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Big Data Availability and Asymmetric Voluntary Disclosures

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Abstract. We exploit staggered releases of satellite data on parking lot traffic across U.S. retailers and conduct the stacked Poisson regression to identify the causal effect of big data availability on corporate voluntary disclosure. We document a significant decrease in management good news forecasts following the satellite data release, whereas bad news forecasts are unaffected. The asymmetric decrease cannot be explained by the demand-side substitution hypothesis. Our evidence suggests that the supply-side "meeting guidance" hypothesis is likely to account for the disappearing good news forecasts. We also derive cross-sectional predictions from the hypothesis and confirm them in the data: The decrease in good news forecasts is more pronounced among short-horizon quarterly guidance than long-term forecasts and when firms have higher institutional ownership, higher operating uncertainty, and higher litigation risk of missing guidance.

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1. Introduction

How does the availability of big data affect corporate voluntary disclosure? Recent computing advancements have enabled the collection of real-time and granular signals of firm fundamentals and the availability of these "big data" has significantly reduced information acquisition costs for capital market investors. Although a growing literature focuses on the value-relevance and informativeness of big data to investors,[1] it is unclear how the *availability* of big data to market participants affects corporate decisions such as voluntary disclosures. One major impediment to this line of inquiries is that the timing of big data availability is rarely known. In this paper, we exploit a setting of precisely identified timing of big data availability and study how firms accordingly change their voluntary disclosure practices.

Specifically, we study the effects of *staggered releases* of high-resolution satellite imagery data on U.S. retailers' parking lot traffic (hereafter "satellite data"). Although the value-relevance and informativeness of big data vary for different types of data and firm business, it is clear that satellite data are highly informative of retail firms' operating performance (Zhu 2019). However, the process leading to the release of satellite data for a *given firm* is complex and costly because, to track the traffic of all operating locations of a particular firm, satellite data vendors have to use advanced technologies and machine learning algorithms to extract meaningful data from a variety of location-based satellite imagery sources. The release of satellite data are a major shock to the information environment of a firm, allowing investors to enjoy nearly real-time access to the data subsequently.

We utilize *staggered releases* of satellite data across firms to empirically identify the causal effects of big data availability on corporate voluntary disclosures at the firm level.[2] The timing of satellite data release is clearly out of managers' control and thus is plausibly exogenous to firms' disclosure practices because data release is mainly a function of technological feasibility (or big data vendors' business objectives).

Regarding voluntary disclosure practices, we focus on management forecasts for two reasons. First and more generally, the majority of existing voluntary disclosure studies use management forecasts as the main measure as they appear to explain a significant portion of the variations in stock returns (Healy and Palepu 2001, Beyer et al. 2010). Second and more specifically to our context, management forecasts are the quantitative financial metrics that link directly to our hypotheses.

Our research design employs the stacked difference-in-differences (DID) regression approach (Baker et al. 2022), which is estimated with a Poisson model when the outcome variable is a count variable (Cohn et al. 2022). Specifically, we view satellite release in a given year as an event for the treated firms and create event-specific cohorts, including the pre- and postevent treated and control observations. We then stack these cohorts according to the event time and estimate a DID regression with cohort-specific firm and year fixed effects. The control observations include not-yet- or never-treated observations during our sample period.

We document the baseline result that treated firms decrease their management forecasts by about 17.5% relative to control firms following the satellite data release. More importantly, the decrease is concentrated in good news forecasts (relative to analysts' expectation), whereas the decrease in bad news forecasts is neither economically nor statistically significant.

The asymmetric decrease cannot be explained by demand-side hypotheses, such as a general substitution between public information and voluntary disclosure (Diamond 1985, Diamond and Verrecchia 1991, Balakrishnan et al. 2014) or any specific decrease in demand from institutional investors (Ajinkya et al. 2005, Jung 2013). Moreover, the asymmetry results cannot be explained by the supply-side story that managers tend to withhold bad news from investors (Kothari et al. 2009, Ali et al. 2019).

The asymmetric decrease following satellite data release is consistent with a "meeting guidance" hypothesis, which follows managers' asymmetric incentives to meet or beat their own earnings guidance (Skinner 1994, Kasznik and Lev 1995, Kasznik 1999, Matsumoto 2002, Graham et al. 2005). As illustrated in Figure A.1, the intuition behind this hypothesis is that, as big data reveal relatively precise signals of the true state (e.g., good or bad state), the market adjusts its earnings expectation toward the true state sufficiently enough to create "asymmetric risk" for the managers to miss their own earnings guidance: The manager becomes reluctant to issue guidance to further "talk up" the market expectation in the good state because big data make it close to the true earnings expectation and thus the risk of missing the guidance is higher. By contrast, the manager's incentive to "walk down" the market expectation in the bad state remains strong due to the "threshold" effect that the market expectation is still above the true earnings expectation and walking it down is necessary to meet or beat the market expectation.

The meeting guidance hypothesis predicts that, under a set of general assumptions, the availability of big data will motivate managers to continue issuing bad news forecasts but discourage them from issuing good news forecasts.[3] The meeting guidance hypothesis also generates a set of cross-sectional predictions regarding the asymmetric decrease: The decrease in good news forecasts is stronger for short-horizon quarterly guidance than long-term forecasts (because satellite data provide more short-term value-relevant information); for firms with higher institutional ownership (because institutional investors are more likely to directly have access to satellite data); for firms with higher operating uncertainty (because the risk of missing guidance is higher); and for firms with higher expected litigation risk (because the reputation costs associated with missing guidance are higher). Our results support these unique predictions in the cross section of retail firms.

Besides forecast frequency, the meeting guidance hypothesis can potentially have indirect implications (although not direct predictions) on forecast precision. A decrease in forecast frequency and a reduction in forecast precision can potentially be substitutable (Cheng et al. 2013, Li and Zhang 2015). As managers become more concerned with missing their own guidance, they are less likely to issue precise good news forecasts to avoid providing "smoking gun" evidence that damages their reputation and increases legal liability (Baginski et al. 2002, Rogers and Van Buskirk 2009, Houston et al. 2019). Consistent with this implication, we find that managers are less likely to issue precise forecasts after the release of satellite data.

We acknowledge that other types of big data (e.g., credit card transactions and mobile device transactions) may also be released to investors during our sample period.[4] In addition, the release of satellite data may be correlated with some unobserved covariates that also affect firms' disclosure decisions. We take several steps to mitigate potential endogeneity concerns. First, we verify the parallel trend assumption by showing that the pretreatment trends are indistinguishable between the treated and control firms. Second, we present evidence that it is the data release date that causes the change in disclosure policy as opposed to the data start date, which is usually earlier than the release date.[5] Third, we restrict the control sample to not-yet-treated firm-year observations and thus remove the inherent differences between the treated and control groups. Fourth, we match treated and control samples using the entropy balancing method, which eliminates most of the differences in observed firm characteristics between treated and control firms. Fifth, we demonstrate that satellite data releases have little relationship with the underlying firm's prior disclosure policy and thus alleviate the concern for reverse causality.

Our study contributes to the literature in three main aspects. First, although the literature on voluntary disclosures is voluminous, we contribute specifically to the work related to the causal impact of external information environment on voluntary disclosures. Notably, Balakrishnan et al. (2014) use analyst coverage as exogenous shocks to managers' incentives to provide voluntary disclosures, but they do not consider asymmetric changes in voluntary disclosures.[6] We focus on the release of satellite data that are highly value-relevant to retail firms and document new evidence of an asymmetric decrease in voluntary disclosures.

Second, the stream of literature on the asymmetry of voluntary disclosures identifies managers' career concerns and litigation risk as potential explanations (Skinner 1994, 1997; Baginski et al. 2002; Kothari et al. 2009; Baginski et al. 2018). We demonstrate that big data availability can also have a first-order effect and show more comprehensively how other determinants of voluntary disclosures (e.g., market expectation, investor sophistication, underlying uncertainty, and managers' concerns about reputation/litigation risk) interplay with big data availability. One inherent limitation of this study is that we can only examine retail firms. To the extent that management forecasts are equally important to other firms and that managers' incentives are generally similar, we expect that our results are potentially generalizable to other industries.[7] Nevertheless, we draw inferences using a sample of retail firms, which are inevitably different from other industries in various dimensions, and the generalization to any other industry needs to be taken with caution.

Third, our paper adds to the research on the growing importance of technology advancements and big data for capital markets and corporate decisions. Most recent studies focus on the information content of big data from the perspective of market efficiency and asset management (Zhu 2019, Kang et al. 2021, Katona et al. 2024). Several recent studies, including Froot et al. (2017) and Blankespoor et al. (2022), use proprietary big data as a proxy for managers' private information and investigate how managers disclose their private information. Kang (2024) explores whether the public availability of big data crowds out the value of private information acquired through lending relationships. Our paper contributes to this line of literature by investigating how the public availability of big data influences firm voluntary disclosures.

2. Literature Review and Hypothesis Development

2.1. Technology Development and Big Data

The recent development of technologies and the emergence of big data have significantly changed the way information is produced and disseminated (Miller and Skinner 2015). For example, Brown et al. (2015) show that mobile communications significantly influence local information flow and local investor activities. Froot et al. (2017) develop real-time corporate sales indexes for U.S. retail stores from mobile devices and show that these measures contain important information of firm fundamentals. In a related paper, Blankespoor et al. (2022) construct a real-time revenue measure from transaction-level credit and debit card sales and show that managers are less likely to disclose negative information early in the quarter but reduce their withholding of negative news as the quarter progresses. Both papers view big data as a proxy for managers' private information and find that managers do not fully disclose their private information and instead bias their disclosures down when they possess positive private information.

Satellite imagery has emerged as an important data source for economic studies. However, only recently have high-resolution satellite imagery data been used to investigate firm performance. Limited examples include Zhu (2019), who shows that the availability of satellite imagery and consumer transactions increases stock price informativeness and disciplines managers' actions by reducing opportunistic insider trading and improving investment efficiency. Kang et al. (2021) use satellite data to examine the effects of information acquisition costs and find that investors adjust their holdings more in response to local performance. Katona et al. (2024) find that stock prices do not fully incorporate the value-relevant information embedded in satellite imagery data before the public disclosure of retail firms' performance and unequal access to big data among market participants does not necessarily facilitate stock price discovery.

Although existing studies mainly focus on how the use of big data impacts financial markets and asset management, there is scarce evidence on how firms react to the big data revolution when making corporate decisions (Goldstein et al. 2021). One major impediment in this line of inquiries is that the timing of big data availability to market participants is rarely known.

2.2. Hypothesis Development

Although there is a large body of work on corporate voluntary disclosures, studies on the *causal* impact of changes in the information environment are limited. Balakrishnan et al. (2014) exploit the setting of firms losing analyst coverage due to plausible exogenous shocks (i.e., coverage terminations) and thus experiencing decreased supply of public information. They find that firms subsequently provide more voluntary disclosures, consistent with the general substitution hypothesis (Diamond 1985, Diamond and Verrecchia 1991). This substitution effect would predict that managers respond to exogenous shocks of big data availability by decreasing voluntary disclosures of both good news and bad news.

The meeting guidance hypothesis yields *asymmetric* predictions regarding how managers change their voluntary disclosures of good news and bad news. We summarize the general intuition here and provide more details in Appendix A. The main idea is that, as big data reveal relatively precise signals of the true state (e.g., good or bad state), the market adjusts its earnings expectation toward the true state sufficiently enough in the good state that the managers face a higher risk of missing their own guidance conveying good news. By contrast, the managers still wish to issue guidance conveying bad news in the bad state due to a threshold effect that the market expectation is still above the true earnings expectation and further walking it down is necessary to meet or beat the market expectation.

Consider the following example in Figure A.1. Assume that the market and the manager both have an initial expectation of the firm's earnings per share (EPS) to be \$2. The manager is privately informed that the EPS will be \$3 conditional on the good state and \$1 conditional on the bad state. When satellite data are not available, in the good state the manager may issue a good news EPS guidance of \$2.7, which is higher than the market expectation of \$2 but lower than the true expectation of \$3. Given the uncertainty of EPS realization, managers create a \$0.3 buffer zone to prevent missing their own guidance. In the bad state, managers issue a bad news EPS guidance of \$0.7, which is not only lower than the market expectation of \$2 but also lower than the true expectation of \$1, again creating a \$0.3 buffer zone to avoid missing guidance.

When satellite data become available, they convey relatively precise signals of the true EPS under good or bad state, and the market revises its prior expectation of the firm's EPS in a Bayesian fashion. Assume that the market revises its EPS expectation upward (or downward) by \$0.8 when the satellite data signal good (or bad) state (i.e., \$2 + \$0.8 = \$2.8 or \$2 − \$0.8 = \$1.2). Because the manager wishes to leave a \$0.3 buffer zone, any good news forecast will no longer be issued as further "talking up" the market expectation will significantly increase the chance of missing guidance. By contrast, in the bad state, the market expectation of \$1.2 is still higher than the manager's expectation of \$1.0. To meet or beat the market expectation, the manager will continue to issue a bad news forecast of \$0.7 (i.e., maintaining a similar buffer zone of \$0.3).

The above example illustrates how the availability of satellite data and the managers' incentives to meet their own guidance generate an asymmetric effect on management forecasts. Appendix A demonstrates the same intuition by introducing a parsimonious model with stochastic disturbances to earnings. The theoretical development of the meeting guidance hypothesis is based on four common assumptions. First, the availability of satellite data enables the market to revise its expectation under a partial adjustment model (i.e., a Bayesian fashion with nonzero weight on its prior expectation). The market's partial adjustment is consistent with the evidence provided by Katona et al. (2024) that stock prices partially incorporate the value-relevant information embedded in satellite data. Second, managers have relatively more precise information about earnings than the market does. It is well documented that corporate insiders have access to private information that outside investors do not have (Fama 1991). Third, managers face asymmetric loss function with respect to meeting and missing their own guidance. Managers believe that meeting earnings guidance is important, which establishes a reputation for accuracy and minimizes legal liabilities (Kasznik 1999). Graham et al. (2005) survey and interview more than 400 executives and also find that executives attempt to avoid setting disclosure precedents that are hard to maintain. Managers believe that if a firm has previously guided analysts to the earnings target, then missing the target can indicate that a firm is managed so poorly that it cannot accurately predict its own future. Not being able to hit the target may also be interpreted as evidence of hidden problems at the firm. Meeting or beating earnings targets is crucial for firms to build credibility with the market and benefit their stock valuation. Fourth, managers are truthful in the sense that their issued forecasts are in the same direction as the actual earnings expectation relative to the market expectation. Specifically, managers only issue good news forecasts in the good state when the actual earnings expectation is higher than the market expectation and only issue bad news forecasts in the bad state when the actual earnings expectation is lower than the market expectation. If managers misguide the market and are later discovered when actual earnings are revealed, they will face severe damage in their reputation and credibility to the capital markets (Richardson et al. 2004, Hilary et al. 2014). Stocken (2000), for instance, shows analytically that in a repeated game setting, a manager's concern with the credibility of his disclosure is often sufficient to ensure that he will almost always truthfully reveal his private information. Campbell et al. (2020, p. 1143), for instance, cite a number of studies focusing on management forecasts (Skinner 1994, Kothari et al. 2009, Bamber et al. 2010, Baginski et al. 2018), as well as 10-K disclosures (Li et al. 2013, Kimbrough and Wang 2014) and conclude that "The collective evidence in these studies shows that—despite the existence of managers who strategically manipulate voluntary disclosure—on average, in a repeated setting, managers are truthful in their voluntary disclosures."

We formalize the prediction from the above illustrative example and analytical model as follows.

Hypothesis 1. *The release of satellite data leads to a decrease in management forecasts, and such a decrease is mainly concentrated in good news forecasts.*

It's important to note that we do not assume managers are aware of the availability of satellite data and the timing of their release to investors. All we need is that the managers can learn the market expectation from public signals such as stock price movements. Nonetheless, anecdotal evidence does suggest that after satellite data become available, managers become aware that market participants are using that data to analyze their firms' performance.[8]

We also test several cross-sectional predictions on the asymmetric decrease in management forecasts embedded in the development of the meeting guidance hypothesis. First, the asymmetric decrease is more pronounced when the market's expectation adjustment (i.e., the partial adjustment coefficient c in our model) is larger conditional on the satellite data. As the informativeness of the satellite data are more relevant for short-term performance (Kang et al. 2021, Cao et al. 2024, Katona et al. 2024), this expectation adjustment effect is more pronounced for short-term expectations, making it riskier to provide short-term good news forecasts. In addition, this expectation adjustment effect is more pronounced when institutional ownership is higher, because institutional investors are more likely to directly have access to satellite data. Second, the asymmetric decrease hinges on the underlying uncertainty (i.e., the variance of EPS distribution σ^2 in our model) as the risk of missing their own guidance becomes higher when the managers face higher operating uncertainty.[9] Third, the asymmetric decrease in good news forecasts should be more pronounced when the costs associated with missing managers' own guidance are higher (e.g., when the reputational cost and litigation risk are higher), because when facing higher costs, managers prefer a larger "buffer zone" between the actual earnings expectation and the intended management forecast (i.e., a higher b that governs the managers' choice of the buffer zone in our model), leading to an asymmetrically higher likelihood to stop issuing good news forecasts. The above discussions lead to the following hypothesis.

Hypothesis 2. *The decrease in good news forecasts following satellite data release is more pronounced among short-horizon quarterly guidance than long-term forecasts, and when firms have higher institutional ownership, higher operating uncertainty, and higher costs (e.g., litigation risk) of missing guidance.*

The meeting guidance hypothesis potentially has further indirect implications on the precision of issued management forecasts. Although not formally analyzed within our analytical framework, the managers might view a decrease in forecast frequency and a decrease in forecast precision as substitutable (Cheng et al. 2013, Li and Zhang 2015). The intuition is that as managers become more concerned with missing their own guidance, they are less likely to issue precise good news forecasts to avoid providing "smoking gun" evidence that damages their reputation and increases legal liability (Rogers and Van Buskirk 2009). For instance, a forecast of "our earnings will be in the range of \$2.70 and \$2.90" is preferred by the managers to a forecast of "our earnings will be \$2.80." Therefore, we make the following hypothesis.

Hypothesis 3. *After the release of satellite data, managers are less likely to issue precise good news forecasts.*

The meeting guidance hypothesis differs from the supply-side story in that managers tend to withhold bad news from investors (Kothari et al. 2009, Ali et al. 2019). Other major supply-side considerations would predict an *increase* in voluntary disclosures. First, big data availability reduces the uncertainty regarding the management's possession of information, which forces the managers to disclose (Dye 1985, Jung and Kwon 1988), leading to more management forecasts. Second, managers face strong incentives, such as career concerns, to withhold bad news and gamble that subsequent events will turn in their favor (Baginski et al. 2018). Big data availability makes it more difficult for managers to hide bad news, resulting in more bad news disclosure. Third, to the extent that big data also become available to product market competitors, the proprietary cost concerns regarding voluntary disclosure should decrease (Verrecchia 1983, Darrough and Stoughton 1990, Teoh and Hwang 1991), which in turn predicts more management forecasts.

3. Research Design, Data, and Sample Construction

3.1. Research Design

We exploit the staggered release of satellite data on parking lot traffic as an exogenous shock to the information asymmetry between corporate insiders and outside investors for publicly listed U.S. retail firms. The availability of satellite data provides outside investors with near real-time information on parking lot traffic, which is an important proxy for firm operating performance and significantly improves the business observability of U.S. retail firms. The staggered nature of satellite data release provides a set of counterfactuals for how corporate voluntary disclosure would have evolved in the absence of satellite data and so allows us to disentangle the effect of satellite data from other forces shaping the decisions of corporate disclosure policy. In addition, satellite data are provided by third-party data vendors and out of managers' control, which are more likely to be exogenous from the viewpoint of individual firms.

Following previous studies (Baker et al. 2022), we apply the stacked regression approach. Specifically, we create event-specific cohorts, including the treated observations and the control observations, and stack these cohorts according to the event time (i.e., the satellite release). The control observations include not-yet- or never-treated firm-year observations during our sample period. We stack these cohorts together and estimate a DID regression as follows:

$$Disclosure_{i,t,c} = \alpha_{i,c} + \alpha_{t,c} + \beta_1 Treated_{i,c} \times Post_{t,c} + \gamma \boldsymbol{z_{i,t,c}} + \varepsilon_{i,t,c}, \tag{1}$$

where the dependent variable, $Disclosure_{i,t}$, is a measure of voluntary disclosure of firm i in year t for cohort c; $Treated_{i,c}$ is a dummy variable that equals one if the satellite data on parking lot traffic is released for firm i in cohort c; $Post_{t,c}$ is a dummy variable that equals one if year t is after the satellite data release in cohort c; $\alpha_{i,c}$ and $\alpha_{t,c}$ represent cohort-specific firm and year fixed effects, respectively; $\boldsymbol{z_{i,t,c}}$ is a vector of control variables. As suggested by recent studies (Cohn et al. 2022), when the dependent variable is a count or count-like variable, modeling conditional mean functions of count data via ordinary least squares (OLS) of log(1 + count) leads to uninterpretable and biased treatment effect estimates. To address this issue, we estimate Equation (1) with the Poisson regression model as in Cohn et al. (2022) when the dependent variable is the frequency of management forecasts. We use the OLS regression model for other outcome variables.

The DID coefficient estimate β_1 on $Treated_{i,c} \times Post_{t,c}$ captures the effect of the information shock caused by the satellite data release on retail firms' voluntary disclosure. Including cohort-specific firm fixed effects ($\alpha_{i,c}$) ensures that the DID estimate reflects average within-firm changes in voluntary disclosure when satellite data become available to outside investors. Cohort-specific year fixed effects ($\alpha_{t,c}$) control for concomitant aggregate economic conditions and management forecast trends. To account for the potential cross correlations within firms and over time, standard errors are clustered at both the firm and year levels.

Following previous literature (Ali et al. 2014), our control variables ($\boldsymbol{z_{i,t,c}}$) include stock return volatility (*RetVol*), absolute change in annual earnings per share scaled by stock price (*AbsChEPS*), market-adjusted stock return (*MktAdjRet*), research and development expense scaled by book assets (*R&D*), the natural logarithm of market value of equity (*Size*), analyst coverage (*Coverage*), institutional fractional ownership (*InstOwn*), equity or debt issuance dummy (*D_Issuance*), market-to-book equity ratio (*MB*), leverage (*Lev*), the standard deviation of earnings (*StdEarn*), positive earnings change dummy (*D_PosChEarn*), and analyst optimism (*Optimism*).

The key identifying assumption that guarantees the consistency of the DID estimates is that conditional on all covariates and fixed effects, treated and control firms have parallel trends in the absence of satellite data release. In this case, the coefficient on $Treated_{i,c} \times Post_{t,c}$ estimates the causal treatment effects of satellite data release on voluntary disclosure of retail firms. We perform extensive tests to validate this identifying assumption in the following section of empirical results.

3.2. Data Sources

We obtain satellite imagery data of parking lot traffic for U.S. retailers from two major data vendors: RS Metrics (RS) and Orbital Insight (OB). RS is the first major data vendor that has released real-time parking lot traffic data of a wide range of U.S. retail firms based on satellite imagery starting from the first quarter of the year 2011. OB is the most prominent competing data vendor, which began to release similar data in the second quarter of the year 2015 and covered the largest number of U.S. retail firms at the end of 2018. The data vendors obtain satellite imagery from diverse imagery providers, apply deep learning algorithms to classify information or detect objects in each image, and utilize data science to contextualize each observation. The images have a high resolution of nearly 50 square centimeters per pixel, which allows the data vendors to accurately distinguish cars from neighboring objects. Kang et al. (2021) provide a comprehensive review of the process based on which OB uses proprietary algorithms to extract car count information from satellite images. The final data consist of daily store-level and firm-level information about parking lot car counts and parking lot utilization across major U.S. retailers.

We further obtain detailed information from the two data vendors on the exact time when the satellite imagery data of each retail firm started to be released to their clients. As disclosed by the data vendors, their clients include hedge funds, asset management firms, government entities, and nonprofit organizations. When a data vendor releases the satellite data of a retail firm, it also releases the historical satellite data of that firm. Thus, the release date is generally later than the "start date" of the satellite data. After the initial release date of the satellite data for a specific retail firm, the data vendors will keep ingesting all images of the firm's tracked stores from imagery providers and providing the processed data to investors at the daily frequency in nearly real time.

Previous studies find that the satellite-based parking lot traffic data can reliably predict firm performance, suggesting that the data contains value-relevant information (Zhu 2019, Kang et al. 2021, Cao et al. 2024, Katona et al. 2024). We verify these findings in our sample, which provides a more comprehensive coverage of retail firms and extends to a longer sample period than previous studies. We show that parking lot traffic growth positively predicts retail firms' sales growth, income growth, and earnings surprises. We present detailed results and discussions in Section IA.1 and Table IA.1 of the Online Appendix.

We obtain management forecast and analyst forecast data from Institutional Brokers' Estimate System (I/B/E/S). Share price and trading data are obtained from the Center for Research in Security Prices (CRSP) and accounting data from the Compustat database. Information of institutional investors is obtained from the Thomson Reuter's 13F database. Equity and debt issuance data are obtained from SDC Platinum database.

3.3. Sample Construction and Summary Statistics

We combine the satellite data from RS and OB and generate a comprehensive data set covering all the U.S. retail firms whose satellite data have been released by the two major data vendors from 2011 to 2018. We obtain 142 unique retail firms after merging the satellite data with the CRSP-Compustat data (i.e., the treated firms). RS releases data for 48 firms and OB for 139 firms, among which the data of 45 firms are released by both data vendors. RS and OB release the data of these retail firms at different times. When the satellite data of a retail firm have been released by both data vendors, we use the earlier time as the event time. Figure IA.1 in the Online Appendix presents the number of satellite data release events from 2011 to 2018. It is evident that the release of satellite data is staggered over time, with the highest numbers in 2016 mainly due to the reason that OB substantially expanded its data coverage in that year.

We then identify 931 control firms as those with the same six-digit Global Industry Classification Standard (GICS) codes as the treated firms and form our initial sample of 7,578 firm-year observations.[10] To mitigate the influence of newly listed firms, we delete firm-year observations in the first two years after the initial public offering (Fama and French 1993). We further require that the firms in the sample have historically appeared in the I/B/E/S guidance database. The final sample consists of 5,515 firm-year observations, including 1,393 observations of treated firms and 4,122 observations of control firms.

Table 1 presents the sample selection process (Panel A) and the industry distribution of treated firms (Panel B). Our final sample with available management forecast data covers 117 treated firms in 12 GICS industries whose satellite imagery data are gathered and eventually released by either of the two commercial satellite data vendors and 526 control firms in the same industries whose satellite data have not been released by the end of 2018. Table IA.2 in the Online Appendix compares the average firm characteristics of treated and control firms. It is evident that treated and control firms differ in several dimensions. For example, treated firms are bigger, covered by more analysts, and have higher institutional ownership than control firms. Our final sample covers 54,059 management forecasts. Table IA.3 in the Online Appendix presents the distribution of the metrics and precision of all management forecasts. We consider management forecasts on all metrics including not only earnings per share, but also capital expenditure, sales, and so on. All management forecasts in our sample are quantitative with a precision score ranging from three to one. There are no qualitative forecasts with a precision score of zero in our merged sample.

When estimating our stacked DID regression model (1), we stack the cohorts, each including all observations of treated firms that experience the release of satellite data in a year (treated observations) and all other firm-year observations that are not-yet- or never-treated (effective controls). Table 2 presents the summary statistics of all variables used in the paper for the stacked sample. We winsorize all continuous variables at the 1% and 99% levels to minimize the influence of outliers. The total number of management forecasts issued over a fiscal year is denoted as *MgmtFcst*, which aggregates both annual and quarterly forecasts at the firm-year level. Firms in our sample, on average, issue 9.509 forecasts per year. The detailed construction of all empirical variables is described in Appendix B.

4. Empirical Results

4.1. Baseline DID Regression Results

We apply the stacked regression approach to identify the effect of satellite data release on corporate voluntary disclosure. We follow the specification in Equation (1) and present the baseline results on the frequency of management forecasts in Table 3. Because the dependent variable, $MgmtFcst_{i,t,c}$, is a count variable, we apply the Poisson regression model as the main specification in columns 1 and 2. We report the OLS regression model as a robustness check in columns 3 and 4.

The DID coefficients on $Treated_{i,c} \times Post_{t,c}$ are significantly negative across all specifications. For Poisson regression models, the coefficients can be approximately interpreted as percentage changes. For example, the coefficient in column 1 of the stacked Poisson regression is -0.225 with a z-statistic of -3.96, suggesting that after the release of satellite data, treated firms decrease their management forecast frequency by 20.1% ($1\text{-}e^{-0.225}$) relative to control firms. The DID estimate does not change much after firm-level controls are added in column 2, which shows a 17.5% ($1\text{-}e^{-0.192}$) decrease relative to control firms (z-statistic = -3.74). This indicates that the identified effect does not coincide systematically with firm-specific characteristics and the unobserved omitted variable bias is possibly limited (Altonji et al. 2005). The coefficients on control variables are also consistent with prior literature (Ali et al. 2014). For instance, firms issue fewer management forecasts when they face greater uncertainty and make more forecasts when they are larger.

Table 1. Sample Selection and Industry Distribution of the Treated Sample

Panel A: Sample selection table

Sample selection steps	Total firm-year observations	Total firms	Treated firms	Control firms
Initial sample over 2008–2018	7,578	1,073	142	931
Less: Firm-year observations in the first two years after the initial public offering	−34	−7	0	−7
Less: Firms missing in the IBES guidance database	−1,990	−384	−25	−359
Less: Firms that have only one observation in the sample period	−39	−39	0	−39
Final sample	5,515	643	117	526

Panel B: Industry distribution of the treated sample after merging with management forecasts

GICS industries	Number	Percentage
Chemicals	1	0.9%
Household Durables	1	0.9%
Textiles, Apparel, and luxury goods	7	6.0%
Hotels, Restaurants, and Leisure	23	19.7%
Media	1	0.9%
Distributors	3	2.6%
Multiline Retail	13	11.1%
Specialty Retail	53	45.3%
Food and Staples Retailing	11	9.4%
Food Products	2	1.7%
Healthcare Providers and Services	1	0.9%
Consumer Finance	1	0.9%
Total	117	100.0%

Notes. This table presents the selection and composition of the sample. Panel A reports the sample selection process for the final unstacked firm-year sample, showing the number of firm-year observations and the number of total, treated, and control firms after each sample selection step. The treated sample includes U.S. retail firms with parking lot traffic data eventually released by either of the two commercial satellite data vendors: RS Metrics and Orbital Insight. There are in total 142 firms whose satellite data are released from 2011 to 2018, among which 117 firms have at least one management forecast in the I/B/E/S data set. We further delete firms that have only one observation in the sample period due to the incorporation of firm fixed effects in our analysis. We identify control firms as those with the same GICS industries as the treated firms, which span over 12 GICS industries. The final sample includes 5,515 firm-year observations with 117 treated firms and 526 control firms. Panel B reports the six-digit GICS industry distribution of the 117 treated firms in the final sample after merging the CRSP-Compustat merged database with management forecast data.

For OLS regression models, the DID coefficient is interpreted as the change in the frequency of management forecasts. For example, the estimated coefficient in column 3 is −3.117 (*t*-statistic = −4.47), suggesting that after the release of satellite data, treated firms decrease their management forecast frequency by −3.117 relative to control firms. Given that the average management forecast frequency is 9.509, the magnitude of the decrease is economically significant. The coefficient is −2.868 (*t*-statistic = −4.36) in column 4, which remains similar after controlling for firm-specific characteristics.[11]

4.2. Major Identification Assessment

The causal interpretation of the DID estimate depends crucially on the parallel trend assumption. To validate that the baseline results are not driven by the preexisting trend difference between treated and control firms, we examine the dynamic effect of satellite data release as suggested by previous studies (Bertrand and Mullainathan 2003, Roberts and Whited 2013). We replace $Post_{t,c}$ in the baseline regression of Equation (1) with three dummy variables: $Post_{-2\le t\le -1,c}$ is a dummy variable that equals one if year t is within two years before the satellite data of treated firms is released in cohort c and zero otherwise; $Post_{0\le t\le 1,c}$ is a dummy variable that equals one if year t is in the year or one year after the satellite data of treated firms is released in cohort c and zero otherwise; and $Post_{t\ge 2,c}$ is a dummy variable that equals one if year t is two years or more after the satellite data of treated firms is released in cohort c and zero otherwise.

Results are reported in columns 1 and 2 in Panel A of Table 4. The coefficient on $Treated_{i,c}\times Post_{-2\le t\le -1,c}$ allows us to assess whether there is any effect on management forecasts prior to the release of satellite data. Finding such an "effect" before satellite data release could be a symptom of different pretrends between treated and control firms. The results show that the coefficient on $Treated_{i,c}\times Post_{-2\le t\le -1,c}$ are economically small and statistically insignificant for all specifications, suggesting that the pretreatment trends are indistinguishable between the treated and control firms and thus validating the parallel trend assumption of our identification. The coefficients on $Treated_{i,c}\times Post_{0\le t\le 1,c}$ and

Table 2. Summary Statistics

Variable	Mean	Standard deviation	P25	Median	P75
MgmtFcst	9.509	10.121	0.000	6.000	15.000
GoodNewsFcst	1.088	1.978	0.000	0.000	2.000
BadNewsFcst	1.742	2.773	0.000	0.000	3.000
ShortFcst	3.929	5.461	0.000	2.000	5.000
LongFcst	5.676	6.375	0.000	3.000	9.000
GoodNewsShortFcst	0.478	1.180	0.000	0.000	1.000
GoodNewsLongFcst	0.610	1.223	0.000	0.000	1.000
BadNewsShortFcst	0.861	1.678	0.000	0.000	1.000
BadNewsLongFcst	0.881	1.585	0.000	0.000	1.000
Precision	2.301	0.365	2.000	2.214	2.500
Precision_GoodNews	2.119	0.325	2.000	2.000	2.000
Precision_BadNews	2.112	0.268	2.000	2.000	2.000
RetVol	0.123	0.077	0.072	0.102	0.152
AbsChEPS	0.137	0.326	0.012	0.032	0.096
MktAdjRet	0.138	0.530	−0.170	0.084	0.356
R&D	0.006	0.017	0.000	0.000	0.000
Size	6.718	2.100	5.258	6.820	8.164
Coverage	8.861	6.579	3.833	7.417	12.500
InstOwn	0.665	0.289	0.483	0.754	0.897
D_Issuance	0.259	0.438	0.000	0.000	1.000
MB	2.253	4.016	1.014	1.760	2.987
Lev	0.550	0.253	0.368	0.529	0.700
StdEarn	0.061	0.073	0.016	0.032	0.075
D_PosChEarn	0.459	0.498	0.000	0.000	1.000
Optimism	0.047	0.361	−0.028	−0.005	0.021

Notes. This table reports the mean, standard deviation, 25th percentile, median, and 75th percentile of firm characteristics for the stacked sample. The sample period is from 2008 to 2018 and contains 35,983 firm-year observations. Firm characteristics include the number of management forecasts (*MgmtFcst*), the number of good news forecasts (*GoodNewsFcst*), the number of bad news forecasts (*BadNewsFcst*), the number of quarterly guidance (*ShortFcst*), the number of long-term forecasts (*LongFcst*), the number of good news quarterly guidance (*GoodNewsShortFcst*), the number of good news long-term forecasts (*GoodNewsLongFcst*), the number of bad news quarterly guidance (*BadNewsShortFcst*), the number of bad news long-term forecasts (*BadNewsLongFcst*), the precision of management forecasts (*Precision*), the precision of good news forecasts (*Precision_GoodNews*), the precision of bad news forecasts (*Precision_BadNews*), stock return volatility (*RetVol*), absolute change in annual earnings per share scaled by stock price (*AbsChEPS*), market-adjusted stock return (*MktAdjRet*), research and development expense scaled by book assets (*R&D*), the natural logarithm of the market value of equity (*Size*), analyst coverage (*Coverage*), institutional ownership (*InstOwn*), equity or debt issuance dummy (*D_Issuance*), market-to-book equity ratio (*MB*), leverage (*Lev*), standard deviation of earnings (*StdEarn*), positive earnings change dummy (*D_PosChEarn*), and analyst optimism (*Optimism*). Detailed variable definitions are reported in Appendix B. All continuous variables are winsorized at the 1% and 99% levels.

$Treated_{i,c} \times Post_{t\geq 2,c}$ allow us to track the effect on management forecasts after the release of satellite data over time. Consistent with a causal interpretation of our baseline results, we find that these coefficients are significantly negative at the 1% level. Also, the estimated coefficients on $Treated_{i,c} \times Post_{0\leq t\leq 1,c}$ are economically smaller than those on $Treated_{i,c} \times Post_{t\geq 2,c}$, suggesting that it takes time for firms to adjust their voluntary disclosure policy in response to the information shock of satellite data release.

To further visualize the pretrend test, we estimate the DID coefficient β_T prior to and after the event year of satellite data release by performing the following regression:

$$Disclosure_{i,t,c} = \alpha_{i,c} + \alpha_{t,c} + \sum\nolimits_T \beta_T Treated_{i,c} \times Post_{T,c} + \gamma \boldsymbol{z_{i,t,c}} + \varepsilon_{i,t,c}, \tag{2}$$

where T represents the event years from $t = -3$ to $t \geq 3$, where $t = 0$ is the event year of satellite data release. Figure 1(a) plots the estimated coefficients and 95% confidence intervals of β_T for the frequency of management forecasts. Event years of $t < -3$ are used as the benchmark. It is evident that before satellite data release (when $t \leq -1$), the estimated coefficient is small and statistically insignificant, confirming that there is no significant difference in the pretreatment trend between the treated and control groups. After satellite data release (when $t \geq 0$), however, the estimated coefficient becomes significantly negative, indicating that there is a significant decrease in management forecasts of treated firms compared with control firms.

Another identification check is the importance of the timing of data releases as opposed to the start of the data. As noted earlier, when a data vendor releases the satellite data of a retail firm, it also releases the historical satellite data of that firm. We expect that it is the release date that causes the change in disclosure policy as opposed to the start date of satellite data. We thus perform the following stacked Poisson regression:

$$\begin{aligned} Disclosure_{i,t,c} = \alpha_{i,c} + \alpha_{t,c} + \beta_1 Treated_{i,c} \\ \times Post_{start\leq t<release,c} + \beta_2 Treated_{i,c} \\ \times Post_{t,c} + \gamma \boldsymbol{z_{i,t,c}} + \varepsilon_{i,t,c}. \end{aligned} \tag{3}$$

We add $Treated_{i,c} \times Post_{start\leq t<release,c}$ to our main regression model in Equation (1). $Post_{start\leq t<release,c}$ is a dummy variable that equals one if the satellite data on parking lot traffic has started but not yet been released to the market for firm i by year t in cohort c and zero otherwise.

The results are reported in columns 3 and 4 in Panel A of Table 4. It is evident that, although the coefficients on $Treated_{i,c} \times Post_{t,c}$ remain significantly negative across various specifications, the coefficients on $Treated_{i,c} \times Post_{start\leq t<release,c}$ are statistically and economically insignificant. These results confirm that when satellite data are possessed by the data vendor but not released to the market participants, the data have no impact on the frequency of management forecasts. In other words, only after the satellite data are released to the market participants, is there a significant decrease of management forecasts for treated firms relative to control firms.

As shown in Table IA.2 in the Online Appendix, treated and control firms differ in several characteristics. To further alleviate the concern that our results are driven by differences in observed firm characteristics, we take

Table 3. Frequency of Management Forecasts and Satellite Data Release

	Poisson		OLS	
	(1)	(2)	(3)	(4)
Treated* × *Post	**−0.225*****	**−0.192*****	**−3.117*****	**−2.868*****
	(−3.96)	**(−3.74)**	**(−4.47)**	**(−4.36)**
RetVol		−0.401**		−3.491***
		(−2.38)		(−3.05)
AbsChEPS		−0.102		−0.526
		(−1.44)		(−1.49)
MktAdjRet		−0.009		−0.022
		(−0.40)		(−0.11)
R&D		4.704		26.160
		(1.05)		(0.93)
Size		0.170***		1.282***
		(4.83)		(5.01)
Coverage		−0.002		−0.005
		(−0.35)		(−0.11)
InstOwn		0.120		1.037*
		(1.61)		(1.68)
D_Issuance		−0.003		0.127
		(−0.13)		(0.53)
MB		−0.003		−0.018
		(−1.08)		(−0.70)
Lev		0.096		0.561
		(0.62)		(0.53)
StdEarn		0.035		−0.006
		(0.10)		(−0.00)
D_PosChEarn		−0.003		−0.043
		(−0.15)		(−0.28)
Optimism		−0.117***		−0.751***
		(−3.45)		(−3.53)
Cohort firm fixed effects	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes
Observations	33,084	33,084	35,983	35,983
Pseudo- or adjusted R^2	0.584	0.591	0.772	0.778

Notes. Dependent variable = *MgmtFcst*. This table reports the estimation results of the following stacked difference-in-differences regressions.

$$MgmtFcst_{i,t,c} = \alpha_{i,c} + \alpha_{t,c} + \beta_1 Treated_{i,c} \times Post_{t,c} + \gamma \boldsymbol{z_{i,t,c}} + \varepsilon_{i,t,c}.$$

We stack cohort-specific datasets that include all firms that experienced the release of satellite data in a year (treated) and all other firm-year observations that are not-yet- or never-treated (effective controls). Columns 1 and 2 report the stacked Poisson regression and columns 3 and 4 report the stacked OLS regression. The dependent variable, $MgmtFcst_{i,t,c}$, represents the number of management forecast for firm i in year t in cohort c. $Treated_{i,c}$ is a dummy variable that equals one if the satellite data on parking lot traffic is released for firm i in cohort c. $Post_{t,c}$ is a dummy variable that equals one if year t is after the satellite data release in cohort c. Control variables $\boldsymbol{z_{i,t,c}}$ include: stock return volatility, absolute change in annual earnings per share scaled by stock price, market-adjusted stock return, research and development expense scaled by book assets, natural logarithm of market value of equity, analyst coverage, institutional ownership, equity or debt issuance dummy, market-to-book equity ratio, leverage, standard deviation of earnings, positive earnings change dummy, and analyst optimism. All continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are reported in Appendix B. All regressions include cohort-specific firm ($\alpha_{i,c}$) and year ($\alpha_{t,c}$) fixed effects. The z-statistics (for columns 1 and 2) or t-statistics (for columns 3 and 4) based on two-way clustered standard errors at firm and year levels are reported in parentheses. Coefficients on main variables of interest are in bold. The sample period is from 2008 to 2018.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

two approaches to minimize the differences between treated and control firms.

In the first approach, we restrict the control sample to not-yet-treated firm-year observations in the stacked regression. The treated and control samples now belong to the same set of firms that are eventually treated. Thus, the inherent differences between the treated and control groups can be ruled out as a driver of our results. We report the results in columns 1 and 2 in Panel B of Table 4. The estimated DID coefficients remain economically large and statistically significant.

Table 4. Assessing Identification

Panel A: Pretrend test and timing test (start or release of the data)

	Pretrend test		Timing test	
	(1)	(2)	(3)	(4)
$Treated_{i,c} \times Post_{-2\leq t\leq -1,c}$	**−0.032**	**−0.043**		
	(−0.88)	**(−1.17)**		
$Treated_{i,c} \times Post_{0\leq t\leq 1,c}$	**−0.189*** **	**−0.176*** **		
	(−3.59)	**(−3.28)**		
$Treated_{i,c} \times Post_{t\geq 2,c}$	**−0.289*** **	**−0.242*** **		
	(−4.14)	**(−3.96)**		
$Treated_{i,c} \times Post_{t,c}$			**−0.168** **	**−0.157*** **
			(−2.51)	**(−2.65)**
$Treated_{i,c} \times Post_{start\leq t<release,c}$			**0.076**	**0.047**
			(1.51)	**(1.08)**
Controls	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes
Observations	33,084	33,084	33,084	33,084
Pseudo-R^2	0.585	0.591	0.584	0.591

Panel B: Not-yet-treated as effective controls and entropy balancing

	Not-yet-treated as effective controls		Entropy balancing	
	(1)	(2)	(3)	(4)
$Treated_{i,c} \times Post_{t,c}$	**−0.196*** **	**−0.182*** **	**−0.242*** **	**−0.212*** **
	(−3.03)	**(−3.00)**	**(−3.78)**	**(−4.12)**
Controls	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes
Observations	5,784	5,784	33,084	33,084
Pseudo-R^2	0.489	0.502	0.509	0.516

Notes. Dependent variable = *MgmtFcst*. This table reports tests of the identification strategy. We perform the stacked difference-in-differences Poisson regression and the dependent variable is *MgmtFcst*. $Treated_{i,c}$ is a dummy variable that equals one if the satellite data on parking lot traffic is released for firm *i* in cohort *c*. Columns 1 and 2 in Panel A present the dynamic effects of satellite data release on management forecast frequency and tests for pretrend differences between the treated and control firms. We replace $Post_{t,c}$ in the baseline regression with three dummy variables: $Post_{-2\leq t\leq -1,c}$ is a dummy variable that equals one if year *t* is within two years before the satellite data of treated firms is released in cohort *c* and zero otherwise; $Post_{0\leq t\leq 1,c}$ is a dummy variable that equals one if year *t* is in the year or one year after the satellite data of treated firms is released in cohort *c* and zero otherwise; $Post_{t\geq 2,c}$ is a dummy variable that equals one if year *t* is two years or more after the satellite data of treated firms is released in cohort *c* and zero otherwise. Columns 3 and 4 in Panel A present the timing test, in which we add $Post_{start\leq t<release,c}$, which is a dummy variable that equals one if the satellite data on parking lot traffic has started but has not been released for treated firms in year *t* of cohort *c* and zero otherwise. Columns 1 and 2 in Panel B report the baseline regression by restricting the effective controls to not-yet-treated firm-year observations. Columns 3 and 4 in Panel B present the baseline regressions by employing entropy balancing, which creates weights for each control observation so that the means and variances of firm characteristics for treated and control samples are similar. Control variables are the same as those in the baseline regression. All continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are reported in Appendix B. All regressions include cohort-specific firm and year fixed effects. The *z*-statistics based on two-way clustered standard errors at firm and year levels are reported in parentheses. Coefficients on main variables of interest are in bold. The sample period is from 2008 to 2018.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

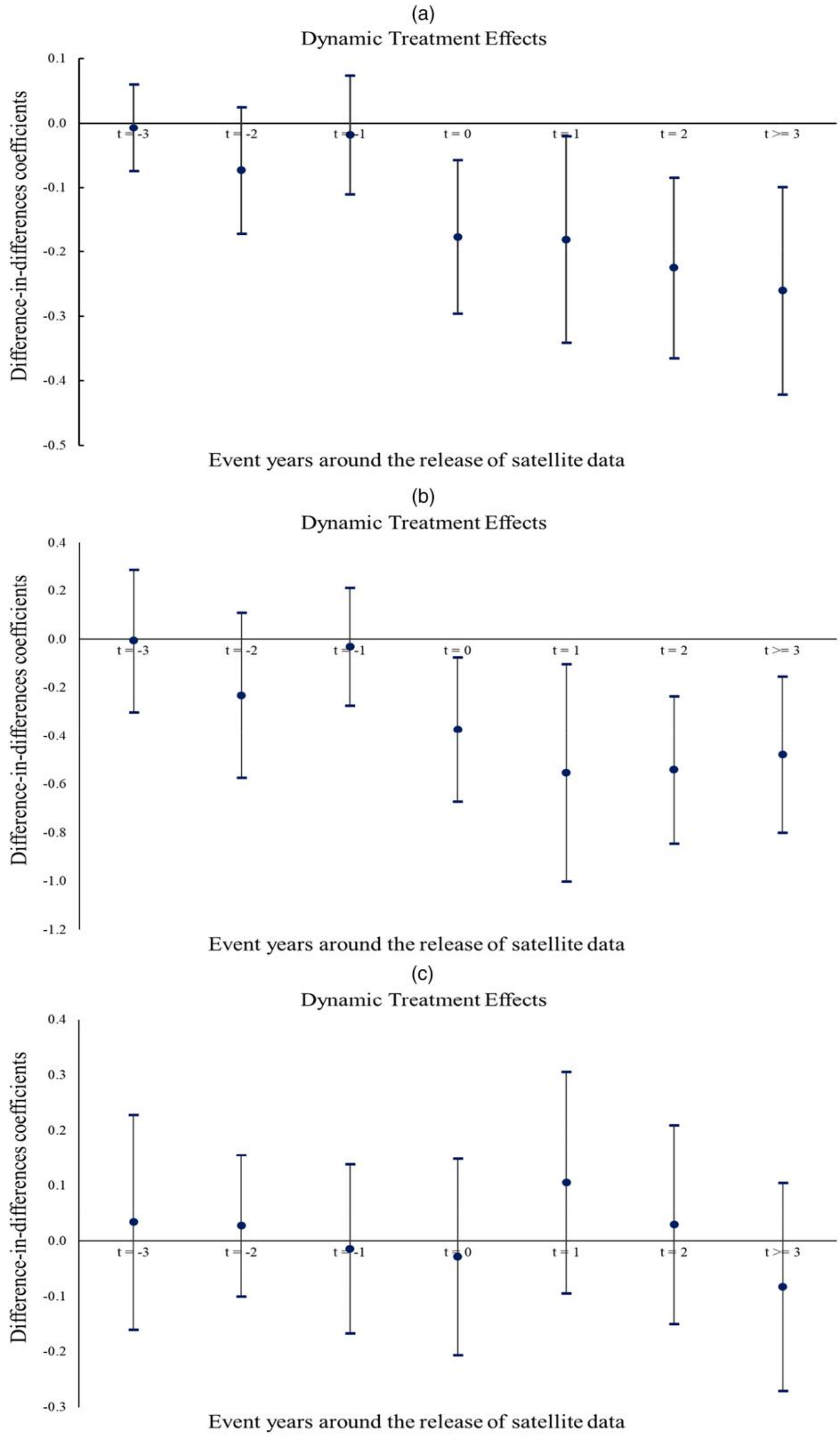
In the second approach, we match treated and control samples using the entropy balancing method, which creates weights for each control observation so that the means and variances of the treated and control samples are similar. The matching procedure eliminates the differences in the first and second moments of observed firm characteristics. The results of the regression employing entropy balancing are reported in columns 3 and 4 in Panel B of Table 4. The DID coefficients remain similar to our baseline results.

4.3. Management EPS Forecast Frequency of Good and Bad News

In this section, we investigate the effect of satellite data release on the disclosure of good news and bad news earnings forecasts separately, which are bifurcated based on analyst consensus forecasts. In all the good news versus bad news analyses, we focus specifically on management EPS forecasts because analysts' non-EPS forecasts (e.g., net income, return on assets, etc.) are scarce.

To test the effect of satellite data release on the two types of forecasts, we employ the same stacked DID

Figure 1. (Color online) Parallel Trend Analysis: Dynamic Treatment Effect on Management Forecasts



Notes. This figure presents the difference-in-differences coefficients prior to and after the event year of satellite data release ($t = 0$) in the regression of Equation (2) and their 95% confidence intervals for all management forecasts (a), good news forecasts (b), and bad news forecasts (c). Event years of $t < -3$ are used as the benchmark.

regression approach with a Poisson model to estimate Equation (1) for good news and bad news forecast frequency, respectively. Following previous literature (Kothari et al. 2009, Ali et al. 2019), good news and bad news forecasts are defined as management forecasts of quarterly or annual EPS that are above or below the analysts' most recent consensus forecasts.[12] We follow Rogers and Van Buskirk (2013) and construct updated analyst forecast consensus by incorporating the latest information in earnings announcements for bundled management forecasts.[13] We provide details on the construction of updated analyst forecast consensus in Section IA.2 of the Online Appendix. We then classify bundled management forecasts into good or bad news forecasts based on the updated analyst forecast consensus.

Table 5 reports the estimation for good news (columns 1 and 2) and bad news (columns 3 and 4) EPS forecast frequency. It is evident that the DID coefficients on $Treated_{i,c} \times Post_{t,c}$ are significantly negative for good news forecasts. For example, the DID coefficient is -0.440 with z-statistic of -3.59 in column 2, indicating that compared with the control firms, treated firms experience a significant decrease of 35.6% ($1\text{-}e^{-0.440}$) in the frequency of good news forecasts after their satellite data are released. In contrast, the DID coefficients on $Treated_{i,c} \times Post_{t,c}$ are close to zero and statistically insignificant for bad news forecasts (e.g., -0.002 with z-statistic of -0.02 in column 4), suggesting that treated firms do not experience a significant decrease in bad news forecasts, measured relative to control firms. The Wald test χ^2 statistics and p-values are reported to test the differences in coefficients on $Treated_{i,c} \times Post_{t,c}$ for good news and bad news forecasts, indicating the differences are statistically significant.[14] Figure 1, (b) and (c), plots the DID coefficients prior to and after the event year of satellite data release for good news forecasts and bad news forecasts separately, confirming no significant pretreatment trend difference between treated and control groups.

4.4. Heterogeneous Effects of Satellite Data Release on Management Forecasts

The meeting guidance hypothesis not only predicts the asymmetric decrease in management forecasts but also suggests that the decrease in good news forecasts should vary with the informativeness of satellite data (partial adjustment coefficient c in our model), uncertainty about firm operating performance (variance $\sigma^2$of EPS distribution), and the costs of missing guidance (buffer zone parameter b). These additional predictions are formally stated in Hypothesis 2, and we test them in this section.

4.4.1. Quarterly Guidance vs. Long-Term Forecasts. To examine whether the decrease in good news forecasts is more or less pronounced for short-horizon quarterly guidance than long-term forecasts, we define "quarterly guidance" as those forecasts with a horizon less than or equal to 90 days (from the fiscal end) and "long-term forecasts" as those forecasts with a horizon greater than 90 days. We test how much managers reduce their quarterly guidance or long-term forecasts after satellite date release by estimating the stacked DID regression in Equation (1) with a Poisson model.

Table 6 reports the results. The dependent variables are the number of quarterly guidance in columns 1 and 2 and the number of long-term forecasts in columns 3 and 4. We document that the negative coefficients on $Treated_{i,c} \times Post_{t,c}$ carry larger magnitudes and higher statistical significance for quarterly guidance. For instance, the DID coefficient is -0.298 (z-statistic = -3.77) for quarterly guidance in column 2 but is only -0.093 (z-statistic = -1.86) for long-term forecasts in column 4. The Wald test χ^2 statistic is 16.87 (p = 0.00) for the difference in coefficients between columns 2 and 4.

We further test whether the decrease in good news forecasts is more pronounced for quarterly guidance. In columns 5 and 6, the dependent variables are the number of good news quarterly guidance, whereas the dependent variables in columns 7 and 8 are the number of good news long-term forecasts. As expected, the estimated coefficients on $Treated_{i,c} \times Post_{t,c}$ are more negative and carry a higher statistical significance for good news quarterly guidance than for good news long-term forecasts. The coefficient for quarterly guidance is nearly twice as large as that for long-term forecasts. For instance, the DID coefficient is -0.538 (z-statistic = -3.37) for good news quarterly guidance in column 6 but is only -0.263 (z-statistic = -1.88) for good news long-term forecasts in column 8. The Wald test χ^2 statistic is 4.20 (p = 0.04) for the difference in coefficients between columns 6 and 8. We also verify that estimated DID coefficients are insignificant when we use bad news quarterly guidance (columns 9 and 10) or bad news long-term forecasts (columns 11 and 12) as the dependent variables.[15]

4.4.2. Institutional Ownership. To examine the prediction that the decrease in management forecasts, especially good news forecasts, is more pronounced when firms have higher institutional ownership, we estimate the stacked Poisson regression of management forecast frequency by adding an interaction term between satellite data release and institutional ownership to the baseline regression model in Equation (1):

$$\begin{aligned} Disclosure_{i,t,c} = {} & \alpha_{i,c} + \alpha_{t,c} + \beta_1 Treated_{i,c} \times Post_{t,c} \times X_{i,c} \\ & + \beta_2 Treated_{i,c} \times Post_{t,c} + \beta_3 Post_{t,c} \\ & \times X_{i,c} + \gamma \mathbf{z_{i,t,c}} + \varepsilon_{i,t,c}, \end{aligned} \quad (4)$$

where $X_{i,c}$ represents a variable that interacts with

Table 5. Management EPS Forecast Frequency of Good News and Bad News

	Good news forecasts		Bad news forecasts	
	(1)	(2)	(3)	(4)
Treated × Post	**−0.481*** **	**−0.440*** **	**−0.041**	**−0.002**
	(−3.84)	**(−3.59)**	**(−0.53)**	**(−0.02)**
RetVol		−0.687		−0.611
		(−1.16)		(−1.44)
AbsChEPS		0.007		0.122
		(0.04)		(1.43)
MktAdjRet		0.144***		−0.147***
		(2.73)		(−4.11)
R&D		11.550		1.382
		(1.57)		(0.18)
Size		0.134*		0.386***
		(1.77)		(6.54)
Coverage		0.007		0.009
		(0.58)		(1.29)
InstOwn		0.286		0.119
		(1.10)		(0.82)
D_Issuance		−0.070		−0.027
		(−1.40)		(−0.82)
MB		−0.006		−0.004
		(−0.70)		(−0.75)
Lev		−0.366		0.195
		(−1.31)		(0.68)
StdEarn		1.156		−0.043
		(1.42)		(−0.06)
D_PosChEarn		0.251***		−0.144***
		(5.17)		(−10.25)
Optimism		−0.299**		0.001
		(−2.50)		(0.01)
Cohort firm fixed effects	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes
Observations	21,554	21,554	22,338	22,338
Pseudo-R^2	0.274	0.285	0.346	0.360
	(1)–(3)		(2)–(4)	
Wald-test χ^2	24.35		23.71	
p-value	0.00		0.00	

Notes. This table presents the stacked difference-in-differences Poisson regression of management forecasts conveying different news. The dependent variables are *GoodNewsFcst* in columns 1 and 2 and *BadNewsFcst* in columns 3 and 4. A management EPS forecast is classified as good (bad) news if the point estimate, or the midpoint of the range forecast, is above (below) the analyst consensus forecast before the management forecast. For open-ended management forecasts, the forecast is classified as good (bad) news when its bottom (upper) bound is higher (lower) than the analyst consensus forecast. Following Rogers and Van Buskirk (2013), we correct the potential measurement errors of forecast news when management forecasts are bundled with earnings announcements by updating analyst expectations with the latest information in earnings announcements. We then classify management forecast news based on the updated analyst forecast consensus. All continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are reported in Appendix B. All regressions include cohort-specific firm and year fixed effects. The z-statistics based on two-way clustered standard errors at firm and year levels are reported in parentheses. The Wald test χ^2 statistics and p-values are reported to test the difference in coefficients on *Treated* × *Post* for good news and bad news forecasts. Coefficients on main variables of interest are in bold. The sample period is from 2008 to 2018.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

$Treated_{i,c} \times Post_{t,c}$ and captures high institutional ownership in this test ($HighInstOwn_{i,c}$), which is a dummy variable that equals one if firm i has high institutional ownership (above the median) at the end of the year before the satellite data release for cohort c and zero otherwise.

Results are reported in Panel A of Table 7. The dependent variable is the number of management forecasts (*MgmtFcst*, columns 1 and 2), good news forecasts (*GoodNewsFcst*, columns 3 and 4), and bad news forecasts (*BadNewsFcst*, columns 5 and 6), respectively. For management forecasts in columns 1 and 2, the coefficients on $Treated_{i,c} \times Post_{t,c} \times HighInstOwn_{i,c}$ are negative but insignificant. When we focus on good news forecasts in columns 3 and 4, the estimated coefficients on $Treated_{i,c} \times Post_{t,c} \times HighInstOwn_{i,c}$ are significantly negative in both specifications, suggesting that after satellite data release, treated firms decrease good news forecasts significantly more when their institutional ownership is high. For instance, the estimated coefficient

Table 6. Management Forecast Frequency: Quarterly Guidance vs. Long-Term Forecasts

	Quarterly guidance		Long-term forecasts		Good news Quarterly guidance		Good news Long-term forecasts		Bad news Quarterly guidance		Bad news Long-term forecasts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated* × *Post	**−0.344*****	**−0.298*****	**−0.115****	**−0.093***	**−0.580*****	**−0.538*****	**−0.302****	**−0.263***	**−0.062**	**−0.011**	**−0.015**	**0.002**
	(−4.18)	**(−3.77)**	**(−2.17)**	**(−1.86)**	**(−3.55)**	**(−3.37)**	**(−2.20)**	**(−1.88)**	**(−0.54)**	**(−0.11)**	**(−0.19)**	**(0.02)**
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,800	31,800	32,038	32,038	19,965	19,965	18,953	18,953	20,904	20,904	19,468	19,468
Pseudo-R^2	0.524	0.529	0.501	0.507	0.271	0.284	0.188	0.197	0.332	0.344	0.246	0.258
	(1)–(3)		(2)–(4)		(5)–(7)		(6)–(8)		(9)–(11)		(10)–(12)	
Wald test χ^2	20.76		16.87		4.38		4.20		0.30		0.02	
p-value	0.00		0.00		0.04		0.04		0.58		0.88	

Notes. This table presents the stacked difference-in-differences Poisson regression of quarterly guidance vs. long-term management forecasts. Quarterly guidance refers to forecasts with a horizon less than or equal to 90 days. Long-term forecasts are defined as forecasts with a horizon greater than 90 days. The dependent variables are the quarterly guidance in columns 1 and 2, long-term forecasts in columns 3 and 4, good news quarterly guidance in columns 5 and 6, good news long-term forecasts in columns 7 and 8, bad news quarterly guidance in columns 9 and 10, and bad news long-term forecasts in columns 11 and 12. All regressions include cohort-specific firm and year fixed effects. The z-statistics based on two-way clustered standard errors at firm and year levels are reported in parentheses. The Wald test χ^2 statistics and p-values are reported to test the difference in coefficients on *Treated* × *Post* for quarterly guidance and long-term management forecasts. Coefficients on main variables of interest are in bold. The sample period is from 2008 to 2018.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

in column 4 is −0.391 (z-statistic = −2.13), suggesting that the decrease in good news forecasts for firms with high institutional ownership is 32.4% (1-$e^{-0.391}$) more than that for firms with low institutional ownership. The coefficients on $Treated_{i,c} \times Post_{t,c}$ become small and statistically insignificant, suggesting that the release has attenuated effects on good news forecasts for firms with low institutional ownership. Moreover, as expected, institutional ownership has no impact on bad news forecasts. Specifically, the estimated coefficients on $Treated_{i,c} \times Post_{t,c} \times HighInstOwn_{i,c}$ are close to zero in columns 5 and 6. The Wald test χ^2 statistics and p-values are reported to test the difference in coefficients on $Treated_{i,c} \times Post_{t,c} \times HighInstOwn_{i,c}$ for good news and bad news forecasts. For example, the Wald test χ^2 statistic is 3.65 (p = 0.06) for the difference in coefficients between columns 4 and 6.

4.4.3. Operating Uncertainty.

We empirically test how the negative relationship between satellite data release and management forecast frequency varies with the uncertainty of firm operating environment. We use cash flow volatility as the proxy for firm-level operating uncertainty, which is defined as the variance in a firm's annual operating cash flow scaled by assets over the past five-year period following Jayaraman (2008). We estimate the stacked Poisson regression of management forecast frequency by adding an interaction term between satellite data release and operating uncertainty. We set $X_{i,c}$ in Equation (4) as high operating uncertainty ($HighCFVol_{i,c}$), which is a dummy variable that equals one if firm i has high cash flow volatility (above the median) at the end of the year before the satellite data release for cohort c and zero otherwise.

Results are reported in Panel B of Table 7. For all management forecasts in columns 1 and 2, the coefficients on $Treated_{i,c} \times Post_{t,c} \times HighCFVol_{i,c}$ are insignificant, whereas the coefficients on $Treated_{i,c} \times Post_{t,c}$ remain significantly negative. More importantly, when we investigate good news forecasts, the estimated coefficients on $Treated_{i,c} \times Post_{t,c} \times HighCFVol_{i,c}$ are significantly negative, suggesting that after satellite data release, treated firms decrease the frequency of good news forecast more when they have high operating uncertainty. For example, the coefficient is −0.430 (z-statistic = −2.47) in column 4, which means that the decrease in good news forecasts for firms with high operating uncertainty is 34.9% (1-$e^{-0.430}$) more than that for firms with low operating uncertainty. The coefficients on $Treated_{i,c} \times Post_{t,c} \times HighCFVol_{i,c}$ are statistically insignificant and much smaller in magnitude for bad news forecasts in columns 5 and 6. The Wald test χ^2 statistics and p-values are reported to test the difference in coefficients on $Treated_{i,c} \times Post_{t,c} \times HighCFVol_{i,c}$ for good news and bad news forecasts. For example, the

Table 7. Cross-Sectional Analysis: Effect of Institutional Ownership, Operating Uncertainty, and Expected Litigation Risk

	Management forecasts		Good news forecasts		Bad news forecasts	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Institutional ownership						
Treated × Post× HighInstOwn	**−0.111**	**−0.112**	**−0.398****	**−0.391****	**−0.098**	**−0.039**
	(−1.57)	**(−1.43)**	**(−2.24)**	**(−2.13)**	**(−1.02)**	**(−0.35)**
Treated × Post	−0.149*	−0.113	−0.171	−0.130	0.020	0.021
	(−1.74)	(−1.36)	(−1.08)	(−0.90)	(0.23)	(0.22)
Post × HighInstOwn	0.124**	0.093*	0.144	0.082	0.181**	0.093
	(2.49)	(1.82)	(1.37)	(0.90)	(1.98)	(1.07)
Controls	No	Yes	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,084	33,084	21,554	21,554	22,338	22,338
Pseudo-R^2	0.585	0.591	0.275	0.286	0.346	0.361
			(3)–(5)		(4)–(6)	
Wald test χ^2			2.53		3.65	
p-value			0.11		0.06	
Panel B: Operating uncertainty						
Treated × Post × HighCFVol	**−0.089**	**−0.026**	**−0.452****	**−0.430****	**0.097**	**0.223***
	(−0.91)	**(−0.31)**	**(−2.53)**	**(−2.47)**	**(0.76)**	**(1.86)**
Treated × Post	−0.192***	−0.182***	−0.330**	−0.297**	−0.079	−0.078
	(−3.86)	(−3.65)	(−2.43)	(−2.18)	(−0.88)	(−0.87)
Post × HighCFVol	0.015	0.005	0.021	0.002	−0.106	−0.083
	(0.29)	(0.11)	(0.30)	(0.03)	(−1.22)	(−1.13)
Controls	No	Yes	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,084	33,084	21,554	21,554	22,338	22,338
Pseudo-R^2	0.584	0.591	0.275	0.286	0.346	0.361
			(3)–(5)		(4)–(6)	
Wald test χ^2			10.00		14.63	
p-value			0.00		0.00	
Panel C: Expected litigation risk						
Treated × Post × HighLitRisk	**−0.184****	**−0.137***	**−0.282***	**−0.265***	**−0.055**	**0.017**
	(−2.36)	**(−1.67)**	**(−1.70)**	**(−1.69)**	**(−0.52)**	**(0.15)**
Treated × Post	−0.107	−0.104	−0.298*	−0.267*	0.000	−0.006
	(−1.38)	(−1.36)	(−1.92)	(−1.77)	(0.00)	(−0.06)
Post × HighLitRisk	0.012	0.007	0.139**	0.112*	−0.124**	−0.126**
	(0.49)	(0.32)	(2.23)	(1.89)	(−2.26)	(−2.13)
Controls	No	Yes	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,084	33,084	21,554	21,554	22,338	22,338
Pseudo-R^2	0.585	0.591	0.275	0.286	0.346	0.361
			(3)–(5)		(4)–(6)	
Wald test χ^2			2.07		3.17	
p-value			0.15		0.08	

Notes. This table reports the results of the following stacked difference-in-differences Poisson regression.

$$MgmtFcst_{i,t,c} = \alpha_{i,c} + \alpha_{t,c} + \beta_1 Treated_{i,c} \times Post_{t,c} \times X_{i,c} + \beta_2 Treated_{i,c} \times Post_{t,c} + \beta_3 Post_{t,c} \times X_{i,c} + \gamma \boldsymbol{z_{i,t,c}} + \varepsilon_{i,t,c},$$

where $X_{i,c}$ is a dummy variable that equals $HighInstOwn_{i,c}$, $HighCFVol_{i,c}$, and $HighLitRisk_{i,c}$ for Panels A, B, and C, respectively. $HighInstOwn_{i,c}$ is a dummy variable that equals one if firm i has high institutional ownership (above the median) at the end of the year before the satellite data release for firms in cohort c and zero otherwise. $HighCFVol_{i,c}$ is a dummy variable that equals one if firm i has high cash flow volatility (above the median) at the end of the year before the satellite data release for firms in cohort c and zero otherwise. Cash flow volatility is defined as the variance in a firm's annual operating cash flow scaled by assets over the past five-year period following Jayaraman (2008). $HighLitRisk_{i,c}$ is a dummy variable that equals one if firm i has high expected litigation risk (above the median) at the end of the year before the satellite data release for firms in cohort c and zero otherwise. Firm-level expected litigation risk is calculated based on the coefficient estimates reported in Kim and Skinner (2012, model 4 of table 7), which predicts the probability of litigation based on a list of firm characteristics. The dependent variable is the number of management forecasts (columns 1 and 2), good news forecasts (columns 3 and 4), and bad news forecasts (columns 5 and 6), respectively. All continuous variables are winsorized at the 1% and 99% levels. All regressions include cohort-specific firm and year fixed effects. The z-statistics based on two-way clustered standard errors at firm and year levels are reported in parentheses. The Wald-test χ^2 statistics and p-values are reported to test the difference in coefficients on *Treated* × *Post* × *X* for good news and bad news forecasts. Coefficients on main variables of interest are in bold. The sample period is from 2008 to 2018.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

Wald test χ^2 statistic is 14.63 ($p = 0.00$) for the difference in coefficients between columns 4 and 6.

4.4.4. Costs of Missing Guidance. To empirically test the prediction that the asymmetric reduction in management forecasts should be closely related to the costs of missing earnings guidance, we use expected litigation risk as a proxy for the legal and reputational costs (Kim and Skinner 2012), which captures the managers' incentives to avoid missing their own guidance. We expect that the decrease in management forecasts, especially good news forecasts, should be more pronounced when the expected litigation risk is higher.

To estimate the expected litigation risk faced by individual firms, we calculate the probability of litigation based on the coefficient estimates reported in model 4 of table 7 by Kim and Skinner (2012). We classify our sample into firms with high (above the median) and low (below the median) expected litigation risk. We then set $X_{i,c}$ in the stacked Poisson regression model of Equation (4) as $HighLitRisk_{i,c}$, which is a dummy variable that equals one if firm i has high expected litigation risk (above the median) at the end of the year before the satellite data release for cohort c and zero otherwise.

Panel C of Table 7 reports the results for management forecasts (columns 1 and 2), good news forecasts (columns 3 and 4), and bad news forecasts (columns 5 and 6), respectively. In columns 1 and 2, the estimated coefficients on $Treated_{i,c} \times Post_{t,c} \times HighLitRisk_{i,c}$ are significantly negative, suggesting that after satellite data release, treated firms significantly decrease their management forecasts and such a decrease is more pronounced for firms with high litigation risk (relative to control firms). Consistent with the prediction of our hypothesis, the effect of litigation risk is mainly concentrated on good news forecasts. The estimated coefficients on $Treated_{i,c} \times Post_{t,c} \times HighLitRisk_{i,c}$ are significantly negative for good news forecasts in columns 3 and 4. For instance, the coefficient in column 4 is -0.265 (z-statistic $= -1.69$), suggesting that the decrease for high-litigation risk firms is 23.3% ($1\text{-}e^{-0.265}$) more than that for low-litigation risk firms. The coefficients are insignificant for bad news forecasts in columns 5 and 6. The Wald test χ^2 statistics and p-values are reported to test the difference in coefficients on $Treated_{i,c} \times Post_{t,c} \times HighLitRisk_{i,c}$ for good news and bad news forecasts. For example, the Wald test χ^2 statistic is 3.17 ($p = 0.08$) for the difference in coefficients between columns 4 and 6.

4.5. Precision of Management Forecasts

Lastly, we test the implication of the meeting guidance hypothesis on the precision of management forecasts, which is formally stated in Hypothesis 3. We use *Precision* as the dependent variable in the stacked regression model of Equation (1). Following previous literature (Baginski and Hassell 1997, Baginski et al. 2002), we assign each forecast a score ranging from zero to three, which gives the highest value to the most precise forecasts. We designate a score of zero if the forecast is a qualitative forecast, one if the forecast is an open-ended range, two if the forecast is a closed range, and three if the forecast is a point estimate. *Precision* is defined as the average score of management forecasts made by a firm during a fiscal year (Houston et al. 2019).

Panel A in Table 8 reports the stacked DID regression of management forecast precision on satellite data release.[16] We report the results for all management forecasts, good news forecasts, and bad news forecasts in columns 1 and 2, 3 and 4, and 5 and 6, respectively.[17] The DID coefficients on $Treated_{i,c} \times Post_{t,c}$ are negative, although insignificant for all management forecasts. When we further bifurcate management forecasts into good news and bad news forecasts, we find significant negative coefficients for good news forecasts. For example, the coefficient is -0.057 (t-statistic $= -2.62$) in column 4, indicating that after their satellite data are released, treated firms decrease the average precision of good news forecasts by 0.057 relative to control firms. The coefficients for bad news forecasts are close to zero and statistically insignificant.

As an alternative approach, instead of using the average precision of all management forecasts, we use the number of management forecasts within each precision score during a fiscal year as the outcome variable. Panel B in Table 8 reports the stacked Poisson regression for all management forecasts (columns $1-3$), good news forecasts (columns $4-6$), and bad news forecasts (columns 7 and 8), respectively.[18] We find that the DID coefficients are significant negative for precise forecasts with a precision score of three (point estimate) or two (closed-end range), and the results are driven by good news forecasts. The DID coefficients are insignificant for imprecise forecasts with a precision score of one (open-end range). Taken together, our results show that after satellite data release, retail firms not only decrease the frequency of good news forecasts but also tend to reduce the precision associated with good news forecasts. These results provide further support for the meeting guidance hypothesis.

5. Additional Tests

5.1. Test for Reverse Causality: Do Management Forecasts Induce Satellite Data Release?

To further address the endogeneity concern, in particular the reverse causality from voluntary disclosure to the release of satellite data, we examine whether the pre-2011 firm characteristics can predict the number of years until the satellite data of a firm is released in the following cross-sectional OLS regression for both

Table 8. Precision of Management Forecasts

	Management forecasts		Good news forecasts		Bad news forecasts	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Precision of management forecasts						
Treated × Post	**−0.029**	**−0.026**	**−0.058*****	**−0.057*****	**−0.001**	**−0.005**
	(−1.20)	**(−1.00)**	**(−3.12)**	**(−2.62)**	**(−0.03)**	**(−0.17)**
Controls	No	Yes	No	Yes	No	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,542	26,542	13,661	13,661	14,162	14,162
Adjusted R^2	0.418	0.419	0.266	0.272	0.394	0.397

Panel B: Number of management forecasts within each precision score								
Precision score	3	2	1	3	2	1	3	2
Treated × Post	**−0.306*****	**−0.182*****	**0.230**	**−0.613****	**−0.355*****	**−0.142**	**0.005**	**−0.019**
	(−3.77)	**(−2.92)**	**(0.63)**	**(−2.22)**	**(−2.84)**	**(−0.29)**	**(0.02)**	**(−0.26)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,233	30,905	18,037	11,041	20,576	3,780	13,448	21,233
Pseudo-R^2	0.431	0.564	0.245	0.211	0.256	0.127	0.251	0.339

Notes. This table reports the stacked difference-in-differences regression of management forecast precision. In Panel A, the dependent variable is the precision of all management forecasts (columns 1 and 2), good news forecasts (columns 3 and 4), and bad news forecasts (columns 5 and 6), respectively. Each forecast is assigned a score ranging from zero to three, which gives the highest value to the most precise forecasts. We designate a score of zero if the forecast is a qualitative forecast, one if the forecast is an open-ended range, two if the forecast is a closed range, and three if the forecast is a point estimate. Precision is defined as the average score of management forecasts made by a firm during a fiscal year. In Panel B, the dependent variable is the number of management forecasts (columns 1–3), good news forecasts (columns 4–6), and bad news forecasts (columns 7 and 8) within each precision score in a fiscal year, respectively. Note that the bad news forecasts in our sample only have precision scores of three and two but do not have a precision score of one. All continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are reported in Appendix B. All regressions include cohort-specific firm and year fixed effects. The *t*-statistics (for Panel A) or *z*-statistics (for Panel B) based on two-way clustered standard errors at firm and year levels are reported in parentheses. Coefficients on main variables of interest are in bold. The sample period is from 2008 to 2018.

*, **, and ***Statistical significance at the 10%, 5%, and 1% levels, respectively.

treated and control firms:[19]

$$YearsToRelease_i = \alpha_t + \beta MgmtFcst_i + \gamma \boldsymbol{z_i} + \epsilon_i, \qquad (5)$$

where the dependent variable, $YearsToRelease_i$, is the number of years until the satellite data are released for a treated firm i and is set to 20 for all control firms;[20] $MgmtFcst_i$ and $\boldsymbol{z_i}$ are pre-2011 management forecast frequency and firm characteristics, which include all control variables used in our previous main regression.

The results are reported in Table IA.4 of the Online Appendix. In column 1, the explanatory variables include the number of management forecasts and other firm characteristics. In column 2, the explanatory variables include the number of good news management forecasts, the number of bad news management forecasts, and other firm characteristics. We find that the estimated coefficients on *MgmtFcst*, *GoodNewsFcst*, and *BadNewsFcst* are all statistically and economically insignificant, confirming that management disclosure frequency itself does not lead to the initiation of satellite data release. Our results thus alleviate the endogeneity concern of reverse causality. Among all firm characteristics, only analyst coverage bears a significant coefficient at the 5% level.

5.2. Are Satellite Data More Informative About Good News or Bad News?

A related question is whether the informativeness of satellite data are different for good news and bad news? If satellite data are more informative for good news than for bad news, they might be more relevant and have a stronger effect on good news forecasts. We test this possibility by running the following regression of a retail firm's performance measures on its traffic growth of the same quarter:

$$\begin{aligned} Performance_{i,t} = {} & \alpha_i + \alpha_t + \beta_1 Traffic\ Growth(+)_{i,t} \\ & + \beta_2 Traffic\ Growth(-)_{i,t} + \gamma \boldsymbol{z_{i,t}} + \epsilon_{i,t}, \end{aligned} \qquad (6)$$

where the dependent variable, $Performance_{i,t}$, is quarterly sales growth (in %), net income growth (in %), and market-adjusted cumulative abnormal returns around the five-day [−2,2] event window of quarterly earnings announcement (in %) for firm i in quarter t. Traffic growth is calculated as the weighted average of quarterly store-level percentage change in car count for each retail firm (in %) in the same quarter. *Traffic Growth*(+) represents traffic growth with good news, which equals traffic growth when it is positive in a quarter and zero otherwise. *Traffic Growth*(−) represents traffic growth with bad news, which equals traffic growth when it is negative in a quarter and zero otherwise. The control variables, $z_{i,t,c}$, include lagged sales growth, quarterly stock market returns, and other firm characteristics used in our baseline regression.

The results are reported in Panel B of Table IA.1 in the Online Appendix. We find that the coefficients on both *Traffic Growth*(+) and *Traffic Growth*(−) are positive for all three performance measures, suggesting that satellite data are informative about both good and bad news of firm performance. The magnitude of the coefficients is generally larger on *Traffic Growth*(−) than *Traffic Growth*(+) in our sample, although the difference is only statistically significant for CAR[−2,2] as suggested by the *F*-statistics of the Wald tests.[21]

The bottom line here is that satellite data are not more revealing (or even less revealing) for good news than for bad news. If the satellite data are more revealing for bad news than for good news, it follows that the partial adjustment of market expectation would be smaller in the good state, which makes managers less likely to stop issuing good news forecasts (under our meeting guidance hypothesis). This would actually weaken the relationship between satellite data release and the decrease in good news forecasts.

5.3. Management Forecast Frequency and Satellite Data Release: Excluding Preannouncements

To test the robustness of our analysis to preannouncements, we conduct the baseline regression by excluding preannouncement forecasts, which are defined as management forecasts issued after fiscal quarter-end and before the formal earnings announcement following previous studies (Zhang 2012, Cheng et al. 2013, Balakrishnan et al. 2014). Preannouncement forecasts represent 6.56% of our management forecast sample. Table IA.5 in the Online Appendix reports the results. The main findings remain similar to our previous analysis.

5.4. Management Forecast Frequency and Satellite Data Release by a Single Data Vendor

In our main analysis, we use two sources of data to identify the release date, which enables us to have a more comprehensive sample. In this section, we separately test the effect of satellite data release by a single data vendor: RS or OB. We stack cohort-specific data sets that include all firms that experience the release of satellite data in a year by RS (or OB) and all other firm-year observations that are not-yet-treated by RS (or OB) or never-treated. Table IA.6 in the Online Appendix reports the results. Panel A presents the results for RS, which releases satellite data for 37 firms. Panel B presents the results for OB, which releases satellite data for 116 firms. We show that using the satellite data release of a single data vendor yields similar inferences, which facilitates the comparability of our findings to other studies that rely on only a single data vendor.

5.5. Management Forecast Frequency and Satellite Data Release: Quarterly Tests

Our baseline regression is based on events at the yearly frequency rather than quarterly frequency due to the concern that the number of treated firms for each quarter is small, which may weaken the power of the empirical tests (i.e., reduce the signal to noise ratio). Panel B of Figure IA.1 in the Online Appendix plots the number of release events across year-quarters during our sample period. We observe that only 7 of 32 quarters have more than five treated firms.

However, quarterly tests can take advantage of more variation in the data and are particularly useful for capturing variations in the timing of data availability in 2016, when the number of treated firms peaks. As a robustness test, we perform the stacked DID Poisson regression of management forecast frequency based on treated events at quarterly frequency and report the results in Table IA.7 in the Online Appendix. We stack cohort-specific data sets that include all firms that experienced the release of satellite data in a year-quarter (treated) and all other firm-quarter observations that are not-yet- or never-treated (effective controls). We show that the DID coefficients are significantly negative for all management forecasts and good news forecasts but insignificant for bad news forecasts, confirming our previous findings in the yearly tests.

5.6. Management Forecast Frequency and Satellite Data Release: Informativeness of Historical Satellite Parking Lot Traffic Data

The meeting guidance hypothesis predicts that managers are more likely to cut forecasts when the market expectation adjusts toward the true earnings expectation under the good state. Such an adjustment should increase with the precision or the informativeness of the satellite data.

To capture the informativeness of the satellite data, we estimate the sensitivity of sales growth with respect to the same-quarter traffic growth of the firm using historical satellite parking lot traffic data. A higher sensitivity means a higher informativeness of traffic growth data for firm operating performance. We replace $Treated_{i,c}$ in the stacked DID regression with two dummy variables: $Treated[HighSensitivity]_{i,c}$ is a dummy variable that equals one if the satellite data on parking lot traffic is released and the sales growth-traffic growth sensitivity is above the sample median for treated firm i in cohort c; $Treated[LowSensitivity]_{i,c}$ is a dummy variable that equals one if the satellite data on parking lot traffic is released and the sales growth-traffic growth sensitivity is below the sample median for treated firm i in cohort c. The results are reported in Table IA.8 of the Online Appendix. We show that when the informativeness of traffic growth data is higher, the negative effect of satellite data release on the frequency of management forecasts, especially good news forecasts, is stronger.

5.7. Incidence of Meeting or Beating Market Expectation and Satellite Data Release

An implication of the meeting guidance hypothesis is that if managers stop issuing forecasts when the market expectation is higher than their intended forecast level in the good state, the incidence of meeting or beating the market expectation will decrease. We test this implication by rolling up the quarterly incidences to the annual level to match the rest of our analysis and investigate how the incidences change after satellite data releases.

The results are reported in Table IA.9 in the Online Appendix. We show that the DID coefficient is significantly negative, suggesting that the incidences of meeting or beating the market expectation for treated firms, relative to control firms, indeed decrease after satellite data releases. The results suggest that as the availability of alternative data facilitates information discovery of the market, managers' ability to guide the market and achieve their own goal of earnings target is reduced.

5.8. Firm's Overall Information Environment

An important question closely related to our findings is how the satellite data release impacts the overall information environment of the firm? According to the meeting guidance hypothesis, the decrease in good news forecasts does not necessarily adversely affect the total information environment because such a decrease is a consequence of the market having already updated its expectation based on the new signals from the satellite data (i.e., satellite data and management guidance act as if they are "substitutes" under a good state, so the total information environment does not decrease). In fact, the availability of satellite data can improve the overall information environment when the market expectation is higher than the managers' intended guidance in the good state.

Using the precise timing of data releases, we perform three tests along the lines of Zhu (2019) and confirm her findings that the total information environment improves after the satellite data release. The results are reported in Table IA.10 in the Online Appendix. First, we follow Zhu (2019) to investigate the contemporaneous earnings response coefficient, which is defined as the relation between the absolute value of unexpected earnings and announcement period absolute returns. We document that the contemporaneous earnings response coefficient decreases after satellite data release, which suggests that the information of satellite data has already been incorporated into the market expectation before the actual earnings are announced, consistent with the partial adjustment assumption in our meeting guidance hypothesis. Second, we follow Zhu (2019) to investigate the future earnings response coefficient, which is defined as the relation between current returns and future earnings. We document that the future earnings response coefficient increases after satellite data release, which suggests that current returns reflect future earnings to a greater extent after satellite data release, reflecting higher long-run price informativeness. Third, we document that the absolute level of earnings surprise decreases after satellite data release, which provides additional corroborating evidence that after satellite data release, the market better incorporates the information of satellite data before earnings announcements, leading to lower absolute level of earnings surprise.[22]

6. Conclusion

Exploiting staggered releases of real-time satellite data of parking lot traffic for U.S. retail firms, we provide evidence suggesting that big data availability causes retail firms to reduce the frequency of management forecasts, especially for those conveying good news. Although this asymmetric reduction in management forecasts cannot be explained by the general substitution between price informativeness and firm voluntary disclosure, our evidence is consistent with managers' incentives to meet their own earnings guidance. The economic intuition is that, as big data reveal relatively precise signals of the true state, the market adjusts its earnings expectation toward the true state sufficiently enough to create asymmetric risk for the managers to miss their own earnings guidance. The managers become reluctant to issue guidance to further talk up the market expectation in the good state, but their incentive to walk down the market expectation in the bad state remains strong. Further evidence suggests that the observed asymmetric reduction exhibits cross-sectional variations that are predicted by the meeting guidance hypothesis.

Our results have important implications for the trend of corporate voluntary disclosures under the ever-improving information technologies that make big data available to investors. To the extent that our results from satellite data can be generalized to other types of big data or the presence of any additional data, the major implication of our results is that the increasing availability of new data will lead to "disappearing" good news forecasts. This phenomenon, however, does not suggest that new data availability disciplines managers by curbing their disclosure optimism. By contrast, it may be driven by the relatively more pronounced asymmetric incentive for managers to meet or beat market expectations introduced by new data availability. Overall, our study suggests that, in the era of big data, investors should be more vigilant about managers' asymmetric incentive when making voluntary disclosures.

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Appendix A. Illustrative Model and Numerical Example

We put forth the following parsimonious model to articulate our thoughts. The setting we consider includes three time periods, Time 0, 1, and 2, and two types of agents, the market and managers. The market represents the opinions of all market participants, including investors and analysts. At Time 0, the market and managers have the same expectation of firm i's EPS to be realized at Time 2, which is μ_0. At Time 1, managers receive a private signal, which reveals the true state of firm i and the true distribution of its EPS at Time 2. There are two states, the good state and the bad state. In the good state, the distribution of firm i's EPS is a normal distribution with a mean of $\mu_0 + a$ and a variance of σ^2, or $N(\mu_0 + a,\ \sigma^2)$. In the bad state, the distribution of firm i's EPS is a normal distribution with a mean of $\mu_0 - a$ and a variance of σ^2, or $N(\mu_0 - a,\ \sigma^2)$. At Time 2, EPS realizes following the above distribution in each state.

We then consider two scenarios depending on the availability of satellite data.

Scenario 1: Satellite traffic data are not available at Time 1. Then the market maintains its expectation of firm i's EPS at μ_0. To keep investors informed, managers choose to issue an EPS guidance. Because of the uncertainty in the realization of earnings at Time 2, managers have the incentive to be conservative when issuing the EPS guidance to avoid falling short of their guidance. In the good state, managers will issue a good news forecast with EPS of $\mu_0 + a(1 - b\sigma)$ (where $a > 0,\ 0 < b < 1/\sigma$), which is higher than the market's expectation of firm i's EPS at Time 2 (which is μ_0) but lower than the managers' expectation (which is $\mu_0 + a$).

The difference between the managers' expectation and the earnings guidance is $ab\sigma$, which represents the "buffer zone" created by the managers to prevent missing their own earnings guidance. Note that both b and σ are related to risks (which will be further discussed below). Briefly, σ captures the fundamental uncertainty. b determines the probability that managers will miss their own earnings guidance, which is $\Phi(-ab)$, and thus captures managers' concerns over reputational or legal risk.

In the bad state, managers will issue a bad news forecast with EPS of $\mu_0 - a(1 + b\sigma)$ (where $a > 0,\ 0 < b < 1/\sigma$), which is not only lower than the market's expectation of firm i's EPS at Time 2 (which is μ_0) but also lower than the managers' expectation (which is $\mu_0 - a$). The difference between the managers' expectation and the earnings forecast is $ab\sigma$, which again represents the "buffer zone" created by managers to prevent missing earnings guidance.

Scenario 2: Satellite traffic data become available and convey a noisy signal about firm i's EPS to the market. The market revises its prior expectation of firm i's EPS toward the true state following a partial adjustment model: $\mu_1 = \mu_0 + ca = (1 - c)\mu_0 + c(\mu_0 + a)$ under the good state (when the satellite traffic data convey good news) and $\mu_1 = \mu_0 - ca = (1 - c)\mu_0 + c(\mu_0 - a)$ under the bad state (when the satellite traffic data convey bad news), where $0 < c < 1$. c is the partial adjustment coefficient, which represents the degree of adjustment toward to the true state.

The managers' decision on whether to issue an EPS forecast depends on the difference between their intended guidance and the market expectation of firm i's EPS. As discussed above, in the good state, managers' intended EPS guidance is $\mu_0 + a(1 - b\sigma)$, which is lower than their expected EPS (which is $\mu_0 + a$) because the realization of EPS in Time 2 is uncertain and managers intentionally create a buffer zone of $ab\sigma$ to avoid missing their own guidance. Managers will only issue a good news forecast when their intended guidance is higher than the market expectation: $\mu_0 + a(1 - b\sigma) > \mu_0 - ca$, or $c + b\sigma - 1 < 0$. In other words, managers will no longer issue a good news EPS forecast when $c + b\sigma - 1 > 0$. Our hypotheses below will discuss in more details about these parameters and their empirical implications.

In the bad state, managers' intended EPS guidance is $\mu_0 - a(1 + b\sigma)$, which is again lower than their expected EPS as managers create a buffer zone to avoid missing guidance. The key insight is that in the bad state, managers' intended EPS guidance is always lower than the market expectation $(\mu_0 - ca)$, or $c - b\sigma$ is always less than one.[23] As a result, the managers will *always* issue a bad news forecast.

We provide a numerical example to illustrate our model. We set the parameters as follows: $\mu_0 = 2$, $a = 1$, $\sigma = 1$, $b = 0.3$, and $c = 0.8$; μ_0, a, and σ are chosen without loss of generality. We choose b and c so that the following condition holds: $c + b\sigma - 1 = 0.8 + 0.3 \times 1 - 1 = 0.1 > 0$. Figure A.2 graphically presents the numerical example.

At Time 0, the market and managers both have an expectation of firm i's EPS to be \$2. At Time 1, managers receive a private signal, which reveals the true state of firm i and suggests that EPS at Time 2 follows a normal distribution of $N(3,1)$ in the good state and $N(1,1)$ in the bad state.

At Time 1, when satellite data are not available, the market remains its EPS expectation at \$2. In the good state, managers issue a good news EPS guidance of $2 + 1 \times (1 - 0.3 \times 1) = \$2.7$, which is higher than the market expectation of \$2 but lower than the true expectation of \$3. Given the uncertainty of EPS realization at Time 2, managers create a \$0.3 buffer zone to prevent missing their guidance. In the bad state, managers issue a bad news EPS guidance of $2 - 1 \times (1 + 0.3 \times 1) = \$0.7$, which is not only lower than the market expectation of \$2 but also lower than the true expectation of \$1, again creating a \$0.3 buffer zone to avoid missing guidance. This scenario is graphically presented in Figure A.2(a).

When satellite traffic data become available and convey a noisy signal of the true EPS, the market revises its prior expectation of firm i's EPS. In the good state, the market revises its EPS expectation to $2 + 0.8 \times 1 = \$2.8$. Because the managers' intended guidance is \$2.7, which is lower than the market expectation, managers will no longer issue any good news forecast as further "talking up" the market expectation will significantly increase the chance of missing guidance. In the bad state, the market revises its EPS expectation to $2 - 0.8 \times 1 = \$1.2$. Because the managers' intended guidance is \$0.7, which is lower than the market expectation, managers will continue to issue a bad news forecast to further "walk down" the market expectation, which is higher than the true expectation of firm i's EPS at \$1. This scenario is graphically presented in Figure A.2(b).

The above example illustrates how the availability of satellite data and the managers' incentives to meet their own guidance generate an asymmetric effect on management forecasts: After satellite data release, managers stop issuing good news forecasts but continue to issue bad news forecasts.

It is worth noting that, currently, we only allow satellite data to change the market expectation of earnings, that is, the mean of the market belief about the EPS distribution (the first moment). What if the availability of satellite data decreases the variance of the market belief about EPS distribution (the second moment)? To see the separate effects of satellite release on variance and subsequent management forecast decisions, let's assume for simplicity that satellite data only decrease the variance but do not change the mean of the market belief about the EPS distribution, which remains to be μ_0. Under our current setup, managers have perfect information about the true distribution of EPS at Time 2, which means that managers know exactly μ_0, a, and σ^2. It follows that the difference between managers' intended guidance (e.g., $\mu_0 + a(1 - b\sigma)$ in the good state) and the market expectation (μ_0), which determines the managers' decision to issue a forecast or not, will remain the same as if satellite data is not available (i.e., $= a(1 - b\sigma)$). Thus, managers' decision on whether to issue an EPS forecast will not change. The key intuition is that, as long as the managers have precise information about the actual earnings distribution (which is independent of the availability of satellite data), the decrease in the variance of the market belief about EPS distribution affects neither the market expectation (the first moment) nor the managers' intended guidance, and hence there is no effect on management guidance decisions.

How to think about the implications of our model if we allow the market to learn from the manager's decision to not issue a forecast and the manager to adjust her own forecasting strategy in response to the market expectation in the style of a full rational expectation model? In the classic rational expectation model without disclosure costs or other frictions (Grossman 1981, Milgrom 1981), the market will interpret nondisclosure as bad news. In our context, if managers do not provide guidance in the good state, the market will interpret it as a signal that the managers' expectation is lower than its prevailing expectation (after observing the satellite data). Therefore, the market may rationally respond by lowering its expectation, which in turn provides an incentive for managers to provide good news forecasts (when the market expectation is below the managers' intended guidance). Overall, the rational expectation of the market (conditional on observing no guidance in the good state) works against our finding of fewer management forecasts from the managers.

Figure A.1. (Color online) Illustrative Example

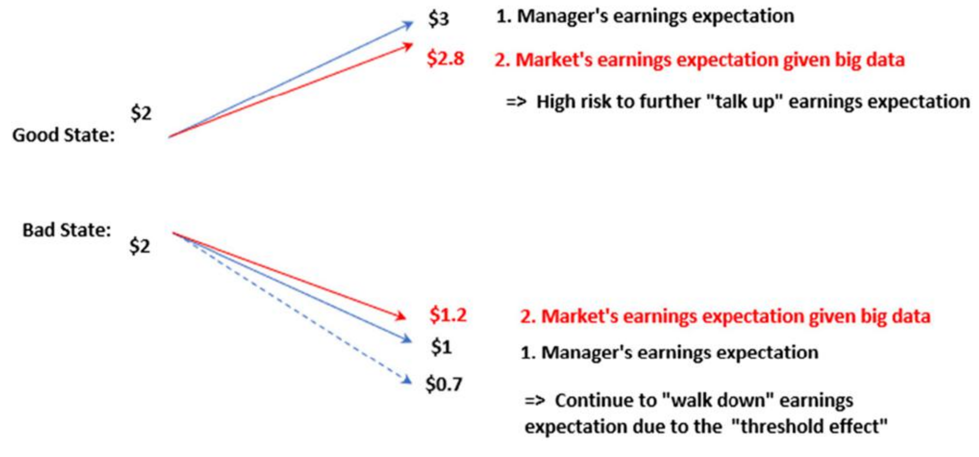
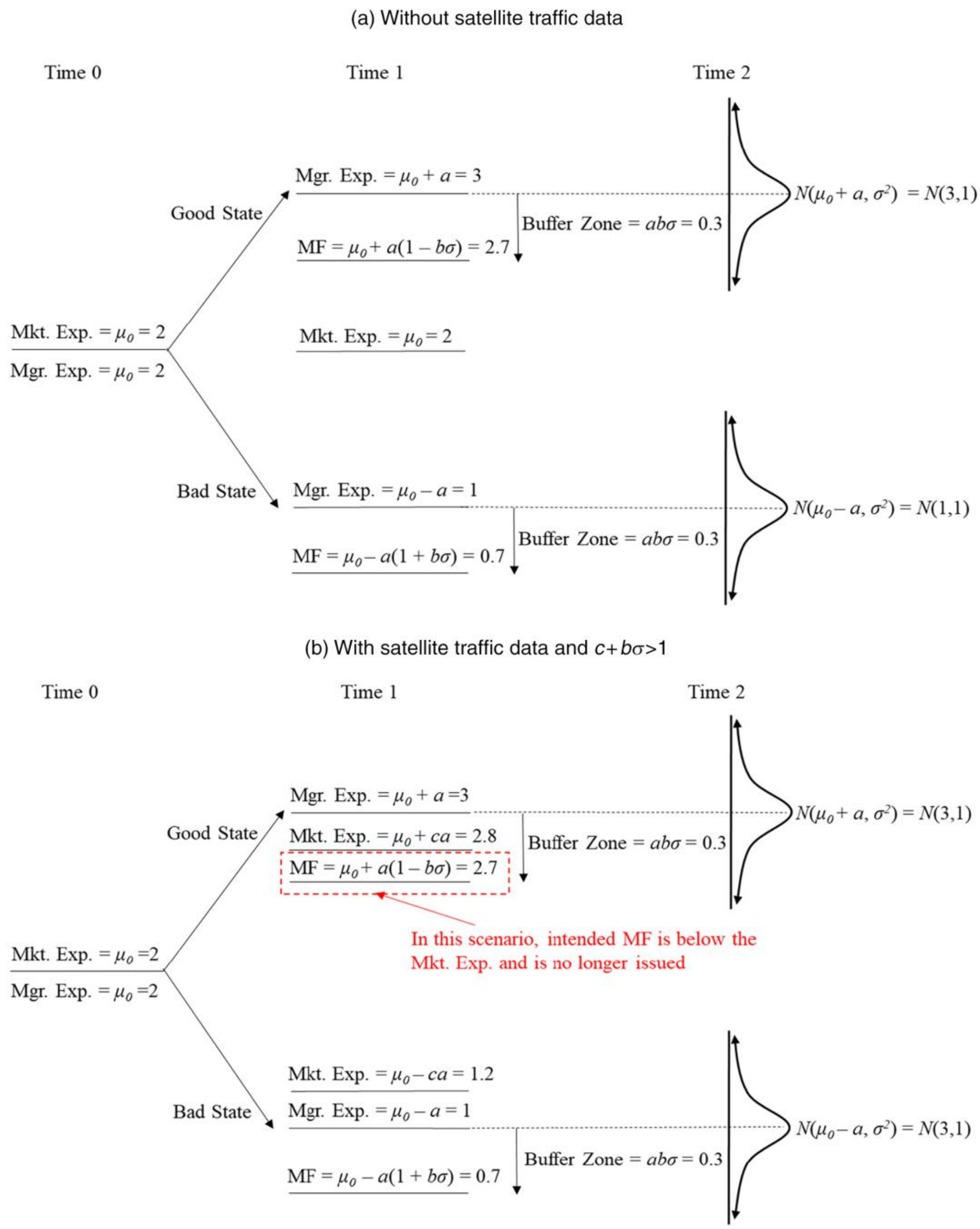


Figure A.2. (Color online) Model: Numerical Example



Notes. We set the parameters as follows: $\mu_0 = 2$, $a = 1$, $\sigma = 1$, $b = 0.3$, and $c = 0.8$. (a) Scenario when satellite traffic data are unavailable. (b) Scenario when satellite traffic data become available and the condition $c + b\sigma > 1$ holds.

Appendix B. Variable Definitions

Variable	Definition
Disclosure measures	
MgmtFcst	The total number of management forecasts issued over a fiscal year.
GoodNewsFcst	The total number of good news management EPS forecasts. A management EPS forecast is classified as good news if the point estimate, or the midpoint of the range forecast, is above the analyst consensus forecast before the management forecast. For open-ended management forecasts, the forecast is classified as good when its lower bound is higher than the analyst consensus forecast. Following Rogers and Van Buskirk (2013), we correct the potential measurement errors of forecast news when management forecasts are bundled with earnings announcements by updating analyst expectations with the latest information in earnings announcements. We then classify management forecast news based on the updated analyst forecast consensus.
BadNewsFcst	The total number of bad news management EPS forecasts. A management EPS forecast is classified as bad news if the point estimate, or the midpoint of the range forecast, is below the analyst consensus forecast before the management forecast. For open-ended management forecasts, the forecast is classified as bad when its upper bound is lower than the analyst consensus forecast.
ShortFcst	The total number of short-term management forecasts (quarterly guidance) issued over a fiscal year. Quarterly guidance includes those with horizons less than or equal to 90 days.
LongFcst	The total number of long-term management forecasts issued over a fiscal year. Long-run forecasts include those with horizons greater than 90 days.
GoodNewsShortFcst	The total number of good news quarterly EPS guidance issued over a fiscal year.
GoodNewsLongFcst	The total number of good news long-term management EPS forecasts issued over a fiscal year.
BadNewsShortFcst	The total number of bad news quarterly EPS guidance issued over a fiscal year.
BadNewsLongFcst	The total number of bad news long-term management EPS forecasts issued over a fiscal year.
Precision	Each forecast is assigned a score ranging from zero to three, which gives the highest value to the most precise forecasts. We designate a score of zero if the forecast is a qualitative forecast, one if the forecast is an open-ended range, two if the forecast is a closed range, and three if the forecast is a point estimate. Precision is defined as the average score of management forecasts made by a firm during a fiscal year.
Precision_GoodNews	The average score of good news management EPS forecasts made by a firm during a fiscal year.
Precision_BadNews	The average score of bad news management EPS forecasts made by a firm during a fiscal year.
Firm-level control variables	
RetVol	Stock return volatility, calculated as the standard deviation of monthly stock returns over a firm's fiscal year, with a requirement of at least six months of observations.
AbsChEPS	The absolute value of the annual change in earnings per share divided by stock price at the beginning of the fiscal year.
MktAdjRet	Market-adjusted stock return, defined as the firm's buy-and-hold 12-month fiscal year stock return minus the CRSP value-weighted stock return over the same period.
R&D	R&D expense divided by the book value of assets at the beginning of the fiscal year.
Size	Firm size, defined as the natural logarithm of the market value of equity.
Coverage	Analyst coverage, defined as the average number of analysts making earnings forecasts for a firm over a fiscal year.
InstOwn	Institutional fractional ownership, collected from the Thomson Reuters CDA/Spectrum Institutional(13f) Holdings database and represents institutional holdings at the beginning of the fiscal year.
D_Issuance	Equity or debt issuance dummy, which takes a value of one if a firm issues public equity or public debt in a subsequent two-year period, and zero otherwise.
MB	Market-to-book equity ratio, defined as the market value of equity divided by the book value of equity.
Lev	Leverage, defined as total liabilities minus deferred taxes scaled by total book assets.
StdEarn	Standard deviation of earnings, defined as the standard deviation of earnings before extraordinary items over the prior five years, with a requirement of at least three years of observations.
D_PosChEarn	Positive earnings change dummy, which takes the value of one if the annual earnings per share divided by stock price of the current year is higher than that of the previous year, and zero otherwise.
Optimism	Analyst optimism, defined as the difference between analyst forecast consensus at the beginning of the fiscal year and the actual earnings per share, scaled by the absolute value of actual earnings per share.
Conditioning variables	
HighInstOwn	A dummy variable that equals one if firm i has high institutional ownership (above the median) at the end of year $t-1$, and zero otherwise.
HighCFVol	A dummy variable that equals one if firm i has high cash flow volatility (above the median) at the end of year $t-1$, and zero otherwise. Cash flow volatility is defined as the variance in a firm's annual operating cash flow scaled by assets over the past five-year period following Jayaraman (2008).
HighLitRisk	A dummy variable that equals one if firm i has high expected litigation risk (above the median) at the end of year $t-1$, and zero otherwise. Firm-level expected litigation risk is calculated as the probability of litigation based on the coefficient estimates reported in model 4 of table 7 by Kim and Skinner (2012).

Endnotes

[1] See Froot et al. (2017), Zhu (2019), Kang et al. (2021), Blankespoor et al. (2022), and Katona et al. (2024).

[2] For instance, Zhu (2019) designates June 30, 2014, as the data release date for all firms and is unable to detect significant changes in management forecasts. Zhu (2019, footnote 20) discusses the findings regarding voluntary disclosure and explicitly acknowledges her data limitations on page 2032. Powered by the precise timing of data releases, we focus on changes in voluntary disclosures while confirming her findings of the improvement in total information environment after the satellite data release.

[3] We provide a parsimonious model in Appendix A to formalize these assumptions and theoretical predictions.

[4] From the empirical standpoint, the major advantage of the satellite data is knowing the precise timing of data availability to investors (although it is unclear when other alternative data become available to investors for each firm). Regarding their economic usefulness, different data generally have their own unique values. For instance, credit card or mobile device data can be used to measure daily or hourly traffic changes and to analyze consumer behavior at the transaction level, while satellite data do not exist in such high frequency and cannot provide transaction level information. However, to the extent that transactions at a retail store are not made by credit card alone or by a specific mobile app, the credit card or mobile device data only capture part of the total sales of a specific store, whereas satellite-based retail traffic data see every car in the parking lot and provide comprehensive information about total sales at each store.

[5] When the data vendors commercially release the satellite data of a specific company to its customers, the release date is generally later than the "start date" of the satellite traffic data. For example, when RS Metrics released the satellite traffic data of Best Buy Co. on March 19, 2013, the satellite traffic data actually starts from October 30, 2010.

[6] Prior studies focus on traditional institutions such as sell-side analysts, institutional or active investors, and banks, and provide evidence consistent with the demand-side effect. For example, see Langberg and Sivaramakrishnan (2008) and Balakrishnan et al. (2014) regarding analysts; Ajinkya et al. (2005), Jung (2013), Boone and White (2015), Bourveau and Schoenfeld (2017), and Khurana et al. (2018) regarding institutional or active investors; and Lo (2014), Vashishtha (2014), and Chen and Vashishtha (2017) regarding banks.

[7] The frequency of management forecasts for retail firms are in line with the underlying population (conditional on sales scaled by asset). Specifically, the median and mean management forecasts in our sample are 7 and 9.71 (in the unstacked sample), respectively. For the Compustat-IBES population within the same sales decile, the median and mean management forecasts during our sample period are 6 and 8.91, respectively, and the statistical differences between our sample and the population are insignificant.

[8] We extensively search the Factiva news database and find that within three years after the satellite data is released, about 20% of our sample firms appear at least once in the news articles stating that satellite parking lot traffic data is used to evaluate firm performance by various investors and analysts. Given that the news articles are public information, we expect the managers to be aware of the usage of the satellite data. Two news articles involving Whole Foods and Kroger and Lowe's and Home Depot explicitly state that the managers are aware of the usage of satellite parking lot data by investors (https://www.cnbc.com/2017/10/04/whole-foods-parking-lots-were-busier-post-amazon-satellites-show.html and https://www.wsj.com/articles/facing-an-activist-investor-lowes-appoints-new-directors-1516369275). In unreported figure, we plot the number of news observations three years prior to and after the event year of satellite data release ($t = 0$) for the 24 retail firms identified in the Factiva database. We find that before satellite data release (when $t \leq -1$), the number of news articles is close to zero; after satellite data release (when $t \geq 0$), the number of news articles starts to significantly increase. The evidence provides additional assurances on the measurement quality of the data release date.

[9] Regarding short-term versus long-term forecasts, this uncertainty effect generates the opposite prediction that managers may be more likely to reduce long-term forecasts because they face higher uncertainty about long-term earnings and may wait until they feel more certain about their meet-or-beat likelihoods.

[10] Our analyses remain qualitatively similar when control firms are selected based on the two-digit Standard Industrial Classification (SIC). Considering that our first satellite release is in 2011, we start our sample in 2008, three years before the first event.

[11] Causal inferences rest on the stable unit treatment value assumption (SUTVA), which requires that the potential outcome for a given firm responds only to its own treatment status and is unrelated to the treatment status of other firms (i.e., no spillovers). The SUTVA might be violated in the presence of intraindustry information transfers (Foster 1981, Baginski 1987, Ramnath 2002, Koo et al. 2017, Kim et al. 2018). In our context, when the satellite data of a treated firm is released, the market may not only revise its expectation about the treated firm but also revise its expectation about similar firms. Such information transfers may lead to fewer management forecasts, especially good news forecasts, among the control firms in the same industry and our main results will be underestimated.

[12] Specifically, a management forecast is classified as good (bad) news if the point estimate, or the midpoint of the range forecast, is above (below) the analyst consensus forecast before the management forecast. For open-ended management forecasts, the forecast is classified as good (bad) when its bottom (upper) bound is higher (lower) than the analyst consensus forecast.

[13] In recent years, especially after the passage of Regulation Fair Disclosure (Reg FD) in 2000, an increasing number of management forecasts are issued in conjunction with earnings announcements, which are referred to as bundled forecasts (Anilowski et al. 2007). The conventional classification of forecast news may be biased for bundled forecasts due to measurement errors.

[14] The Wald test for the difference in coefficients in a Poisson regression follows a χ^2 distribution.

[15] We have also taken a closer look at this issue by further bifurcating quarterly guidance into late guidance (horizon $\leq$ 45 days) versus early guidance (45 days < horizon $\leq$ 90 days) and obtain similar inferences (i.e., the decrease in management forecasts, especially good news forecasts, is more pronounced for short-horizon forecasts than for long-term forecasts).

[16] Because the dependent variable is a continuous variable, we estimate the stacked regression with the OLS model.

[17] Because precision is measured as the average score of all management forecasts/good news forecasts/bad news forecasts made by a firm during a fiscal year and a firm may issue both good news and bad news forecasts in a given fiscal year, the total number of observations for both good news forecasts and bad news forecasts sample exceeds that of all management forecasts sample.

[18] It is worth noting that the bad news forecasts in our sample only have precision scores of three and two but do not have a precision score of one.

[19] Because pre-2011 firm characteristics are required to predict the number of years until the satellite data of a firm is released, the sample size in the reverse causality test (596 firms) is smaller than

that in the full sample (643 firms) due to (1) firms enter into the sample after 2011 or (2) firms lack control variables before 2011.

[20] Because control firms never experience the satellite data release by the end of our sample period, we set the number of years to an arbitrarily large number of years (i.e., 20). Our inferences are not sensitive to the choice of the number of years chosen.

[21] Katona et al. (2024) also find that the coefficient on *Traffic Growth*(−) is larger than that of *Traffic Growth*(+) in predicting same-quarter retail firm performance, although they do not test the difference in the two coefficients. Our results might slightly differ from theirs because our sample covers more retail firms than those in Katona et al. (2024), which only includes 44 major retailers.

[22] Prior results from and Zhu (2019) and Katona et al. (2024) do not necessarily contradict each other. Although Zhu (2019) focuses on the information asymmetry between corporate insiders and outside investors, Katona et al. (2024) focuses on the information asymmetry between different groups of outside investors (e.g., sophisticated investors with access to satellite data and unsophisticated investors without the access).

[23] This is because c is the partial adjustment coefficient, which is bounded between zero and one; b is the parameter that managers choose to setup the buffer zone, which is always larger than zero; and σ is the standard deviation of the EPS distribution, which is also larger than zero.

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