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Gone with the Big Data: Institutional Lender Demand for Private Information

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ABSTRACT

I explore whether the value of borrowers' private information is an important determinant of institutional lender participation in syndicated loans. Institutional lenders have been shown to exploit their access to borrowers' private information by trading on it in financial markets. As a shock to these lenders' private information advantage, I utilize the release of the satellite image data of car counts in store parking lots of U.S. retail firms. The satellite data provides accurate and near-real-time signals of firm performance, which undermines the value of borrowers' private information obtained through syndicate participation. I find that once the satellite data becomes commercially available, institutional lenders are less likely to participate in syndicated loans. Consistent with institutional lenders' information-demand channel, the effect of the satellite data coverage is more pronounced when borrowers are opaque or disseminate private information to their lenders earlier. The satellite data coverage further attenuates institutional lending when the data is more accurate in predicting borrower performance. I also show that institutional lenders' reduced demand for private information leads to less favorable loan terms for borrowers. Overall, these findings suggest that big data sources can crowd out the value of private information acquired through lending relationships.

1. Introduction

Over the past two decades, the influx of nonbank institutional lenders as syndicated loan participants has driven the growth of the large corporate loan market (Ivashina and Sun 2011a; Jiang et al. 2010; Lim et al. 2014; Peyravan 2020).[1] The outstanding amounts of syndicated institutional loans increased from $100 billion in 2000 to $1 trillion in 2018 (FDIC 2019). The migration of corporate credit risk to institutional lenders has been facilitated in part by low interest environments and tighter banking regulations after the global financial crisis (Irani et al. 2021). Importantly, institutional lenders are not subject to stringent banking regulations and have been shown to exploit their private information advantages in the equity, bond and credit derivatives markets by trading on borrowers' private information gained through lending relationships (e.g., Acharya and Johnson 2007; Bushman et al. 2010; Han and Zhou 2014).[2] Moreover, the informed trading opportunities that are embedded in the lending relationship generate economically significant profits (e.g., Ivashina and Sun 2011b; Massoud et al. 2011; Peyravan 2020). To shed more light on institutional lending, I examine whether institutional lenders' demand for valuable private information is a significant determinant of their participation in syndicated loans.

The primary empirical challenge in estimating institutional lender demand for borrowers' private information is that lenders' information acquisition is not observable.

[1] Institutional lenders typically include investment banks, insurance and finance companies, mutual funds, pension funds, collateralized loan obligations (CLOs), private equity funds, and hedge funds.
[2] Over the course of a loan, borrowers regularly provide their lenders with non-public information, which includes monthly financial statements, covenant compliance certificates, amendment requests and financial projections (Carrizosa and Ryan 2017; Standard & Poor's 2020).

To overcome this challenge, I take advantage of the availability of alternative data that undermines the value of borrowers' private information. Specifically, I employ satellite image data from Orbital Insight that tracks the number of cars in store parking lots for a subset of U.S. retailers. This data has two important advantages. First, the satellite data provides valuable information about underlying firm performance (Kang et al. 2021b; Katona et al. 2021). Second, the data is updated on a daily basis, therefore, investors who purchase the data can obtain timely updates on firm performance even before firms publicly disclose their performance. These two unique aspects of the satellite data are important in addressing my research question as they feature key characteristics of the private information (i.e., early access to information about borrowers' performance) exploited by institutional lenders for their insider trading.

When institutional lenders can access near-real-time information on a borrower's performance through this alternative source of information, the value of early access to borrowers' performance information through syndicate participation diminishes. Moreover, even if institutional lenders do not directly employ the alternative data, the information advantages of these institutional lenders relative to other investors should also decline when other investors can take advantage of the satellite data, thus reducing incumbent institutional lenders' expected profits from their informed trading (Kyle 1985; Holden and Subrahmanyam 1992; Foster and Viswanathan 1996; Back et al. 2000; Akins et al. 2012; Katona et al. 2021). As a result, institutional lenders should have a lower demand for private information acquired through lending relationships, decreasing their incentives to extend loans to borrowers covered by the satellite data. Therefore, I predict that the probability of institutional lenders participating in a loan syndicate is lower when the satellite data on a borrower becomes commercially available.

To isolate the effect of changes in the value of borrowers' private information, I employ a difference-in-differences approach that compares the probability of institutional lenders participating in loans to firms with the satellite data coverage ("treatment borrowers") and firms without such coverage ("control borrowers") before and after the coverage initiation of the satellite data. I focus on institutional lenders that engage in investment businesses, including investment banking, asset management, private equity, and hedge-fund management. These investment businesses provide a platform for institutional lenders to extract benefits from their timely access to value-relevant information about their borrowers. Furthermore, I require these institutional lenders not to be subsidiaries of bank holding companies, as banks are subject to greater regulatory scrutiny and typically have stronger internal controls, which may diminish institutional investors' opportunity to insider trade on borrowers' private information.[3]

Consistent with my prediction, I find that institutional lenders are less likely to issue loans to borrowers when those borrowers are covered by the satellite data, controlling for borrower and loan characteristics as well as firm, quarter of loan origination, credit rating, and loan type fixed effects. Economically, the probability that institutional lenders issue loans to treatment borrowers relative to that of control borrowers decreases by 10% in the post-coverage-initiation period.

[3] I consider U.S. bank holding companies that are identified by the Financial Stability Board (FSB) as global systemically important banks (G-SIB) which include JP Morgan, Bank of America, Wells Fargo, Citigroup, Goldman Sachs, Morgan Stanley, Bank of NY Mellon, and State Street.

To assess the validity of the parallel-trend assumption in difference-in-differences estimation, I demonstrate that the probabilities that institutional lenders issue loans to treatment and control borrowers are not statistically different in the pre-period when the satellite data is not commercially available. To further mitigate concerns that the results may be affected by other confounding factors, I also control for differences in observable characteristics across treatment and control borrowers using an entropy balancing approach. Using this matching technique, I find consistent evidence that the satellite data coverage decreases institutional lending.

Next, I perform falsification tests using other types of institutional lenders that are unlikely to exploit early access to borrowers' private information for insider trading purposes. First, institutional lenders will have limited demand for private information when they do not have a trading operation and thus cannot exploit their information advantages. Second, institutional lenders affiliated with large bank holding companies face higher regulatory costs than independent institutional lenders and typically have controls in place to prevent the transfer of sensitive borrower information from loan officers to traders in other investment divisions (Carey et al. 1998; Peyravan 2020; Kang et al. 2021a). These lenders therefore are less likely to trade on borrowers' private information. Consistent with limited information demand of institutional lenders without investment businesses and bank-affiliated institutional lenders, I fail to find evidence that these lenders have a lower probability of issuing loans to borrowers covered by the satellite data.

To reinforce institutional lenders' information demand mechanism, I perform a number of cross-sectional tests. I expect the negative effect of the satellite data coverage on institutional lenders' participation to be more pronounced for lenders that had a higher demand for borrowers' private information in the pre-coverage period (i.e., lenders that likely participated in syndicated loans primarily to obtain borrower's private information). Following the coverage initiation of the satellite data, the participation in syndicated loans should become even less valuable to these institutional lenders because the alternative data is likely to substitute, at least partially, for borrowers' private information.

First, I conjecture that institutional lenders should have a higher demand for private information when borrowers are opaque. Opaque borrowers provide imprecise public information that encourages private information acquisition and informed trading (Diamond 1985; Bushman 1991; Kim and Verrecchia 1991).[4] Second, I expect institutional lenders to exhibit a higher information demand when borrowers disseminate private information to their lenders earlier because timely information is more valuable to the lenders' trading activities.[5] Consistent with these predictions, I show that the satellite data coverage reduces institutional lending to a greater extent when borrowers are opaque or disseminate private information to their lenders earlier.

[4] I measure a borrower's information opacity based on its analyst coverage, issuance of earnings forecasts, and press releases.
[5] I measure early dissemination of borrower information based on whether a borrower issues loans with a higher number of performance (income-statement based) covenants or obtains loans from reputable lead arrangers (Bushman et al. 2010, Bushman and Wittenberg-Moerman 2012; Christensen and Nikolaev 2012).

I next investigate whether the satellite data coverage has a greater effect when the data is more accurate in predicting borrower performance. Increased precision of an alternative source of information can further crowd out the value of private information acquired through lending relationships. Therefore, when the satellite data provides more precise forecasts of borrower performance, I expect institutional lenders to have a lower demand for private information through loan participation. I indeed find that the effect of the satellite data coverage on institutional lending is stronger for borrowers for which the satellite data is more accurate.[6]

Lastly, I examine whether institutional lenders' lower information demand affects borrowers' credit outcomes. I find that when institutional lenders stop funding loans to borrowers in the post-coverage-initiation period, these borrowers pay higher interest rates, obtain smaller loan amounts, and issue loans with shorter maturities. Such unfavorable loan terms are consistent with the lower information demand leading to a decrease in credit supply for borrowers covered by the satellite data, suggesting that institutional lenders' information demand is an important factor that shapes loan contractual terms.

This paper makes several contributions. First, I contribute to the growing literature on nonbank institutional lending. Recent studies document that institutional lenders trade on borrower information that they obtain from their lending relationships (Ivashina

[6] I measure the accuracy of the satellite data using high correlation between car count signals and firm performance or lower variability of car count signals across the firm's stores.

and Sun 2011b; Massoud et al. 2011; Peyravan 2020)[7]. Moreover, institutional lenders accelerate the speed of stock-price discovery, especially for borrowers with weak public disclosure (Bushman et al. 2010), and stimulate greater borrower voluntary disclosure (Peyravan and Wittenberg-Moerman 2021). While these studies primarily explore the consequences of institutional lender participation on capital markets, I demonstrate that the demand for valuable private information is an important factor for institutional lenders' decisions to participate in syndicated loans. Relatedly, I contribute to the literature on the effect of institutional lender participation on loan pricing by providing evidence on institutional lenders' lower information demand adversely affecting loan terms for borrowers (Jiang et al. 2010; Ivashina and Sun 2011a; Lim et al. 2014).

Second, I contribute to the emerging literature on the role of alternative big data sources that are used by a subset of sophisticated investors in capital markets. Prior studies find that big data is a useful supplementary source of information that affects price informativeness, managerial actions, and information asymmetries among investors (Jame et al. 2016; Zhu 2019; Kang et al. 2021b; Katona et al. 2021). Relatedly, there is a growing literature on the effects of machine learning and information sharing technologies on lending decisions (e.g., Sutherland 2018, Costello et al. 2020; Kang et al. 2021d; Lu 2021; Bartlett et al. 2022). However, there is little work on how the availability of alternative big data sources affects credit market dynamics. Using the big data source

[7] Peyravan (2020), who primarily focuses on the insider trading activities of dual holders (institutional investors that simultaneously holds a firm's loan and equity), also finds that these investors are more likely to invest in equities of borrowers with weak financial reporting quality. While these findings imply that institutional lenders tend to pursue opaque borrowers, my study directly examines whether institutional lenders' demand for private information is an important determinant of their syndicate lending participation by utilizing the satellite data coverage as a shock to these lenders' information advantage.

that is available to a subset of sophisticated investors, I demonstrate that the availability of the data source undermines information demand of institutional lenders, reducing their supply of credit.

Finally, I also contribute to the nascent literature on the importance of noncredit sources of income in private lending. Prior studies show that relationship lenders are more likely to obtain mandates for their borrowers' security underwritings and M&A deals (e.g., Drucker and Puri 2005; Yasuda 2005). These cross-sold products typically generate substantial income and can enhance the profitability of lending relationships. Therefore, banks take borrowers' cross-selling potentials into account when initiating new lending relationships (Kang et al. 2021c). I complement these studies by showing that the potential trading benefits embedded in the lending relationship can significantly influence institutional lenders' incentives to retain these relationships.

The next section presents the hypothesis development. Section 3 describes data and sample selection. Section 4 reports main results, and Section 5 concludes.

2. Background and Hypothesis Development

2.1 Satellite Imagery Data

Satellite images are photos of Earth's surface collected by remote sensing satellites operated by government programs or commercial entities. Satellite images have detailed and high-spatial resolution; therefore, they are huge in size and mostly in an unstructured format, which is often referred to as "big data." Recent advancements in machine learning and cloud computing techniques have made it feasible to parse out vast quantities of satellite images across the globe and extract useful information from them each day, which enables investors to “explore the world in real-time.” Investors can receive real-time updates on various economic activities measured based on satellite images of store parking lots, manufacturing centers, oil refineries, petrochemical plants, agricultural land, and mining operations among others. These data help, for example, gauge a country's fuel supply, predict crop yields, estimate damages from natural disasters, and track flows and disruptions along supply chains.

In this paper, I employ satellite image data provided by Orbital Insight that tracks the number of cars in parking lots for a subset of publicly listed U.S. firms. Orbital Insight was founded in 2013 and the car count data became commercially available to its clients in the third quarter of 2015. At the end of each day, Orbital Insight collects satellite images from its various providers including Landsat (a joint program by NASA and U.S. Geological Survey), DigitalGlobe, Airbus, and Planet Labs. Once these satellite images are gathered, Orbital Insight counts the number of cars in each parking lot using a proprietary computer vision and machine learning algorithm which includes procedures to enhance accuracy of the car count data. For example, if multiple stores share the same parking lot, the algorithm identifies the area of the parking lots in front of each store’s entrance and records the number of cars specific to the store. In this case, the algorithm provides information on a contamination level of each store’s car count data based on the probability of inaccurately counting the number of cars. Moreover, the car count data is adjusted based on the time stamp of the satellite images to ensure comparability over time. Satellite images taken outside of operating hours and for stores with covered parking lots are excluded. Orbital Insight provides the car count data to its clients the following morning.

2.2 Related Literature and Hypothesis Development

Over the past two decades, nonbank lenders have played an increasing role in supplying credit to corporations. In the syndicated loan market, nonbank lenders have grown their share from 40% in 2000 to 60% in 2014 (Peyravan 2020). Low interest environments and tighter banking regulations after the global financial crisis facilitated the migration of corporate credit risk to nonbank lenders (Irani et al. 2021). Recent studies examine characteristics of nonbank loans and show that they have higher interest spreads, have more flexible covenants, and are more likely to be secured while nonbank borrowers are smaller, less profitable, and have few financing alternatives (Lim et al. 2014; Chernenko et al. 2019; Loumioti 2019).

Nonbank lenders include a growing number of institutional lenders who also engage in investment businesses in financial markets (e.g., investment managers, hedge funds, private equity funds, and investment banks). As syndicate participants, these lenders have access to borrowers' performance information before it is publicly disclosed to market participants. Over the course of a loan, borrowers typically provide information to lenders on a monthly basis, including financial performance updates, covenant compliance reports, amendment requests and financial projections, and allow lenders to visit their sites (Carrizosa and Ryan 2017; Gustafson et al. 2020; Standard & Poor's 2020). Regulators, banks and borrowers expressed considerable concerns about institutional lenders' access to private information (e.g., SEC 2012; Standard & Poor's 2020). To address these insider trading concerns, some participants may decide to waive their right to access private information of their borrowers (Amiraslani et al. 2021).

Despite U.S. laws prohibiting trading on material private information regulations[8], prior studies show that institutional lenders exploit their information advantages by engaging in insider trading in the equity, bond, and credit derivatives markets (Acharya and Johnson 2007; Bushman et al. 2010; Ivashina and Sun 2011b; Massoud et al. 2011; Han and Zhou 2014; Peyravan 2020). In addition, insider trading generates economically significant profits. For example, institutional lenders can make abnormal profits of around $5 million by short-selling borrowers' stocks during the 20-day window around negative credit events (Massoud et al. 2011) or achieve 5% to 8% excess annual returns by trading borrowers' stocks (Ivashina and Sun 2011b; Peyravan 2020).

I examine whether the value of borrowers' private information is an important determinant for the institutional lenders' incentives to have lending relationships with borrowers. Empirical evidence on this topic is limited because lenders' acquisition of private information is not directly observable. Recent studies use Freedom of Information Act (FOIA) requests to identify private information acquisition. Glaeser et al. (2021) show that information asymmetry between managers and outsiders promotes private information acquisition measured by FOIA requests submitted to the U.S. Securities and

[8] The Securities Exchange Act of 1934 and the Insider Trading Sanctions Act of 1984 are two federal laws that regulate insider trading.

Exchange Commission. Down et al. (2021) find that lead arrangers file FOIA requests to the Food and Drug Administration to obtain private information about their borrowers. While FOIA requests reveal non-public information, these requests are fulfilled with a considerable delay. Therefore, FOIA requests may not be useful for institutional lenders' instantaneous trading activities. To overcome the empirical challenges, I take advantage of the satellite image data from Orbital Insight that provides daily updates on the number of cars in store parking lots. This data has two important advantages. First, the car count data provides valuable information by accurately predicting firm performance (Kang et al. 2021b; Katona et al. 2021). Second, the data is updated daily; therefore, investors can purchase the data to obtain timely updates on firm performances before firms publicly disclose their performance. These two unique aspects of the data comprise the key characteristics of the private information exploited by institutional lenders for their informed trading in financial markets.

When institutional lenders can access the satellite data that provides timely information on borrowers' performance, the value of private information acquired through lending relationships declines. Moreover, when other investors can also acquire the satellite data and trade on timely information about firm performance, institutional lenders expect greater competition in financial markets. The competition among informed investors reduces expected profits from their informed trading and discourages private information acquisition (e.g., Holden and Subrahmanyam 1992; Foster and Viswanathan 1993, 1996; Back et al 2000; Akin et al. 2012). As a result, institutional lenders should have a lower demand to acquire private information by extending loans to borrowers covered by the satellite data. Building on these arguments, I predict that the probability that institutional lenders participate in syndicated loans is lower after the satellite data on a borrower becomes commercially available.

However, there are a number of factors that may confound this prediction. First, factors other than the value of private information can dominate institutional lenders' incentives to have lending relationships with borrowers. For example, prior studies suggest that institutional lenders pursue syndicated loans because these loans offer high interest rates (Lim et al. 2014). Second, the satellite data may be less informative than what institutional lenders can directly learn through syndicate relationships. Third, the satellite data may complement rather than substitute the private information of institutional lenders. For example, the satellite data may help institutional lenders to better interpret and trade on the private information about borrower performance (Kim and Verrecchia 1994; McNichols and Trueman 1994). Fourth, the costs associated with both acquiring and processing the satellite data can be prohibitive to investors (e.g., Blankespoor et al. 2020). Therefore, institutional lenders may continue to demand early access to borrower information through their lending relationships. For these reasons, whether the availability of the satellite data attenuates institutional lending remains an open question.

3. Sample, Data, and Descriptive Statistics

3.1 Data Sources and Sample Selection

I obtain loan characteristics from DealScan and borrower characteristics from Compustat and CRSP. I collect analyst coverage data from I/B/E/S, press release data from RavenPack, and borrower credit ratings from Compustat and Mergent FISD. Satellite data coverage and store-level car count data are from Orbital Insight. I select loans issued by U.S. borrowers in the same industries as borrowers covered by the satellite data, resulting in 6,907 loan packages over the 2011 and 2019 period. I eliminate borrowers with missing Compustat identifiers, resulting in 2,684 loan packages. I match this sample to Compustat and further eliminate loans with insufficient borrower and loan characteristics. The final sample contains 98 treatment borrowers with the satellite data coverage and 546 control borrowers without the data coverage, corresponding to 2,129 loan packages syndicated by 677 lenders.

To identify institutional lenders, I first classify lenders as either commercial bank lenders or nonbank lenders. Following Lim et al. (2014), I identify a lender as a *commercial bank* lender if its lender type in DealScan is "US Bank," "Foreign Bank," "Thrift/S&L," "African bank," "Asian-Pacific Bank," "Eastern Europe/Russian Bank," "Middle Eastern Bank," or "Western European Bank." I also classify a lender as a commercial bank lender if a lender's SIC 4-digit code is between 6011 and 6082, or 6712, 6719. For each lender identified as commercial bank, I manually check whether the lender mainly engages in commercial banking business and exclude lenders if they do not mainly accept deposits and extend individual or business loans.[9] I classify all remaining lenders as *nonbank lenders*.

Next, I further classify nonbank lenders based on whether they are affiliated with bank holding companies using these lenders' business descriptions from their company websites, annual reports, Bloomberg, or Capital IQ. I classify a lender as a *bank-affiliated-institutional lender* if it is a subsidiary of the U.S. bank holding company. For each *independent institutional lender* that is not affiliated with banks, I next identify whether it engages in investment businesses based on DealScan lender type. An independent institutional lender is considered to have an investment operation if its lender type in DealScan is "Inst. Invest. Prime Fd," "Inst. Invest. Prime Hedge Fd," "Inst. Invest. Prime CDO," "Investment bank," "Mutual Fund," "Distressed (Vulture) Fund." In addition, I check each lender's business description to determine whether the lender engages in investment businesses, including investment banking, asset management, private equity, and hedge fund management.[10] Finally, I classify remaining lenders as independent institutional lenders that do not engage in investment businesses. These lenders include captive finance companies, lease companies, and farm credit institutions.

3.2 Descriptive Statistics

[9] For example. I exclude from commercial bank lenders Goldman Sachs Group, ORIX USA Corp and Pilgrim Group.

[10] I focus on the independent institutional lenders that engage in investment businesses

Table 1 presents descriptive statistics of the main variables used in the analyses. A total of 16.5% of the loans in the sample are issued with at least one independent institutional lender engaging in investment businesses (*Inst. Lender*).[11] A total of 33.2% of loans are issued after the third quarter of 2015 when the satellite data becomes commercially available (*Post*). Treatment borrowers issue 19.4% of sample loans (*Treatment Firm*). My sample borrowers are relatively large (*Assets*) and have an average leverage ratio (*Leverage*) of 0.332. The mean market-to-book ratio (*MTB*) is 3.23, the mean sales growth (*Sales Growth*) is 0.148, and the mean interest coverage ratio (*Interest Coverage*) is 65.5. [12] The sample borrowers have an average return on asset (*ROA*) of 0.027, an average Altman Z-score (*Altman Z*) of 3.546, an average age (*Age*) of 24 years, and show 5.5% of stock return before the loan issuance (*Past Return*). With respect to loan characteristics, the mean value of loan size (*Amount*) suggests that sample loans are relatively large (USD $3.2 billion), have an average maturity (*Maturity*) of approximately four years, and have an average all-in-drawn spread of 195 bps (*Interest Spread*). Around 49% of loans are secured (*Secured*) and 9% of them have a guarantor (*Guarantor*). Detailed variable definitions are reported in Appendix A.

4. Research Design and Empirical Results

[11] I note that 24.8% and 5.9% of the loans in the sample are issued with at least one bank-affiliated-institutional lender (*Inst. Lender Bank Affiliated*) and independent institutional lender without investment operations (*Inst. Lender No Investment*).

[12] The median value of *Interest Coverage* is 8.4. Main results are robust to winsorizing it at 95% level (with its mean and SD of 22.1 and 39.09 respectively).

I organize my empirical analyses as follows. First, I examine the effect of the satellite data coverage on institutional lender participation in syndicated loans. Next, I further explore the information demand channel by investigating whether the observed effect is stronger when institutional lenders are expected to have a higher demand for borrowers' private information in the pre-coverage period. Lastly, I examine whether institutional lenders' information demand affects borrowers' credit outcomes.

4.1 Satellite Image Data and Institutional Lending

I begin my analyses by investigating whether the probability that institutional lenders issue a loan is lower after the satellite data on a borrower becomes commercially available. My empirical strategy exploits the fact that a subset of U.S. borrowers is covered by the satellite data after the third quarter of 2015.[13] I employ a difference-in-differences analysis using control borrowers in the same industries (SIC 4-digit) as the treatment borrowers covered by the data.[14] Specifically, I estimate the following model:

$$\textit{Inst. Lender} = \beta_0 + \beta_1 \textit{Treatment Firm} \times \textit{Post} + \textit{Controls} + \textit{Fixed Effects} + \varepsilon, \quad (1)$$

In Model (1), the dependent variable (*Inst. Lender*) is equal to one if the loan is issued with at least one institutional lender that is not affiliated with bank holding companies and is engaged in investment businesses (institutional lender hereafter), and zero otherwise. The variable of interest is *Treatment Firm* × *Post*, where *Treatment Firm* is

[13] It is important to note that firms do not have control over whether they are covered by these data.
[14] Main results are robust to using SIC 3-digit industries.

equal to one if the borrower is covered by the satellite data during the post-coverage-initiation period (and zero otherwise) and *Post* is equal to one if the loan is issued after the satellite data becomes commercially available (and zero otherwise). If institutional lenders have a lower probability of participation in loans to borrowers after those borrowers are tracked by the satellite data, I expect a negative and significant coefficient on *Treatment Firm* × *Post*.

I control for borrower characteristics that can influence institutional lending decisions, which include a borrower's size (*Assets*), liquidity (*Current Ratio*), leverage (*Leverage*), market price (*MTB*), sales growth (*Sales Growth*), interest coverage (*Interest Coverage*), profitability (*ROA*), credit risk (*Altman Z*), age (*Age*), and stock performance (*Past Return*). I also control for loan characteristics, including loan amount (*Amount*), maturity (*Maturity*), and whether a loan is secured (*Secured*) or has a guarantor (*Guarantor*). I include firm fixed effects to control for unobservable time-invariant characteristics of each firm. I also include year fixed effects to control for time-varying factors common to all sample firms.[15] I estimate the Model (1) using both a logit and OLS model. In the OLS model, I substitute year fixed effects with year-quarter fixed effects and further include credit rating and loan type fixed effects.[16] I cluster standard errors at the firm level.

I present my main findings in Table 2. First, I report the results of univariate tests

[15] I include year fixed effects using indicator variables for trailing 12 months ending in September of each year to ensure that *Post* does not have within-year variances. Thus, the coefficients on both *Treatment Firm* and *Post* are not estimated because they are perfectly collinear with year and firm fixed effects.
[16] Due to issues regarding a large number of fixed effects in nonlinear models (e.g., Maddalla 1987; Greene 2004), I include only year and firm fixed effects in the logit model.

in Panel A. I find that when investors can access the satellite data (*Post* = 1), 8.7% of loans are issued with institutional lenders for treatment borrowers, compared to 19.4% of loans for control borrowers. In contrast, when the satellite data is not available to investors (Post = 0), 16.0% of loans are issued with institutional lenders for treatment borrowers, compared to 16.3% of loans for control borrowers. I find that the difference-in-differences ((8.7% - 19.4%) – (16.0% - 16.3%)) is statistically significant at the 1% level. This evidence is consistent with my prediction that institutional lenders are less likely to issue loans to borrowers after these borrowers become covered by the satellite data.

Next, I present estimation results of Model (1) in Panel B of Table 2. In column (1) (columns (2) and (3)), I employ a logit model (OLS models). I find a negative and significant coefficient on *Treatment Firm* x *Post* for all specifications.[17] Economically, relative to the control borrower, the probability of institutional lenders issuing a loan to the treatment borrower is lower by 13.8% after the coverage-initiation of the satellite data. I measure economic significance based on the OLS specification in column (3), where I include firm, year-quarter, credit rating, and loan type fixed effects. These findings reinforce my prediction that the probability of institutional lenders issuing a loan is lower for borrowers tracked by satellite data.[18]

[17] With respect to controls, the negative and significant coefficients on *ROA* and *Past Return* suggest that borrowers with higher profitability or higher prior buy and hold return are less likely to obtain loans from institutional lenders. The negative and significant coefficient on *Altman Z* indicates that borrowers with higher credit risk attract institutional lenders. Institutional lenders are also more likely to participate in secured loans (*Secured*).

[18] I employ several alternative specifications to ensure that my results are not sensitive to research design choices. First, I re-estimate Model (1) using continuous dependent variables of the proportion (%) or the number of institutional lenders in the loan package and find robust results (reported in Panel A of Appendix B). Also, a subset of treatment borrowers in my sample are covered by the satellite data provided

The key identifying assumption of the difference-in-differences analysis is the parallel-trend assumption that institutional-lending trends would be the same for both treatment and control borrowers in the absence of the satellite data coverage. In other words, it assumes that control borrowers provide the appropriate counterfactual of the trend that treatment borrowers would have followed if they had not been covered by the satellite data (Angrist and Pischke 2008). To examine whether the parallel-trend assumption holds, I estimate the following model:

$$\begin{aligned} \textit{Inst. Lender} = \beta_0 + \beta_1 \textit{Treatment Firm} \times \textit{Trend}_{t=-3,-4} + \beta_2 \textit{Treatment Firm} \times \textit{Trend}_{t=1,2} + \\ \beta_3 \textit{Treatment Firm} \times \textit{Trend}_{t=3,4} + \textit{Controls} + \textit{Fixed Effects} + \varepsilon, \end{aligned} \tag{2}$$

In Model (2), I replace *Treatment Firm* x *Post* variable in Model (1) with separate interaction variables between *Treatment Firm* and trend variables. Each trend variable is equal to one for every two-year sample period before and after the initiation of the satellite data coverage (and zero otherwise). I exclude from the trend variables the last two-year period immediately prior to the release of the satellite data (from 4th quarter in 2013 to 3rd quarter in 2015); therefore, this period serves as a benchmark period. In Figure 1, I graphically depict the estimation results of Model (2). I find that the counterfactual treatment effect in the pre-coverage period (i.e., the coefficient on *Treatment Firm* ×

by RS Metrics. Main results are robust to using *Post RM* as the main variable of interest, which is equal to one if the loan is issued after the satellite data from either RS Metrics or Orbital Insight become commercially available, and zero otherwise (results are tabulated in Panel B of Appendix B). Moreover, SafeGraph is a major provider of mobile GPS location data. Main results continue to hold when I exclude periods after SafeGraph released their foot traffic data in 2018 (results are tabulated in Panel C of Appendix B).

$Trend_{t=-3,-4}$) is statistically indistinguishable from the benchmark period while treatment effects in the post-coverage-initiation period (i.e., the coefficients on *Treatment Firm* × $Trend_{t=1,2}$ and *Treatment Firm* × $Trend_{t=3,4}$) are significantly different from the benchmark period. These results provide support for the parallel-trend assumption.[19]

While firms cannot self-select to be covered by the satellite data, I recognize other factors that may confound my results. For example, if treatment borrowers and control borrowers differ in many dimensions, satellite data coverage may be endogenous with respect to these differences. In Panel E of Appendix B, I compare firm characteristics between the treatment and control borrowers. Treatment borrowers are more profitable and older while they exhibit lower sales growth and have lower credit risk relative to the control borrowers.[20] Although I control for time invariant firm characteristics by including firm fixed effects in all the analyses, to further alleviate this concern, I employ the entropy balancing approach. This matching technique achieves covariate balance between treatment and control observations by re-weighting control observations, which ensures that the mean and the variance are identical along the matching variables for both treatment and control samples. Moreover, the entropy balancing reduces bias from nonlinear relationships between observable characteristics and the dependent variable

[19] I also plot the probability of institutional lending for treatment and control borrowers separately during the sample period (untabulated). I visually check that these univariate trends do not indicate a violation of the pre-trend assumption. In addition, I restrict the main sample to the pre-period and estimate the Model (1) after interacting *Treatment Firm* with a continuous trend variable of *Year* which is the year of loan issuance. I do not find a significant coefficient on *Treatment Firm* x *Year* which provides support for the parallel trend assumption.

[20] I also examine whether characteristics of the treatment borrowers change in the post-coverage period relative to those of the control borrowers, which potentially drive the main results. However, I failed to find such evidence using borrower characteristics such as assets, credit rating, leverage, interest coverage, MTB, earnings guidance (untabulated).

(Hainmueller 2012; McMullin and Schonberger 2020). In Panel C, Table 2, I present the estimation results using the entropy balanced sample and continue to find a negative and significant coefficient on *Treatment Firm* x *Post*, consistent with the satellite data coverage curbing institutional lending.

4.2 Falsification Test

In this section, I perform falsification tests to provide additional support for institutional lenders' information demand mechanism. I suggest that when the satellite data provides accurate and near-real-time signals on firm performance, institutional lenders have a lower demand to acquire borrower private information for insider trading purposes. Therefore, if the information demand is instrumental to the relationship between the satellite data coverage and institutional lending, my main results should not hold or be much weaker for other types of lenders that are unlikely to exploit early access to borrowers' private information by engaging in informed trading.

Institutional lenders affiliated with bank holding companies are less likely to trade on borrower information obtained through lending relationships because these lenders are subject to stringent banking regulations and face higher regulatory oversight (Carey et al. 1998; Peyravan 2020). Moreover, bank-affiliated lenders tend to be larger organizations and have controls in place to prevent the transfer of sensitive borrower information from loan officers to traders in other investment divisions who may exploit it (Carey et al. 1998; Peyravan 2020; Kang et al. 2021a; Peyravan and Wittenberg-Moerman 2021). Therefore, I focus on loans issued with institutional lenders that are subsidiaries of bank holding companies. *Inst. Lender Bank Affiliated* is equal to one if the loan is issued with at least one bank-affiliated-institutional lender but is not issued with independent institutional lenders (and zero otherwise).

To exploit private information advantages for potential insider trading, lenders need to engage in investment businesses which can provide a platform to extract benefits using value-relevant information about their borrowers. Using loans issued with independent institutional lenders, I further identify those loans issued with lenders that do not engage in the investment businesses. *Inst. Lender No Investment* is equal to one if the loan is issued with at least one independent institutional lender *not* engaging in investment businesses but is not issued with independent institutional lenders that engage in investment businesses (and zero otherwise).

I perform the falsification test by re-estimating Model (1) with each of these variables as the dependent variable. I report the results in Panel A, Table 3. Consistent with my prediction, I failed to find a significant coefficient on *Treatment Firm* x *Post* across all specifications where either *Inst. Lender Bank Affiliated* or *Inst. Lender No Investment* is the dependent variable. Next, I re-estimate Model (1) using a multinomial logit model. For this analysis, I create a dependent variable that takes the value of one if *Inst. Lender Bank Affiliated* is equal to 1, two if *Inst. Lender No Investment* is equal to 1 and, three if *Inst. Lender* is equal to 1, and zero otherwise. As reported in Panel B, Table 3, I failed to find significant coefficients on *Treatment Firm* x *Post* when the dependent variable takes the value of one or two, which suggests that the satellite data coverage does not affect loans issued with bank-affiliated-institutional lenders or independent institutional lenders without investment operations. These results are consistent with these lender types having low demand for borrowers' private information.

4.3 Institutional Lenders' Information Demand

To further support the information demand mechanism, I investigate whether the effect of the satellite data coverage on institutional lending is more pronounced if institutional lenders had a higher demand for borrowers' private information in the pre-coverage period. While higher information demand can stimulate institutional lenders to participate in syndicated loans, this participation becomes less valuable in the post-coverage-initiation period when the satellite data substitutes, at least partially, for borrowers' private information. Thus, I predict the effect of the satellite data coverage on institutional lending to be stronger for borrowers that attracted higher institutional lenders' information demand prior to the initiation of the data coverage.

4.3.1 Borrower Opacity

I perform several analyses that exploit cross-sectional variances in institutional lenders' information demand based on borrower characteristics in the period before the satellite data becomes available. First, I examine whether the effect of the satellite data coverage on institutional lending is more pronounced for opaque borrowers. Opaque borrowers provide imprecise public signals; therefore, traders have more heterogeneous beliefs about them, which encourages private information acquisition and informed trading (Verrecchia 1982; Diamond 1985; Bushman 1991). Moreover, when a borrower is opaque, lenders are endowed with greater information advantages, which increase the value of borrowers' private information. Therefore, institutional lenders should have a higher information demand for opaque borrowers when alternative information sources are not available.

To measure a borrower's information opacity, I begin with a borrower's analyst coverage. As an important information intermediary, financial analysts actively engage in private information production and provide accurate and timely information about firm performance to investors (Brown et al. 1987; Fried and Givoly 1982; Healy and Palepu 2001). Moreover, increased analyst following reduces the likelihood of insider trades and discourages insider purchases (Frankel and Li 2004). *No Analyst Coverage* is equal to one if the borrower does not have equity analyst coverage in the pre-coverage period (and zero otherwise).

As another measure of borrower opacity, I consider a borrower's disclosure choices – decisions to issue earnings forecasts and press releases. Public disclosures may preclude costly private information acquisition (Diamond 1985, Verrecchia 2001) and are important determinants for a firm's information opacity (e.g., Beyer et al. 2010). *No Earnings Forecast* is equal to one if the borrower does not issue earnings forecasts in the pre-coverage period (and zero otherwise). *Low Press Releases* is equal to one if the average number of press releases by the borrower, measured in the pre-coverage period, is less than the sample median (and zero otherwise).

Using these borrower opacity variables, I assign loans to the high and low opacity partitions and re-estimate Model (1). In Panel A of Table 4, I find a negative and significant coefficient on *Treatment Firm* x *Post* in the low analyst partition (i.e., *No Analyst Coverage* = *1*). Importantly, I show that the magnitude of the coefficient on *Treatment Firm* x *Post* is statistically higher in the low analyst partition than in the high analyst partition. Next, in Panel B of Table 4, the coefficients on *Treatment Firm* x *Post* are negative and significant using both low disclosure partition (i.e., *No Earnings Forecast* = *1*) and high disclosure partition (i.e., *No Earnings Forecast* = *0*). However, the magnitude of the coefficient is statistically higher for the low disclosure partition, consistent with non-guider borrowers attracting higher information demand. Lastly, as reported in Panel C of Table 3, I find that the coefficient on *Treatment Firm* x *Post* is negative and significant in the low press release partition (i.e., *Low Press Releases* = *1*) and its magnitude is statistically higher than the magnitude in the high press release partition (*Low Press Releases* = *0*). Economically, using the low press release partition, the probability that an institutional lender issues a loan to the treatment borrower is lower by 18.7% relative to the control borrower after the coverage-initiation of the satellite data. Overall, these results suggest that satellite data coverage attenuates institutional lending to a greater extent when borrowers are opaque.

4.3.2 Early Dissemination of Borrower Private Information

To strengthen the information demand mechanism, I next perform additional cross-sectional tests to determine whether the satellite data coverage has a stronger effect when borrowers disseminate private information to their lenders earlier. Prior studies suggest that timely access to borrower information facilitates informed trading by incumbent lenders (Bushman et al. 2010; Carrizosa and Ryan 2017). Because timely information is more valuable for instantaneous trading activities, I expect institutional lenders to have a higher information demand when borrowers disseminate their information to lenders on a timely basis.

I first measure early dissemination of borrower information based on whether a borrower issues a higher number of performance covenants (Bushman et al 2010, Christensen and Nikolaev 2012; Christensen et al. 2016; Carrizosa and Ryan 2017).[21] Performance covenants are based on earnings and cash flow metrics and are frequently set tightly relative to the underlying performance variables. Moreover, these covenants often obligate borrowers to provide information about their current performances to lenders more frequently. Therefore, performance covenants enable lenders to monitor borrowers efficiently, which accelerates timely acquisition of private information about borrowers (Bushman et al. 2010; Carrizosa and Ryan 2017). *High Perf. Covenants* is equal to one if the average number of performance covenants for loans issued by the borrower, measured in the pre-coverage period, is greater than the sample median (and zero otherwise).

Next, I use lender reputation as another measure of timely dissemination of borrower information to lenders. The reputation of a lead arranger reflects its expertise and commitment to monitor borrowers (e.g., Diamond 1989; Boot et al. 1993; Chemmanur

[21] Following Christensen and Nikolaev (2012), I classify cash interest coverage ratio, debt service coverage ratio, level of EBITDA, fixed charge coverage ratio, interest coverage ratio, ratio of debt to EBITDA, and ratio of senior debt to EBITDA covenants as performance covenants

and Fulghieri 1994). Reputable lead arrangers have been documented to collect greater private information about borrowers and communicate it earlier to syndicate participants (Bushman et al. 2010; Bushman and Wittenberg-Moerman 2012).[22] Therefore, I expect that institutional lenders have a higher information demand when they participated in loans syndicated by reputable lead arrangers in the pre-coverage period. *High Reputation* is equal to one if the borrower obtains loans issued with one of the top five lead arrangers in the pre-coverage period (and zero otherwise).

I partition sample observations based on these measures of timely dissemination of borrower information and re-estimate Model (1). As I report in Panel A of Table 5, the coefficient on *Treatment Firm* x *Post* is significant in the high covenant partition (i.e., *High Perf. Covenants* = *1*) but not in the low covenant partition (i.e., *High Perf. Covenants* = *0*). I also show that the coefficient on *Treatment Firm* x *Post* indicates statistically higher magnitude in the high covenant partition than in the low covenant partition. Further, in Pane B of Table 5, I show a negative and significant coefficient on *Treatment Firm* x *Post* in the high reputation partition (i.e., *High Reputation* = 1) but not in the low reputation partition (i.e., *High Reputation* = 0). In addition, the coefficient on *Treatment Firm* x *Post* has a significantly higher magnitude in the high reputation partition. Economically, using the high reputation partition, relative to the control borrower, the probability of an institutional lender issuing a loan to the treatment borrower is lower by 29.4% after the coverage-initiation of the satellite data. Taken together, these findings suggest that the

[22] Also, reputable lenders experience higher reputational losses if they withhold important private information about borrowers from participants (Down et al. 2021).

effect of satellite data coverage on institutional lending is more pronounced when the flow of borrowers' private information to lenders is faster, which further supports institutional lenders' information demand channel.

4.4 Accuracy of Satellite Image Data

In this section, I investigate whether the satellite data coverage has a greater effect on institutional lending when the data is more accurate in predicting borrowers' performance. When alternative sources of information provide signals with higher precision, traders can generate higher profits from their informed trading (Grossman and Stiglitz 1980; McNichols and Trueman 1994). Therefore, more precise satellite data can further crowd out the value of private information acquired through lending relationships, leading to the reduction in institutional lender participation.

I measure the accuracy of the satellite data for each borrower using its store-level car counts. A borrower has more accurate satellite data when the correlation between its car count signals and firm performance is higher or the variability of its car count signals across stores is lower. *Treatment Firm High Corr (Treatment Firm Low Corr)* is equal to one if the average correlation between quarterly changes in car counts and quarterly changes in sales of the borrower is greater (lower) than the sample median, and zero otherwise. *Treatment Firm High SD (Treatment Firm Low SD)* is equal to one if the average standard deviation of quarterly changes in car counts across stores is greater (lower) than the sample median, and zero otherwise. Using each of these car count accuracy variables, I estimate the following model:

$$Inst.\ Lender = \beta_0 + \beta_1 Treatment\ Firm\ High\ Accuracy \times Post + \beta_2 Treatment\ Firm\ Low\ Accuracy \times Post + Controls + Fixed\ Effects + \varepsilon, \quad (3)$$

In this model, I replace *Treatment Firm* x *Post* variable in Model (1) with separate interactions between *Post* and high (or low) accuracy of car count variables.[23] In Panel A of Table 6, I present results of the analysis using *Treatment Firm High Corr (*and *Treatment Firm Low Corr)*. I find a negative and significant coefficient on *Treatment Firm High Corr* x *Post* but do not find a significant coefficient on *Treatment Firm Low Corr* x *Post*, and the difference between these two coefficients is statistically significant. I also find similar results using *Treatment Firm High SD (*and *Treatment Firm Low SD)*. As I report in Panel B of Table 6, the coefficient on *Treatment Firm Low SD* x *Post* is negative and significant across all specifications, and its magnitude is significantly higher than the coefficient on *Treatment Firm High SD* in OLS specifications. Economically, when the car count signal exhibits lower variability, the probability that an institutional lender issues a loan to the treatment borrower is lower by 18.4% after the coverage-initiation of the satellite data. Overall, these results suggest that institutional lenders have a lower demand to acquire private information by extending loans to borrowers when more precise satellite data further crowds out the value of borrowers' private information. These findings not only further support the information demand mechanism but also provide evidence on the

[23] Accuracy of the car count signals cannot be measured for control borrowers whose car count data is not available.

validity of the satellite data coverage as a proxy for the value of borrowers' private information.

4.5 Institutional Lenders' Demand for Private Information and Borrowing Terms

Thus far, I provide robust evidence that the information demand for borrowers' private information is an important factor for institutional lenders' decisions to issue loans to borrowers. In the last set of analysis, I explore whether the information demand of institutional lenders influences borrowers' credit outcomes. When the satellite data coverage reduces credit supply from institutional lenders, borrowers may obtain less favorable loan terms (e.g., Ivashina and Sun 2011a; Lim et al. 2014). On the other hand, the satellite data provides useful information about borrower performance, which may help mitigate adverse selection concerns of syndicate participants and incentivize them to supply more credit (Bushman et al. 2016; Kang et al. 2021c). In this case, borrowers may obtain more favorable loan terms despite the lower information demand of institutional lenders after the initiation of the satellite data coverage. To investigate this question, I estimate the following OLS model:

$$\begin{aligned} \textit{Loan Term} = {} & \beta_0 + \beta_1 \textit{Treatment Firm} \times \textit{Post No Inst. Lender} \times \textit{Had Inst. Lender} + \\ & \beta_2 \textit{Treatment Firm} \times \textit{Post Inst. Lender} \times \textit{Had Inst. Lender} + \textit{Main Effects} + \\ & \textit{Lower Order Interactions} + \textit{Controls} + \textit{Fixed Effects} + \varepsilon, \end{aligned} \tag{4}$$

Where the dependent variable of *Loan Term* is one of the following three borrowing terms: the natural logarithm of the all-in-drawn spread (*Interest Spread),* the natural logarithm of loan amounts (*Amounts*), and the natural logarithm of the loan maturity in months (*Maturity*).[24] To estimate the effect of the reduction in institutional lenders' participation, I identify the following loans issued in the post-coverage-initiation period: loans issued without institutional lenders participation (*Post No Inst. Lender),* loans issued with institutional lender participation (*Post Inst. Lender*), and loans issued to a borrower who had institutional lender participation in its loans issued before the satellite data became available (*Had Inst. Lender*). The main variable of interest is the triple interaction term - *Treatment Firm* × *Post No Inst. Lender* × *Had Inst. Lender.* This variable measures loans issued by treatment borrowers (*Treatment Firm* = 1) who do not obtain loans from institutional lenders in the post period (*Post No Inst. Lender* = 1) but had lending relationships with institutional lenders in the pre-coverage period (*Had Inst. Lender* = 1), which indicates that these borrowers experience a reduction in information demand from institutional lenders.

As I report in Table 7, I find a positive (negative) and significant coefficient on *Treatment Firm* × *Post No Inst. Lender* × *Had Inst. Lender* in the *Interest Spread* (*Amounts* or *Maturity*) specification. The results indicate that when institutional lenders stop issuing loans to borrowers following the initiation of the satellite data coverage, borrowers pay higher interest rates, obtain smaller loan amounts, and issue loans with shorter maturities.[25] These unfavorable loan terms are consistent with the reduced information

[24] I include all main effects and lower order interactions of each triple interaction variable in Model (4) but do not specify them for brevity.

[25] I restrict sample to the treatment borrowers and re-estimate Model (4) and continue to find a positive (negative) and significant coefficient on *Post No Inst. Lender* x *Had Inst. Lender* in *Interest Spread* (*Amounts* or *Maturity*) specification (reported in Panel F of Appendix B).

demand leading to lower credit supplies from institutional lenders.[26] Overall, these findings suggest that institutional lender demand for borrowers' private information is an important factor that can influence the contract outcomes of syndicated loans.

5. Conclusion

I show that the value of borrowers' private information is a significant determinant for institutional lenders' participation in syndicated loans. As a shock to institutional lenders' private information advantages, I utilize the release of the satellite image data of the car counts in store parking lots of U.S. retail firms. I predict that accurate and near-real-time information on borrower performance through the satellite data diminishes the value of borrowers' private information; therefore, institutional lenders have a lower demand for the private information obtained through lending relationships. Consistent with my prediction, I find that institutional lenders are less likely to participate in loan syndicates when the satellite data on a borrower becomes commercially available. Supporting the information demand argument, I further show that the satellite data coverage further attenuates institutional lending when borrowers are opaque, disseminate private information to their lenders earlier, or when the satellite data provides more accurate forecasts of borrower performance. Lastly, I find that the lower information demand of institutional lenders leads to unfavorable credit outcomes for borrowers.

[26] I am cautious in the inferences from Table 7 because the *Post No Inst. Lender* and *Had Inst. Lender* variables can be endogenously determined based on the institutional lenders' perceived costs and benefits from the lending relationships with borrowers.

My study is not without limitations. My sample is restricted to retail firms because satellite images of store parking lots are only available for those firms. Although I believe that information demand of institutional investors is an important determinant of their participation in loan syndicates, I caution against generalizing my results to firms in other industries. I leave it for future research to explore whether the information demand significantly influences institutional lending and credit outcomes for non-retailer borrowers. In addition, future research can further identify other sources of big data and examine how institutional lenders' information demand varies with unique features of these data.

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APPENDIX A

Variable Definitions

Variable		Definition
Age	=	The number of years since a firm appears in the Compustat (Compustat).
Altman Z	=	Altman (1963) Z-score as estimated by the following model: Z= $3.3X_1$ + $0.99X_2$+ $0.6X_3$ + $1.2X_4$ + $1.4X_5$, where X_1 is defined as the ratio of earnings before interest and taxes to total assets, X_2 is defined as the ratio of total sales to total assets, X_3 is defined as the ratio of market value of equity to total liabilities, X_4 is defined as the ratio of current assets to total assets, X_5 is defined as the ratio of retained earnings to total assets. All variables are measured in the year preceding the loan's issuance (Compustat).
Amounts	=	The natural logarithm of loan amounts of the largest facility in the loan package (DealScan).
Assets	=	The natural logarithm of total assets, measured in the year preceding the loan's issuance (Compustat).
Current Ratio	=	The ratio of current assets to current liabilities, measured in the year preceding the loan's issuance (Compustat).
Guarantor	=	An indicator variable equal to 1 if the loan is guaranteed, and 0 otherwise (DealScan).
Had Inst. Lender	=	An indicator variable equal to 1 if the loan is issued after the satellite image data becomes commercially available and the borrower had lending relationships with institutional lenders (*Inst. Lender)* when the satellite image data was not commercially available, and 0 otherwise (Orbital Insight).
High Perf. Covenants	=	An indicator variable equal to 1 if the average number of performance covenants for loans issued by the borrower, measured in the pre-period before the satellite image data becomes commercially available, is greater than the sample median, and 0 otherwise (DealScan).
High Reputation	=	An indicator variable equal to 1 if the borrower obtains loans issued by one of the top 5 lead arrangers in the pre-period before the satellite image data becomes commercially available, and 0 otherwise (DealScan, Bloomberg).
Inst. Lender Bank Affiliated	=	An indicator variable equal to 1 if the loan is issued with at least one bank-affiliated-institutional lender but is not issued with independent institutional lenders, and 0 otherwise (DealScan).
Inst. Lender	=	An indicator variable equal to 1 if the loan is issued with at least one independent institutional lender that engages in investment businesses, and 0 otherwise (DealScan).
Inst. Lender No Investment	=	An indicator variable equal to 1 if the loan is issued with at least one independent-institutional lender that does *not* engage in investment businesses but is not issued with an independent institutional lender that engages in investment businesses, and 0 otherwise (DealScan).

APPENDIX A (continued)

Variable Definitions

Variable		Definition
Interest Coverage	=	The ratio of earnings before interest and taxes to interest expense, measured in the year preceding the loan's issuance (Compustat).
Interest Spread	=	The natural logarithm of the all-in-drawn spread of the largest facility in the package (DealScan).
Leverage	=	The ratio of long-term debt plus debt in current liabilities to total assets, measured in the year preceding the loan's issuance (Compustat).
Low Press Releases	=	An indicator variable equal to 1 if the average number of press releases by the borrower, measured in the pre-period before the satellite image data becomes commercially available, is greater than the sample median, and 0 otherwise (RavenPack).
Maturity	=	The natural logarithm of the loan maturity in months (DealScan).
MTB	=	The ratio of market value to book value of equity, measured in the year preceding the loan's issuance (Compustat).
No Analyst Coverage	=	An indicator variable equal to 1 if the borrower does not have equity analyst coverage, measured in the pre-period before the satellite image data becomes commercially available, and 0 otherwise (IBES).
No Earnings Forecast	=	An indicator variable equal to 1 if the borrower does not issue earnings forecasts, measured in the pre-period before the satellite image data becomes commercially available, and 0 otherwise (IBES).
Past Return	=	The accumulated daily stock return measured over 150 calendar days ending 30 days prior to the loan's issuance (DealScan, CRSP).
Post	=	An indicator variable equal to 1 if the loan is issued after the satellite image data becomes commercially available, and 0 otherwise (Orbital Insight).
Post Inst. Lender	=	An indicator variable equal to 1 if the loan is issued with institutional lenders (*Inst. Lender*) after the satellite image data becomes commercially available, and 0 otherwise (Orbital Insight).
Post No Inst. Lender	=	An indicator variable equal to 1 if the loan is not issued with institutional lenders (*Inst. Lender*) after the satellite image data becomes commercially available, and 0 otherwise (Orbital Insight).
ROA	=	The ratio of net income to total assets, measured in the year preceding the loan's issuance (Compustat).
Sales Growth	=	The ratio of total sales in year t to total sales in year t-1 minus one, measured in the year preceding the loan's issuance (Compustat).
Secured	=	An indicator variable equal to 1 if the loan is secured, and 0 otherwise (DealScan).
Treatment Firm	=	An indicator variable equal to 1 if the borrower is covered by the satellite data after it becomes commercially available (Orbital Insight).

APPENDIX A (continued)
Variable Definitions

Variable		Definition
Treatment Firm High Corr	=	An indicator variable equal to 1 if the average correlation between quarterly changes in store level car counts and quarterly changes in sales for the borrower, measured in the post-period after the satellite image data becomes commercially available, is greater than the sample median, and 0 otherwise (Orbital Insight).
Treatment Firm Low Corr	=	An indicator variable equal to 1 if the average correlation between quarterly changes in store level car counts and quarterly changes in sales for the borrower, measured in the post-period after the satellite image data becomes commercially available, is less than the sample median, and 0 otherwise (Orbital Insight).
Treatment Firm High SD	=	An indicator variable equal to 1 if the average standard deviation of quarterly changes in car counts across stores, measured in the post-period after the satellite image data becomes commercially available, is greater than the sample median, and 0 otherwise (Orbital Insight).
Treatment Firm Low SD	=	An indicator variable equal to 1 if the average standard deviation of quarterly changes in car counts across stores, measured in the post-period after the satellite image data becomes commercially available, is less than the sample median, and 0 otherwise (Orbital Insight).
Maturity	=	The natural logarithm of the loan maturity in months (DealScan).
MTB	=	The ratio of market value to book value of equity, measured in the year preceding the loan's issuance (Compustat).
No Analyst Coverage	=	An indicator variable equal to 1 if the borrower does not have equity analyst coverage, measured in the pre-period before the satellite image data becomes commercially available, and 0 otherwise (IBES).

APPENDIX B
Additional Analyses

This table reports the results of additional analyses. Panel A examines whether the main results are robust to using continuous dependent variables that capture the extent of institutional lender participation. Column (1) estimates Tobit model using the dependent variable of *Inst. Lender Proportion* which is the proportion (%) of institutional lenders in the loan package. Column (2) estimates Poisson model using the dependent variable of *Inst. Lender Counts* which is the number of institutional lenders in the loan package. Panel B reports the result of analysis whether the main results are robust to using *Post RM* which is an indicator variable equal to 1 if the loan is issued after the satellite image data from either RS Metrics or Orbital Insight become commercially available, and 0 otherwise. Panel C tests whether the main results are robust after excluding sample periods when SafeGraph released their mobile GPS location data in 2018. Panel D restricts the main sample to the pre-period and estimates the Model (1) after interacting *Treatment Firm* with a continuous trend variable of *Year* which is the year of loan issuance. Panel E compares the mean and standard deviation of the explanatory variables between the treatment and control firms to provide evidence of covariate balancing in the estimation using an entropy balancing approach. Panel F examines whether the reduced information demand from institutional lenders affects borrowers' credit outcomes using the treatment sample. t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All other variables are defined in Appendix A of the manuscript.

Panel A: Continuous Dependent Variables

	Inst. Lender Proportion	*Inst. Lender Counts*
	(1)	(2)
Treatment Firm x Post	**-25.589*** **	**-0.772***
	(-3.05)	**(-1.95)**
Assets	0.415	-0.035
	(0.25)	(-0.22)
Current Ratio	0.806	0.166
	(0.40)	(1.22)
Leverage	-8.005	0.033
	(-1.05)	(0.08)
MTB	0.287	0.007
	(1.50)	(0.78)
Sales Growth	3.151	0.330
	(0.68)	(1.57)
Interest Coverage	-0.015*	-0.001*
	(-1.85)	(-1.82)
ROA	-45.120***	-0.862
	(-3.14)	(-1.12)
Altman Z	-0.203	-0.041
	(-0.26)	(-0.84)
AGE	-0.005	-0.009
	(-0.03)	(-0.49)

APPENDIX B (continued)
Additional Analyses

Panel A: Continuous Dependent Variables (continued)

	Inst. Lender Proportion	*Inst. Lender Counts*
	(1)	(2)
Past Return	-9.600	-0.351
	(-1.56)	(-1.17)
Amounts	1.664	0.109
	(0.77)	(1.07)
Maturity	15.954*	1.009**
	(1.91)	(2.12)
Secured	13.197***	0.483**
	(3.36)	(2.09)
Guarantor	3.138	0.345
	(0.53)	(0.89)
Model	Tobit	Poisson
Firm FE	Yes	Yes
Year FE	Yes	Yes
Year-Quarter FE	No	No
Credit Rating FE	No	No
Loan Type FE	No	No
Observations	2,129	945

Panel B: RS Metrics Data

	Inst. Lender		
	(1)	(2)	(3)
Post RM	**-0.928***	**-0.090****	**-0.120*****
	(-1.77)	**(-2.14)**	**(-2.77)**
Model	Logit	OLS	OLS
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	904	2,129	2,129
Adj. (Pseudo) R-squared	0.066	0.228	0.245

APPENDIX B (continued)
Additional Analyses

Panel C: Excluding Periods after 2018

	Inst. Lender		
	(1)	(2)	(3)
Treatment Firm x Post	**-1.515****	**-0.148*****	**-0.168*****
	(-2.46)	**(-3.02)**	**(-3.51)**
Model	Logit	OLS	OLS
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	721	1,866	1,866
Adj. (Pseudo) R-squared	0.099	0.232	0.245

Panel D: Continuous Trend Variable

	Inst. Lender		
	(1)	(2)	(3)
Treatment Firm x Year	**0.111**	**0.008**	**0.003**
	(0.55)	**(0.37)**	**(0.12)**
Model	Logit	OLS	OLS
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	446	1,422	1,422
Adj. (Pseudo) R-squared	0.118	0.214	0.215

APPENDIX B (continued)

Additional Analyses

Panel E: Covariate Balancing

	Pre-Matching					*Post-Matching*				
	Treatment Mean	Control Mean	Treatment SD	Control SD	Diff Mean	Treatment Mean	Control Mean	Treatment SD	Control SD	Diff Mean
Assets	8.174	8.038	1.549	1.839	0.136	8.174	8.173	1.549	1.549	0.001
Current Ratio	1.581	1.602	0.86	1.004	-0.021	1.581	1.58	0.86	0.86	0.001
Leverage	0.311	0.356	0.276	0.264	-0.045***	0.311	0.311	0.276	0.276	0.000
MTB	3.202	3.237	9.83	8.847	-0.035	3.202	3.202	9.83	9.827	0.000
Sales Growth	0.054	0.171	0.142	0.378	-0.117***	0.054	0.054	0.142	0.142	0.000
Interest Coverage	72.63	63.79	268.132	291.148	8.84	72.63	72.63	268.132	268.157	0.000
ROA	0.062	0.019	0.077	0.127	0.043***	0.062	0.062	0.077	0.077	0.000
Altman Z	4.673	3.276	2.277	2.909	1.397***	4.673	4.672	2.277	2.277	0.001
AGE	28.96	23.03	17.433	18.73	5.93***	28.96	28.95	17.433	17.433	0.010
Past Return	0.056	0.055	0.245	0.253	0.001	0.056	0.056	0.245	0.245	0.000
Amounts	19.89	19.8	1.031	1.048	0.09	19.89	19.89	1.031	1.031	0.000
Maturity	3.997	3.95	0.189	0.209	0.047***	3.997	3.997	0.189	0.189	0.000
Secured	0.507	0.496	0.501	0.5	0.011	0.507	0.507	0.501	0.5	0.000
Guarantor	0.102	0.086	0.303	0.28	0.016	0.102	0.102	0.303	0.303	0.000

Panel F: Institutional Lenders' Demand for Private Information and Borrowing Terms - Treatment Sample

	Interest Spread		*Amounts*		*Maturity*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post No Inst. Lender	-0.166	0.018	0.872***	1.012***	0.136**	0.148
	(-1.40)	(0.15)	(4.50)	(3.40)	(2.13)	(1.53)
Had Inst. Lender	-0.428***	-0.118	0.698***	0.983***	0.187**	0.150
	(-2.70)	(-0.88)	(2.90)	(2.93)	(2.13)	(1.42)
Post No Inst. Lender x Had Inst. Lender	**0.385****	**0.078**	**-0.925*****	**-1.188*****	**-0.208****	**-0.217***
	(2.46)	**(0.55)**	**(-2.80)**	**(-2.96)**	**(-2.01)**	**(-1.87)**
Assets	-0.008	0.010	0.231*	0.323**	0.004	0.025
	(-0.20)	(0.26)	(1.85)	(2.58)	(0.14)	(1.14)

APPENDIX B (continued)
Additional Analyses

Panel F: Institutional Lenders' Demand for Private Information and Borrowing Terms - Treatment Sample (continued)

	Interest Spread		*Amounts*		*Maturity*	
	(1)	(2)	(3)	(4)	(5)	(6)
Current Ratio	0.014	0.051	0.080	0.020	-0.002	0.005
	(0.33)	(1.22)	(0.82)	(0.19)	(-0.06)	(0.22)
Leverage	0.118	0.305**	-0.036	0.290	-0.169	-0.003
	(0.70)	(2.52)	(-0.06)	(0.53)	(-1.53)	(-0.04)
MTB	-0.002	-0.002	0.005	0.005	-0.000	-0.000
	(-1.50)	(-1.11)	(1.34)	(1.24)	(-0.09)	(-0.44)
Sales Growth	-0.240*	-0.256**	-0.831**	-0.814**	-0.037	-0.217**
	(-1.68)	(-2.14)	(-2.01)	(-2.02)	(-0.34)	(-2.24)
Interest Coverage	0.000	0.000	-0.000	-0.000	0.000	0.000
	(1.00)	(0.35)	(-0.77)	(-0.39)	(0.50)	(0.77)
ROA	-0.263	0.069	2.023**	3.071***	-0.084	0.306
	(-0.82)	(0.24)	(2.19)	(3.84)	(-0.40)	(1.65)
Altman Z	-0.015	-0.026**	-0.051	-0.073**	-0.008	-0.016
	(-1.13)	(-2.11)	(-1.52)	(-2.41)	(-0.66)	(-1.47)
Age	0.002	0.001	-0.016**	-0.020***	-0.001	-0.001
	(0.46)	(0.40)	(-2.32)	(-2.80)	(-0.94)	(-0.76)
Past Return	0.162***	0.103*	-0.258	-0.371*	-0.024	-0.021
	(3.07)	(1.82)	(-1.48)	(-1.76)	(-0.61)	(-0.53)
Amounts	-0.007	-0.041*			0.044**	-0.000
	(-0.22)	(-1.76)			(2.36)	(-0.04)
Maturity	-0.023	-0.011	0.641**	-0.010		
	(-0.31)	(-0.10)	(2.52)	(-0.04)		
Secured	0.141***	0.062	0.080	0.121	0.061	0.018
	(2.81)	(1.30)	(0.41)	(0.64)	(1.49)	(0.47)
Guarantor	-0.162**	-0.063	0.198	0.351	0.001	0.051
	(-2.57)	(-1.56)	(1.34)	(1.62)	(0.03)	(1.56)
Sales Growth	-0.240*	-0.256**	-0.831**	-0.814**	-0.037	-0.217**
	(-1.68)	(-2.14)	(-2.01)	(-2.02)	(-0.34)	(-2.24)
Model	OLS	OLS	OLS	OLS	OLS	OLS
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes
Observations	412	412	412	412	412	412
Adj. (Pseudo) R-squared	0.614	0.755	0.625	0.670	0.235	0.555

FIGURE 1

Parallel Trend of Institutional Lending

This figure plots OLS regression coefficient estimates and two-tailed 90th percentile confidence intervals based on standard errors clustered at the firm level. I replace *Treatment Firm x Post* variable in Model (1) with separate interactions between *Treatment Firm* and trend variables. Each trend variable is equal to one for every around two-year sample period before and after the initiation of the satellite data coverage (and zero otherwise). The last two-year period before the release of the satellite data (from 4th quarter in 2013 to 3rd quarter in 2015) serves as a benchmark.

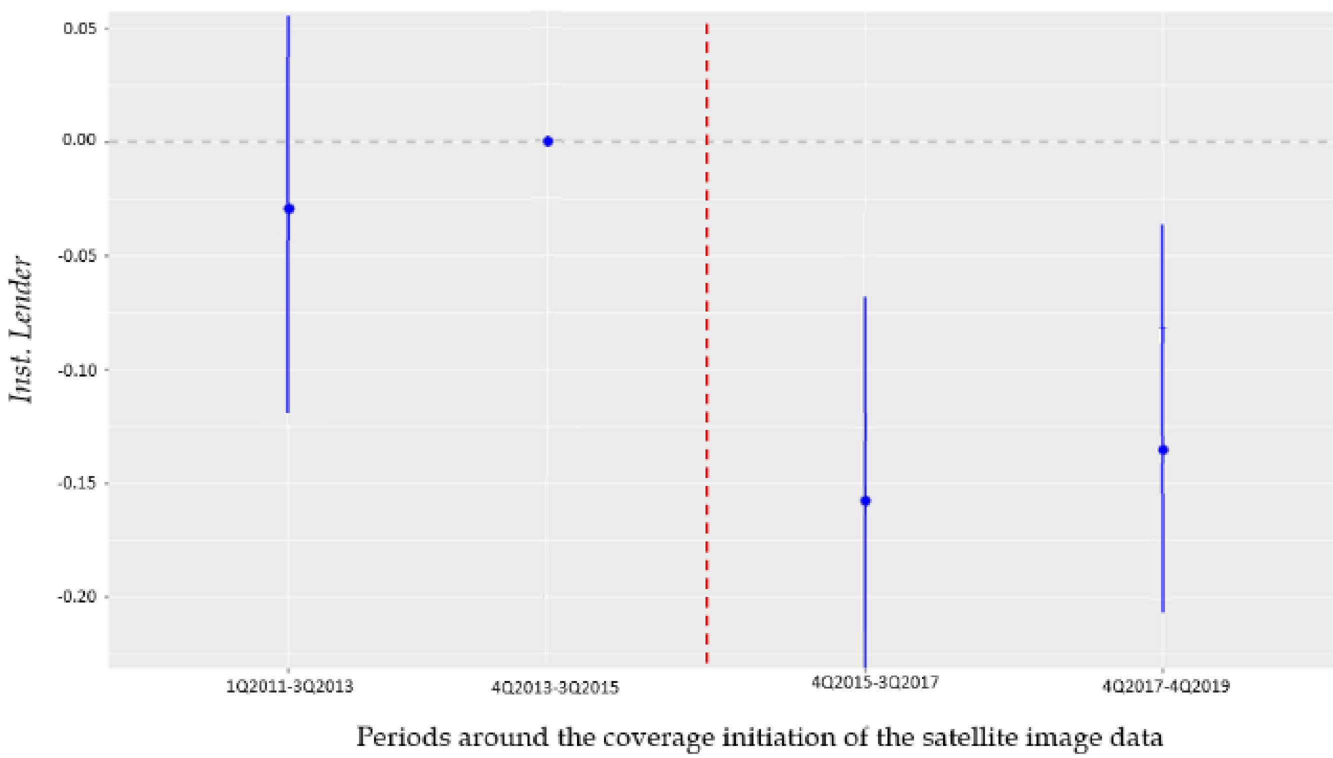

TABLE 1
Descriptive Statistics

This table provides descriptive statistics for the main variables of interest. All variables are defined in Appendix A.

	N	Mean	Median	SD
Inst. Lender	2,129	0.165	0.000	0.372
Post	2,129	0.332	0.000	0.471
Treatment Firm	2,129	0.194	0.000	0.395
Post Inst. Lender	2,129	0.115	0.000	0.320
Post No Inst. Lender	2,129	0.217	0.000	0.412
Had Inst. Lender	2,129	0.104	0.000	0.305
Assets	2,129	8.064	7.961	1.787
Current Ratio	2,129	1.598	1.342	0.978
Leverage	2,129	0.348	0.319	0.267
MTB	2,129	3.230	2.506	9.043
Sales Growth	2,129	0.148	0.070	0.348
Interest Coverage	2,129	65.500	8.409	286.798
ROA	2,129	0.027	0.042	0.120
Altman Z	2,129	3.546	3.290	2.851
Age	2,129	24.178	21.000	18.629
Past Return	2,129	0.055	0.040	0.252
No Analyst Coverage	2,129	0.508	1.000	0.500
No Earnings Forecast	2,129	0.307	0.000	0.461
High Reputation	2,129	0.281	0.000	0.450
Amounts	2,129	19.821	19.808	1.045
Maturity	2,129	3.959	4.096	0.206
Secured	2,129	0.498	0.000	0.500
Guarantor	2,129	0.089	0.000	0.284
Interest Spread	2,129	5.273	5.267	0.339

TABLE 2

Satellite Image Data and Institutional Lending

This table examines whether the probability that institutional lenders issue a loan is lower after the satellite data on a borrower becomes commercially available. Panel A reports the result of univariate analysis. Panel B presents the result of multivariate analysis. Panel C shows the result of analysis using an entropy balancing approach. In Panel B and C, Column 1 (2 and 3) presents the results using a logit (OLS) model. t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Univariate Analysis

Inst. Lender	*Treatment Firm*=0 (a)	*Treatment Firm*=1 (b)	Difference (b) - (a)
Post = 0 (c)	0.163	0.160	-0.003
Post = 1 (d)	0.194	0.087	-0.107***
Difference (d) - (c)	0.031	-0.073**	-0.104**

Panel B: Multivariate Analysis

	Inst. Lender		
	(1)	(2)	(3)
Treatment Firm* x *Post	**-1.123****	**-0.107*****	**-0.138*****
	(-2.43)	**(-2.82)**	**(-3.48)**
Assets	-0.311	-0.021	-0.006
	(-1.35)	(-1.09)	(-0.34)
Current Ratio	0.118	0.011	0.012
	(0.58)	(0.71)	(0.77)
Leverage	-0.585	-0.043	-0.051
	(-0.98)	(-0.61)	(-0.67)
MTB	0.008	0.001	0.001
	(0.79)	(1.00)	(1.00)
Sales Growth	0.332	0.031	0.033
	(0.99)	(0.74)	(0.79)
Interest Coverage	-0.001*	-0.000	-0.000*
	(-1.82)	(-1.56)	(-1.72)
ROA	-1.790*	-0.160	-0.180
	(-1.69)	(-1.41)	(-1.52)
Altman Z	-0.083	-0.010	-0.012**
	(-1.41)	(-1.60)	(-2.00)
Age	-0.001	-0.000	-0.001
	(-0.03)	(-0.00)	(-0.44)
Past Return	-0.545	-0.059	-0.079**
	(-1.34)	(-1.57)	(-2.16)
Amounts	0.206	0.023	0.032**
	(1.58)	(1.60)	(2.03)

TABLE 2 (continued)
Satellite Image Data and Institutional Lending

Panel B: Multivariate Analysis (continued)

	Inst. Lender		
	(1)	(2)	(3)
Maturity	0.685	0.061	0.092
	(1.32)	(1.18)	(1.60)
Secured	0.610**	0.075**	0.063*
	(2.21)	(2.32)	(1.85)
Guarantor	0.607	0.052	0.070
	(1.39)	(1.00)	(1.27)
Model	Logit	OLS	OLS
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	904	2,129	2,129
Adj. (Pseudo) R-squared	0.069	0.230	0.247

Panel C: Entropy Balancing Approach

	Inst. Lender		
	(1)	(2)	(3)
Treatment Firm x Post	**-1.787*** **	**-0.113*** **	**-0.125*** **
	(-2.94)	**(-2.82)**	**(-3.16)**
Model	Logit	OLS	OLS
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	904	2,129	2,129
Adj. (Pseudo) R-squared	N/A	0.483	0.534

TABLE 3

Falsification Test

This table reports the results of falsification tests using different types of institutional lenders as a dependent variable. Panel A presents the result of the falsification test based on OLS and logit model. Columns 1 and 3 (2 and 4) present the results using a logit (OLS) model. In Columns 1 and 2, the dependent variable is *Inst. Lender Bank Affiliated* which is equal to 1 if the loan is issued with at least one bank-affiliated-institutional lender but is not issued with independent institutional lenders, and 0 otherwise. In Columns 3 and 4, the dependent variable is *Inst. Lender No Investment* which is equal to 1 if the loan is issued with at least one independent-institutional lender that does *not* engage in investment businesses but is not issued with an independent institutional lender that engages in investment businesses, and 0 otherwise. Panel B reports the results of falsification tests using a multinomial logit model. t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Falsification Test

	Inst. Lender Bank Affiliated		*Inst. Lender No Investment*	
	(1)	(2)	(3)	(4)
Treatment Firm* x *Post	**-0.317**	**-0.024**	**1.861**	**0.014**
	(-0.68)	**(-0.38)**	**(1.62)**	**(0.48)**
Assets	-0.160	-0.035	0.220	0.021
	(-0.69)	(-1.21)	(0.52)	(1.02)
Current Ratio	-0.237	-0.016	-1.480***	-0.013*
	(-1.23)	(-0.87)	(-4.53)	(-1.78)
Leverage	0.031	-0.010	-1.239	-0.031
	(0.05)	(-0.13)	(-0.84)	(-0.89)
MTB	-0.005	-0.001	0.004	0.000
	(-0.51)	(-0.52)	(0.20)	(0.11)
Sales Growth	-0.204	-0.031	-1.033	-0.028*
	(-0.59)	(-0.74)	(-1.01)	(-1.74)
Interest Coverage	-0.000	-0.000	0.001	-0.000
	(-0.56)	(-0.50)	(0.68)	(-0.13)
ROA	0.245	0.024	-3.575	-0.104
	(0.25)	(0.21)	(-1.28)	(-1.62)
Altman Z	-0.048	-0.009	0.305	0.003
	(-0.74)	(-1.03)	(1.53)	(1.05)
Age	-0.014	-0.002	0.012	0.002*
	(-0.96)	(-0.90)	(0.49)	(1.82)
Past Return	0.324	0.050	-0.809	-0.027
	(1.02)	(1.19)	(-1.40)	(-1.17)
Amounts	0.285**	0.030*	0.037	0.013
	(2.32)	(1.70)	(0.13)	(1.35)

TABLE 3 (continued)
Falsification Test

Panel A: Falsification Test (continued)

	Inst. Lender Bank Affiliated		*Inst. Lender No Investment*	
	(1)	(2)	(3)	(4)
Maturity	0.642	0.077	-0.766	-0.044
	(1.62)	(1.23)	(-0.62)	(-1.11)
Secured	-0.216	-0.023	0.966	0.050***
	(-0.78)	(-0.63)	(1.29)	(2.67)
Guarantor	0.155	0.028	-0.109	-0.010
	(0.43)	(0.60)	(-0.19)	(-0.31)
Model	Logit	OLS	Logit	OLS
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Quarter FE	No	Yes	No	Yes
Credit Rating FE	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes
Observations	1,043	2,129	295	2,129
Adj. (Pseudo) R-squared	0.029	0.248	0.291	0.349

Panel B: Falsification Test - Multinomial Logit Model Analysis

	Inst. Lender Bank Affiliated = 1	*Inst. Lender No Investment* = 1	*Inst. Lender* = 1
	(1)	(2)	(3)
Treatment Firm* x *Post	**-0.894**	**0.807**	**-2.197*****
	(-1.36)	**(0.67)**	**(-2.86)**
Assets	-0.226	0.312	-0.302
	(-0.62)	(0.46)	(-0.86)
Current Ratio	-0.236	-0.604	0.008
	(-0.87)	(-0.68)	(0.03)
Leverage	-0.152	-0.781	-0.622
	(-0.18)	(-0.42)	(-0.66)
MTB	0.001	0.021	0.012
	(0.10)	(0.58)	(0.74)
Sales Growth	-0.263	-1.593	0.245
	(-0.53)	(-1.02)	(0.54)
Interest Coverage	-0.001	0.000	-0.002**
	(-1.20)	(0.22)	(-1.99)
ROA	-0.859	-5.589	-2.767
	(-0.53)	(-1.50)	(-1.50)
Altman Z	-0.095	0.116	-0.100
	(-1.07)	(0.43)	(-1.20)

TABLE 3 (continued)
Falsification Test

Panel B: Falsification Test - Multinomial Logit Model Analysis (continued)

	Inst. Lender *Bank Affiliated* = 1	*Inst. Lender* *No Investment* = 1	*Inst. Lender* = 1
	(1)	(2)	(3)
AGE	-0.010	0.005	-0.004
	(-0.34)	(0.10)	(-0.10)
Past Return	-0.026	-0.694	-0.822
	(-0.05)	(-0.86)	(-1.37)
Amounts	0.345**	0.264	0.397**
	(1.96)	(0.67)	(2.11)
Maturity	0.711	-0.262	0.799
	(1.34)	(-0.16)	(1.10)
Secured	0.115	1.005	0.758*
	(0.28)	(1.05)	(1.81)
Guarantor	0.558	0.135	1.086
	(0.98)	(0.16)	(1.56)
Model	Mlogit	Mlogit	Mlogit
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year-Quarter FE	No	No	No
Credit Rating FE	No	No	No
Loan Type FE	No	No	No
Observations	2,129	2,129	2,129
Adj. (Pseudo) R-squared	0.617	0.617	0.617
Test: [1]*Treatment Firm* x *Post* > [3]*Treatment Firm* x *Post*	p-value: 0.040		
Test: [2]*Treatment Firm* x *Post* > [3]*Treatment Firm* x *Post*		p-value: 0.011	

TABLE 4
Borrower Opacity

This table examines whether the effect of the satellite image data coverage on institutional lender participation is more pronounced when borrowers are opaque. Panel A, B and C report the results of the analyses in which borrower opacity is measured by a borrower's equity analyst coverage (*No Analyst Coverage)*, whether a borrower issues earnings forecasts (*No Earnings Forecast)* and a borrower's press releases (*Low Press Releases).* In all panels, Columns 1 and 2 (3 and 4) present the results using a logit (OLS) model. t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: No Analyst Coverage

	Inst. Lender			
	No Analyst Coverage=0	*No Analyst Coverage=1*	*No Analyst Coverage=0*	*No Analyst Coverage=1*
	(1)	(2)	(3)	(4)
Treatment Firm* x *Post	**-0.426**	**-2.613*****	**-0.071**	**-0.254*****
	(-0.79)	**(-2.91)**	**(-1.42)**	**(-3.79)**
Model	Logit	Logit	OLS	OLS
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Year-Quarter FE	No	No	Yes	Yes
Credit Rating FE	No	No	Yes	Yes
Loan Type FE	No	No	Yes	Yes
Observations	492	412	1,047	1,082
Adj. (Pseudo) R-squared	0.105	0.140	0.252	0.251
Test: [1]*Treatment Firm* x *Post* > [2]*Treatment Firm* x *Post*	p-value: 0.012			
Test: [3]*Treatment Firm* x *Post* > [4]*Treatment Firm* x *Post*			p-value: 0.007	

TABLE 4 (continued)
Borrower Opacity

Panel B: No Earnings Forecast

	Inst. Lender			
	No Earnings Forecast=0	*No Earnings Forecast=1*	*No Earnings Forecast=0*	*No Earnings Forecast=1*
	(1)	(2)	(3)	(4)
Treatment Firm* x *Post	**-0.809***	**-16.590*****	**-0.113*****	**-0.349****
	(-1.75)	**(-13.53)**	**(-2.77)**	**(-2.40)**
Model	Logit	Logit	OLS	OLS
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Year-Quarter FE	No	No	Yes	Yes
Credit Rating FE	No	No	Yes	Yes
Loan Type FE	No	No	Yes	Yes
Observations	649	255	1,475	654
Adj. (Pseudo) R-squared	0.066	0.246	0.255	0.222
Test: [1]*Treatment Firm* x *Post* > [2]*Treatment Firm* x *Post*	p-value: 0.042			
Test: [3]*Treatment Firm* x *Post* > [4]*Treatment Firm* x *Post*			p-value: 0.030	

Panel C: Low Press Releases

	Inst. Lender			
	Low Press Releases=0	*Low Press Releases=1*	*Low Press Releases=0*	*Low Press Releases=1*
	(1)	(2)	(3)	(4)
Treatment Firm* x *Post	**-0.824**	**-1.997****	**-0.091**	**-0.187*****
	(-1.54)	**(-2.33)**	**(-1.55)**	**(-3.33)**
Model	Logit	Logit	OLS	OLS
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Year-Quarter FE	No	No	Yes	Yes
Credit Rating FE	No	No	Yes	Yes
Loan Type FE	No	No	Yes	Yes
Observations	551	353	1,065	1,064
Adj. (Pseudo) R-squared	0.080	0.149	0.197	0.319
Test: [1]*Treatment Firm* x *Post* > [2]*Treatment Firm* x *Post*	p-value: 0.097			
Test: [3]*Treatment Firm* x *Post* > [4]*Treatment Firm* x *Post*			p-value: 0.099	

TABLE 5

Early Dissemination of Borrower Private Information

This table examines whether early dissemination of borrower private information is important to the relationship between the satellite image data coverage and institutional lender participation. Panel A and B report the results of the analyses in which the borrower's information dissemination is measured by the number of performance covenants in the loan (*High Perf. Covenants)* and the lender reputation (*High Reputation)*, respectively. In all panels, Columns 1 and 2 (3 and 4) present the results using a logit (OLS) model. t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: High Performance Covenants

	Inst. Lender			
	High Perf. Covenants=0	*High Perf. Covenants=1*	*High Perf. Covenants=0*	*High Perf. Covenants=1*
	(1)	(2)	(3)	(4)
Treatment Firm* x *Post	**-0.301**	**-1.828*** **	**-0.088**	**-0.187*** **
	(-0.35)	**(-3.01)**	**(-1.24)**	**(-3.82)**
Model	Logit	Logit	OLS	OLS
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Year-Quarter FE	No	No	Yes	Yes
Credit Rating FE	No	No	Yes	Yes
Loan Type FE	No	No	Yes	Yes
Observations	381	523	1,030	1,099
Adj. (Pseudo) R-squared	0.090	0.152	0.242	0.256
Test: [1]*Treatment Firm* x *Post* > [2]*Treatment Firm* x *Post*	p-value: 0.051			
Test: [3]*Treatment Firm* x *Post* > [4]*Treatment Firm* x *Post*			p-value: 0.094	

TABLE 5 (continued)

Early Dissemination of Borrower Private Information

Panel B: Lender Reputation

	Inst. Lender			
	High Reputation=0	*High Reputation=1*	*High Reputation=0*	*High Reputation=1*
	(1)	(2)	(3)	(4)
Treatment Firm* x *Post	**-0.663**	**-2.078*****	**-0.078**	**-0.294*****
	(-1.00)	**(-3.51)**	**(-1.59)**	**(-3.76)**
Model	Logit	Logit	OLS	OLS
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Year-Quarter FE	No	No	Yes	Yes
Credit Rating FE	No	No	Yes	Yes
Loan Type FE	No	No	Yes	Yes
Observations	586	318	1,531	598
Adj. (Pseudo) R-squared	0.061	0.173	0.258	0.223
Test: [1]*Treatment Firm* x *Post* > [2]*Treatment Firm* x *Post*	p-value: 0.057			
Test: [3]*Treatment Firm* x *Post* > [4]*Treatment Firm* x *Post*			p-value: 0.005	

TABLE 6

Accuracy of Satellite Image Data

This table examines whether the effect of the satellite image data coverage on institutional lending is stronger when the data predicts borrowers' performance more accurately. Panel A and B report the results of analysis in which the accuracy of the satellite image data is measured by the correlation between quarterly changes in store car counts and quarterly changes in sales of the borrower (*Treatment Firm High Corr*, *Treatment Firm Low Corr*) and the average standard deviation of quarterly changes in car counts across stores (*Treatment Firm High SD, Treatment Firm Low SD)*, respectively. In all panels, Columns 1 (3 and 4) presents the results using a logit (OLS) model. t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Panel A: Accuracy of the Satellite Image Data - High Correlations

	Inst. Lender		
	(1)	(2)	(3)
Treatment Firm High Corr* x *Post	**-1.852*** **	**-0.176*** **	**-0.194*** **
	(-2.78)	**(-3.82)**	**(-4.16)**
Treatment Firm Low Corr* x *Post	**-0.451**	**-0.067**	**-0.080**
	(-0.80)	**(-1.28)**	**(-1.54)**
Model	Logit	OLS	OLS
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	904	2,129	2,129
Adj. (Pseudo) R-squared	0.073	0.239	0.248
Test: *Treatment Firm Low Corr* x *Post* > *Treatment Firm High Corr* x *Post*	p-value: 0.042	p-value: 0.038	p-value: 0.029

Panel B: Accuracy of the Satellite Image Data - Low Standard Deviation

	Inst. Lender		
	(1)	(2)	(3)
Treatment Firm High SD* x *Post	**-0.654**	**-0.082***	**-0.094***
	(-1.13)	**(-1.66)**	**(-1.92)**
Treatment Firm Low SD* x *Post	**-1.572*** **	**-0.165*** **	**-0.184*** **
	(-2.61)	**(-3.34)**	**(-3.59)**
Model	Logit	OLS	OLS
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Year-Quarter FE	No	No	Yes
Credit Rating FE	No	No	Yes
Loan Type FE	No	No	Yes
Observations	904	2,129	2,129
Adj. (Pseudo) R-squared	0.071	0.238	0.247
Test: *Treatment Firm High SD* x *Post* > *Treatment Firm Low SD* x *Post*	p-value: 0.115	p-value: 0.094	p-value: 0.075

TABLE 7
Institutional Lenders' Demand for Private Information and Borrowing Terms

This table examines whether the information demand from institutional lenders affects borrowers' credit outcomes. In Columns 1 and 2, the dependent variable is *Interest Spread.* In Columns 3 and 4, the dependent variable is *Amounts.* In Columns 5 and 6, the dependent variable is *Maturity.* The main variable of interest is *Treatment Firm* x *Post No Inst. Lender* x *Had Inst. Lender* which captures loans issued by treatment borrowers (*Treatment Firm* = 1) who do not obtain loans from institutional lenders in the post period (*Post No Inst. Lender* = 1) but had lending relationships with institutional lenders in the pre-coverage period (*Had Inst. Lender = 1*). t-statistics in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

	Interest Spread		*Amounts*		*Maturity*	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Firm x *Post No Inst. Lender*	0.038	0.029	0.156	0.146	0.001	0.015
	(1.04)	(0.77)	(1.45)	(1.32)	(0.04)	(0.52)
Treatment Firm* x *Post No Inst. Lender	**0.348*** **	**0.233***	**-0.580***	**-0.596***	**-0.237** **	**-0.174***
x *Had Inst. Lender*	**(2.68)**	**(1.72)**	**(-1.72)**	**(-1.72)**	**(-2.35)**	**(-1.90)**
Treatment Firm x *Post Inst. Lender*	0.089	0.048	-0.716***	-0.704***	-0.102*	-0.092
	(0.99)	(0.50)	(-3.80)	(-3.42)	(-1.73)	(-1.39)
Treatment Firm x *Post Inst. Lender*	-0.393***	-0.284**	0.605**	0.639**	0.243***	0.157*
x *Had Inst. Lender*	(-3.30)	(-2.38)	(2.43)	(2.49)	(2.97)	(1.91)
Post No Inst. Lender	-0.075	-0.037	-0.100	-0.132	0.039	0.027
	(-1.43)	(-0.77)	(-0.93)	(-1.33)	(1.19)	(0.98)
Had Inst. Lender	-0.009	0.016	-0.057	-0.093	-0.028	-0.002
	(-0.17)	(0.35)	(-0.34)	(-0.73)	(-0.77)	(-0.06)
Post No Inst. Lender x *Had Inst. Lender*	-0.000	-0.022	-0.158	-0.077	0.040	0.000
	(-0.00)	(-0.35)	(-0.76)	(-0.46)	(0.82)	(0.01)
Assets	-0.038*	-0.020	0.273***	0.246***	-0.017	-0.018
	(-1.92)	(-1.10)	(5.32)	(4.78)	(-1.33)	(-1.35)
Current Ratio	-0.002	0.004	-0.031	-0.037	0.013	0.005
	(-0.19)	(0.37)	(-1.00)	(-1.31)	(1.20)	(0.53)
Leverage	0.035	0.055	0.075	0.128	-0.065	-0.077*
	(0.66)	(1.00)	(0.47)	(0.93)	(-1.54)	(-1.86)
MTB	-0.001	-0.001	0.003	0.002	0.000	0.000
	(-1.44)	(-1.50)	(1.41)	(1.08)	(0.30)	(0.98)
Sales Growth	-0.063**	-0.044*	0.025	-0.066	-0.020	-0.029
	(-2.36)	(-1.83)	(0.34)	(-1.02)	(-0.98)	(-1.48)
Interest Coverage	-0.000	-0.000	-0.000**	-0.000*	-0.000	-0.000
	(-0.52)	(-0.54)	(-2.02)	(-1.81)	(-0.59)	(-0.54)
ROA	-0.160*	-0.142	0.828***	0.832***	0.073	0.062
	(-1.78)	(-1.64)	(3.36)	(3.52)	(0.96)	(0.95)

TABLE 7 (continued)

Institutional Lenders' Demand for Private Information and Borrowing Terms

	Interest Spread		*Amounts*		*Maturity*	
	(1)	(2)	(3)	(4)	(5)	(6)
Altman Z	-0.005	-0.007	0.019*	0.023**	-0.003	-0.002
	(-0.75)	(-1.17)	(1.65)	(2.00)	(-0.78)	(-0.53)
Age	0.003**	0.002	-0.009**	-0.007*	0.001	0.001
	(2.02)	(1.36)	(-2.41)	(-1.73)	(0.38)	(0.45)
Past Return	0.050*	0.039	0.013	0.002	0.004	0.009
	(1.88)	(1.54)	(0.17)	(0.03)	(0.18)	(0.52)
Amounts	-0.033**	-0.051***			0.041***	0.035***
	(-2.29)	(-4.28)			(4.93)	(4.44)
Maturity	-0.124***	-0.036	0.494***	0.509***		
	(-3.26)	(-0.89)	(5.08)	(4.53)		
Secured	0.120***	0.068***	0.064	0.009	0.055***	0.018
	(5.09)	(3.32)	(1.02)	(0.15)	(3.30)	(1.10)
Guarantor	-0.118***	-0.051*	0.259**	0.187*	0.004	-0.009
	(-3.65)	(-1.93)	(1.99)	(1.67)	(0.14)	(-0.36)
Model	OLS	OLS	OLS	OLS	OLS	OLS
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	No	Yes	No	Yes	No	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes
Observations	2,129	2,129	2,129	2,129	2,129	2,129
Adj. (Pseudo) R-squared	0.585	0.681	0.658	0.694	0.263	0.454