Dividend Policy in the Era of Big Data*

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The releases of real-time satellite data of U.S. retail firms' parking lot traffic reduce information asymmetry between managers and outside investors. Using the staggered releases of satellite data as a quasi-natural experiment, we test the competing dividend theories based on information asymmetry and agency costs. We find that retail firms substantially increase dividend payouts after their satellite-based traffic data are released, and the increase in dividends is concentrated in firms with poor investment opportunities. Further analyses show that the effect of satellite data release is stronger when firms have more entrenched managers, less severe financial constraints, or higher ownerships by sophisticated investors. Additionally, we find that firms finance the dividend increase by reducing low-quality investment while their high-quality investment (R&Ds) remains intact. These results support the "outcome model" that dividend payout is a complement of corporate governance, and show that big data can have substantial effects on firms' corporate policies.

Keywords: Alternative Data; Satellite Imagery Data; Dividend Policy; Outcome Model; Substitute Model; Signaling Model; Corporate Governance

JEL Classification: G31, G32, G34, G35

1. Introduction

The recent technological advances and vast proliferation of data can transform the ways firms operate. For example, information asymmetry between corporate insiders and outside investors looms large in the corporate world and has significant impacts on corporate policies. With the help of newly available alternative data, outside investors can close their information gap relative to firm managers and more effectively monitor the firms' operations. While existing literature documents that the use of alternative data can have substantial effects on asset management and financial markets, to this date we have only limited evidence about the real effect of alternative data on corporate policies. In this paper, we investigate if the emergence of alternative data affects firms' corporate policies through improved information transparency.

We explore the staggered releases of the satellite imagery data of parking lot traffic for 142 U.S. publicly traded retailers. Zhu (2019) provides novel evidence that the satellite data releases increase the underlying retail firm's stock price efficiency, reduce the profitability of insider trading, and reduce investment inefficiency, suggesting that the satellite data serves as an additional mechanism for outside investors to monitor firm managers.[1] We differ from existing studies by investigating how the releases of satellite data affect the underlying firms' corporate policies. Specifically, we study firms' dividend policy for two reasons. First, dividend payout is a major corporate policy and firms' paying dividends is a puzzle especially for U.S. firms.[2] Second and more importantly, previous studies propose competing dividend theories that are centered on information asymmetry, and these theories

[1] As stated by Deloitte in a 2017 report, "*A well-known application of alternative data is satellite imagery analysis of parking lots, which is replacing the old school approach of physical foot traffic counts with clickers*." Katona, Painter, Patatoukas, and Zeng (2020) also find that the satellite-based data of parking lot traffic data contains value-relevant information about firm performance. Kang, Stice-Lawrence, and Wong (2020) use the satellite data as a measure of timely information about retail stores' performance and use it to examine investors' local information advantage.

[2] In a frictionless world, dividend policy is irrelevant to firm value (Modigliani and Miller 1958; Miller and Modigliani 1961). However, firms in the real world follow deliberately designed dividend policies (Black 1976). Dividend payout is especially puzzling for U.S. firms because shareholders on average pay higher taxes on dividends than on capital gains (Allen and Michaely 2003).

generate diverging predictions regarding the effect of satellite data. Therefore, the staggered releases of satellite data provide us with a quasi-natural experiment to test the competing dividend theories.

The release of satellite data can reduce the information asymmetry between corporate insiders and outside investors, and help investors better monitor the managers (Zhu, 2019). To illustrate this intuition, a 2018 *Wall Street Journal* article reports that, "*When D.E. Shaw & Co. sought to explain to Lowe's Cos. why it thought the home-improvement giant was underperforming rival Home Depot Inc., the New York hedge fund was armed with a data set that included an analysis of the number of cars in the two chains' parking lots from two years of satellite imagery… The fund … had accessed the images and counted the cars to help bolster an argument that the retailer wasn't attracting enough customers...*" Given the effect of satellite data on reducing information asymmetry and improving investors' monitoring, the three major theories of dividend policy have opposite predictions about how the satellite data release may influence firms' dividend policy.[3]

First, the satellite data may *complement* the role of dividends, leading to an *increase* in dividends after the release of satellite data. Specifically, the "outcome model" of agency theory (e.g., La Porta, Lopez-de Silanes, Shleifer, and Vishny 2000) builds on the premise that because of agency conflicts, firm managers have incentives to divert profits for personal use or finance value-destroying projects that provide personal benefits. As a result, outside investors will push managers to pay dividends which reduces the amount of free cash flows that managers may otherwise waste. In this scenario, the release of satellite data will cause an *increase* in dividends because the data enable investors to better monitor firm managers.

Second, the satellite data may *substitute* the role of dividends, leading to a *decrease* in dividends after the release of satellite data. This prediction is based on the other two major dividend theories. Specifically, the "substitute model" of agency theory suggests that given the needs for firms to raise external funding, managers have incentives to establish a reputation for not expropriating outside

[3] Section 2 discusses the related literature on dividend theories.

investors so that their firms can raise external financing at a low cost. Paying dividends therefore serves as a costly commitment of managers to not misuse corporate earnings (e.g., Myers 2000). Additionally, the "signaling model" suggests that because of the information asymmetry between firms and investors, managers of high-quality firms use dividends as a costly signal of private information about future cash flows or risk (e.g., Bhattacharya 1979; Grullon, Michaely, and Swaminathanet 2002). These two models suggest that dividends are *substitutes* for effective governance or publicly available information, and therefore predict a *decrease* in dividend payment after the satellite data releases because of the enhanced corporate governance and the increase in new information supply.

To test the competing predictions about the complementing and substituting roles of the satellite data, we obtain the satellite imagery data of parking lot traffic from two major data vendors, RS Metrics (RS) and Orbital Insight (OB), which cover 142 publicly traded U.S. retail firms ("treated firms") from 2011 to 2018. The satellite data releases for these firms started in a staggered manner between 2011 and 2017, with the highest number in 2016 when OB expands its coverage substantially.[4] To perform difference-in-differences analyses, we further include firms in the same industries as event firms but without satellite data coverage ("control firms"). Our final sample consists of 6,323 firm-years from 2009 to 2018, including 1,211 firm-years for treated firms and 5,112 firm-years for control firms.[5] To our knowledge, our satellite data is the largest of its kind used in the existing literature.

We first revisit the informativeness of the satellite data for our sample firms. We find that the traffic growth calculated using the satellite data reliably predicts retailers' sales growth, income growth, and earnings surprises. We further examine if sophisticated investors indeed utilize the satellite data. When a vendor starts to release a retail firm's satellite data, the firm's entire historical satellite data back to 2011 is also released. We measure sophisticated investors' trading by short selling as well as

[4] OB added 41 retailers in the summer of 2016.

[5] We choose 2009 as the beginning of our sample period because it provides a pre-event period (at least two years) for even the earliest release events in 2011 and in the meantime excludes the financial crisis of 2007-2008 in which firms' dividend policies are severely interrupted.

hedge fund ownership, and find that sophisticated investors respond strongly to the traffic growth *after* the vendors start to release the satellite data but not before the release of satellite data. These results suggest that, consistent with the existing literature, the satellite-based parking lot traffic data contains timely and valuable information about firm performance and it is utilized by outside investors (Zhu 2019; Katona et al. 2020; Kang, Stice-Lawrence, and Wong 2020).

Next, we start to test the competing dividend predictions by estimating the difference-in-differences regression of dividends on satellite data release. The dependent variable is either dividend yield (dividends scaled by market capitalization) or dividend payout ratio (dividends scaled by earnings). The main independent variable is *PostRelease*, which is a dummy variable that equals one if the satellite data has been released for a firm-year and zero otherwise. We also control for a broad set of firm characteristics as well as firm and year fixed effects. We find that the coefficient of *PostRelease* is significantly positive in the regressions of both of dividend measures, suggesting that firms significantly *increase* dividend payout after their satellite data is released. This result is also economically significant. For example, satellite data release on average increases a retailer's dividend payout ratio by 11 percentage points, or an over 50 percent increase from its mean. This result is consistent with the complementing role of satellite data rather than the substituting role of satellite data.

The staggered releases of satellite data provide a quasi-natural experiment because the timing of release is chosen by the two third-party data vendors rather than firm managers. However, we acknowledge that the staggered releases may not fully address the selection problem that data vendors may time the releases based on some factors that is also related to dividend policy. Our regression results alleviate this concern because we find that controlling of a broad set of firm characteristics causes very little change in the estimated difference-in-differences coefficients. We nevertheless conduct three analyses to further address the selection concern. First, we investigate the parallel trends assumption which is central to a causal inference (Bertrand and Mullainathan 2003; Roberts and

Whited 2013), and find that the treatment and control firms' pre-treatment trends are indistinguishable. Second, we conduct two placebo falsification tests by using pseudo treated firms or pseudo-event windows. In a sharp contrast to our baseline results, we find little change in dividend policy after the pseudo-events. Third, we find that the initiation of satellite data release has little relation with the underlying firm's prior dividend policy and firm characteristics. These analyses further alleviate the selection concern.

We conduct several robustness tests. First, we restrict the sample to only treated firms to address the concern that the difference-in-differences estimates are simply driven by control firms. Second, we use alternative approaches to select control firms, such as propensity score matching (PSM) or using Standard Industrial Classifications (SIC) rather than the six-digit GICS industry classification. Third, we examine alternative measures of dividend policy including dividend-to-asset ratio and a dummy of paying dividends. Our finding holds in all these robustness tests.[6]

Next, we conduct in-depth analyses of the complementing role of the satellite data. As emphasized in La Porta et al. (2000), the outcome model is much more relevant to firms with poor investment opportunities because for firms with good investment opportunities, outside investors will accept low dividends to support high reinvestment rates. We measure growth opportunities using sales growth and Tobin's Q, and find that, consistent with the outcome model, the increases in dividends after satellite data releases are much larger among firms with poor investment opportunities than among firms with good investment opportunities.

We also conduct several cross-sectional analyses. We expect the complementing role of the satellite data to be more important for firms with higher levels of managerial entrenchment where the improved external monitoring will have a larger marginal effect. Moreover, we expect the effect of

[6] We also examine stock repurchases which is an alternative way for firms to distribute cash to shareholders, although the drivers of repurchases and dividends are different from each other. We find (weak) evidence that share repurchases also significantly increase after satellite data releases.

satellite data to increase sophisticated institutional ownership because sophisticated institutional investors have greater incentives and abilities to utilize the satellite data in their monitoring. Additionally, we expect the effect of satellite data to be mitigated among financially constrained firms because for these firms, investors may reframe from pushing for dividends as the retained earnings can help avoid external financing in case of unexpected financing needs. Consistent with our predictions, we find that the increases in dividends after satellite data releases are significantly larger for firms with higher levels of managerial entrenchment (as measured by anti-takeover provisions), higher ownerships by sophisticated investors, or less severe financial constraints.

Finally, we investigate how the increase in dividends is financed. In the outcome model (complementing role of satellite data), the increased dividend payment is financed by the reduction in value-destroying investment projects. Consistent with increased dividends being financed by reduction in investment, we find that treated firms exhibit much lower asset growth and corporate investment after the release of satellite data relative to the control firms. Interestingly, we observe little decline in treated firms' research development (R&D) expenditure, which is widely documented as "good" investment associated with positive future performance. In contrast, we find no evidence of changes in treated firms' external financing, such as short-term debt, long-term debt, and equity issuance, after the release of satellite data. Taken together, these results support the prediction of the complementing role of satellite data that firms reduce value-destroying investment to finance the increase in dividends after the satellite data release.

Our study extends the finance literature on the growing importance of technology advancements and alternative data. Previous studies have examined the use of alternative data in financial markets and asset management (e.g., Chen De, Hu, and Hwang, 2014; Froot, Kang, Ozik, and Sadka, 2017; Da, Huang, and Yun, 2017). In contrast, there has been limited evidence to this date about the real effect of alternative data on corporate policies. Our study contributes to the existing literature by providing new evidence that alternative data can significantly impact corporate policies by closing the information gap between managers and outside investors. Our paper complements the recent study of Zhu (2019), which finds that the release of satellite-based traffic data provides an additional external monitoring mechanism for outside investors.

Second, our findings contribute to the literature on dividend policy and its important role in mitigating the agency problem (e.g., Easterbrook 1984; Jensen 1986). Financial researchers have developed competing theoretical models and conducted various empirical tests to explore the determinants of firms' dividend policies (e.g., Brav, Graham, Harvey, and Michaely, 2005; Leary and Michaely, 2011; Michaely and Roberts, 2012). Using the staggered releases of satellite data as a quasi-natural experiment that lowers the information asymmetry between managers and outside investors, we test the implications of several dividend theories, and our results support the outcome model that dividend payments are a mechanism for investors to mitigate the agency problem (La Porta et al. 2000).

2. Related Literature

2.1 Application of Satellite Data

Alternative data, also referred to as big data due to their large quantity and the need for advanced technologies to process them, are of growing importance for financial research. Satellite imagery data has emerged as an important category of alternative data used for economic and financial studies. For example, researchers have used the satellite imagery data of land use to investigate deforestation and its relation to economic growth (Skole and Tucker 1993; Foster and Rosenzweig 2003). Foster, Gutierrez, and Kumar (2009) use the satellite-based measure of air quality to study the effect of pollution on infant mortality. Chen and Nordhaus (2011) and Henderson, Storeygard, and Weil (2012) use the satellite data on night light to measure economic output and growth. Holmes and Lee (2012) use the satellite data on crop choices to investigate the driving factors of land usage.

Guiteras, Jina, and Mobarak (2015) use the satellite data on floods to study the economic consequences of climate change. A recent study by Mukherjee, Panayotov, and Shon (2020) uses cloud cover as an exogenous shock to satellite data quality and finds that satellite data provide valuable information that supplements the government disclosure of macro data.

Three recent studies examine the satellite-based data of U.S. retailers' parking lot traffic. Zhu (2019) studies Orbital Insight's satellite-based parking lot traffic releases and finds that the data releases increase the underlying retail firm's stock price efficiency. Furthermore, Zhu finds that the data releases reduce the profitability of insider trading and investment inefficiency, suggesting that alternative data can serve as an additional mechanism for outside investors to monitor firm managers. Katona et al. (2020) find that the satellite-based data of parking lot traffic data contains value-relevant information about firm performance. Such information is not fully impounded into stock prices as investors' unequal access to the satellite data increases information asymmetry among market participants. Kang, Stice-Lawrence, and Wong (2020) consider the satellite data of parking lot traffic as a timely measure of a retail store's performance and use it to examine investors' local information advantage. They find that institutional investors' trades are much more strongly associated with local stores' satellite data than nonlocal stores. We differ from these three studies in that we examine how the releases of satellite data affect firms' corporate policies.

2.2 Theories of Dividend Policy and Testable Hypotheses

Miller and Modigliani (1961) suggest that dividend policy is irrelevant to firm value in perfect and complete financial markets. However, in the presence of market frictions such as agency costs, asymmetric information, and taxes, dividend policy becomes important to firm valuation and investment decisions. As discussed below, the three major dividend theories suggest that the satellite data can either complement or substitute for the role of dividends, and therefore generate different predictions about how the release of satellite data affects firms' dividend policy.

2.2.1 The Complementing Role of Satellite Data: The "Outcome Model" of Dividend Policy

Agency models of dividends suggest that dividend policy plays a useful role in addressing agency conflicts between firm managers and outside investors (Easterbrook 1984; Jensen 1986; Zwiebel 1996; Fluck 1999; Myers 2000; La Porta et al. 2000). Specifically, managers have incentives to divert profits for personal uses or value-destroying projects that provide personal benefits. Thus, outside investors prefer dividends to retained earnings because dividend payouts reduce the amount of free cash flows that managers may otherwise waste (Jensen 1986). Dividend payouts also force managers to raise external funds more often and therefore face more frequent scrutiny by outside investors (Easterbrook 1984).

The "outcome model" posits that dividends are an outcome of effective governance (e.g., Jensen 1986; La Porta et al. 2000). Effective governance makes it difficult or costly for managers to use corporate earnings for personal benefits. As a result, managers of firms with effective governance tend to pay more dividends than managers of firms with poor governance. Consistent with the outcome model, prior studies find that dividend payouts are significantly higher for firms located in countries with stronger minority shareholder protection (La Porta et al. 2000), firms with higher managerial ownership (Fenn and Liang 2001), and publicly listed firms (Michaely and Roberts 2011).

Since the satellite-based parking lot traffic data provides outside investors with timely and valuable information about firm performance, the release of satellite data tends to enhance outside investors' ability to effectively monitor firm managers (Zhu 2019). In this case, the *complementing role* of the satellite data predicts that the release of satellite data will cause an *increase* in firms' dividend payments.

2.2.2 The Substituting Role of Satellite Data: The "Substitute Model" and the "Signaling Model" of Dividend Policy

The satellite data can serve as *substitutes* for dividends under the "substitute model" or the "signaling model" of dividend policy, in which case the releases of satellite data will cause a *decrease* in firms' dividends.

The "substitute model" of dividend policy argues that dividends are a substitute for corporate governance (e.g., Myers 2000; La Porta et al. 2000). Given the need for firms to raise external funds from the capital markets, managers use dividend payouts as a costly commitment to establish a good reputation of not expropriating outside investors so that they can raise external financing at a low cost. As a result, in "substitute model", dividend payouts are lower for firms with stronger corporate governance (e.g., Hu and Kumar 2004; John, Knyazeva, and Knyazeva 2011, 2015).

Dividend signaling models (e.g., Bhattacharya 1979; Miller and Rock 1985; John and Williams 1985) posit that managers of high-quality firms use dividends as a costly signal to convey private information about their firms' future prospects to the market. As a result, dividend increases (decreases) convey good (bad) news about firms and cause positive (negative) price reactions. Consistent with the signaling model, previous studies find that a dividend increase causes price appreciation and a dividend cut causes price decline (e.g., Asquith and Mullins 1983; Healy and Palepu 1988).[7]

These two models suggest that dividends are substitutes for good corporate governance ("substitute model") or publicly available information ("signaling model"). To the extent that the satellite data facilitates investors' monitoring and supplies new information, the satellite data plays a substituting role for dividends. Therefore, the release of the satellite data will cause a *decrease* in firms' dividend payouts.

3. Data and Research Design

3.1. Data and Sample Construction

[7] More recent studies debate about the specific content of dividend signal, such as managers' views of future earnings (Nissim and Ziv 2001; Ham, Kaplan, and Leary 2019; DeAngelo, DeAngelo, and Skinner 1996; Benartzi, Michaely, and Thaler 1997; Grullon, Michaely, and Swaminathan 2002) or changes in firm risks (Grullon, Michaely, and Swaminathan 2002; Michaely, Rossi, and Weber 2018; Sun, Wang, and Zhang 2018).

We obtained satellite imagery data of parking lot traffic for U.S. retailers from two major data vendors, RS Metrics (RS) and Orbital Insight (OB). RS Metrics is the first U.S. data vendor that releases real-time parking lot traffic data based on satellite image from the first quarter of 2011. OB, the most prominent competing data vendor to RS, started to release similar data from the second quarter of 2015. Their data consists of daily store- and firm-level parking lot car counts and parking lot utilization for major U.S. retailers. To illustrate the satellite imagery data, we present in Figure 1 an example of parking lot image for a Walmart store in Arizona provided by OB. A "mask" for each parking lot is drawn to prevent cars of other stores being counted. Each circle in the figure represents a car identified by computer algorithms. Only circles within the shaded area are counted towards the Walmart store.

We merge the satellite data from RS and OB with the CRSP-Compustat data, and generate a comprehensive dataset covering 142 publicly listed U.S. retail firms from 2011 to 2018 ("event firms").[8] RS releases data for 48 firms and OB releases data for 139 firms, with 45 firms covered by both vendors. To our knowledge, this is the largest dataset of its kind used in the existing literature. RS and OB started to release satellite data for different retailers at different times.[9] Figure 2 presents the distribution of the release events where a retailer's satellite imagery data was released by at least one of the two vendors for the first time. It is evident that the release events are staggered from 2011 to 2017, with the highest number in 2016 mainly because OB expands its coverage substantially in that year.[10] When a vendor starts to release the satellite data of a retail firm, it also releases the historical satellite data of this firm from 2010. [11]

We use these 142 retailers as treated firms and start the sample period from 2009, which is

[8] We exclude a financial firm in the data with SIC code between 6000-6999.
[9] We obtain confidential information from RS and OB about the exact time when the satellite imagery data of each retail firm starts to be released.
[10] Orbital Insight added 41 retailers in the summer of 2016.
[11] Once the data vendor develops algorithms to count parking lot traffic for a retail firm, the vendor can easily apply the algorithms to the retail firm's historical data and calculate the historical car counts.

two years before the first release event. We choose 2009 because it provides a pre-event period for even the earliest release events and excludes the financial crisis of 2007-2008 in which firms' dividend policies are very volatile. To conduct the difference-in-differences analysis, we include control firms that are not covered by either vendor. We following Katona et al. (2020) and select control firms as those in the same six-digit Global Industry Classification Standard (GICS) codes as the treated firms, which include 13 GICS industries.[12] We follow the literature (e.g., Fama and French 1993) and delete firms in the first two years from IPOs.

We obtain retail firms' stock data including dividends and share prices from the Center for Research in Security Prices (CRSP), and accounting data from the CRSP-COMPUSTAT merged database. We obtain data on institutional ownership from the Thomson Reuter's 13F database, and analysts forecast data from the Institutional Brokers' Estimate System (I/B/E/S). The data of managerial ownership and compensation are from Execucomp, and the corporate governance measures are from ISS/RiskMetrics. We winsorize all continuous variables at the 1% and 99% levels to exclude outliers. Our final sample consists of 6,323 firm-years from 2009 to 2018, including 1,211 firm-years for treated firms and 5,112 firm-years for control firms.

3.2. Summary Statistics

Table 1 presents summary statistics of the variables used in the paper. We follow the literature (e.g., Grullon and Michaely 2002) and use two measures of dividend payouts. The first measure is dividend yield, defined as cash dividend scaled by the market value of common equity. The second measure is the dividend payout ratio (dividend-to-earnings ratio, Div/E), defined as cash dividend scaled by the net income.[13] The construction of the variables used in this paper are described in Section A of the Appendix.

12 These GICS codes include 151010, 252010, 252030, 253010, 254010, 255010, 255030, 255040, 301010, 302020, 351020, 402020, 502020.

[13] We treat Div/E as missing if dividend is positive but earning is negative.

The sample retail firms have an average dividend yield of 1.09% and an average dividend payout ratio of 21.63%, with 43.4% of the firms paying non-zero dividends. The standard deviations for both dividend measures are about twice as much as their means, which indicates that dividend payouts vary significantly among sample firms. Regarding other major firm characteristics, the sample retail firms have an average annual asset growth of 7.86%, leverage ratio of 27.8%, Tobin's Q of 1.78, profitability ratio (scaled by assets) of 12.2%, and institutional ownership of 59.4%. These summary statistics are similar to those of the Compustat firm universe.

3.3. Empirical Model and Identification Strategy

We exploit the staggered releases of satellite data for U.S. retail firms as exogenous shocks to the information asymmetry between managers and outside investors. The satellite data provides outside investors with almost real-time information on parking lot traffic - a proxy for sales growth and operating performance, resulting in a decrease in information asymmetry. The staggered nature of satellite data releases provides a set of counterfactuals with the absence of satellite data and thus allows us to disentangle the effect of satellite data from other drivers of dividend policies. In addition, the satellite data is provided by third-party data vendors, which is out of managers' control and likely exogenous to firm fundamentals. We further use within-firm and within-year generalized difference-in-differences models to control for unobserved firm attributes and temporal trends in payout policies.[14] The specification is as follows:

$$Y_{it} = \alpha_i + \alpha_t + \beta PostRelease_{it} + \gamma X_{it-1} + \epsilon_{it}, \qquad (1)$$

where Y_{it} is a measure of dividend payout of firm i in year t; $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm i by time t, and zero otherwise; α_i and α_t represent firm and year fixed effects, respectively; X_{it-1} is a vector of control variables. The difference-

[14] In line with Bertrand, Duo, and Mullainathan (2004), Roberts and Whited (2013), and Yagan (2015), we use the term "difference-in-differences" simply to describe a model that compares trends in corporate policies between different groups of treated and control firms.

in-differences coefficient estimate, β, captures the effect of satellite data release on dividend payout. Including firm fixed effects ensures that β reflects average within-firm changes in dividend payout in response to satellite data release. Year fixed effects control for general trend of dividend payments. The standard errors are two-dimensionally clustered by firm and year to account for the potential cross correlations within firms and over time.

The key identifying assumption that guarantees the consistency of the difference-in-differences estimate is that conditional on all covariates and fixed effects, treated and control firms have parallel trends in the absence of satellite data release. We will perform extensive tests to validate this identifying assumption in the empirical analysis. We control for a broad set of firm characteristics following previous literature, including firm size, leverage, profitability, asset tangibility, cash holdings, Tobin's Q, institutional ownership, analyst coverage, ratio of retained earnings to total equity, and cash flow uncertainty. These firm characteristics have been documented by previous studies to be associated with dividend policies (e.g., Fama and French 2002; Brav, Graham, Harvey, and Michaely 2005, DeAngelo, DeAngelo, and Stulz 2006; Chay and Suh 2009; Crane, Michenaud, and Weston 2016; Grennan 2019).

4. Empirical Results

4.1. Information in Satellite Data and the Usage by Sophisticated Investors

Existing studies find that the satellite-based data on parking lot traffic data contains useful information about firm performance and that outside investors actively utilize the satellite data (Zhu 2019; Katona et al. 2020; Kang, Stice-Lawrence, and Wong 2020). Since we use a larger sample with a longer sample period than the previous studies, we first examine if these findings also hold for our sample firms. For brevity, we discuss the main results in this subsection while leaving more details in Section B of the Appendix.

We first examine if traffic growth calculated using satellite-based car counts can predict the underlying retail firms' performance. We examine three main performance measures including sales growth, income growth, and stock returns. As discussed with details in Section B of the Appendix, we find that, consistent with the existing literature, retail firms' quarterly traffic growth significantly and positively predicts all three performance measures. The results are not only statistically significant but also economically significant.

Next, we conduct two tests to examine if outside investors utilize the satellite-based data of parking lot traffic. Our first test investigates whether traffic growth predicts investors' short selling prior to earnings announcement. We follow the literature (e.g., Engelberg, Reed, and Ringgenberg 2018) and examine two measures of short selling: short interest and utilization rate. We find that short selling significantly decreases in traffic growth in the period after satellite data is released to outside investors but has little relation with traffic growth in the pre-release period. This sharp contrast indicates that sophisticated investors actively use satellite data in their trading. For the second test, we examine hedge fund holdings and observe the similar contrast: while there is little relation between satellite-data-based traffic growth and hedge fund holdings before the release of satellite data, there is a strong positive relation between hedge fund holdings and traffic growth in the post-release period. These results (discussed with details in Section C of the Appendix) indicate that, consistent with the existing literature (Zhu 2019; Katona et al. 2020; Kang, Stice-Lawrence, and Wong 2020), outside investors utilize the satellite data in decision making.

4.2. Release of Satellite Data and Dividend Policy

4.2.1. Difference-in-Differences Regressions

In this section, we test the competing predictions about the firms' dividend policy. As discussed in Section 2.2, we expect that the release of satellite data will cause an *increase* in dividend payment if the satellite data plays a complementing role. In contrast, we expect the release of satellite data to cause a *decrease* in dividend payment if the satellite data plays a substituting role.

We conduct the difference-in-differences analysis (Equation (1)) and present the results in Table 2. Columns (1) presents the regression of dividend yield on the *PostRelease* dummy, and Column (2) further controls for firm characteristics. The coefficient on *PostRelease* is positive and significant at the 1% level in both models. The coefficient of 0.663 (t-stat 3.26) in Column (2) indicates that after the releases of satellite data, retail firms on average increase their dividend yield by 0.663 percentage point. This result is economically significant given that the average dividend yield for our sample firm is 1.09 percentage point. Additionally, the coefficient on *PostRelease* changes little after the inclusion of control variables, suggesting that the unobserved omitted variables bias is likely to be limited (Altonji, Elder, and Taber 2005).

Columns (3) and (4) present the regressions of dividend payout ratio, and the coefficient of *PostRelease* is positive and significant at the 5% level in both models. The coefficient of 11.009 (t-stat 2.53) in Column (4) indicates that dividend payout ratio increases by 11.01 percentage points after the release of satellite data. This increase is about half of the average dividend payout ratio for our sample firms (21.63%, Table 1). Taken together, the results in Table 2 provide strong evidence that, consistent with the complementing role of the satellite data, dividend payout significantly *increases* after the satellite data of retail firms are released.

4.2.2. Assessment of Identification

The consistency of the difference-in-differences estimate crucially depends on the parallel trend assumption. To validate that the baseline results are not driven by pre-existing trend differences between treated and control firms, we examine the dynamic effect of satellite data release as suggested by Roberts and Whited (2013). Specifically, we replace $PostRelease_{it}$ with three dummy variables: $PostRelease_{\{i,-2\leq t\leq -1\}}$ is a dummy variable that equals one if year t is within two years before the satellite data of firm i is released, and zero otherwise; $PostRelease_{\{i,0\leq t\leq 1\}}$is a dummy variable that equals one if year t is in the year or one year after the satellite data of firm i is released, and zero otherwise; $PostRelease_{\{i, t\geq 2\}}$ is a dummy variable that equals one if year t is two years or more after the satellite data of firm i is released, and zero otherwise. The dummy variable $PostRelease_{\{i,-2\leq t\leq -1\}}$ allows us to detect any trend before the release of satellite data and therefore assess the parallel trend assumption. Additionally, $PostRelease_{\{i,0\leq t\leq 1\}}$ and $PostRelease_{\{i, t\geq 2\}}$ allow us to track the effect of satellite data release on dividend payout in different post-event windows.

The regression results are reported in Panel A of Table 3, which show that the coefficient on $PostRelease_{\{i,-2\leq t\leq -1\}}$ is economically small and statistically insignificant in all four regressions. This result indicates that the pre-treatment trends are indistinguishable between the treated and control firms and thus validates the parallel trend assumption of our identification. We further find that the estimated coefficient on $PostRelease_{\{i,0\leq t\leq 1\}}$ is economically smaller and less significant than those on $PostRelease_{\{i, t\geq 2\}}$. This result is consistent with the fact that firms' dividend policies are relatively sticky and take time to adjust after the information shock of alternative data.

To visualize the dynamic treatment effect, we estimate the difference-in-differences coefficients prior to and after the release year of satellite data by performing the following regression:

$$Y_{it} = \alpha_i + \alpha_t + \sum_j \beta_j PostReleased_{\{i,j\}} + \gamma X_{it} + \epsilon_{it}, \tag{2}$$

where j represents the years from t < -3 to t > 3, where t=0 is the release year of satellite data. The coefficients β_j capture the dynamic effect of satellite data release. Figure 3 plots the coefficient estimates and their 95% confidence intervals. The coefficient for t < -3 is used as the benchmark and set to zero. It is evident from the figure that before satellite data release, the coefficient estimate is small and statistically insignificant, confirming that there is no significant difference in the pre-treatment trend between the treated and control groups. However, the coefficient estimate becomes significantly positive one year after satellite data release, indicating that there is a significant increase in dividend payout of treated firms compared with control firms.[15]

We further address the potential endogeneity concerns by conducting two placebo tests. In the first placebo test, every year we replace the treated firms with the same number of randomly chosen control firms whose satellite data are not released in our sample period. Then we repeat the difference-in-differences regression using these "pseudo" treated firms and control firms in the same industry during our sample period from 2009 to 2018. Columns (1) and (2) in Panel B of Table 3 report the regressions of dividend yield and dividend payout ratio, respectively, which show that the coefficient of *PostRelease* in this placebo test is economically small and statistically insignificant in both regressions.

In the second placebo test, we use the same treated firms but move the years of the releases of their satellite data (i.e., event year) backward by ten years. In other words, we use the true treated firms but "pseudo" treatment event years to repeat the baseline regressions. The "pseudo" sample period starts from 1999 to 2008. The results are reported in Columns (3) and (4) in Panel B of Table 3, which show that the coefficient of *PostRelease* is small and insignificant. Taken together, our placebo tests lend additional support for the validity of our identification strategy.

Finally, we directly examine if the initiation of satellite data can be predicted by firm fundamentals especially dividends in the previous period. We take the sample of treated firms and construct an initiation dummy which equals one for the firm-year of the initiation of satellite data release, and zero otherwise. We then estimate OLS or probit regressions of the initiation dummy on changes in dividends and a broad set of firm characteristics in the previous year. The results in Table 4 show that none of the coefficients is significant, indicating that the initiation decision has little relation with changes in the examined firm fundamentals.

[15] The estimated coefficient at $t = 0$ is insignificant, suggesting that it takes some time for firms to change their dividend payout policy.

4.2.3. Robustness Tests

We conduct a broad set of robustness tests using alternative samples, alternative model specifications, and alternative measures. First, to address the concern that our difference-in-differences results are simply driven by control firms, we restrict the sample to only treated firms. Since the satellite data of treated firms start to be released at different times, this alternative approach uses these firms in the pre-release years as the control group. This test allows us to fully control for any unobserved firm-specific trends in dividend payout and further alleviates the concern on the parallel trend assumption. Columns (1) and (2) in Panel A of Table 5 show that the coefficient of *PostRelease* is very similar to our baseline results for both the regressions of dividend yield (0.463, t-stat 2.22) and the regression of dividend payout ratio (13.080, t-stat 2.08).

Second, we use alternative approach to select control firms by matching each treated firm with a similar firm in the same industry based on the propensity-score-matching (PSM) procedure. We first estimate a logit regression to model the probability that the satellite data of a retailer is released based on the firm characteristics including size, Tobin's Q, institutional ownership, analyst coverage, retained earnings, and return volatility. We then match each treatment firm to a control firm using the nearest neighbor matching technique with no replacement. Columns (3) and (4) in Panel A of Table 5 show that the coefficients on *PostRelease* remain significantly positive.

Third, we conduct a robustness test by selecting control firms based on the two-digit Standard Industrial Classification (SIC) rather than the six-digit GICS industry classification and present the results in Columns (1) and (2) of Panel B, Table 5. Additionally, we construct an alternatively sample by excluding firms with negative earnings following La Porta et al. (2000). Columns (3) and (4) in Panel B present these results. We find that our results hold in both robustness tests.

In panel C of Table 5, we present robustness tests using two alternative measures of dividend policy. Columns (1) and (2) present the results using dividend-to-assets ratio, and Columns (3) and (4) presents the results using a dummy of dividend payment, which equals one if the firm pays dividends in year *t*, and zero otherwise. We find that the coefficient on *PostRelease* remains both economically and statistically significant in these regressions. For example, the coefficient is 0.051 (t-stat 2.36) in Column (4), which indicates that the likelihood of paying dividends on average increases by 5.1 percentage points after the release of satellite data.

5. Further Analyses of the Complementing Role of the Satellite Data

Our results so far show that dividend payout significantly increases after the release of satellite data. This finding is consistent with the complementing role of satellite data (i.e., outcome model of the dividend policy). In this section, we conduct a number of further analyses of this finding.

5.1. The Role of Investment Opportunities

Investment opportunities play an important role in the outcome model of dividend policy. As emphasized by La Porta et al. (2000), for firms with good investment opportunities, outside investors are willing to accept low dividends to support high reinvestment rates because they expected such investments to pay off in the future. In contrast, outside investors will push firms with poor investment opportunities to pay dividends so that the cash will not otherwise be wasted. As a result, the outcome model of dividend policy is much more relevant to firms with poor investment opportunities than to firms with good investment opportunities.[16] Therefore, under the outcome model, we expect the complementing role of satellite data to have a larger impact on dividends among firms with poor investment opportunities.

We test this predication by estimating the following regression:

$$Y_{it} = \alpha_i + \alpha_t + \beta_1 PostRelease_{it} \times LowGrowth_{it} + \beta_2 PostRelease_{it} +$$

[16] Figure 1 of La Porta et al. (2000) demonstrates this divergence across investment opportunities. Additionally, they show that the substitute model of dividend policy applies to firms with good investment opportunities because those firms have greater needs to raise external funding and in turn building good reputation.

$$\beta_3 LowGrowth_{it} + \gamma X_{it-1} + \epsilon_{it}. \quad (3)$$

which is similar to equation (1) but including the interaction of *PostRelease* and a dummy for low-growth firms. Following La Porta et al. (2000), we use sales growth to measure a firm's investment opportunities. For robustness, we also use Tobin's Q as an alternative measure of investment opportunities. $LowGrowth_{it}$ is a dummy variable indicating that firm *i* has low growth in year *t*, which equals one if a firm's sales growth or Tobin's Q is below the median, and zero otherwise. We expect β_1, our main variable of interest, to be significantly positive, which indicates that low-growth firms experience greater increases in dividends after satellite data release than high-growth firms.

Columns (1) to (4) of Table 6 report the regressions results using dividend yield as the dependent variable. Columns (1) and (2) use sales growth as the growth measure, and we find that β_1 is significantly positive in both models. The coefficient estimate of 0.461 in Column (2) suggests that low-growth firms experience an additional 0.461 percentage-point increase in dividend yield than high-growth firms. We find similar results when using Tobin's Q to measure growth opportunities in Columns (3) and (4).

The results are similar for the regressions of dividend payout ratio in Columns (5) to (8), in which $\beta_1$is significantly positive in all four regressions. For example, the coefficient in Column (6) suggests that low-growth firms experience an additional increase in dividend payout ratio of 11.141 percentage points than high-growth firms. Taken together, these results provide further support for the complementing role of satellite data.

5.2. Cross-Sectional Analyses

5.2.1 Cross-Sectional Analysis Based on Corporate Governance

In the outcome model of dividend policy, outside investors prefer dividends over retained earnings as they are concerned of the agency costs. For example, La Porta et al. (2000) shows that dividends are the highest among firms with both weak corporate governance and low growth. As a result, we expect to find that the increase in dividend payout after satellite data release is more pronounced for low-growth firms with high levels of managerial entrenchment. We perform the regression in equation (3) for the subsamples based on managerial entrenchment. We use two measures of managerial entrenchment, including the entrenchment index (E-Index, Bebchuk, Cohen, and Ferrell 2008) and the alternative takeover protection index (ATI, Cremers and Nair 2005), where higher index values indicate more severe entrenchment.[17]

Table 7 presents the regression results. For brevity, we report the results using sales growth to measure growth opportunity. The results are similar when we use Tobin's Q as the measure of growth opportunities for these analyses. Columns (1) to (4) present the results for the two samples based on E-Index, where the high E-index subgroup includes firms whose E-index are equal to or above the median, and the low E-index subgroup includes firms whose E-index are below the median. We find that, consistent with our prediction, The coefficient of $PostRelease_{it} \times Low$ is significantly positive for the high E-index subsample but small and insignificant for the low E-index subsample. The results are similar when we measure managerial entrenchment with ATI in Columns (5) to (8). Overall, our results on managerial entrenchment provide further evidence that supports the outcome model of dividend policy and the complementing role of satellite data as an alternative governance mechanism.

5.2.2 Cross-Sectional Analysis Based on Ownerships by Sophisticated Investors

Access to satellite data is limited to sophisticated investors due to the high purchase prices. According to our discussions with data vendors, the clients of the satellite data are generally institutional investors such as quantitative hedge funds, traditional long-short hedge funds, and equity

[17] The E-Index includes the six anti-takeover provisions tracked by the Institutional Shareholder Services (ISS): staggered boards, limitation on amending bylaws, limitation on amending charter amendments, supermajority requirements for mergers, poison pills, and golden parachutes. The ATI includes three provisions: staggered boards, blank check preferred stock, and restrictions on shareholder voting to call special meetings or act through written consent.

research teams at banks. Moreover, the outcome model relies on outside investors' monitoring of firm managers, and sophisticated institutional investors have both the incentives and the abilities of monitoring (e.g., Gillan and Starks 2000, 2007). As a result, the complementing role of satellite data should be stronger for firms with higher ownerships of sophisticated investors.

We use two measures of sophisticated investor ownership. The first measure is hedge fund ownership because hedge funds are among the major clients of satellite data vendors, and existing literature has documented the active monitoring by hedge funds (e.g., Brav, Jiang, and Kim 2015; Denes, Karpoff, and McWilliams 2017). The second measure is ownership of monitoring institutions constructed following Chen, Harford, and Li (2007).[18] Monitoring institutions are block holders who actively collect information and monitor firm managers.

We divide the sample firms into two subgroups based on sophisticated investor ownerships, and then estimate the regression in equation (3) for both subsamples. Table 8 presents the regression results, in which Columns (1) to (4) use the ownerships of hedge funds, and Columns (5) to (8) use the ownerships of monitoring institutions. The coefficient on $PostRelease_{it} \times LowGrowth_{it}$ is positive in all four regression models for firms with high ownership by sophisticated investors, and statistically significant in two regressions (marginally insignificant in the other two). In contrast, for firms with low ownership of sophisticated investors, the coefficient on the interaction term is small and insignificant in each of the four regressions. These results suggest that sophisticated investors play a crucial role of utilizing the satellite data to push for a change in dividend policy. These results also support the previous studies of investor activism, especially hedge fund activism where hedge funds take active measures to influence their firms' corporate policies, such as increases in dividend payout (e.g., Brav, Jiang, and Kim 2009; Klein and Zur, 2009 and 2011; Johnson and Swem 2015; Gantchev,

[18] Specifically, we define monitoring institutions as the institutions that meet three criteria: (1) top five institutional investors of a firm-year in terms of shares ownership; (2) independent from corporate management (Brickley, Lease, and Smith 1988); and (3) classified as dedicated institutions (Bushee 2001).

Gredil, and Jotikasthira 2019).

5.2.3 Cross-Sectional Analysis Based on Financial Constraints

While the outcome model suggests that shareholders have incentives to push managers to pay dividends, they may refrain from doing so when firms are financially constrained. This is because the retained earnings can provide additional benefits by helping the financially constrained firms avoid costly external financing in case of unexpected financing needs (e.g., Almeida, Campello, and Weisbach 2004; Leary and Michaely 2011). As a result, we expect to find that the complementing governance role of satellite data is weaker among firms that are financially constrained.

We perform the regression in equation (3) for the subsamples based on measures of financial constraints. We examine three widely used measures of financial constraints including the KZ Index (Kaplan and Zingales 1997; Lamont, Polk, and Saaá-Requejo 2001), the HP index (Hadlock and Pierce 2010) and the WW Index (Whited and Wu 2006).[19] We construct a low-constraint (high-constraint) dummy which equals one if a firm's KZ, HP, or WW indexes is below (above) the median, and zero otherwise.

Columns (1) to (4) of Table 9 present the regression results for the KZ index. We find that the coefficient on $PostRelease_{it} \times LowGrowth_{it}$ is significantly positive for firms with low KZ indices. For example, the coefficient of 1.320 in Column (3) indicates that for financially unconstrained firms, the post-release increase in dividend yield is 1.320 percentage points higher for low-growth firms than for high-growth firms. In contrast, the coefficient on $PostRelease_{it} \times LowGrowth_{it}$ is insignificant for high KZ firms, suggesting that among financially constrained firms, the increases in dividend payouts are not significantly different between low-growth firms and high-growth firms. The

[19] KZ Index = -1.002×(IB + DP)/lagged PPENT) + 0.283×(AT+ PRCC F × CSHO - CEQ - TXDB)/AT + 3.139×(DLTT + DLC)/(DLTT + DLC + SEQ) - 39.368×(DVC +DVP)/lagged PPENT - 1.315×(CHE/lagged PPENT). HP Index = -0.737×Size) + 0.043×Size^2 - 0.040×Age. WW Index = -0.091×(IB + DP) - 0.062×(indicator set to one if DVC + DVP is positive, and zero otherwise) + 0.021×(DLTT/AT) - 0.044×log(AT) + 0.102×industry sales growth - 0.035×sales growth).

results are similar when we measure financial constraints using the HP index (Columns (5) to (8)) and the WW index (Columns (9) and (12)). These results suggest that when firms are financially constrained, the complementing governance role of satellite data is mitigated by the extra benefits of retained earnings.

5.3. Satellite Data Release and Share Repurchase

Firms can also use share repurchases besides dividend payout to distribute cash to shareholders. Previous studies, however, have shown that dividends and share repurchases are driven by different factors. For example, Guay and Harford (2000) find that dividend changes are related to permanent cash-flow shocks while share repurchases are related to transitory cash flow shocks. While we focus on dividends because of the rich theory on dividend policy, we examine the effect of satellite data on share repurchases in this subsection.

We construct two measures of share repurchase. The first measure, repurchase yield (Rep/MV), is defined as repurchase (PRSTKC) scaled by the market value of common equity. The second measure, repurchase-earnings ratio (Rep/E), is defined as repurchase scaled by the net income. We estimate the difference-in-differences regression (equation (1)) using share repurchases as dependent variable and report the results in Table 10. We find that the coefficient on *PostRelease* is insignificantly positive in the regressions of repurchase yield, and significantly positive in the regressions of repurchase-earnings ratio. In the full model of Column (4), the coefficient indicates that following the satellite data releases, the event firms on average increase their repurchase-to-earnings ratio by 18.71 percentage points relative to the control firms. These results provide (weak) evidence that the releases of satellite data also cause increases in firms' share repurchases.

5.4. Investment and External Financing

The complementing role of satellite data (the outcome model) is realized by helping outside investors better monitor their firms and push the managers to distribute extra cash instead of diverting them to value-destroying investment. Therefore, we predict that the increased dividend payment is financed by the reduction in value-destroying investment projects rather than external financing.

We estimate the difference-in-differences regression (equation (1)) for corporate investment and external financing. We examine three measures of corporate investment including asset growth, fixed asset investment, inventory investment, and research and development (R&D) expenditure. While existing literature documents that firms' investments are generally associated with poor future performance (Titman, Wei, and Xie 2004; Cooper, Gulen, and Schill 2008), R&D expenditure is widely regarded to be value-enhancing and associated with positive future performance (e.g., Chan, Lakonishok, and Sougiannis 2001). Columns (1) to (4) in Panel A of Table 11 present the regression results. We find that the coefficient of *PostRelease* is significantly negative in the regressions of asset growth, fixed investment, and inventory investment, which show that these three investment measures significantly decrease for treated firms after satellite data releases. These results are also economically significant. For example, the coefficient in Column (1) indicates that asset growth of treated firms decreases by 5.05 percentage points after satellite data release relative to that of control firms. Interestingly, we find that the coefficient of *PostRelease* is insignificantly positive in the regression of R&D expenditure (Column (4)). This contrast with other investment measures suggests that while event firms cut overall investment to finance the increased dividend payouts, the "good investment", i.e., R&D investment, remain intact.

Next, we estimate the difference-in-differences regressions of measures of external financing, including change in short-term debt, change in long-term debt, and equity issuance. The results are reported in Panel B of Table 11. The coefficient on *PostRelease* is insignificant in all three regressions. These results show that treated firms do not increase their external financing relative to control firms after satellite data release. To summarize, the results in Table 11 consistently show that the increases in dividends after satellite data release are financed by cutting value-destroying investments while the healthy investments and external financing remain intact.

7. Conclusion

Exploiting the staggered releases of real-time satellite data of parking lot traffic for retail firms, we examine how the emergence of alternative data affects firms' corporate policies. We first document that the satellite data contains timely and useful information about firms' future performance and the sophisticated investors actually utilize the data. We then conduct difference-in-differences regressions to test the competing predictions about how the satellite data releases affect firms' dividend policy. Specifically, the "outcome model" of dividends suggests that satellite data complements dividend payment, and therefore predicts an *increase* in dividends after the release of satellite data. The "substitute model" and "signaling model" suggest that satellite data substitute for dividend payment, and predict a *decrease* in dividends after the releases of satellite data. We find that, consistent with the complementing role of satellite data, firms significantly *increase* their dividend payouts after the release of their satellite data. We alleviate the selection concern by conducting the parallel trend analysis as well as placebo falsification tests. This finding is also robust to a broad set of robustness tests using alternative samples and alternative measures.

We further show that the increase in dividends after satellite data release is stronger among firms with poor investment opportunities, which is a key prediction of the outcome dividend model. The effect of satellite data release on dividends is also stronger for firms with higher levels of managerial entrenchment, higher ownerships by sophisticated investors, or less severe financial constraints. Additionally, we find that event firms finance the increased dividends by cutting overall corporate investment but not R&D which is considered "good" corporate investment. These results together provide additional evidence that supports the complementing role of satellite data.

Despite the fast-growing finance literature on the rapid technology advancements and alternative data, there has been little research on the real effect of alternative data on corporate policies.

Our findings shed light on this question and provide new evidence that the emergence of alternative data can close the information gaps between outside investors and firm managers and have significant impact on corporate policies.

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Figure 1

Satellite Image of Parking Lot

This figure presents an example of how satellite images of parking lots are converted into car counts. The area highlighted in blue is the parking lot of a Walmart store in Arizona at 2:29 pm on July 4, 2016. Each of the circles represents a car. Only the cars in the highlighted area are counted towards the Walmart store. In this example, the number of cars on this Walmart store's parking lot is 129. This satellite image is provided by Orbital Insight.

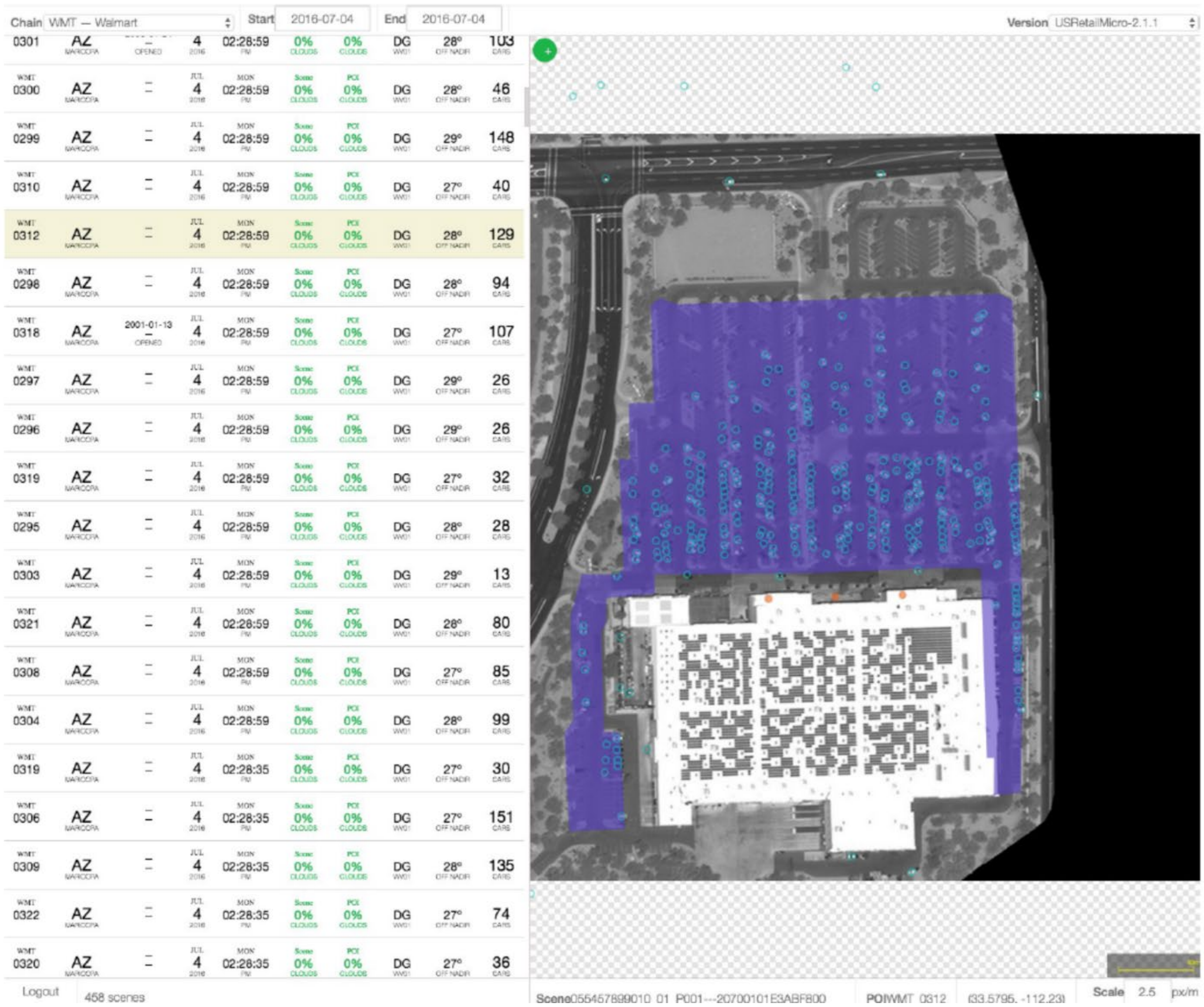

Figure 2
Staggered Release of Satellite Data for U.S. Retail Firms from 2011 to 2018

This figure presents the distribution of the 142 release events over the sample years. For each event, a retailer's satellite imagery data of parking lot traffic started to be released by at least one of the two data vendors (RS Metrics and Orbital Insight). The figure presents the number of release events in each year from 2011 and 2018. The number of release events is shown above each bar.

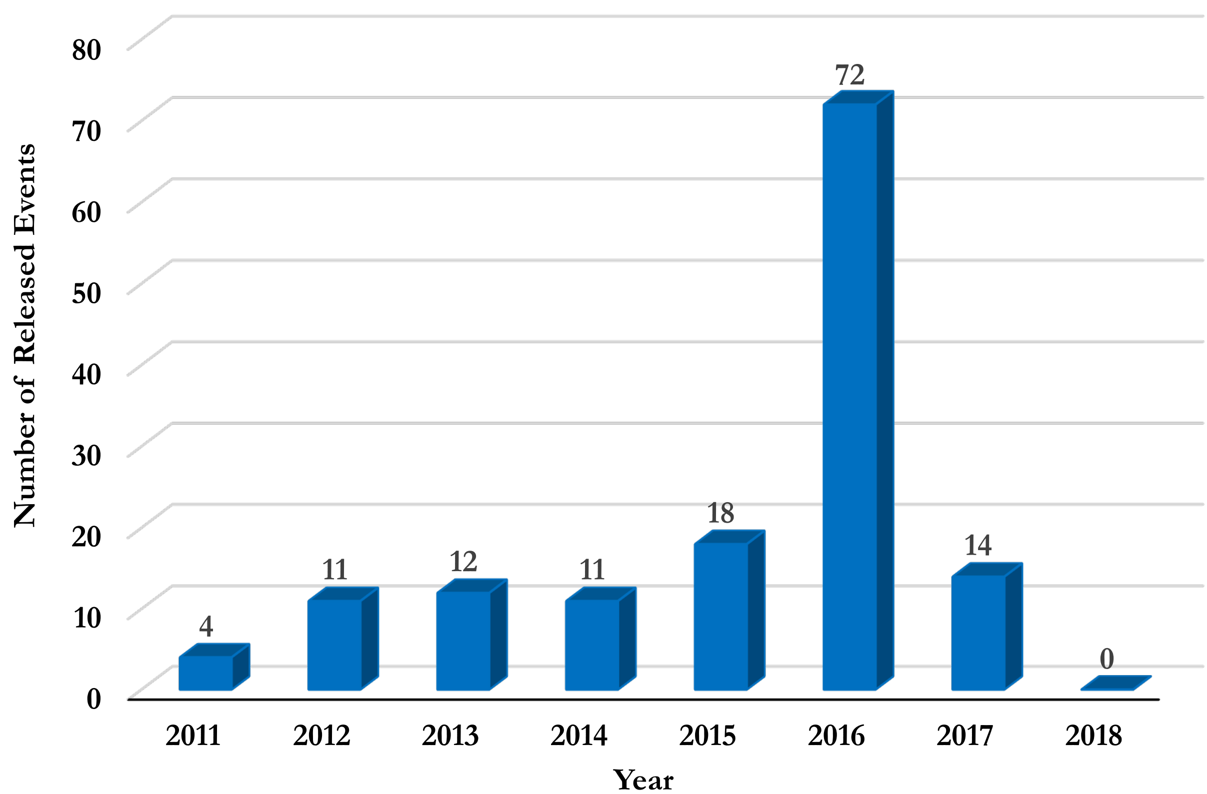

Figure 3

Parallel Trend Analysis: Dynamic Treatment Effect on Dividend Payout

This figure presents the difference-in-differences coefficients on *PostRelease* dummies prior to and after the event year of satellite data release (t =0, labeled with dotted red line) in the baseline regression and their 95% confidence intervals. The coefficient for the period t < -3 is used as the benchmark and set to zero.

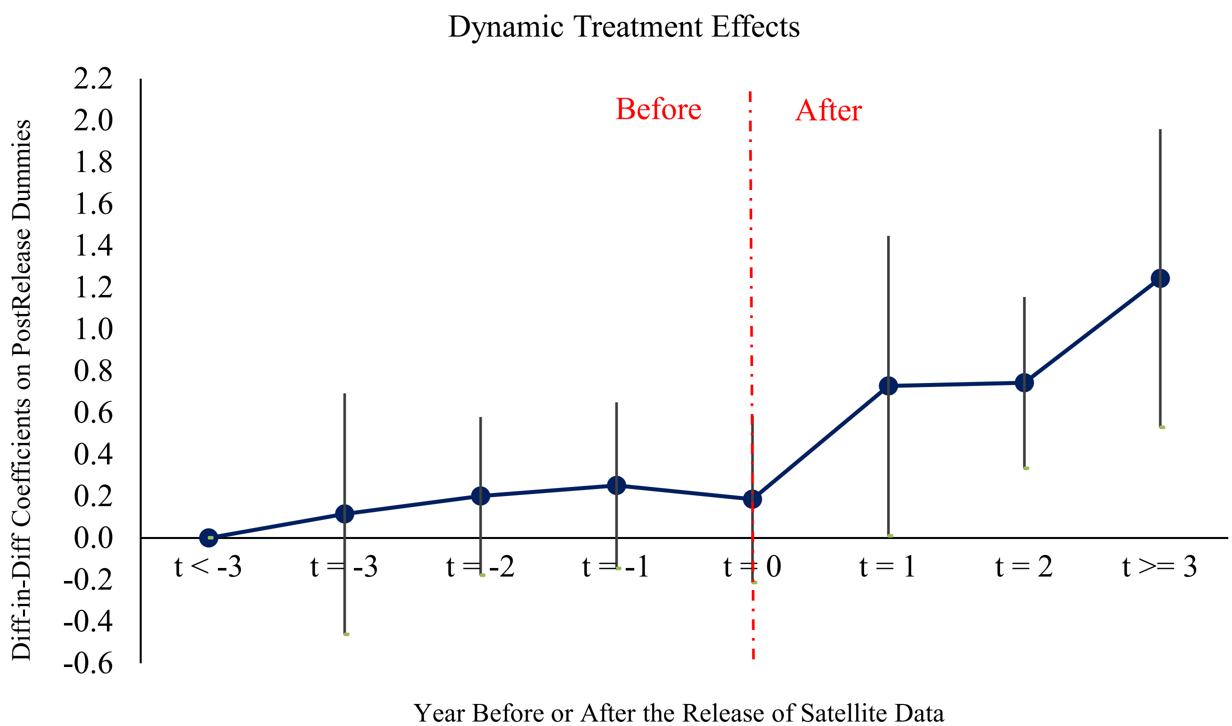

Table 1
Summary Statistics

This table reports the summary statistics of the variables used in this paper. The sample includes annual observations of treated and control firms between 2009 to 2018. All continuous variables are winsorized at 1% and 99% levels. Definitions of all the variables are reported in Appendix A.

Variable	Mean	Std	P25	Median	P75	#Obs
Div/MV (%)	1.093	1.937	0.000	0.000	1.615	6,321
Div/E (%)	21.626	47.999	0.000	0.000	27.504	6,108
DivDum (%)	0.434	0.496	0.000	0.000	1.000	6,323
Rep/MV	2.072	3.714	0.000	0.177	2.669	6,321
Rep/E	47.680	85.432	0.000	10.006	64.601	4,825
RepDum	0.608	0.488	0.000	1.000	1.000	6,323
AssetGrowth	7.860	26.396	-3.322	3.567	11.813	6,289
Investment	7.738	7.891	2.722	5.562	9.820	6,315
Inventory	1.046	4.441	-0.147	0.051	1.682	6,221
R&D	0.727	2.457	0.000	0.000	0.000	6,323
AcqEx	2.168	5.603	0.000	0.000	0.942	6,323
STDebt	0.036	1.942	0.000	0.000	0.000	6,323
LTDebt	0.863	8.578	-2.092	0.000	2.386	6,323
Equity	1.721	5.905	0.000	0.156	0.702	6,323
Size	6.830	1.941	5.509	6.797	8.148	6,289
Leverage	0.278	0.242	0.072	0.242	0.414	6,289
Tobin Q	1.782	1.094	1.103	1.442	2.054	6,321
Profitability	0.122	0.119	0.075	0.124	0.179	6,277
Tangibility	0.273	0.218	0.096	0.222	0.401	6,278
Cash	0.127	0.136	0.031	0.078	0.178	6,289
InstOwn	0.594	0.352	0.283	0.708	0.885	6,323
AnalystCoverage	0.995	1.167	0.000	0.000	2.158	6,323
RetainedEarn	0.140	3.615	0.028	0.558	0.912	6,280
RetVol	0.128	0.076	0.076	0.107	0.156	6,289

Table 2
Difference-in-Differences Regression of Dividend Payout on Satellite Data Release

This table reports the baseline difference-in-differences regression of dividend payout on satellite data release:

$$Y_{it} = \alpha_i + \alpha_t + \beta PostRelease_{it} + \gamma X_{it-1} + \epsilon_{it}, \qquad (1)$$

where the dependent variable Y_{it} is a measure of dividend payout of firm i in year t. Columns (1) and (2) report the results for dividend yield (Div/MV), and columns (3) and (4) report the results for dividend-to-earnings ratio (Div/E). $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm i by the end of year t. X_{it-1} is a vector of control variables. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dividend Yield (%)		**Div/E (%)**	
	(1)	(2)	(3)	(4)
PostRelease	**0.630*** **	**0.663*** **	**10.315** **	**11.009** **
	(3.39)	**(3.26)**	**(2.43)**	**(2.53)**
Size		0.019		-0.452
		(0.19)		(-0.16)
Leverage		-0.866**		-12.304
		(-2.22)		(-1.13)
Tobin Q		-0.058		-0.618
		(-1.35)		(-0.59)
Profitability		0.565		-3.337
		(1.16)		(-0.41)
Tangibility		-0.872		-3.058
		(-1.40)		(-0.26)
Cash		0.286		13.825
		(0.54)		(1.19)
InstOwn		0.099		2.813
		(0.73)		(0.74)
AnalystCoverage		0.065		3.418***
		(0.97)		(2.72)
RetainedEarn		-0.004		-0.123
		(-0.79)		(-0.96)
RetVol		-1.749***		-21.728
		(-3.25)		(-1.52)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,229	6,089	6,010	5,880
Adj. R^2	0.488	0.506	0.383	0.390

Table 3
Assessing Identification: Pre-Trend and Placebo Tests

Panel A reports the dynamic effect of satellite data release on dividend payout and tests for pre-trend. We replace $PostRelease_{it}$ with three dummy variables in the baseline difference-in-differences regression of dividend payout: $PostRelease_{\{i,-2\leq t\leq -1\}}$ is a dummy variable that equals one if year t is within two years before the satellite data of firm i is released, and zero otherwise; $PostRelease_{\{i,0\leq t\leq 1\}}$is a dummy variable that equals one if year t is the year of or one year after the satellite data of firm i is released, and zero otherwise; $PostRelease_{\{i,\ t\geq 2\}}$ is a dummy variable that equals one if year t is two years or more after the satellite data of firm i is released, and zero otherwise. Columns (1) and (3) ((2) and (4)) report the results without (with) the full set of controls for dividend yield and Div/E, respectively. All regressions include firm and year fixed effects. Panel B presents two placebo tests. In the first placebo test (columns (1) and (2)), every year we replace the treated firms with the same number of randomly chosen control firms whose satellite data have never been released by the end of 2018. In the second placebo test (columns (3) and (4)), we assume that the onset of satellite data release occurs 10 years before it actually started and perform the baseline analysis in the sample period from 1999 to 2008. All regressions include the full set of controls, firm fixed effects, and year fixed effects. The t-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Dynamic Effects of Satellite Data Release: Pre-Trend Analysis

	Dividend Yield (%)		**Div/E (%)**	
	(1)	(2)	(3)	(4)
$PostRelease_{\{i,\ -2<=t<=-1\}}$	0.184	0.169	2.109	2.039
	(1.18)	(1.07)	(0.57)	(0.58)
$PostRelease_{\{i,\ 0<=t<=1\}}$	**0.372****	**0.387****	4.997	5.801
	(2.19)	**(2.11)**	(0.98)	(1.14)
$PostRelease_{\{i,\ t>=2\}}$	**0.825*****	**0.882*****	**13.441****	**14.489****
	(3.68)	**(3.93)**	**(2.14)**	**(2.46)**
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,229	6,089	6,010	5,880
Adj. R^2	0.487	0.505	0.383	0.390

Panel B: Placebo Tests

	Pseudo Treated Firms		**Pseudo Treatment Events**	
	Dividend Yield (%)	*Div/E (%)*	*Dividend Yield (%)*	*Div/E (%)*
	(1)	(2)	(3)	(4)
PostRelease	0.057	0.969	0.420	0.518
	(0.34)	(0.25)	(0.55)	(0.09)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,884	4,721	8,222	7,893
Adj. R^2	0.503	0.395	0.146	0.142

Table 4
Test of Reverse Causality: Can Changes in Dividend and Firm Characteristics Predict the Initiation of Satellite Data Release?

This table reports the regression of the initiation of satellite data release on changes in dividend and firm characteristics. The sample include the treated sample of retail firms in the five-year period before and after the initiation year of satellite data release. We estimate the following regression:

$$ReleaseInitiation_{it} = \alpha_t + \beta\Delta Div_{it-1} + \gamma\Delta X_{it} + \epsilon_{it},$$

where $ReleaseInitiation_{it}$ takes a value of one if year *t* is the initiation year of satellite data release for firm *i*, and zero otherwise. $\Delta Div_{it-1}$is the lagged change in dividend yield or dividend-to-earnings ratio relative to the previous year. ΔX_{it} includes change of all control variables used in our previous main regression, where the change is measured relative to the previous year. Since the specification of firm-differencing removes unobserved firm-specific fixed effects, only time fixed effects are in the regression. Columns 1-2 present the results of the OLS regression and columns 3-4 of the logit regression. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	OLS		**Logit**	
	(1)	(2)	(3)	(4)
	ΔDiv. Yield (%)	*ΔDiv/E(%)*	*ΔDiv. Yield (%)*	*ΔDiv/E(%)*
ΔDiv	-0.007	-0.000	-0.042	0.003
	(-0.99)	(-1.58)	(-1.31)	(0.44)
ΔSize	-0.065	-0.023	-0.664	-0.500
	(-0.65)	(-0.24)	(-0.68)	(-0.50)
ΔLeverage	-0.019	-0.069	-0.380	0.330
	(-0.14)	(-0.69)	(-0.26)	(0.18)
ΔTobin Q	0.022	0.021	0.277	0.313
	(0.98)	(0.87)	(1.55)	(1.28)
ΔProfitability	-0.121	-0.075	-1.409	-0.254
	(-0.69)	(-0.39)	(-0.65)	(-0.08)
ΔTangibility	-0.067	-0.081	-0.433	-0.631
	(-0.28)	(-0.40)	(-0.17)	(-0.16)
ΔCash	-0.081	-0.093	-0.928	-1.147
	(-0.40)	(-0.47)	(-0.32)	(-0.45)
ΔInstOwn	-0.008	-0.022	-0.155	-0.464
	(-0.13)	(-0.41)	(-0.19)	(-0.35)
ΔAnalystCoverage	0.005	-0.012	0.015	-0.105
	(0.13)	(-0.28)	(0.03)	(-0.14)
ΔRetainedEarn	-0.000	0.000	-0.002	-0.002
	(-0.05)	(0.08)	(-0.09)	(-0.11)
ΔRetVol	-0.880	-0.461	-9.415	1.025
	(-0.80)	(-0.41)	(-0.81)	(0.05)
Year FE	Yes	Yes	Yes	Yes
# Obs	1,203	1,153	909	1,109
Adj. R^2(Pseudo R^2)	0.207	0.216	0.178	0.185

Table 5
Robustness Tests: Alternative Samples, Specifications, or Measures

This table reports the robustness tests using alternative samples, alternative specifications, or alternative measures. Panel A reports the results based on two alternative samples. The treated-only sample (columns (1) and (2)) is restricted to firms whose satellite data are eventually released by the end of 2018. The PSM sample (columns (3) and (4)) is constructed by matching each treated firm with a similar firm in the same industry based on the propensity-score-matching (PSM) procedure. We implement the PSM procedure by first estimating a logit regression to model the probability that the satellite data of a retailer is released based on Size, Tobin's Q, InstOwn, AnalystCoverage, RetainedEarn, and RetVol. Panel B reports the results based on two alternative specifications. Columns (1) and (2) select control firms based on the two-digit Standard Industrial Classification (SIC). Columns (3) and (4) exclude observations with negative earnings. Panel C reports the OLS regression results based on two alternative measures of dividend payout. One is dividend-to-assets ratio (Div/TA, columns (1) and (2)) and the other is the dividend payout dummy (DivDum, columns (3) and (4)). All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Alternative Samples

	Treated-Only Sample		**PSM Sample**	
	Dividend Yield (%)	*Div/E (%)*	*Dividend Yield* (%)	*Div/E (%)*
	(1)	(2)	(3)	(4)
PostRelease	**0.463****	**13.080****	**0.550*****	**10.652****
	(2.22)	**(2.08)**	**(2.62)**	**(2.27)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,204	1,158	2,193	2,105
Adj. R^2	0.502	0.369	0.534	0.409

Panel B: Alternative Specifications

	Alternative Industry Classification Based on Two-Digit SIC		**Exclude Firms with Negative Earnings**	
	Dividend Yield (%)	*Div/E (%)*	*Dividend Yield* (%)	*Div/E (%)*
	(1)	(2)	(3)	(4)
PostRelease	**0.625*****	**8.134****	**0.607*****	**12.266****
	(3.93)	**(2.49)**	**(2.96)**	**(2.46)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,882	13,539	4,627	4,627
Adj. R^2	0.569	0.488	0.531	0.381

Panel C: Alternative Measures

	Div/TA		DivDum	
	(1)	(2)	(3)	(4)
PostRelease	**0.525*****	**0.502*****	**0.044****	**0.051****
	(3.03)	**(2.80)**	**(2.12)**	**(2.36)**
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,231	6,089	6,231	6,089
Adj. R^2	0.610	0.637	0.795	0.807

Table 6

Satellite Data Release and Dividend Payout: The Role of Investment Opportunities

This table tests how the effect of satellite data release on dividend payout varies with firms' investment opportunities by estimating the following regression:

$$Y_{it} = \alpha_i + \alpha_t + \beta_1 PostRelease_{it} \times LowGrowth_{it} + \beta_2 PostRelease_{it} + \beta_3 LowGrowth_{it} + \gamma X_{it-1} + \epsilon_{it}, \qquad (3)$$

where Y_{it} is a measure of dividend payout of firm *i* in year *t*; $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm *i* by time *t*, and zero otherwise; α_i and α_t represent firm and year fixed effects, respectively; X_{it-1} is a vector of control variables. We use sales growth and Tobin's Q to measure firm growth opportunities. $LowGrowth_{it}$ ($LowSG_{it}$ *or* $LowQ_{it}$) is a dummy variable indicating that firm *i* has low growth opportunity at time *t*, which equals one if a firm's sales growth or Tobin's Q is below the median, and zero otherwise. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Dividend Yield (%)				***Div/E (%)***			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostRelease × LowSG	**0.462****	**0.461****			**11.518*****	**11.141*****		
	(2.52)	**(2.53)**			**(2.67)**	**(2.60)**		
LowSG	0.152***	0.182***			2.889**	3.542***		
	(3.00)	(3.36)			(2.18)	(2.61)		
PostRelease × LowQ			**0.536****	**0.548****			**15.213*****	**15.106****
			(2.24)	**(2.30)**			**(2.58)**	**(2.48)**
LowQ			0.155*	0.199**			0.804	1.127
			(1.85)	(2.47)			(0.53)	(0.65)
PostRelease	0.366*	0.400*	0.391***	0.411***	3.923	4.866	4.148	4.845
	(1.79)	(1.76)	(3.00)	(2.80)	(1.07)	(1.24)	(0.97)	(1.05)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,229	6,089	6,229	6,089	6,010	5,880	6,010	5,880
Adj. R^2	0.490	0.509	0.490	0.508	0.385	0.392	0.385	0.392

Table 7

Dividend Payout of Low-Growth firms after Satellite Release: The Effect of Managerial Entrenchment

This table tests the effect of managerial entrenchment on the dividend payout of low growth firms after satellite data release. The regression design is the same as in Table 5 except that we estimate the regressions for the two subsamples of managerial entrenchment. Models (1) to (4) present the results for the subsamples based on E-Index, where the high E-index subgroup includes firms whose E-index are equal to or above the median, and the low E-index subgroup includes firms whose E-index are below the median. Models (5) to (8) present the results for the subsamples based on ATI, where the high ATI subgroup includes firms whose ATI are equal to or above the median, and the low ATI subgroup includes firms whose ATI are below the median. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Entrenchment Measured by E-Index				**Entrenchment Measured by ATI**			
	High E-Index		Low E-Index		High ATI		Low ATI	
	Div. Yield	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostRelease×LowSG	**0.642*** **	**20.491*** **	0.272	5.755	**0.709*** **	**19.103*** **	-0.047	6.396
	(3.87)	**(3.12)**	(0.29)	(0.20)	**(3.21)**	**(2.90)**	(-0.05)	(0.47)
LowSG	0.093	5.054**	0.084	-1.387	0.086	5.801***	-0.052	-6.538
	(1.60)	(2.15)	(0.34)	(-0.22)	(1.21)	(2.65)	(-0.41)	(-1.27)
PostRelease	0.259	-3.238	1.012	25.861*	0.366*	3.806	1.051	9.226
	(1.23)	(-0.70)	(1.32)	(1.94)	(1.79)	(0.86)	(1.14)	(0.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,112	2,031	646	629	2,237	2,162	552	531
Adj. R^2	0.591	0.323	0.570	0.381	0.568	0.345	0.672	0.380

Table 8

Dividend Payout of Low-Growth firms after Satellite Release: The Effect of Sophisticated Investor Ownership

This table tests the effect of financial constraints on the dividend payout of low growth firms after satellite data release. The regression design is the same as in Table 5 except that we estimate the regressions for the two subsamples of financial constraints. Models (1) to (4) present the results for the subsamples based on hedge fund ownership, where the high ownership subgroup includes firms whose hedge fund ownerships are equal to or above the median, and the low hedge fund ownership subgroup includes firms whose hedge fund ownerships are below the median. Models (5) to (8) present the results for the subsamples based on the monitoring institutional ownership, where the high monitoring institutional ownership subgroup includes firms whose monitoring institutional ownerships are equal to or above the median, and the low monitoring institutional ownership subgroup includes firms whose monitoring institutional ownerships are below the median. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Hedge Fund Ownership				**Monitoring Institutional Ownership**			
	High Ownership		Low Ownership		High Ownership		Low Ownership	
	Div. Yield	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostRelease×LowSG	0.539	**18.724*** **	0.234	0.981	**0.919*** **	24.624	-0.059	-3.927
	(1.56)	**(2.77)**	(0.78)	(0.11)	**(3.34)**	(1.64)	(-0.09)	(-0.30)
LowSG	0.195***	6.210***	0.222**	1.477	-0.087*	-2.614	0.248***	2.556
	(2.82)	(2.60)	(2.46)	(0.61)	(-1.92)	(-0.71)	(2.91)	(0.87)
PostRelease	0.575	1.390	0.297	4.814	0.080	-1.440	0.763	4.796
	(1.49)	(-0.10)	(1.28)	(0.85)	(1.57)	(-0.00)	(1.33)	(0.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,959	2,849	2,973	2,868	1,111	1,060	1,088	1,060
Adj. R^2	0.433	0.305	0.467	0.368	0.738	0.410	0.550	0.291

Table 9

Dividend Payout of Low-Growth firms after Satellite Release: The Effect of Financial Constraints

This table tests the effect of financial constraints on the dividend payout of low growth firms after satellite data release. The regression design is the same as in Table 5 except that we estimate the regressions for the two subsamples of financial constraints. Models (1) to (4) present the results for the subsamples based on KZ Index, where the high KZ subgroup includes firms whose KZ index are equal to or above the median, and the low KZ index subgroup includes firms whose KZ index are below the median. Models (5) to (8) present the results for the subsamples based on the HP index, where the high HP subgroup includes firms whose HP index are equal to or above the median, and the low HP subgroup includes firms whose HP index are below the median. The regression design is the same as in Table 5 except that we estimate the regressions for the two subsamples of managerial entrenchment. Models (9) to (12) present the results for the subsamples based on WW Index, where the high WW subgroup includes firms whose WW index are equal to or above the median, and the low WW subgroup includes firms whose WW index are below the median. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Entrenchment Measured by KZ Index				**Entrenchment Measured by HP Index**				**Entrenchment Measured by WW Index**			
	High KZ		Low KZ		High HP		Low HP		High WW		Low WW	
	Div. Yield	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*	*Div. Yield*	*Div/E*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PostRelease×LowSG	-0.019	0.783	**1.320*** **	**36.446*** **	-0.002	16.497	**0.694*** **	**10.283***	0.071	-0.019	**0.450***	**13.678*** **
	(-0.16)	(0.42)	**(3.56)**	**(3.31)**	(-0.01)	(1.02)	**(2.70)**	**(1.65)**	(0.16)	(-0.00)	**(1.79)**	**(2.79)**
LowSG	0.110***	1.572	0.238***	5.953*	0.284***	4.981*	0.104	2.572**	0.265**	5.447**	0.108*	1.660
	(3.18)	(1.09)	(2.74)	(1.77)	(2.72)	(1.93)	(1.62)	(2.08)	(2.57)	(2.27)	(1.72)	(1.23)
PostRelease	0.029	-5.987	0.486	9.278*	0.531*	6.146	0.283	-1.228	0.495	7.270	0.420*	2.338
	(0.28)	(-1.33)	(1.42)	(1.78)	(1.92)	(1.44)	(0.96)	(-0.21)	(1.13)	(1.35)	(1.79)	(0.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,831	2,738	2,829	2,731	3,009	2,940	3,049	2,902	2,901	2,831	3,010	2,871
Adj. R^2	0.638	0.359	0.507	0.371	0.423	0.339	0.481	0.323	0.393	0.382	0.501	0.320

Table 10

Difference-in-Differences Regression of Share Repurchases on Satellite Data Release

This table reports the baseline difference-in-differences regression of share repurchases on satellite data release:

$$Y_{it} = \alpha_i + \alpha_t + \beta PostRelease_{it} + \gamma X_{it-1} + \epsilon_{it},$$

where the dependent variable Y_{it} is a measure of share repurchases of firm *i* in year *t*. Columns (1) and (2) report the results for repurchase yield (Rep/MV) and columns (3) and (4) for repurchase-to-earnings ratio (Rep/E). $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm *i* by the end of year *t*. X_{it-1} is a vector of control variables. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Rep/MV (%)		**Rep/E (%)**	
	(1)	(2)	(3)	(4)
PostRelease	0.292	0.437	**14.886***	**18.711****
	(0.81)	(1.32)	**(1.88)**	**(2.37)**
Size		0.668***		13.580*
		(3.32)		(1.85)
Leverage		-2.869***		-71.560***
		(-3.16)		(-3.02)
Tobin Q		0.026		-1.415
		(0.36)		(-0.59)
Profitability		1.448*		-15.562
		(1.76)		(-0.67)
Tangibility		0.882		15.076
		(1.06)		(0.55)
Cash		1.220**		50.405*
		(1.97)		(1.77)
InstOwn		0.672		10.231
		(1.54)		(0.88)
AnalystCoverage		0.080		11.012**
		(0.51)		(2.35)
RetainedEarn		0.015		0.262
		(0.65)		(0.43)
RetVol		-5.025***		-137.987***
		(-5.40)		(-3.89)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,229	6,089	4,721	4,627
Adj. R^2	0.315	0.333	0.235	0.256

Table 11
Difference-in-Differences Regressions of Financing and Investment Decisions on Satellite Data Release

This table reports the difference-in-differences regressions of financing measures (Panel A) and corporate investment measure (Panel B) on satellite data release:

$$Y_{it} = \alpha_i + \alpha_t + \beta PostRelease_{it} + \gamma X_{it-1} + \epsilon_{it},$$

where the dependent variable Y_{it} is a measure of financing or corporate investment. The corporate investment measures in Panel A include asset growth, fixed assets investment (*investment*), inventory investment, and R&D investment. The financing measures in Panel B include change in short-term debt (*STDebt*), change in long-term debt (*LTDebt*), and new equity issuance (*Equity*) of firm *i* in year *t*. $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm *i* by the end of year *t*. X_{it-1} is a vector of control variables. All regressions include firm and year fixed effects. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Regressions of Investment Measures

	Asset Growth	**Fixed Investment**	**Inventory Invest.**	**R&D**
	(1)	(2)	(3)	(4)
PostRelease	**-5.051****	**-1.537****	**-0.919*****	0.017
	(-2.55)	**(-2.47)**	**(-3.46)**	(0.20)
Size	-22.255***	-2.199	-1.324***	-0.749**
	(-5.98)	(-1.54)	(-4.67)	(-2.16)
Leverage	-21.785***	-8.348***	-1.171*	0.589
	(-3.66)	(-3.89)	(-1.89)	(1.08)
Tobin Q	5.882***	1.214***	0.269**	0.219*
	(6.03)	(3.74)	(2.43)	(1.87)
Profitability	22.834***	17.218***	8.248***	-0.847
	(3.91)	(3.40)	(6.50)	(-0.96)
Tangibility	5.385	-27.293***	1.886**	-0.962
	(0.52)	(-4.08)	(1.96)	(-1.02)
Cash	-3.663	4.281**	4.557***	-1.707
	(-0.41)	(2.21)	(3.21)	(-1.13)
InstOwn	3.182	2.717***	0.442	0.310
	(1.08)	(3.39)	(1.56)	(1.42)
AnalystCoverage	0.414	0.792**	0.058	0.022
	(0.33)	(2.34)	(0.30)	(0.53)
RetainedEarn	0.173	0.104	0.026	-0.012
	(1.52)	(1.25)	(1.28)	(-0.63)
RetVol	4.065	-0.305	1.147	0.820
	(0.45)	(-0.06)	(0.53)	(1.00)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,089	6,034	6,021	6,089
Adj. R^2	0.239	0.195	0.260	0.873

Panel B: Regressions of Financing Measures

	STDebt	LTDebt	Equity
	(1)	(2)	(3)
PostRelease	-0.025	0.134	-0.227
	(-0.23)	(0.25)	(-1.32)
Size	-0.008	-1.740***	-2.760***
	(-0.05)	(-3.24)	(-5.28)
Leverage	-1.885***	-21.157***	4.150***
	(-8.09)	(-8.35)	(4.79)
Tobin Q	0.025	1.203***	0.752***
	(0.59)	(3.76)	(3.52)
Profitability	0.688	2.680	-10.155***
	(1.12)	(0.97)	(-3.06)
Tangibility	0.904**	10.330***	-2.026
	(2.15)	(4.00)	(-1.20)
Cash	-0.258	-3.771	-3.470***
	(-0.49)	(-1.53)	(-2.68)
InstOwn	0.046	-0.248	1.158**
	(0.29)	(-0.25)	(2.59)
AnalystCoverage	0.049	0.139	0.172
	(0.93)	(0.38)	(1.03)
RetainedEarn	0.001	-0.030	-0.031
	(0.04)	(-0.61)	(-0.91)
RetVol	-1.753***	-5.975*	3.277
	(-3.36)	(-1.94)	(1.40)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	6,089	6,089	6,089
Adj. R^2	0.019	0.208	0.427

Appendix

A. Variable Definition

Variables	Descriptions
Div/MV	Cash dividend (DVC) scaled by the market value of common equity (PRCC_F × CSHO)
Div/E	Cash dividend (DVC) scaled by the net income or loss (NI)
Div/TA	Cash dividend (DVC) scaled by the total assets (AT)
Div_Dum	A dummy variable equal to one if dividend payment is positive or zero otherwise
Rep/MV	Repurchase (PRSTKC) scaled by the market value of common equity (PRCC_F × CSHO)
Rep/E	Repurchase (PRSTKC) scaled by the net income or loss (NI)
Rep/TA	Repurchase (PRSTKC) scaled by the total assets (AT)
Rep_Dum	A dummy variable equal to one if share repurchase is positive or zero otherwise
FixedInv	Change in gross property, plant, and equipment (PPEGT) scaled by lagged total assets
InventoryInv	Change in inventory stock (INVT) scaled by lagged total assets
R&D	R&D expense (XRD) scaled by total assets
STDebt	Change in short-term debt (DLCCH) scaled by total assets
LTDebt	Change in long-term debt (DLTIS - DLTR) scaled by total assets
Equity	Equity issuance (SSTK) scaled by total assets
Size	The logarithm of total assets
Leverage	Firm leverage, calculated as total liability (DLC + DLTT) scaled by total assets
Tobin's Q	Market value of total assets (PRCC_F × CSHO + AT - CEQ) divided by total assets
Profitability	Firm profitability, calculated as operating income before depreciation (OIBDP) scaled by total assets
Tangibility	Firm tangibility, calculated as total property, plant, and equipment (PPENT) scaled by total assets
Cash	Cash holding (CHE) scaled by total assets
InstOwn	The average quarterly institutional ownership in the current year
AnalystCoverage	The natural logarithm of one plus the average number of analysts following the firm in the fiscal year
RetainedEarn	Retained earnings (RE) scaled by common shareholders' equity (CEQ)
RetVol	The standard deviation of monthly stock returns over the most recent two years

B. Does Satellite Data of Parking Lot Traffic Contain Value-Relevant Information?

We first calculate quarterly traffic growth for each store as the percentage change of car count in the current fiscal quarter relative to that in the same fiscal quarter of previous year, where quarterly car count for a store is calculated as the store's average daily car count of the fiscal quarter. We use the same quarter of previous year as the base to control for seasonality. We then calculate a retail firm's quarterly traffic growth as the value-weighted store-level quarterly traffic growth (in %). The weight for a store is its relative size within the firm, which is defined as the quarterly average car count of a store divided by the sum of the quarterly average car count of all stores within the firm. The average traffic growth for our sample firms is 30.5% with a standard deviation of 47.0%, which indicates a substantial variation in traffic growth across our sample firms.

Since the satellite data is released almost real time, traffic growth of a fiscal quarter is known at the fiscal quarter end. But accounting information of the fiscal quarter is usually disclosed with a delay of a few weeks or even months after the fiscal quarter end. As a result, traffic growth of a fiscal quarter can be used to predict accounting performance and earnings surprise of the same quarter.

Table A1 below reports the regressions of retail firms' performance measures on the firms' traffic growth. In Column (1), the dependent variable is quarterly sales growth, measured as the year-over-year growth of quarterly sales. The main independent variable is traffic growth of the same fiscal quarter. We control for lagged sales growth, stock returns of the same quarter, and a broad set of firm characteristics described in the previous section. We find that the coefficient of traffic growth is 0.016 and significant at the 5% level (t-stat 2.49). This coefficient is also economically significant, suggesting that a one-standard-deviation increase in traffic growth is associated with a 0.75 percentage-point increase in sales growth.[20] Column (2) presents the regression of net income growth, which is defined as the year-to-year growth of quarterly net income. The coefficient of traffic growth is also positive and significant at the 1% level (t-stat 2.74). This coefficient of 0.177 indicates that a one-standard-deviation increase in traffic growth is associated with an 8.3 percentage-point increase in income growth, which is also economically significant.[21]

Table A1
Does Satellite-Based Traffic Growth Predict Retailer Firm's Performance?

This table reports the regressions of firm performance measures on the growth rate of parking lot traffic based on satellite imagery data. The dependent variables are quarterly sales growth (in %), quarterly net income growth (in %), or market-adjusted cumulative abnormal returns (CAR) around a retailer's quarterly earnings announcement (in %). Sales growth for a quarter is calculated as the year-over-year percentage change of quarterly sales. Net income growth for a quarter is calculated as the year-over-year percentage change of

[20] This number is calculated as the coefficient 0.016×47% (the standard deviation of traffic growth) = 0.75%.

[21] This number is calculated as the coefficient 0.177×47% (the standard deviation of traffic growth) = 8.3%.

quarterly net income. CAR is calculated using daily abnormal return in excess of market return. The main independent variable is traffic growth of the same fiscal quarter. The traffic growth for a retailer firm is defined as the year-over-year growth of the retailer firm's quarterly parking lot traffic based on the satellite imagery data. Control variables include lagged sales growth, stock returns of the fiscal quarter (*Qret*), firm size, leverage, Tobin's Q, profitability, asset tangibility, cash, institutional ownership, analyst coverage, ratio of retained earnings to total equity, and return volatility. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	Sales Growth	**NI Growth**	**CAR[0,2]**	**CAR[-2,2]**
	(1)	(2)	(3)	(4)
Traffic Growth	**0.016****	**0.177*****	**0.012****	**0.018*****
	(2.49)	**(2.74)**	**(2.29)**	**(3.56)**
Lagged Sales Growth	0.609***	1.292***	-0.030	-0.022
	(12.00)	(3.02)	(-0.77)	(-0.48)
Qret	0.066***	0.455**	-0.006	0.000
	(8.22)	(2.12)	(-0.37)	(0.02)
Size	-0.112	-5.037	-1.927***	-2.308***
	(-0.20)	(-0.77)	(-4.12)	(-4.91)
Leverage	-1.518	2.666	-1.225	-0.620
	(-0.63)	(0.15)	(-0.81)	(-0.35)
Tobin Q	0.045	0.569	-0.105**	-0.139***
	(1.13)	(1.22)	(-2.15)	(-3.21)
Profitability	1.196	22.309	-13.656***	-16.243***
	(0.59)	(0.36)	(-4.26)	(-4.94)
Tangibility	0.777	-10.203	2.868	3.263
	(0.36)	(-0.21)	(1.06)	(1.40)
Cash	6.013	29.582	2.111	2.544
	(1.91)	(0.90)	(1.03)	(1.15)
InstOwn	0.106	-4.348	-0.273	-0.095
	(0.16)	(-0.41)	(-0.52)	(-0.13)
AnalystCoverage	-0.048	-0.420	0.002	0.001
	(-1.21)	(-1.04)	(0.06)	(0.02)
RetainedEarn	0.137	0.603	0.077	0.029
	(0.69)	(0.43)	(0.41)	(0.16)
RetVol	3.119	165.054***	-5.264*	-5.238*
	(0.85)	(4.36)	(-1.68)	(-1.90)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,333	4,333	4,333	4,333
Adj. R^2	0.620	0.064	0.011	0.016

We further examine if traffic growth predicts earnings surprise. We measure earnings surprise using CARs around the quarterly earnings announcement of the same quarter as traffic growth. Columns (3) and (4) presents regressions of CAR[0, 2] and CAR[-2, 2] on traffic growth, respectively, where CAR is calculated using daily abnormal stock return in excess of market return. The coefficient of traffic growth is positive and significant at the 5% level in both regressions. These results are also economically significant. For example, the coefficient of 0.018 in Column (4) indicates that a one-standard-deviation increase in traffic growth is associated with a 0.85 percentage-point increase in five-day CAR (the [-2,2] window).[22] The observed positive relation between traffic growth and earnings announcement return is consistent with Katona et al.'s (2020) finding that the information in the satellite data is not fully impounded into stock prices.

Overall, our results show that, consistent with existing literature (Zhu 2019; Katona et al. 2020; Kang, Stice-Lawrence, and Wong 2020), the satellite imagery data of parking lot traffic contains timely and valuable information about firm performance.

C. Do Outside Investors Utilize the Satellite Data?

While the satellite imagery data provides timely information about firm performance, a necessary condition for the data release to influence corporate policies is that outside investors trust and use the satellite data. According to our discussions with the data vendors, their client base is diversified with many of the clients being hedge funds. We conduct two tests to examine if outside investors utilize the satellite-based data of parking lot traffic.

As discussed in Section 3.1, when a vendor starts to release satellite data for a retail firm, it also releases the firm's historical satellite data. For the first test, we investigate whether traffic growth predicts investors' short selling prior to earnings announcement. If outside investors use satellite data in their trading, then we expect a much stronger relation between traffic growth and short selling in the post-release period than in the pre-release period. We follow the literature (e.g., Engelberg, Reed, and Ringgenberg 2018) and construct two measures of short selling using the data from Markit. The first measure is short interest, defined as number of shares borrowed scaled by total shares outstanding. The second measure is utilization rate, defined as shares borrowed as a percentage of total lendable shares. We perform the following regression:

$$\begin{aligned}\Delta ShortInterest\ or\ \Delta Utilization_{it} &= \alpha_i + \alpha_t + \beta_1 TrafficGrowth_{it} \times PostRelease_{it} + \beta_2 TrafficGrowth_{it} \\ &+\ \beta_3 PostRelease_{it} + \gamma X_{it-1} +\ \epsilon_{it}, \qquad (1)\end{aligned}$$

where $\Delta ShortInterest_{it}$ is the change in short interest for firm *i* from the end of the fiscal quarter *t* to two days before the quarterly earnings announcement. $\Delta Utilization_{it}$ is the change in utilization rate from the end of the fiscal quarter *t* to two days before the quarterly earnings announcement. $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm *i* by the end of fiscal quarter *t*, and zero otherwise. $TrafficGrowth_{it}$ is the traffic growth for firm *i* in

[22] This number is calculated as the coefficient 0.018×47% (the standard deviation of traffic growth) = 0.85%.

fiscal quarter *t* as defined in the previous section. The coefficient β_2 measures the response of short selling to traffic growth in the pre-release period, and β_1 measures the differential response of short selling to traffic growth in the post-release period relative to the pre-release period.

Columns (1) and (2) of Table A2 below present the regressions of short interest. The full model in Column (2) shows that β_2 is insignificant (t-stat of -0.17). This result shows that, not surprisingly, short selling does not respond to traffic growth in the period before satellite data is released to outside investors. More importantly, β_1 is significantly negative (t-stat of -4.15), suggesting that short selling respond strongly to traffic growth in the post-release period. Columns (3) and (4) present the regressions using utilization rate, in which we also observe that β_2 is insignificant but β_1 is negative and significant at the 1% level.

Table A2
Do Sophisticated Investors Utilize Satellite Data?

This table reports firm-level regressions of short selling or hedge fund holdings on the satellite-based traffic growth and its interaction with a post-release dummy. where $\Delta ShortSelling_{it}$ is the cumulative change in the lender quantity on loan divided by shares outstanding of firm *i* from the end of the fiscal quarter *t* to two days before the quarterly earnings announcement (in %). $\Delta Utilization_{it}$ is the cumulative change in the value of assets on loan from lenders divided by the total lendable quantity from the end of the fiscal quarter *t* to two days before the quarterly earnings announcement (in %). $HF\ Holdings_{it}$ is measured by the number of shares owned by hedge funds divided by total shares outstanding at the closest calendar quarter end subsequent to the end of fiscal quarter *t*. $PostRelease_{it}$ is a dummy variable that equals one if the satellite data has been released for firm *i* by the end of fiscal quarter *t*, and zero otherwise. $TrafficGrowth_{it}$ is the weighted average of quarterly store-level percentage change in car count for firm *i* in fiscal quarter *t*. X_{it-1} is a vector of control variables. The *t*-statistics based on standard errors clustered at both the firm and year levels are reported in parenthesis. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

	ΔShort Selling		**ΔUtilization**		**HF Holdings**	
	(1)	(2)	(3)	(4)	(5)	(6)
Traffic Growth× PostRelease	**-0.002*** **	**-0.003*** **	**-0.008** **	**-0.011*** **	**0.025*** **	**0.014*** **
	(-5.57)	**(-4.15)**	**(-2.03)**	**(-3.59)**	**(3.52)**	**(2.62)**
Traffic Growth	-0.000	-0.000	0.000	0.000	-0.007	-0.002
	(-0.31)	(-0.17)	(0.09)	(0.16)	(-1.26)	(-0.55)
PostRelease	0.054	0.105	0.269	0.348	0.459	-0.369
	(0.77)	(1.10)	(1.43)	(1.45)	(0.60)	(-0.50)
Lag Sales Growth		0.003		0.008*		-0.016
		(0.73)		(1.71)		(-0.50)
Qret		-0.001		-0.005		-0.001
		(-0.43)		(-0.80)		(-0.11)
Size		-0.121		-0.080		1.152
		(-1.31)		(-0.23)		(0.76)
Leverage		0.454		0.620		-0.853
		(1.12)		(0.47)		(-0.18)
Tobin Q		-0.000		-0.000		-0.033
		(-0.11)		(-0.06)		(-0.52)

	ΔShort Selling		ΔUtilization		HF Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Profitability		-0.005		0.373		1.713
		(-0.01)		(0.31)		(0.26)
Tangibility		0.275		1.538*		-6.718
		(1.03)		(1.69)		(-0.62)
Cash		-0.212		-1.409		-7.507
		(-0.32)		(-1.15)		(-0.96)
InstOwn		-0.187		-0.584		12.054***
		(-1.16)		(-0.94)		(3.84)
AnalystCoverage		0.000		-0.004		0.015
		(0.02)		(-0.27)		(0.71)
RetainedEarn		0.039*		0.078***		0.229
		(1.92)		(2.59)		(1.00)
RetVol		-1.173**		-4.846***		-9.281
		(-2.05)		(-3.61)		(-0.87)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,005	4,399	5,018	4,404	4,370	3,809
Adj. R^2	0.022	0.028	0.022	0.023	0.624	0.657

For the second test, we examine the differential relation between hedge fund holdings and traffic growth between the pre-release period and the post-release period. This test is motivated by the fact that many clients of the data vendors are hedge funds. The regression design is similar as above except that we use hedge fund holdings, measured as the number of shares owned by hedge funds divided by total shares outstanding at the closest calendar quarter end after the end of fiscal quarter *t*.[23] Columns (5) and (6) of Table A2 show that the coefficient on $TrafficGrowth_{it}$ is insignificant, indicating little relation between traffic growth and hedge fund holdings before the release of satellite data. The coefficient on $TrafficGrowth_{it} \times PostRelease_{it}$ is positive and significant at the 1% level in both columns. For example, the coefficient of 0.014 in column (6) indicates that a one-standard-deviation increase in traffic growth is associated with a 1.4% increase in hedge fund holdings in the post-release period relative to the pre-release period.

In sum, the results in Table A2 suggest that outside investors especially sophisticated investors trade on the satellite data on parking-lot traffic. These results provide evidence that outside investors trust and make use of the satellite data.

[23] We thank Vikas Agarwal for providing us the data on hedge fund holdings, which is constructed following Agarwal, Jiang, Tang, and Yang (2013), Agarwal, Fos, and Jiang (2013), and Agarwal, Ruenzi, and Weigert (2017).