walmart and Target, but also retailers in financial distress, such as J.C. Penney and Sears. Figure 1 presents the number of Walmart stores covered by R.S. Metrics for each state in the U.S. For example, R.S. Metrics covers over 200 stores in California, Texas, and Florida. The figure shows that R.S. Metrics covers all states in the U.S. Such rich coverage improves the accuracy of the signal that predicts firm sales and earnings at the firm level because the negative and positive measurement errors at the store level are largely canceled in aggregate at the firm level. For each processed satellite imagery, R.S. Metrics provides the date of the satellite imagery, the individual store location, the number of cars parked in the store parking lot, and the total number of available parking spaces in the parking lot.

3.2 Sample

We combine satellite data from R.S. Metrics with stock returns, consolidated trading volume, stock prices, and total shares outstanding from CRSP, financial data from Compustat, analyst data from I/B/E/S, and institutional holding data from the Thomson-Reuters Institutional Holdings (13F) database. To conduct the difference-in-differences analyses, as described in detail in Section 4, we include three years before and after the release of satellite imagery data (i.e., [t-3, t+3]) and exclude the release year (year 0). We retain 5,145 firm–quarter observations after excluding observations with missing values for the variables required in the regression analyses.

3.3 Summary statistics

Table 1 reports summary statistics for the main variables used in our analysis. The descriptive statistics for the full sample are generally consistent with other studies that use R.S. Metrics data (Panel A). As R.S. Metrics' coverage decision is likely nonrandom, one might have concerns that firm characteristics affect both the coverage decision and the level of ERCs. Thus, we report firm characteristics for treated and control firms in Panel B. Comparing with control firms in our sample, treated firms tend to be larger, more profitable, have more analyst followings, and have more institutional ownership. It is important to note that R.S. Metrics' tendency to cover larger firms biases against finding larger price reactions to earnings news because the ERC literature documents well that larger and heavily followed firms have lower ERCs than smaller and less followed companies (Bamber and Cheon, 1995; Bamber, Barron, and Stober, 1997).

4. Research design

Building on prior theoretical work (e.g., Kim and Verrecchia, 1991; Fisher and Verrecchia, 2000), we use earnings response coefficients to measure the informativeness of unexpected earnings, i.e., the degree to which stock prices react to a given amount of earnings news.

We employ a stacked difference-in-differences research design to examine our main hypothesis regarding the effect of satellite data availability on the informativeness of unexpected earnings. For each treated firm, the pre-period is the three years (12 quarters) before the year that satellite data becomes available (i.e., years t-3, t-2, and t-1), and the post-period is the three years (12 quarters) after the year that satellite data becomes available (i.e., years t+1, t+2, and t+3). We exclude the year the satellite data becomes available (year t) from our sample to allow sufficient time for sophisticated investors and other market participants to become aware of and access the data. The treatment group contains firms covered by R.S. metrics. For each treated firm, we assign all firms within the same industry group as control firms (four-digit SIC code) but not covered by

R.S. metrics in the post-period.[6] To investigate whether treatment firms experience an increase in ERC relative to control firms, we estimate Equation (1):

$$CAR[-1, 1]_{i,t} / CAR[-2, 2]_{i,t} = a_0 + a_1\, UE\_Rank_{i,t} + a_2\, UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t} + a_3\, UE\_Rank_{i,t} \times Treat_{i,t} + a_4\, UE\_Rank_{i,t} \times Post_{i,t} + a_5\, Treat_{i,t} \times Post_{i,t} + a_6\, Treat_{i,t} + a_7\, Post_{i,t} + Controls_{i,t} + UE\_Rank_{i,t} \times Controls_{i,t} + \text{Year-quarter and Firm Fixed Effects} + e_{i,t}, \quad (1)$$

where $CAR[-1, 1]_{i,t}$ ($CAR[-2, 2]_{i,t}$) is the cumulative abnormal return over trading days [-1, 1] ([-2, 2]) around earnings announcements. We compute daily abnormal return as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio over the same period. The benchmark portfolios are constructed using Fama and French's (1992) method. For June of year *t*, we classify all firms with CRSP share codes 10 and 11 into 25 portfolios by size at the end of June of year *t* and by the book-to-market ratio at the end of December of year *t-1*. We measure unexpected earnings based on consensus analyst forecasts issued within 90 days before the earnings announcement, scaled by price at the end of the fiscal quarter. The variable $UE\_Rank_{i,t}$ is the decile ranking of unexpected earnings, ranging from 0 to 9. A ranking of 0 (9) represents the decile with the lowest (highest) unexpected earnings. We use the ranked measure of unexpected earnings to reduce the influence of outliers in the estimation of ERCs (Hirshleifer et al. 2009). $TREAT_{it}$ is an indicator variable that equals one if R.S. metrics covers firm *i* in year *t*, and zero otherwise. $POST_{it}$ equals one for the post-period of firm *i*, and zero otherwise. Our main variable of interest is a_2, the coefficient of $UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t}$, which captures the change in ERCs for treated firms relative to control firms from the pre- to the post-period.

[6] As some of control firms are also covered by Orbital Insight, we also require control firms are not covered by Orbital Insight in the post-period of the treated firm.

We include factors that prior research has shown to be associated with market reactions to earnings news. Specifically, we include firm size, *Size*, the book-to-market ratio, *B.M.*, and idiosyncratic return volatility, *IdioVol*, to control for cross-sectional differences in the riskiness of firms (Fama and French, 1992). We include stock price, *log(Price)*, to control for trading costs at the individual stock level (Bhushan, 1994). We also include a loss indicator, *Loss*, to control for the asymmetric market reactions to positive and negative earnings. We include analyst coverage, *log(#Analysts)*, and institutional ownership, *InstOwn*, because these intermediaries have been shown to affect the dissemination of earnings news (e.g., Utama and Cready, 1997; Ali et al., 2008). We include analyst forecast dispersion, *Dispersion*, to control for information uncertainty around earnings announcements. We include *Big4*, an indicator variable of Big 4 auditors, to control for the perceived credibility of reported earnings (Teoh and Wong 1993). We include *log(#EA)*, the total number of earnings announcements made on the same date, to control for busy earnings announcement periods. We include an indicator variable for the fourth fiscal quarter, *Qtr4*, to control for differential market reactions to annual earnings announcements. $UE\_Rank_{i,t} \times Controls_{i,t}$ is a set of interactions between $UE\_Rank_{i,t}$ and control variables. Finally, we include year-quarter and firm fixed effects to control for unobserved heterogeneity over time and across firms. Following Hirshleifer et al. (2009), we cluster standard errors by the earnings announcement date to mitigate the concern of residual cross-sectional correlation on those dates.

In Panel B of Table 1, we report the summary statistics of control variables for treated and control firms. In our sample, treated firms are significantly larger, more profitable, have more analyst followings, and have more institutional ownership. To alleviate the concern that the coverage decisions by R.S. metrics are nonrandom, we use an entropy balancing procedure to ensure the mean and variance of all control variables are comparable for treatment and control samples, including firm size, *Size,* the book-to-market ratio, *B.M.,* idiosyncratic return volatility, *IdioVol*, stock price, *log(Price)*, a loss indicator, *Loss*, analyst coverage, *log(#Analysts)*, institutional ownership, *InstOwn*, analyst forecast dispersion, *Dispersion*, an indicator variable of Big 4 auditors, *Big4*, the total number of earnings announcements made on the same date, *log(# EA)*, and an indicator variable for the fourth fiscal quarter, *Qtr4*. In addition, the entropy balancing approach can reduce the bias arising from nonlinear relationships between the dependent variable and observable characteristics (Hainmueller 2012; McMullin and Schonberger 2020). Furthermore, since the treatment firms account for only 16% of our sample, propensity score matching would substantially reduce the sample size and, thus, the testing power. In contrast, the entropy balancing approach, which is often used in studies with unbalanced treatment and control groups (see Shroff et al. 2017; Ferri et al. 2018), allows us to preserve sample size.

5. Results

5.1 Main results

Table 2 presents the results from estimating Equation (1) with the entropy-balanced sample. In Columns (1) and (2), we present the results using $CAR[-1, 1]_{i,t}$ as the dependent variable, and in Columns (3) and (4), we present the results using $CAR[-2, 2]_{i,t}$ as the dependent variable. We control for the interactions between the control variables and $UE\_Rank_{i,t}$ in Columns (2) and (4). We do not tabulate coefficients on the interactions between the control variables and $\mathrm{UE\_Rank}_{i,t}$ for parsimony. Consistent with prior literature on ERCs, we find that $UE\_Rank_{i,t}$ is positive and statistically significant in all specifications. In all columns, we find that the coefficient on the triple interaction term, $UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t}$, is significantly positive (a_2 = 0.01, t-statistic = 2.59 in Column (1); a_2= 0.009, t-statistic = 2.33 in Column (2); a_2= 0.014, t-statistic = 3.00 in Column (3); a_2= 0.011, t-statistic = 2.53 in Column (4)), suggesting a significantly greater increase in ERCs for treated firms relative to control firms following the availability of satellite data. The availability of satellite data also has significant economic implications. In Column (2), the three-day decile ranked ERC for treated firms is 0.040 (0.030 + 0.009 + 0.000 + 0.001) after satellite data becomes available, indicating that the three-day cumulative abnormal return increases by 4% for each decile increase in unexpected earnings. The evidence suggests that the ERC for treated firms increases by 29% from its pre-period level of 0.031 (0.031 = 0.030 + 0.001). The coefficient on $Post_{i,t} \times Treat_{i,t}$ is negative and statistically significant across all columns. This coefficient represents the difference-in-differences effect when unexpected earnings are in the lowest decile (a ranking of 0). The negative coefficient suggests that treated firms have larger negative market reactions to negative earnings surprises (i.e., a higher ERC) after satellite data becomes available. Overall, the results in Table 3 provide evidence of a higher level of ERC following the availability of satellite data.

Note that we rely on analyst forecasts as a proxy for investors' expectations. While the satellite data provided both analysts and investors with relevant information about retail firms' underlying economic performance, analysts may not fully incorporate this information into their forecasts. If analysts only partially integrated this data, their forecasts may have become a less accurate proxy for investors' expectations for treatment firms in the post period, i.e., a larger measurement error of unexpected earnings for these firms. The resulting increase in measurement error will bias ERCs downward (Kothari, 2001), making it more difficult to detect the increase in ERCs for treatment firms.

To assess this possibility, our untabulated analysis examines whether consensus analyst forecasts of retail firms' earnings are more accurate after satellite data become available. We find no evidence of a change in the accuracy of consensus analyst forecasts for treatment firms relative to control firms. This finding is consistent with Katona et al. (2023), which suggests that financial analysts and mutual fund managers have not widely adopted satellite data. In summary, because of measurement error in earnings surprises, our findings likely represent a lower bound on the effect of satellite data.

5.2 Parallel trends assumption

The key identification assumption for the difference-in-differences estimation is the parallel trends assumption: in the absence of treatment, treated and control firms should have parallel trends in ERCs. While this assumption is not directly testable, following Roberts and Whited (2013), we examine the trends in ERCs prior to the availability of satellite data (treatment). Specifically, we rerun Equation (1) each year in the period from three years before to three years after the availability of satellite imagery data and plot the estimated ERCs for both treated and control groups in Figure 2. Regressions are based on an entropy-balanced sample, which re-weights control observations to match the treatment observations better. In Figure 2, we do not find a significant difference in ERCs between treated and control groups before the availability of the satellite data. In contrast, in the post-period, the treated group has an increase in ERCs. Overall, this evidence suggests that the assumption of parallel trends is reasonable.

5.3 Financial reporting quality

Next, we explore whether satellite data helps stakeholders monitor management, thereby disciplining managers' opportunistic reporting choices. Hence, we examine whether the availability of satellite imagery data on car traffic in retail firms' parking lots is associated with an improvement in the quality of financial reports.

First, we construct two quarterly measures of financial reporting quality using discretionary accruals, *Abs(DACC_TA)* and *Abs(DACC_WAC)*, defined as the absolute value of abnormal accruals estimated based on total operating accruals and working capital accruals, respectively.[7] We measure abnormal accruals as residuals of the Dechow and Dichev (2002) model modified by McNichols (2002). Specifically, Dechow and Dichev (2002) map current accruals into current, past, and future FASB-defined operating cash flows. McNichols (2002) modifies the Dechow and Dichev (2002) model by adding sales growth and PP&E to control for the effect of performance on short-term working capital accruals. The residuals from the modified Dechow and Dichev (2002) model reflect the extent to which accruals do not map into FASB-defined operating cash flows—due to intentional and unintentional estimation errors—and inversely measure the quality of the accruals that are reported. In addition, following Collins et al. (2017), we control for nonlinear performance and growth when measuring *Abs(DACC_TA)* and *Abs(DACC_WAC)* in the quarterly setting.

Second, since satellite imagery data is closely linked to a retailer's sales revenue, discretionary accruals may not indicate the reporting quality of revenue. Therefore, we use revenue-related restatements as an alternative measure of revenue misreporting even though the effect on restatement is ex ante unclear. We obtain these restatements from Audit Analytics over our sample period and define an indicator variable, *Restatement*, which equals one if the financial statements for quarter *t* are restated and zero otherwise.

To investigate the effect of the availability of satellite data on financial reporting quality, we estimate the following DID model at the firm-quarter level:

$$Abs(DACC)\ or\ Restatement = a_0 + a_1\, Post_{i,t} \times Treat_{i,t} + a_2\, Treat_{i,t} + a_3\, Post_{i,t} + Controls_{i,t} + Year\text{-}quarter\ and\ Firm\ Fixed\ Effects + e_{i,t}, \quad (2)$$

[7] The accrual-based measure is more appropriate for our setting than fraud-based measures (e.g., AAER restatements) because the impact of satellite data on the latter is ambiguous. On one hand, satellite data could deter managerial misreporting, thereby reducing the likelihood of restatements. On the other hand, investors might use satellite data to detect fraud, potentially increasing the likelihood of restatements.

Where the dependent variable is one of two accrual quality measures, *Abs(DACC_TA)* and *Abs(DACC_WAC)* — a higher value of the absolute value of discretionary accruals indicates lower financial reporting quality — or the indicator variable, *Restatement*. Control variables include firm size, market-to-book ratio, profitability (measured by sales growth and a loss indicator), return volatility, Big 4 auditors, sales growth, analyst coverage, analyst forecast dispersion, institutional ownership, and an indicator variable for the fourth fiscal quarter. In addition, we include year-quarter and firm-fixed effects to control for unobserved heterogeneity over time and across firms. Lastly, we cluster standard errors by firm and earnings announcement date.

Table 3 presents the estimation results of Equation (2). Panel A presents the results for two measures of accrual quality. In columns (1) and (2), for both measures of modified Dechow and Dichev (2002) 's accrual quality, we find that the coefficient on $Post_{i,t} \times Treat_{i,t}$ is negative and statistically significant (a_1 = -0.005, t-statistic = -3.30 in Column (1); a_1 = -0.005, t-statistic = -3.38 in Column (2)). This evidence is consistent with satellite data disciplining managers' opportunistic reporting behavior, thereby improving financial reporting quality.

Panel B presents results for *Restatement*. Column (1) reports OLS estimates, while Column (2) reports probit estimates without fixed effects. In both cases, the coefficient on $Post_{i,t} \times Treat_{i,t}$ is negative and statically significant (a_1 = -0.026, t-statistic = -2.81 in Column (1); a_1 = -0.746, z-statistic = -2.95 in Column (2)), suggesting that the availability of satellite data reduces the likelihood of revenue related restatements.

5.4 Information uncertainty reduction around earnings announcements

Next, we test the *information mosaic channel*. If satellite data helps investors estimate the reporting bias and thus better understand the implications of reported earnings for future cash flows, uncertainty about earnings after earnings announcements should go down. Following Neilson (2022), we use option implied volatility around earnings announcements to proxy for investor uncertainty about earnings. Prior studies use option implied volatility to measure investors' uncertainty about fundamentals, which could be affected by several firm and market characteristics. To isolate the impact of earnings news on investors' uncertainty, we employ the change in option implied volatility in a short window around earnings announcements. To examine the relation between the availability of satellite data and changes in implied volatility around earnings announcements, we estimate the following OLS model:

$$\Delta ImpVol_{i,t} = a_0 + a_1 Post_{i,t} \times Treat_{i,t} + a_2 Treat_{i,t} + a_3 Post_{i,t} + Controls_{i,t} + \text{Year-quarter and Firm Fixed Effects} + e_{i,t}, \quad (3)$$

where the dependent variable $\Delta ImpVol_{i,t}$ is the percent change in the firm's 91-day option implied volatility from two days after the earnings announcement to two days before it. In addition, we measure the $\Delta ImpVol_{i,t}$ from one day after to one day before the earnings announcement. Control variables include firm size, market-to-book ratio, profitability (measured by sales growth and a loss indicator), return volatility, Big 4 auditors, sales growth, analyst coverage, analyst forecast dispersion, institutional ownership, and an indicator variable for the fourth fiscal quarter. We include year-quarter and firm fixed effects to control for unobserved heterogeneity over time and across firms. Lastly, we cluster standard errors by firm and earnings announcement date.

Table 4 presents the estimation results of Equation (3). In Columns (1) and (2), we find that the coefficient on $Post_{i,t} \times Treat_{i,t}$ is negative and statistically significant (a_1= -2.129, t-statistic = -2.62 in Column (1); a_2= -1.655, t-statistic = -2.49 in Column (2)). This evidence suggests satellite data reduces investors' uncertainty around earnings announcements.

5.5 *Information gathering after earnings announcements*

Furthermore, if the availability of satellite data reduces investors' uncertainty about reporting biases, we expect investors to require less explanation and have less incentive to gather additional information. To test this conjecture, we examine whether the availability of satellite data affects investors' information gathering following earnings announcements.

Recent literature finds evidence supporting that various market participants use financial filings available from the EDGAR database, such as financial analysts (Gibbons, Iliev, and Kalodimos 2019), institutional investors (Chen, Cohen, Gurun, Lou, and Malloy 2020; Crane, Crotty, and Umar 2021), and investors in general (Lee, Ma, and Wang 2015; Loughran and McDonald 2017; Drake, Roulstone, and Thornock 2015). The SEC EDGAR server log files record and store user access statistics for regulatory filings, including annual and quarterly reports (10-K and 10-Q), current reports (8-K), and proxy statements (DEF 14A), among others.

Drake et al. (2016) document that historical filings provide information to assess the accounting discretion exercised by managers. Thus, we measure investors' information gathering in response to uncertainty about reporting biases based on downloads of historical filings stored in the SEC EDGAR database. Using the EDGAR server logs, we construct two measures of SEC EDGAR historical filing downloads: (1) the number of downloads for EDGAR filings in the 24 hours immediately after the earnings announcement (day 0); (2) the number of downloads for EDGAR filings in two days after the announcement (day 2). If the *information mosaic channel* plays a role, we expect investors to download fewer corporate historical filings from EDGAR after satellite data becomes available.

We rerun Equation (3) with two measures of SEC EDGAR filing downloads as the dependent variable in a difference-in-differences model. Table 5 presents results from regression estimations. In both columns, we find that the coefficient on $Post_{i,t} \times Treat_{i,t}$ is negative and statistically significant (a_1 = -0.693, t-statistic = 3.01 in Column (1); a_1 = -0.597, t-statistic = -2.11 in Column (2)). The EDGAR usage results are consistent with the conjecture that satellite data decreases investors' uncertainty about reported earnings and thereby decreases their information gathering.

5.6 *Cross-sectional analysis*

So far, our results suggest that the availability of satellite data improves the informativeness of earnings by (1) serving as a disciplining device and (2) helping investors better quantify reporting biases and process earnings information. Finally, we conduct three cross-sectional tests to better understand when satellite data matters more to investors — specifically, when it better reflects firms' fundamental performance and when it is in higher demand by investors.

5.6.1 Mapping between satellite data and fundamental performance

Our first set of cross-sectional tests examines whether the effect of satellite data is more pronounced when it maps better into a firm's performance. Following Katona et al. (2023), we use firm-level parking lot fill rate at the quarter level as the performance signal based on satellite data. For firm i during quarter q, we first compute the average parking lot fill rate at the store level: average the number of cars parked divided by the number of parking lot spaces available at each store location during the quarter. Second, we calculate the seasonally adjusted parking lot fill rate at the store level by comparing quarter q to quarter $q - 4$. Last, we measure the firm-level parking lot fill rate by averaging seasonally adjusted parking lot fill rate across all stores during quarter q. Like Kang (2023), we use the correlation between the firm-level parking lot fill rate and sales growth to measure the precision of satellite data as a signal of firm performance.[8] Then, we rerun Equation (1) conditional on the precision of satellite data.

$$CAR[-1, 1]_{i,t} \text{ or } CAR[-2, 2]_{i,t} = a_0 + a_1\, UE\_Rank_{i,t} + a_2\, UE\_Rank_{i,t} \times Post_{i,t} \times Treat(High\_Mapping{=}1)_{i,t} + a_3\, UE\_Rank_{i,t} \times Post_{i,t} \times Treat(Low\_Mapping{=}1)_{i,t} + a_4\, UE\_Rank_{i,t} \times Treat(High\_Mapping{=}1)_{i,t} + a_5\, UE\_Rank_{i,t} \times Treat(Low\_Mapping{=}1)_{i,t} + a_6\, UE\_Rank_{i,t} \times Post_{i,t} + a_7\, Treat(High\_Mapping{=}1)_{i,t} \times Post_{i,t} + a_8\, Treat(Low\_Mapping{=}1)_{i,t} \times Post_{i,t} + a_9\, Treat(High\_Mapping{=}1)_{i,t} + a_{10}\, Treat(High\_Mapping{=}1) + a_{11}\, Post_{i,t} + Controls_{i,t} + UE\_Rank_{i,t} \times Controls_{i,t} + \text{Year-quarter and Firm Fixed Effects} + e_{i,t}, \tag{4}$$

where indicator variable *Treat(High_Mapping=1)* (*Treat(Low_Mapping=1)*) equals one if the correlation between the treated firm's parking lot fill rate and its sales growth is greater (lower) than the sample median, and zero otherwise. Table 6 presents the results from estimating Equation (4). In both columns, we find a positive and significant coefficient on $UE\_Rank_{i,t} \times Post_{i,t} \times Treat(High\_Mapping{=}1)_{i,t}$ but not a significant coefficient on $UE\_Rank_{i,t} \times Post_{i,t} \times Treat(Low\_Mapping{=}1)_{i,t}$. The difference between these two coefficients is also statistically significant.

Additionally, we use the number of business segments as another proxy for the relevance of satellite data, as satellite data maps more closely with firm performance when a firm primarily operates in the retail sector. In contrast, when firms have multiple business segments, we expect satellite data to be less correlated with a firm's performance, leading to a smaller effect of satellite data on the price reactions to earnings news. We measure the number of business segments at the four-digit SIC code level for each firm-year and re-estimate Equation (1) on two subsamples: single-segment and multi-segment firms. As expected, Table 7 shows that the coefficient on $UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t}$ is positive and significant only for single-segment firms (columns 1

[8] Our results are robust to use the alternative measure of the mapping between the signal of satellite data and firm performance: the absolute difference between the parking lot fill rate and sales growth for each quarter.

and 3) but not for multi-segment firms (columns 2 and 4). The difference between these coefficients is also statistically significant.[9]

5.6.2 Investor's demand for satellite data

Our second cross-sectional test examines whether the effect of satellite data is more pronounced when investors perceive lower auditor quality. When high-quality auditors reliably verify the accuracy of earnings reports, we expect satellite data to play a less important verification role. We use auditor quality as a proxy for auditors' verification of financial information, as high-quality auditors build their reputation by carefully reviewing accounting numbers (Teoh and Wong, 1993; Frankel, Johnson, and Nelson, 2002).

Following Teoh and Wong (1993), we consider Big 4 auditors to deliver higher audit quality than non-Big 4 auditors[10]. Table 8 estimates Equation (1) based on these two subsamples: firms audited by Big 4 or non-Big 4. Consistent with the perceived credibility explanation, Table 5 shows that firms audited by Big 4 auditors are less affected by the availability of satellite data. In particular, we observe that the coefficient on $UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t}$, is larger among firms that employ non-Big 4 auditors in column 2 (0.048, t=4.57) compared to Big 4 auditors in

[9] The relevance of satellite data is diminished when online sales account for a significant portion of revenue. After reviewing the 10-Ks of 46 treatment firms, we found only 8 firms disclosing the level of on-line sales, and these disclosures were subject to managerial discretion. Given the limited data and its discretionary nature, we chose not to measure relevance based on the proportion of revenue derived from online sales. For retailers, online sales account for a relatively small proportion of total sales. According to the Census Bureau of the Department of Commerce, e-commerce as a percentage of total retail sales ranged from 4.5% in the first quarter of 2011 to 9.9% in the last quarter of 2018. For more details, refer to the quarterly E-Commerce report historical data at: https://www.census.gov/retail/ecommerce/historic_releases.html.

[10] Additionally, we use annual versus quarterly reports as an alternative proxy for auditor effort and quality, given that auditor oversight may primarily benefit annual reports due to the fiscal year-centric nature of audits. We re-estimate Equation (1) using two subsamples: fourth-quarter and non-fourth-quarter reports. In untabulated analysis, we find that the coefficient on $UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t}$ is positive and significant for the non-fourth-quarter subsample but not for the fourth-quarter subsample.

column 1 (0.010, t=2.52) and the difference between these two coefficients is statistically significant (Chi-square = 66.73).

Our final cross-sectional test examines whether the effect of satellite data is more pronounced when investors face greater uncertainty about reporting biases. We hypothesize that the marginal effect of satellite data is greater when uncertainty about managerial reporting biases is greater, as investors are more likely to rely on satellite data to identify the direction and magnitude of the reporting bias. We use Hribar et al.'s (2022) measure, which captures the extent to which GAAP limits managers' reporting discretion, as our proxy. When GAAP imposes fewer limits on reporting discretion, managers have greater latitude in applying accounting standards, and investors face increased uncertainty about potential reporting biases. Using the sample median of Hribar et al.'s (2022) score capturing the extent to which GAAP limits managers' reporting discretion, we divide our data into two subsamples: high uncertainty (firms with below-median scores) and low uncertainty (firms with above-median scores). Table 10 presents the estimation results for Equation (1) across these subsamples. In columns (1) - (4), we observe that the coefficient on the $UE\_Rank_{i,t} \times Post_{i,t} \times Treat_{i,t}$, is only significantly positive for firms with below-median scores on the Hribar et al. (2022) measure. In addition, the Chi-squared test suggests that the DID coefficient is significantly different across the two subsamples in columns (1) and (2).

6. Conclusion

Using satellite imagery data on the parking lot traffic of retail firms as a source of real-time alternative data, we examine whether alternative data complements the information contained in earnings announcements. Using a stacked DID research design, we find that firms experience stronger market reactions to unexpected earnings following the coverage of satellite data. Our results suggest that the availability of satellite imagery data improves the informativeness of earnings. We find evidence consistent with satellite imagery data being used to discipline managers' financial reporting decisions, thereby improving the information content of earnings. We also find evidence consistent with alternative data helping investors estimate the bias in earnings and thus better understand the implications of earnings for future cash flow.

Our evidence adds to the concurrent research on the role of alternative data in capital markets. Current research shows that real-time alternative data provides timely information on underlying firm performance, prompting inquiry into the relevance of less timely accounting information. Our study adds nuance to this conversation and provides evidence that third-party alternative data also adds value to the information contained in financial reports, increasing the market's reliance upon and discernment of reported earnings. In this respect, our study implies that earnings reports continue to be decision useful in the era of new technologies that produce a plethora of informative and timely alternative data.

We caution that our evidence speaks to alternative data that provide objective, externally generated measures of firms' underlying economic activity, such as satellite imagery. Accordingly, our conclusions may not generalize to alternative data that primarily reflects subjective opinions or personal sentiment, such as employee reviews or social media content. In addition, our data do not allow us to separately identify how specific characteristics of alternative data, such as timeliness and independence, shape earnings' information contents. Disentangling these channels is an important avenue for future research.

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Appendix 1. List of Companies Covered by R.S. Metrics in the U.S.

Ticker	Company Name	Coverage Date
BBBY	Bed Bath & Beyond Inc.	1/12/2012
BBY	Best Buy Co., Inc.	3/19/2013
BGFV	Big 5 Sporting Goods Corporation	11/10/2013
BIG	Big Lots, Inc.	12/24/2012
BJRI	BJ's Restaurants, Inc.	11/10/2013
BURL	Burlington Stores, Inc.	6/28/2016
BWLD	Buffalo Wild Wings, Inc.	5/10/2012
CAB	Cabela's Inc.	11/10/2013
CMG	Chipotle Mexican Grill, Inc.	5/20/2012
CONN	Conn's, Inc.	9/10/2015
COST	Costco Wholesale Corporation	8/30/2017
CWH	Camping World Holdings, Inc.	2/23/2017
DDS	Dillard's Inc.	12/20/2016
DG	Dollar General Corporation	6/10/2013
DKS	Dick's Sporting Goods Inc.	9/10/2015
DLTR	Dollar Tree, Inc.	6/10/2014
FDO	Family Dollar	12/28/2016
FIVE	Five Below, Inc.	12/11/2017
HD	The Home Depot, Inc.	6/13/2012
JCP	J.C. Penney Company, Inc.	12/10/2011
JWN	Nordstrom, Inc.	12/20/2016
KMX	CarMax Inc.	1/10/2017
KR	The Kroger Co.	3/10/2016
KSS	Kohl's Corporation	6/14/2013
LL	LL Flooring	8/10/2013
LOCO	El Pollo Loco Holdings, Inc.	5/10/2016
LOW	Lowe's Companies, Inc.	6/13/2012
M	Macy's, Inc.	3/10/2013
MNRO	Monro, Inc.	3/1/2013
OLLI	Ollie's Bargain Outlet Holdings, Inc.	6/14/2018
PIR	Pier 1 Imports, Inc.	4/21/2015
PNRA	Panera Bread	11/10/2011
PRTY	Party City Holdco Inc.	5/10/2016
ROST	Ross Stores, Inc.	3/20/2015
SBUX	Starbucks Corporation	2/12/2012
SFS	Smart & Final Stores, Inc.	11/22/2016
SHLD	Sears Holdings Corporation	6/10/2013
SHW	Sherwin-Williams Company	5/20/2012

SPG	Simon Property Group, Inc.	5/10/2016
SPLS	Staples, Inc.	3/20/2013
TCS	The Container Store Group, Inc.	5/24/2015
TGT	Target Corporation	12/1/2011
TJX	The TJX Companies, Inc.	6/24/2016
TSCO	Tractor Supply Company	2/10/2012
ULTA	Ulta Beauty, Inc.	9/10/2012
WFM	Whole Foods Market, Inc.	2/10/2015
WMT	Walmart Inc.	3/3/2011

Appendix 2. Variable Definitions

Variables	Definitions
CAR[-1,1]	Cumulative abnormal return over trading days [-1, 1] around earnings announcement (day 0). Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio. The benchmark portfolios are constructed using Fama and French's (1992) method. All firms with CRSP share codes 10 and 11 are classified into 25 portfolios by size at the end of June of year t and by the book-to-market ratio at the end of December of year t - 1.
CAR[-2,2]	Cumulative abnormal return over trading days [-2, 2] around earnings announcement (day 0). Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio. The benchmark portfolios are constructed using Fama and French's (1992) method. All firms with CRSP share codes 10 and 11 are classified into 25 portfolios by size at the end of June of year t and by the book-to-market ratio at the end of December of year t - 1.
Abs(DACC_TA)	Modified Dechow-Dichev discretionary accruals, measured as the absolute value of residuals from the Dechow and Dichev (2002) model modified by McNichols (2002) with nonlinear performance and growth controls (Collins et al. 2017). *Abs(DACC_TA)* is estimated with total operating accruals as the dependent variable.
Abs(DACC_WAC)	Modified Dechow-Dichev discretionary accruals, measured as the absolute value of residuals from the Dechow and Dichev (2002) model modified by McNichols (2002) with nonlinear performance and growth controls (Collins et al. 2017). *Abs(DACC_WAC)* is estimated with the change in working capital accruals as the dependent variable.
Restatement	An indicator variable equals one if a firm restates its revenue in the current quarter, and zero otherwise.
Δ *ImpVol [+1,-1]*	The percent change in the firm's 91-day option implied volatility from one day before to one day after the earnings announcement.
Δ *ImpVol [+2,-2]*	The percent change in the firm's 91-day option implied volatility from two days before to two days after the earnings announcement.
Log(#Downloads)_Day0	Total number of downloads of a firm's EDGAR historical filings on the day its earnings are announced.
Log(#Downloads)_Day2	Total number of downloads of a firm's EDGAR historical filings on the second day after earnings are announced (day t+2).

Post	An indicator variable equals one for 3 years (12 quarters) after R.S. metrics covers firm *i*, and zero otherwise.
Treatment	An indicator variable that equals one if R.S. metrics covers firm *i* in year *t*, and zero otherwise
UE	Unexpected earnings based on the consensus analyst forecasts within 90 days before the earnings announcement, scaled by price as of the end of the fiscal quarter.
UE_Rank	Decile ranking of unexpected earnings, ranging from 0 to 9. A ranking of 0 (9) represents the decile with the lowest (highest) unexpected earnings.
Size	Total assets
Price	Stock price at the end of the fiscal quarter
BTM	Book value of common shares divided by the market value of equity.
Growth	Growth in sales
Volatility	Return volatility, as measured by daily return volatility in quarter t.
#Analysts	The number of analysts who provide earnings forecasts for the firm within 90 days before the earnings announcement.
Dispersion	The standard deviation of analyst quarterly EPS forecasts.
Big4	An indicator variable equals one if the auditor is one of the Big 4 auditors in year t, and zero otherwise.
Loss	An indicator variable equals one if income before extraordinary items in quarter t is negative and zero otherwise.
InstOwn	Percentage of common shares held by institutional investors. The data is available from the Thomson-Reuters Institutional Holdings (13F) Database.
# EA	The number of firms announcing earnings on the same day
Qtr4	An indicator variable equals one if quarter t is the fourth quarter of the fiscal year and zero otherwise.

Figure 1. The Number of Walmart Stores Covered by R.S. Metrics in the U.S.

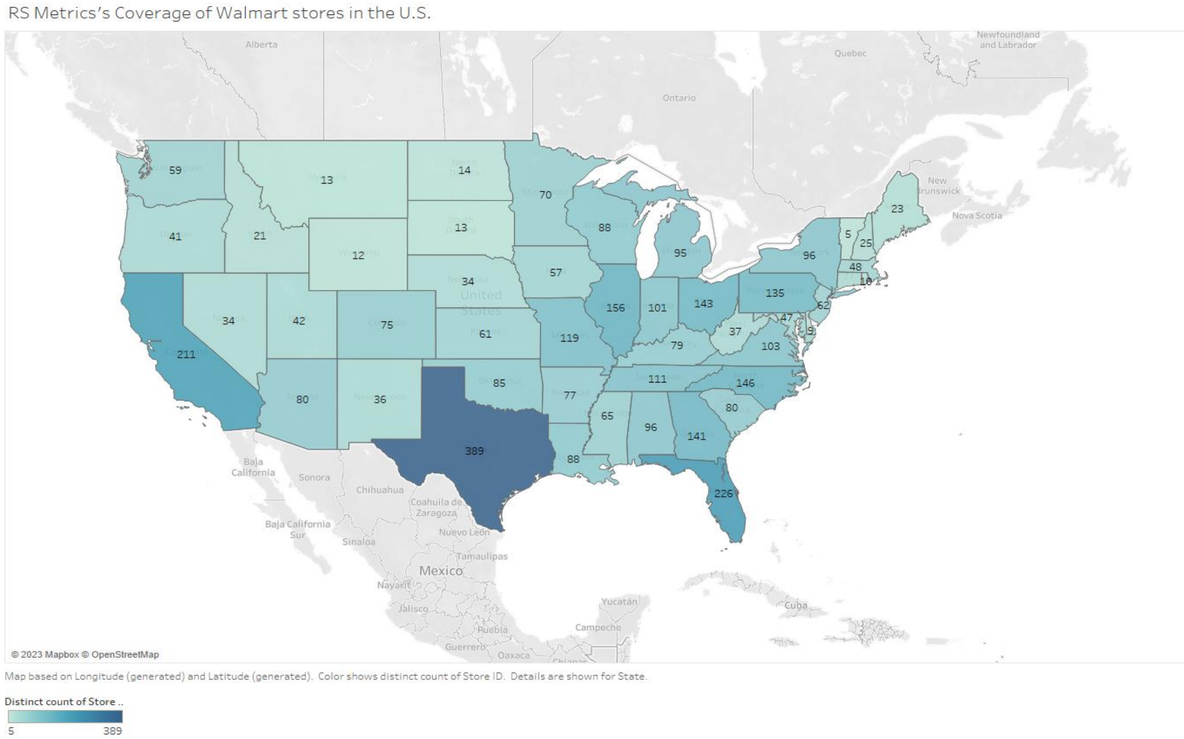

Figure 2. The Trends of ERCs for Treatment and Control Samples

This figure plots the earnings response coefficients (ERCs) estimated from running Equation (1) each year in the period from the three years before to the three years after the availability of satellite imagery data. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations.

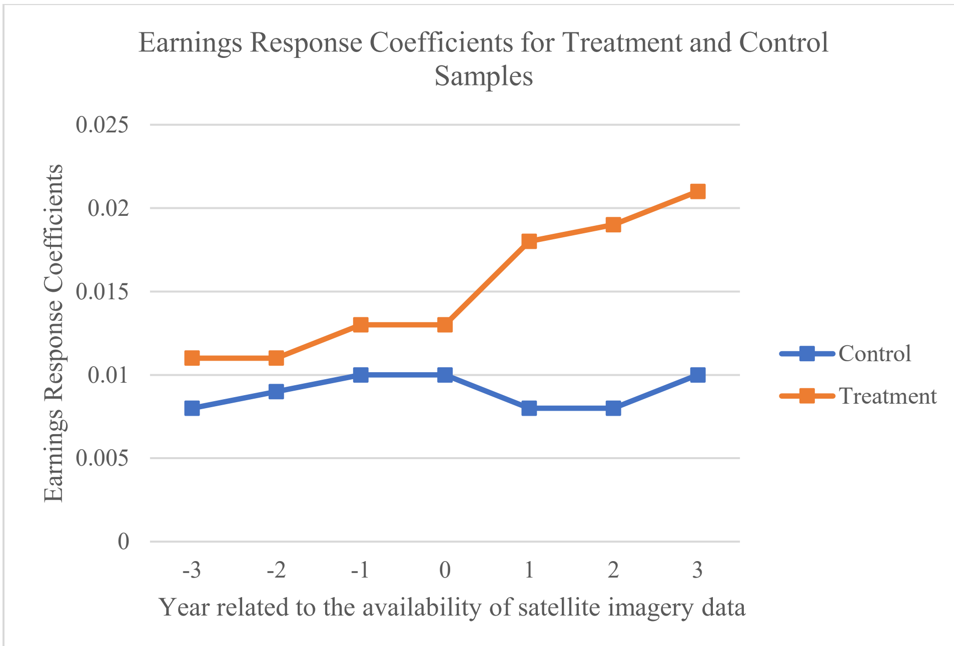

Table 1. Summary Statistics

This table presents descriptive statistics for key variables in our sample. Variable definitions are provided in Appendix 2.

Panel A: Summary statistics for the full sample

	N	Mean	STD	25%	Median	75%
Dependent variables						
CAR[-1,1](%)	5,145	-0.17	7.69	-3.42	-0.17	3.08
CAR[-2,2](%)	5,145	-0.27	8.25	-3.77	-0.27	3.28
Abs(DACC_TA)	4,973	0.02	0.03	0.00	0.01	0.02
Abs(DACC_WCA)	4,973	0.02	0.03	0.00	0.01	0.02
Restatement	5,145	0.01	0.11	0.00	0.00	0.00
Δ *ImpVol[1,-1](%)*	4,875	-3.69	15.35	-9.65	-4.95	-0.12
Δ *ImpVol[2,-2](%)*	4,875	-3.13	19.77	-9.99	-5.02	0.69
#Downloads_Day0	3,590	224.16	534.66	32.00	32.00	129.00
#Downloads_Day2	3,590	149.97	369.74	0.00	11.00	61.00
Firm Characteristics						
UE(%)	5,145	-0.12	1.78	-0.07	0.03	0.19
Total asset	5,145	9,448.57	24,043.76	844.31	2,664.81	8,017.61
Price	5,145	44.72	53.98	16.04	29.65	55.32
BM	5,145	0.52	0.41	0.25	0.44	0.71
Growth	5,145	0.02	0.64	-0.05	0.01	0.08
IdioVol	5,145	0.02	0.01	0.01	0.02	0.02
#Analysts	5,145	10.31	7.99	4.00	7.00	15.00
Dispersion	5,145	0.14	1.77	0.01	0.02	0.05
Big4	5,145	0.90	0.30	1.00	1.00	1.00
Loss	5,145	0.16	0.36	0.00	0.00	0.00
InstOwn	5,145	0.55	0.42	0.00	0.69	0.92
#EA	5,145	269.05	168.85	119.00	239.50	410.00
Qtr4	5,145	0.15	0.35	0.00	0.00	0.00

Panel B: Summary statistics for treatment and control samples

	Treated Sample			Control Sample		
	N	Mean	STD	N	Mean	STD
Firm Characteristics						
Total asset	821	22,933.53	40,103.54	4,324	6,885.06	18,478.03
Price	821	73.17	80.26	4,473	39.31	45.40
BM	821	0.32	0.24	4,473	0.56	0.42
Growth	821	0.03	0.20	4,473	0.02	0.70
IdioVol	821	0.02	0.01	4,473	0.02	0.01
#Analysts	821	18.55	7.19	4,473	8.75	7.13
Dispersion	821	0.05	0.12	4,473	0.15	1.93
Big4	821	0.99	0.11	4,473	0.88	0.33
Loss	821	0.06	0.24	4,473	0.18	0.38
InstOwn	821	0.30	0.43	4,473	0.59	0.40
#EA	821	206.35	168.32	4,473	280.97	166.32
Qtr4	821	0.21	0.41	4,473	0.13	0.34

Table 2: Availability of Satellite Data and ERCs

This table presents results from the estimation of Equation (1). We regress 3-day or 5-day cumulative abnormal returns around earnings announcements (*CAR[-1,1] or CAR[-2,2]*) on the ranked measure of unexpected earnings (*UE_Rank*), indicators for treatment firms, treatment period and their interaction (*Treat, Post, Post × Treat*), control variables, year-quarter fixed effects, firm fixed effects and the interactions of *UE_Rank* with treatment indicators and control variables. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	CAR[-1,1]		*CAR [-2, 2]*	
	(1)	(2)	(3)	(4)
UE_Rank	0.012***	0.030**	0.013***	0.041***
	(7.74)	(2.13)	(6.85)	(2.61)
UE_Rank × Post × Treat	0.010***	0.009**	0.014***	0.011**
	(2.59)	(2.33)	(3.00)	(2.53)
UE_Rank × Post	-0.001	0.000	-0.003	-0.002
	(-0.64)	(0.16)	(-1.12)	(-0.84)
UE_Rank × Treat	-0.001	0.001	-0.003	-0.001
	(-0.23)	(0.21)	(-0.88)	(-0.19)
Post × Treat	-0.047**	-0.044**	-0.055**	-0.047**
	(-2.43)	(-2.39)	(-2.28)	(-2.04)
Post	0.015	0.005	0.016	0.011
	(1.31)	(0.44)	(1.13)	(0.78)
Treat	0.008	0.003	0.027	0.016
	(0.53)	(0.17)	(1.17)	(0.71)
Size	-0.013	0.008	-0.029*	0.007
	(-1.17)	(0.62)	(-1.91)	(0.40)
log(Price)	-0.004	-0.009	0.006	-0.020
	(-0.31)	(-0.63)	(0.37)	(-1.10)
BM	-0.014	-0.050	0.049	0.021
	(-0.47)	(-1.13)	(1.64)	(0.60)
Growth	0.023**	-0.007	0.015	-0.043
	(2.01)	(-0.29)	(1.03)	(-1.44)
IdioVol	0.033	0.228	-0.414	-0.029
	(0.07)	(0.23)	(-0.72)	(-0.03)
log(#Analysts)	-0.008	-0.028	-0.026	-0.057***
	(-0.52)	(-1.59)	(-1.27)	(-2.75)
Dispersion	-0.063	-0.072	0.017	0.087
	(-1.44)	(-1.29)	(0.54)	(1.64)
Big4	-0.072*	-0.094*	0.017	0.012

	(-1.94)	(-1.78)	(0.46)	(0.20)
Loss	-0.025*	0.009	-0.031**	-0.019
	(-1.89)	(0.44)	(-2.01)	(-0.80)
InstOwn	-0.039*	-0.029	-0.034	-0.036
	(-1.76)	(-1.09)	(-0.99)	(-0.98)
Log(#EA)	0.009***	0.017***	0.009**	0.024***
	(2.71)	(2.81)	(2.39)	(3.18)
Qtr4	0.011	0.061	0.079	0.125
	(0.19)	(0.98)	(0.91)	(1.38)
UE_Rank × Controls	No	Yes	No	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	5,145	5,145	5,145	5,145
Adjusted R-squared	0.190	0.219	0.175	0.215

Table 3: Availability of Satellite Data and Financial Reporting Quality

This table presents results from the estimation of Equation (2). In Panel A, we regress the absolute value of discretionary accruals, estimated from the modified Dechow and Dichev (2002) model, on indicators for treatment firms, treatment period and their interaction (*Treat, Post, Post* × *Treat*), control variables, year-quarter fixed effects, and firm fixed effects. In Panel B, we regress the indicator variable of revenue related restatements, *Restatement*, on indicators for treatment firms, treatment period and their interaction (*Treat, Post, Post* × *Treat*), control variables, year-quarter fixed effects, and firm fixed effects. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 1. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

Panel A: Discretionary accruals

	Modified Dechow and Dichev (2002)	
	Abs(DACC_TA)	*Abs(DACC_WAC)*
	(1)	(2)
Post × *Treat*	-0.005***	-0.005***
	(-3.30)	(-3.88)
Post	0.003**	0.003**
	(2.47)	(2.34)
Treat	0.004**	0.003
	(2.15)	(1.57)
Size	-0.003	-0.000
	(-1.30)	(-0.07)
log(Price)	0.001	0.000
	(0.59)	(0.14)
BM	-0.003	0.002
	(-0.66)	(0.62)
Growth	0.001	0.000
	(0.51)	(0.18)
IdioVol	-0.073	-0.098
	(-1.22)	(-1.61)
log(#Analysts)	0.000	-0.000
	(0.14)	(-0.07)
Dispersion	-0.000	-0.000
	(-0.19)	(-0.17)
Big4	0.005	0.004
	(1.47)	(1.13)
Loss	0.002	0.002
	(0.99)	(1.31)
InstOwn	0.014**	0.006*

	(2.52)	(1.78)
Qtr4	0.015***	0.013***
	(3.46)	(2.74)
Year-quarter FEs	Yes	Yes
Firm FEs	Yes	Yes
Observations	4,972	4,972
Adjusted R-squared	0.309	0.327

Panel B: Revenue related restatements

	Restatement	
	OLS	Probit
	(1)	(2)
Post × Treat	-0.026***	-0.746***
	(-2.81)	(-2.95)
Post	-0.003	0.326**
	(-0.42)	(2.51)
Treat	-0.011	0.506***
	(-1.28)	(3.09)
Size	0.044***	-0.014
	(3.24)	(-0.30)
log(Price)	0.003	-0.251***
	(0.34)	(-3.22)
BM	-0.014	-0.568**
	(-0.51)	(-2.45)
Growth	0.009	-0.030
	(0.74)	(-0.58)
IdioVol	-0.018	-0.395
	(-0.04)	(-0.09)
log(#Analysts)	-0.027	0.179*
	(-1.30)	(1.78)
Dispersion	-0.019	0.002
	(-0.29)	(0.31)
Big4	-0.033***	-0.126
	(-2.75)	(-0.75)
Loss	-0.020	-0.141
	(-1.52)	(-0.81)
InstOwn	0.133***	-0.024
	(3.32)	(-0.17)
Qtr4	0.020	-0.372**
	(0.49)	(-2.07)
Year-quarter FEs	Y	N
Firm FEs	Y	N
Observations	5,145	5,145
Adjusted R-squared	0.319	
Pseudo R-squared		0.066

Table 4: Availability of Satellite Data and Change in Implied Volatility

This table presents results from the estimation of Equation (3). We regress the change in implied volatility around earnings announcements on indicators for treatment firms, treatment period and their interaction (*Treat, Post, Post* × *Treat*), control variables, year-quarter fixed effects, and firm fixed effects. The variable Δ *ImpVol* is the percent change in the firm's 91-day option implied volatility from two days before to two days after the earnings announcement. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	Δ *ImpVol*	
	[+1, -1]	[+2, -2]
	(1)	(2)
Post × *Treat*	-1.655**	-2.129***
	(-2.49)	(-2.62)
Post	0.244	-0.139
	(0.50)	(-0.23)
Treat	1.100	1.028
	(1.05)	(0.84)
Abs(UE)	-0.200	-0.056
	(-1.61)	(-0.42)
Size	1.139	-0.861
	(0.59)	(-0.44)
log(Price)	-3.634	-2.328
	(-1.47)	(-1.08)
BM	-2.085	-4.307*
	(-1.21)	(-1.79)
Growth	-0.897	-1.219
	(-1.02)	(-1.11)
IdioVol	-1.746	-4.747**
	(-1.16)	(-2.50)
log(#Analysts)	-0.058	0.060
	(-0.27)	(0.34)
Dispersion	-0.598	-4.842
	(-0.18)	(-1.57)
Big4	1.040	1.367
	(0.93)	(0.92)
Loss	0.579	0.133
	(0.32)	(0.05)
InstOwn	-0.332	-0.571
	(-0.94)	(-1.14)
Log(#EA)	-5.762	-8.452*

	(-1.44)	(-1.95)
Year-quarter FEs	Yes	Yes
Firm FEs	Yes	Yes
Observations	4,875	4,875
Adjusted R-squared	0.096	0.090

Table 5: Availability of satellite data and downloads of EDGAR historical filings

This table presents results from the estimation of Equation (3). We regress the number of downloads of EDGAR historical filings on indicators for treatment firms, treatment period and their interaction (*Treat, Post, Post* × *Treat*), control variables, year-quarter fixed effects, and firm fixed effects. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	Log(#Downloads)	
	Day 0	Day 2
	(1)	(2)
Post × *Treat*	-0.693***	-0.597**
	(-3.01)	(-2.11)
Post	-0.040	-0.035
	(-0.27)	(-0.20)
Treat	0.441	1.033**
	(1.10)	(2.13)
Abs(UE)	-0.006	-0.008
	(-0.27)	(-0.32)
Size	-0.240	-0.109
	(-0.60)	(-0.26)
log(Price)	-0.040	-0.230
	(-0.12)	(-0.72)
BM	0.459	0.393
	(0.84)	(0.61)
Growth	0.416*	0.528**
	(1.76)	(2.20)
IdioVol	0.743	-2.370
	(0.11)	(-0.30)
log(#Analysts)	0.501	0.402
	(1.14)	(0.90)
Dispersion	0.128	0.116
	(1.34)	(1.25)
Big4	0.024	-0.336
	(0.10)	(-1.24)
Loss	-0.035	-0.027
	(-0.15)	(-0.12)
Institutional Ownership	1.011***	0.994*
	(3.88)	(1.80)
Log(#EA)	-0.045	-0.157**
	(-0.65)	(-2.00)

Qtr4	4.149***	3.323***
	(6.49)	(4.69)
Year-quarter FEs	Yes	Yes
Firm FEs	Yes	Yes
Observations	3,590	3,590
Adjusted R-squared	0.745	0.701

Table 6: Availability of Satellite Data and ERCs: Conditional on Precision of Satellite Data

This table provides the estimation results of Equation (1) conditional on the precision of satellite data. The indicator variable *Treat(High_Mapping=1) (Treat(Low_Mapping=1))* equals one if the correlation between the treated firm's parking lot fill rate and its sales growth is greater (lower) than the sample median, and zero otherwise. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	CAR [-1, 1]	*CAR [-2, 2]*
	(1)	(2)
UE_Rank	0.012***	0.013***
	(7.67)	(7.51)
UE_Rank × Post × Treat (High Mapping =1)	0.014***	0.015***
	(2.65)	(2.93)
UE_Rank × Post × Treat (Low Mapping =1)	-0.008	-0.008
	(-1.37)	(-1.22)
UE_Rank × Treat (High Mapping =1)	-0.002	-0.003
	(-0.68)	(-0.92)
UE_Rank × Treat (Low Mapping =1)	0.003	0.003
	(0.78)	(0.71)
UE_Rank × Post	-0.002	-0.002
	(-0.70)	(-0.83)
Post × Treat (High Mapping =1)	-0.079***	-0.087***
	(-3.05)	(-3.37)
Post × Treat (Low Mapping =1)	0.059**	0.062**
	(2.04)	(2.06)
Treat (High Mapping =1)	-0.016	0.043
	(-0.27)	(0.70)
Treat (Low Mapping =1)	-0.010	-0.009
	(-0.21)	(-0.18)
Post	0.017	0.018
	(1.45)	(1.44)
F-test	4.55**	4.79**
Controls	Yes	Yes
UE_Rank × Controls	Yes	Yes
Year-quarter FEs	Yes	Yes
Firm FEs	Yes	Yes
Observations	5,145	5,145
Adjusted R-squared	0.193	0.182

Table 7: Cross-Sectional Analysis based on the Number of Business Segments

This table presents the estimation results of Equation (1) for subsamples of single-segment and multi-segment firms, with the number of business segments defined at the four-digit SIC code level. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	CAR [-1, 1]		*CAR [-2, 2]*	
	Single Segment	Multi Segment	Single Segment	Multi Segment
	(1)	(2)	(3)	(4)
UE_Rank	0.014***	0.010***	0.014***	0.011***
	(8.25)	(3.53)	(8.06)	(3.44)
UE_Rank × Post × Treat	0.012***	0.001	0.013***	0.002
	(2.76)	(0.62)	(2.90)	(0.65)
UE_Rank × Post	-0.003	0.001	-0.004	0.003
	(-1.20)	(0.41)	(-1.46)	(0.78)
UE_Rank × Treat	-0.003	0.004	-0.003	0.003
	(-1.10)	(0.67)	(-1.02)	(0.45)
Post × Treat	-0.054**	-0.009	-0.056**	-0.010
	(-2.37)	(-0.27)	(-2.30)	(-0.27)
Post	0.019	-0.001	0.022	-0.009
	(1.35)	(-0.04)	(1.51)	(-0.45)
Treat	0.016	-0.029	0.018	-0.017
	(0.92)	(-0.87)	(0.90)	(-0.47)
Chi-square Test	2.93*		2.85*	
Controls	Y	Y	Y	Y
UE_Rank × Controls	Y	Y	Y	Y
Year-quarter FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Observations	3,724	1,421	3,724	1,421
Adjusted R-squared	0.204	0.232	0.185	0.251

Table 8: Cross-Sectional Analysis based on Auditor Quality

This table provides the estimation results of Equation (1) for subsamples containing firms audited by Big 4 and non-Big 4 auditors. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	CAR [-1, 1]		*CAR [-2, 2]*	
	Big4	Non-Big4	Big4	Non-Big4
	(1)	(2)	(3)	(4)
UE_Rank	0.012***	0.007	0.013***	0.006
	(7.47)	(1.64)	(7.37)	(1.57)
UE_Rank × Post × Treat	0.010**	0.048***	0.012***	0.067***
	(2.52)	(4.57)	(2.81)	(7.27)
UE_Rank × Post	-0.001	0.004	-0.002	0.001
	(-0.65)	(0.95)	(-0.76)	(0.21)
UE_Rank × Treat	-0.000	-0.001	-0.001	-0.003
	(-0.09)	(-0.21)	(-0.45)	(-0.99)
Post × Treat	-0.047**	-0.069	-0.055***	-0.202***
	(-2.44)	(-1.04)	(-2.67)	(-3.18)
Post	0.016	-0.044*	0.017	-0.037
	(1.32)	(-1.95)	(1.36)	(-1.60)
Treat	0.007	0.033	0.012	0.050
	(0.44)	(0.37)	(0.68)	(0.73)
Chi-square Test	66.73***		83.15***	
Controls	Yes	Yes	Yes	Yes
UE_Rank × Controls	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	4,612	533	4,612	533
Adjusted R-squared	0.187	0.592	0.177	0.637

Table 9: Cross-Sectional Analysis based on Uncertainty of Managerial Reporting Bias

This table provides the estimation results of Equation (1) for subsamples of high and low uncertainty of managerial reporting bias. A firm has high (low) uncertainty of managerial reporting bias if GAAP's limits on managerial reporting discretion of a firm, as measured by Hribar et al. (2022), is below (above) the sample median. Regressions are based on entropy balancing, a quasi-matching technique that re-weights control observations to obtain better matching with the treatment observations. All the variables are defined in detail in Appendix 2. T-statistics based on standard errors are clustered by firm and earnings announcement date in parentheses. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively.

	CAR [-1, 1]		*CAR [-2, 2]*	
	High Uncertainty	Low Uncertainty	High Uncertainty	Low Uncertainty
	(1)	(2)	(3)	(4)
UE_Rank	0.012***	0.015***	0.013***	0.016***
	(4.55)	(6.92)	(4.68)	(6.72)
UE_Rank × Post × Treat	0.014*	0.002	0.011*	0.004
	(1.92)	(0.40)	(1.94)	(0.87)
UE_Rank × Post	-0.001	-0.003	0.000	-0.002
	(-0.17)	(-1.01)	(0.10)	(-0.55)
UE_Rank × Treat	-0.003	0.003	-0.002	0.001
	(-0.50)	(0.88)	(-0.30)	(0.35)
Post × Treat	-0.051	-0.005	-0.036	-0.022
	(-1.36)	(-0.19)	(-0.93)	(-0.79)
Post	0.010	0.005	0.006	0.002
	(0.44)	(0.35)	(0.27)	(0.12)
Treat	-0.032	-0.036*	-0.009	-0.029
	(-0.31)	(-1.69)	(-0.09)	(-1.23)
Chi-square Test	2.88*		2.24	
Controls	Y	Y	Y	Y
UE_Rank × Controls	Y	Y	Y	Y
Year-quarter FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Observations	1,747	1,792	1,747	1,792
Adjusted R-squared	0.203	0.237	0.203	0.231