Private Communication between Managers and Financial Analysts: Evidence from Taxi Ride Patterns in New York City

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April 18, 2022

Acknowledgments:
We thank Jay Cao, Changling Chen, David Cicero (Discussant), Jen Choi, David Chung, Paul Demere (Discussant), Elizabeth Demers, Luminata Enache, Bingxu Fang, Danqi Hu, Chongho Kim, Michael Marin, Mark Myring (Discussant), Nayana Reiter, Sasan Saiy, Anup Srivastava, Xijiang Su, Hongping Tan, Joshua White (Discussant), Christine Wiedman, Biyu Wu (Discussant), Rachel Yoon, Changqiu Yu (Discussant), Rong Zhao, Yaping Zheng (Discussant), and seminar participants at the Rotman School of Management, Villanova-Lehigh University, University of Bristol, Seoul National University, University of Calgary, McGill University, University of Waterloo, University of Southern California, McGill Accounting Research Conference, CAAA (2021), CICF (2021), AAA (2021), UT Austin PhD Symposium (2021), CFEA (2021), HARC (2022), and FARS (2022) for helpful comments and suggestions. We gratefully acknowledge financial support from TD Management Data Analytics Lab.

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Abstract

This study constructs a novel measure that aims to capture face-to-face private communications between firm managers and sell-side analysts by mapping detailed, large-volume taxi trip records from New York City to the GPS coordinates of companies and brokerages. Consistent with earnings releases prompting needs for private communications, we observe that daily taxi ride volumes between companies and brokerages increase significantly around earnings announcement dates (EAD) and reach their peak on EAD. After controlling for an extensive set of fixed effects (*firm*, *analyst*, *year*, and *firm-broker*) and other potential confounding factors, we find that increases in ride volumes around EAD are negatively associated with analysts' earnings forecast errors in periods after EAD and positively associated with the profitability of recommendations issued after EAD (but these effects dissipate over longer horizons). Taken together, our results suggest that analysts may obtain a private source of information orthogonal to their pre-existing information from these in-person meetings, which may help them better understand the implications of current earnings signals for future earnings.

Keywords: Private Communications; Sell-Side Analysts; Taxis; Earnings Forecasts; Stock Recommendations; Reg FD

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1. Introduction

Firm managers spend substantial time meeting privately with analysts and investors (e.g., Thomson Reuters 2009; Soltes 2014; Brown, Call, Clement, and Sharp 2015, 2016, 2019; Solomon and Soltes 2015; Bushee, Jung, and Miller 2017; Bushee, Gerakos, and Lee 2018). As evidenced by a wealth of anecdotes and surveys, such private communications are now found "everywhere," becoming an important source of information to sell-side analysts. Despite the importance of these off-line, non-public interactions, however, little is known about the timing, nature, and value of private communications, primarily due to the data limitations inherent in their private nature. This study seeks to fill this gap by constructing a unique proxy for unobservable, face-to-face private meetings between managers and sell-side analysts from New York City's (NYC) daily taxi trip records.

The NYC Taxi and Limousine Commission (TLC) collects pick-up and drop-off dates and times of all daily taxi trips in NYC, along with their precise pick-up and drop-off locations to ensure high-quality transit service in NYC.[1] We identify the presence and timing of private meetings by mapping these detailed, large-volume taxi trip records to the GPS coordinates of companies in Compustat and brokerages in I/B/E/S. As a result, we identify taxi trips between 264 public companies headquartered in NYC and 92 brokers having research offices in NYC. All identified taxi trips represent *ex-ante* unobservable private communications, as TLC uploads monthly taxi trip records with a six-month lag. Thus, analyzing taxi rides provides a unique setting to study private

[1] All taxi trip records are publicly available on the TLC's website (https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page). Taxis are an important means of transport for New Yorkers. Specifically, NYC has the lowest private car ownership rate (22% compared to the national average of 91%) and the highest utilization of taxis in the U.S. (The office of NYC Mayor 2016). There are approximately 474,000 trips per day (173 million per year) in NYC (NYC TLC Factbook 2016).

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communications that can potentially increase information gaps between participants and others who are left unaware of the occurrence of these private meetings.

We first *validate* the private communications measure by showing that taxi rides plausibly capture increases in information demands triggered by firm-initiated news. Studies document that analysts' research activities are clustered around earnings announcement dates (EAD), suggesting that analysts' incentives to acquire information are heightened around EAD (Ivković and Jegadeesh 2004; Barron, Byard, and Yu 2008; Soltes 2014; Yezegel 2015). Consistent with earnings releases prompting a need for private communications, we find that ride volumes increase significantly around EAD and reach their peak on the day of the earnings announcement. The increase is economically meaningful; the weekly mean of ride volumes around EAD increases by 7.2% compared to four weeks before EAD. Moreover, consistent with taxi rides capturing *sell-side analysts*' activities, we find that the magnitude of increases in ride volumes between a company and broker is significantly greater for brokers having analyst coverage of companies than for those without such coverage. We also find that taxi rides increase significantly on the days of investor conferences and analyst/investor days, whereas we do not find such patterns on the days of shareholder meetings and board meetings, reinforcing the idea that taxi rides capture actual interactions between managers and analysts in business contexts.

Using the validation analyses as a starting point, we examine the value of private communications. While managers have limited ability to convey material non-public information to analysts in private settings under Regulation Fair Disclosure (Reg FD), the unclear definition of materiality allows managers considerable leeway in helping analysts fill in their "mosaic view" of the companies (SEC 2000; Soltes 2018).[2] Thus, private communications may improve the accuracy of

[2] The mosaic approach supports the notion that pieces of information are combined with other information to produce a new picture or insight. The Securities and Exchange Commission permits the mosaic approach, stating, "At the same time, an issuer is not prohibited from disclosing a non-material piece of information to an analyst, even if, unbeknownst to the

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analysts' earnings forecasts and enhance the quality of their stock recommendations by providing analysts with likely non-material pieces of information that can become material, when taken together, within the context of other public and private information that they already have. For example, private communications following EAD could provide analysts with additional details and contexts into firm news and future developments, enabling them to better understand the implications of current earnings signals for future earnings (SEC 2002; Soltes 2014).

Consistent with our prediction, we find that private meetings following EAD are significantly negatively associated with analysts' earnings forecast errors issued in the post-EAD period. This finding is based on multivariate regressions that control for an extensive set of fixed effects (*firm*, *analyst*, and *year* or *firm-broker*), as well as a number of time-varying controls, making the possibility of correlated omitted variables less likely. The decreases are also economically meaningful; a one standard deviation increase in taxi ride volumes is associated with a 7.3% decrease in forecast errors for an average analyst.

Our findings are also robust to several additional confounding factors and different specifications. First, the inferences hold after controlling for information events around EAD, such as earnings surprises, earnings guidance, and 8-K filings, as well as analysts' existing information set proxied by their prior forecast errors. Thus, taxi trips allow analysts to access a private source of information orthogonal to their pre-existing set of private and public information. Second, one may argue that analysts who are already well-informed are more likely to have taxi trips around EAD and issue more accurate forecasts afterward. However, our inferences are unaffected after controlling for analysts' *prior* forecast errors; thus, this alternative is unlikely to explain our results.[3] Third, the

issuer, that piece helps the analyst complete a 'mosaic' of information that, taken together, is material" (https://www.sec.gov/rules/final/33-7881.htm).

[3] Nevertheless, we provide additional evidence that taxi ride volumes around EAD do not explain forecast errors *prior* to EAD (a "falsification test"), thus reinforcing the idea that private communications around EAD help analysts issue more accurate earnings forecasts subsequent to EAD.

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effects of taxi rides on forecast errors are incremental to the effects of other settings that allow private interactions, such as investor conferences and analyst/investor days. Therefore, taxi trips capture distinct subsets of private communications from what prior studies examine and are incrementally useful in forecasting future earnings.

It is worth noting that taxi rides *prior* to EAD are not significantly associated with more accurate earnings forecasts following EAD. Instead, we show that taxi rides undertaken immediately before EAD explain analysts' downward adjustment of near-term earnings forecasts below the current consensus, suggesting that private communications prior to EAD may serve as a direct mechanism to walk down the earnings consensus to create positive earnings surprises. The results suggest that analysts may learn different information about earnings depending on the timing of private communications.

We perform additional analyses to complement our findings on the value of private communication. First, we show that taxi rides following EAD are significantly positively associated with recommendation profitability measured as one-month buy-and-hold abnormal returns, consistent with private communications helping analysts issue more profitable recommendations.[4] Second, private communications can also be helpful for analysts to contextualize non-earnings news, which arrives at the market irregularly via 8-K filings. Following Livnat and Zhang (2012) and Rubin, Segal, and Segal (2017), we examine the association between increases in ride volumes following unanticipated 8-K filings and the timeliness of analysts' earnings forecasts. We find supporting evidence that private communications facilitate the timely incorporation of unanticipated non-earnings information into analysts' earnings forecasts.

[4] However, this effect dissipates over longer estimation windows. Specifically, there is no significant effect on profitability when using a six-month holding period, suggesting the benefit may be short-lived.

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While our findings do not speak directly to whether managers violate Reg FD (and that is *not* the purpose of this study), it is certainly possible that analysts obtain material information during in-person communications. To explore this possibility further, we exploit the fact that Reg FD mandates firms to make any non-public material information shared during private meetings public within 24 hours through filing Form 8-K. If non-public material information is shared and thus triggers 8-K filings, one should observe a positive association between taxi trips and Reg FD-*specific* 8-K filing dates. Consistent with this prediction, we find that taxi ride volumes significantly increase a day before and on the Reg FD-specific 8-K filing dates. Given that such private communications can still occur without triggering Reg FD-specific 8-K filings (Soltes 2018; Gleason, Ling, and Zhao 2020), this evidence may provide a *lower bound* on the likelihood that analysts obtain material information during taxi trips.

Finally, we extend our analyses to explore the *determinants* of taxi rides. We find that firms are more likely to communicate with analysts from large brokerages and analysts having unfavorable recommendations on them. Analysts are more likely to communicate with firms for which they have shorter coverage history. Moreover, they interact more when the firm's stock performs well in the market. Our results are consistent with analysts' incentives to develop relationships with management and firms' incentives to reach out to the broad pool of institutional investors, "re-educate" analysts who have negative views on them, and thus boost their valuations. Taken together, our determinant analyses reflect the idea that taxi rides are jointly determined by cross-sectionally- and time-varying incentives that firms, brokers, and analysts face.[5]

This study contributes to the growing literature on private communications between management and the investment community. First, our findings offer large-sample evidence on the

[5] Note that our inferences regarding forecast errors and stock recommendation profitability are unaffected by including the determinant variables as additional controls.

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value of private communications, extending the findings of Soltes (2014), who examines proprietary records of private interactions between management and analysts from a single NYSE-listed company for one year. Soltes (2014) does not find that private communications improve analysts' forecast accuracy, possibly due to the small sample size. Our large-scale empirical evidence indicates that private communications following firm-initiated news help analysts fill in the information mosaic, adding to our understanding of how analysts use private and public sources of information to generate their research outputs (e.g., Brown et al. 2015; Klein, Li, and Zhang 2020). Our findings highlight the complementary relations between public and private sources of information, suggesting that increases in public disclosures do not diminish the need for private communications in the post-Reg FD era. Moreover, we show that private communications serve different purposes depending on the context and incentives that firms and analysts have. In particular, private communications immediately before earnings releases may suggest managers' incentive to create positive earnings surprises by walking down the consensus. Private in-person meetings also provide analysts with opportunities to develop a relationship with managers.

Second, this paper provides a novel way to (partially) open the black box of private communications that have not been easy to examine due to lack of data availability. Bushee et al. (2018) analyze corporate jet flight patterns to identify unobservable non-deal roadshows where managers travel to meet with institutional investors. Our study focuses on private and unobservable interactions between analysts and managers and highlights analysts' information intermediary role in mitigating costs of monitoring for, acquiring, and analyzing firm disclosures (Bradshaw, Ertimur, and O'Brien 2017; Blankespoor, deHaan, and Marinovic 2020). The existence of such costs often renders firm disclosures a form of private information, presenting a challenge to well-functioning capital markets. Private communications can potentially serve as an important conduit conveying firms' messages to the investment community through the voice of sell-side analysts. In this light, face-to-

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face meetings can represent an efficient communication channel for transmitting complex and tacit messages that might be otherwise difficult through other media.[6]

Third, taxi trips capture private communications beyond investor conferences and analyst/investor days that provide analysts with opportunities to communicate with management privately. Such events occur only infrequently and leave a substantial amount of private communication unexplained (Soltes 2014; Brown et al. 2019). They are also highly visible and involve a large group of analysts. Taxi trips differ in that they capture *unobservable* private interactions between managers and financial analysts and that participating analysts are likely the sole recipients of private information. Our finding that analysts might obtain access to material information through taxi trips suggests that to the extent that they selectively distribute the information to their investing clients, private communications under Reg FD could create an unlevel playing field for excluded market participants.

2. Background and Value of Private Communications

In this section, we first provide institutional background of private communications in the era of Reg FD. We then discuss predictions about the association between private communications and analysts' research outputs.

2.1. Private Communications in the Post-Reg FD Era

In 2000, the Securities and Exchange Commission (SEC) created Reg FD. Reg FD was designed to level the playing field by prohibiting public firms from disclosing material information to selected parties. Since the enactment of Reg FD, firms have increased their public disclosures, suggesting that Reg FD might have shifted managers' preference to public disclosures due to the

[6] Furthermore, by focusing on NYC analysts using hand-collected information on their place of employment, we shed light on the source of the information advantage of local analysts (Bae, Stulz, and Tan 2008).

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monetary and reputation costs associated with violating Reg FD (Bailey, Mao, and Zhong 2003; Heflin, Subramanyam, and Zhang 2003; Wang 2007; Heflin, Kross, and Suk 2016).

However, a growing number of studies document that private meetings thrive in the post-Reg FD period even with the costs associated with Reg FD violations (e.g., Soltes 2014; Solomon and Soltes 2015; Brown et al. 2016; Bushee et al. 2017; Bushee et al. 2018; Brown et al. 2019). The prevalence of private meetings is described in several anecdotes. For example, one sell-side analyst interviewed in Brown et al. (2015; p.14) said, "There was a lot of backroom chatter before Reg FD. Now management has figured out how to 'paper things up' [with an 8-K]. So now we're almost back to where we were pre–Reg FD, but not quite because that backroom chatter is shut down. It's just now it's not in the backroom; it's everywhere."

As illustrated in the anecdote, Reg FD mandates companies to "paper things up" by making any material, non-public information disclosed to selected parties publicly available by promptly filing 8-K disclosures. Nevertheless, private communications can still occur without triggering 8-K filings, as managers have significant discretion in determining whether the information disclosed to selected parties is material (Soltes 2018; Brown et al. 2019; Campbell, Twedt, and Whipple 2020; Gleason et al. 2020).[7] In particular, Reg FD supports the "mosaic" approach, which allows managers to provide non-public information that could help the investment community to fill in its mosaic view of the company.[8] Therefore, in contrast to the intended objectives of Reg FD, private communications

[7] Reg FD does not provide the definition of the terms "material" and "non-public," but relies on existing definitions established in case law (SEC 2000); "Information is material if 'there is a substantial likelihood that a reasonable shareholder would consider it important" in making an investment decision." (TSC Industries, Inc. v. Northway, Inc., 426 U.S. 438, 449 1976; Basic v. Levinson, 485 U.S. 224, 231 1988) Such an unclear definition of materiality may help explain infrequent Reg FD enforcement; there have been fewer than 15 enforcement actions taken by the SEC since the passage of Reg FD in 2000 (Campbell et al. 2020).

[8] The SEC's investigation on Motorola Solutions illustrates how private communications can fill in analysts' mosaic view of the company by providing additional details into the public information (SEC 2002a). Motorola's IR director mentioned in a public conference call that the company was expecting "significant" weakness in its quarterly sales. After seeing analysts' reports issued following the call, the IR director realized that certain analysts had misunderstood the term "significant" and, after seeking the advice of counsel, decided to call the analysts to clarify that "significant" meant a "25% or more decline." However, this investigation did not end up in the enforcement action on the grounds that the counsel's advice was provided in good faith.

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likely remain important information channels that potentially create informational advantages for selected parties.

2.2. The Value of Private Communications

Despite the importance of private communications, studies examining the benefits of private communications to analysts are limited due to the private nature of such interactions. Establishing whether and when private communications occur is empirically challenging as most companies do not record or disclose private meetings. One exception is Soltes (2014), who examines proprietary records of private interactions from a single NYSE-listed firm. While he explains that private communications can provide analysts with additional context to interpret firm news and the opportunity to better understand a firm's operations, Soltes (2014) finds no compelling evidence that private interactions improve the accuracy of earnings forecasts.

Nevertheless, studies employ various methodologies to overcome data limitations and provide evidence on the usefulness of private communications in aiding analysts. Brown et al. (2015) provide survey evidence that sell-side analysts perceive private communications with management as more useful sources of information than public disclosures. Park and Soltes (2018) conduct field research on two companies and provide a detailed example of how discussions during private meetings can exclusively benefit participating analysts. They analyze the questions asked by institutional investors and analysts during private meetings and find that analysts are more likely to ask sensitive questions (i.e., timely and proprietary questions that could violate Reg FD) during private meetings than during public conference calls. The authors observe no instances in which managers decline to answer the questions during private meetings and argue that analysts may obtain access to non-public information that can create informational advantages.

Recent research capitalizes on regulations in China that mandate the disclosure of corporate visits (e.g., Cheng, Du, Wang, and Wang 2016; Han, Kong, and Liu 2018) and finds that site visits

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enhance the accuracy of the analysts' forecasts. However, the findings based on Chinese settings may not generalize to the U.S. Chinese firms need to disclose the content of private communications, including questions asked by analysts and management's answers provided to them during the meetings. The greater transparency in China has changed management's and analysts' behavior regarding what firms to visit and when to visit as well as the content of the information being discussed in private meetings (Ru, Zheng, and Zou 2021). Thus, the context and precise consequences of *unobservable* private communications remain an open question.[9]

2.3 The Value of *Face-to-Face* Meetings

Face-to-face communications potentially offer unique advantages relative to other forms of communication, such as emails and phone calls. First, face-to-face communication is an efficient communication technology that occurs on many levels at the same time – verbal, physical, contextual, intentional, and non-intentional, allowing a depth and speed of feedback that is not otherwise possible through other media (Storper and Venables 2004).[10] These advantages facilitate the transmission of complex and tacit information. Thus, while it may be the case that managers want to avoid mentioning certain information during private meetings, analysts may still infer useful information from reading managers' nonverbal cues, such as body language, facial expressions, and vocal tones (e.g., Bushee, Jung, and Miller 2011; Brown et al. 2015).[11]

[9] Moreover, several institutional differences – China's relatively weaker investor protection, its cultural preference for relationship contracting, and state-owned brokerages – might expose U.S. firms to greater liability for violating Reg FD than Chinese firms, thereby limiting U.S. managers' discretion to discuss their business. Indeed, Brown et al. (2019; p.71) provide corroborating survey evidence; "about 20% (53%) of respondents say that a member of the investment community asks a question at least several times a week (several times a month) that the IRO either does not answer or only partially answers, due to a concern about a possible Reg FD violation." For these reasons, while we expect private communications to have value, we may not find that private communications, on average, carry significant information content.

[10] Compare the SEC's enforcement action against Schering-Plough for violating Reg FD (SEC 2003). In 2002, the management team met privately with analysts and institutional investors, and the analysts who attended the meetings downgraded their ratings immediately. They noted that the CEO's "negative tone," "confidence level," and "downbeat demeanor" were reliable indications of the firm's state, suggesting that face-to-face interactions allow information to be conveyed in multifarious ways at the same time.

[11] The informational value of such nonverbal cues is well recognized; for example, one analyst interviewed in Brown et al. (2015; p.16) said, "We had an FBI profiler come in, and all the analysts and portfolio managers spent four hours with

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Second, face-to-face meetings are relatively safe from liability concerns, compared to other forms of communications that are more likely to leave trails for SEC investigation. When the SEC initiates an investigation, it can issue subpoenas to banks, clearinghouses, and telephone companies, as well as firms and individuals involved in allegations (Driggers 2012). As a result, the information garnered through subpoenas may include trading records, bank records, phone records, emails, instant messages, text messages, hard drives, and contact lists. Thus, as long as firms do not keep records of whom they meet in person, it is difficult for the SEC (or other investigating bodies) to uncover evidence that managers provide material information during private in-person meetings. This point is well illustrated by a quote from Harvey Pitt, a former chairman of the SEC, who presented to SAC Capital's staff about insider trading. He warned, "Don't write or send any email or other electronic communication, or leave any voicemail message for anyone, if you wouldn't want to see it in the media or have it read by regulators (Kolhatkar 2018; p.118)."

Third, face-to-face communications facilitate the development of trust, which increases the reciprocal sharing of information among participants and its perceived trustworthiness (Jarvenpaa and Leidner 1999; Storper and Venables 2004). Trust can be built on the fact that analysts spend time, money, and effort in developing a relationship. Thus, face-to-face meetings, being a form of communication with relatively high monetary and opportunity costs of travel compared to other communication channels, provide a strong signal that analysts are willing to embark on a repeated relationship. For example, Jarvenpaa and Leidner (1999) conduct case studies on global virtual teams in which members interact primarily through electronic networks. They find that global virtual teams may form a "swift" trust, but such trust turns out to be very fragile and temporal, suggesting that face-to-face communications are not replaceable for building trust. Therefore, face-to-face meetings may

this profiler trying to understand how to read management teams, to tell when they're lying, to tell when they were uncomfortable with a question."

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be preferred by analysts as means of building relationship bonds with managers, given that establishing a good relationship with management is critical to success as a sell-side analyst (Brown et al. 2015).

2.4 Predictions

Based on the above arguments, we expect private communications to potentially improve analysts' forecast accuracy and the profitability of their stock recommendations. However, it is important to note that private communications may occur outside of informational reasons, such as facilitating access for buy-side clients and developing an in-depth relationship with management (Soltes 2014; Bushee et al. 2018). Therefore, it is particularly useful to focus on a setting where private communications motivated by informational reasons are most likely to occur to test our prediction. Studies conclude that analysts' research activities are clustered around EAD (e.g., Ivković and Jegadeesh 2004; Barron et al. 2008; Soltes 2014; Yezegel 2015), suggesting that analysts' information-acquiring incentives are heightened around EAD. Therefore, for our primary analyses, we focus on private communications around EAD and predict that the informational benefits of private communications, if any, will manifest more clearly when private communications occur around EAD. Specifically, private communications around EAD may help analysts understand current earnings signals better by providing them with opportunities to gain additional clarification and contexts on the earnings news.[12]

3. Analyzing Taxi Trips in NYC

Analyzing taxi trip patterns within NYC offers a useful setting to study unobservable private communications between managers and analysts. Not only is NYC the biggest money center where private communications are flourishing, but travel by taxi is also an essential means of transportation

[12] In Section 5.3, we examine private meetings around *unscheduled* corporate information events.

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for New Yorkers, given the prohibitively high cost of parking in NYC (The office of NYC Mayor 2016) and the common business practice that analysts have taxi cards with the firms' names (Sell Side Handbook 2017). Moreover, because TLC uploads monthly taxi trip records with six-month lags, we can identify unobservable private communications *ex-ante*. In this light, taxi rides aim to capture subsets of private communications distinct from those occurring in other contexts that have been examined in prior literature: well-publicized events, such as investor conferences (Bushee et al. 2011; Green, Jame, Markov, and Subasi 2014) and analyst/investor days (Kirk and Markov 2016); and site visits in China that are mandated to be disclosed to the public (Cheng et al. 2016; Han et al. 2018). More recently, Bradley, Jame, and Williams (2022) study a subset of non-deal roadshows that is made available to the public on TheFlyOnTheWall.com. While the settings in prior studies allow market participants to learn about the occurrence of private meetings, taxi trips are left unnoticed by market participants for the time being, thereby providing a unique setting to test the value of *private* communications.

3.1. Data and Construction of Taxi Measures

The idea underlying our taxi measure is to map pick-up and drop-off locations of taxi trip records to companies' and brokerages' addresses. [13,14] We collect data from various sources. First, we collect trip-level NYC data from the TLC website. Each trip-level observation contains pick-up and drop-off dates and times, geographic locations in latitude and longitude of the pick-up and drop-off points, trip distance, and fare.[15] TLC began to disclose taxi trip records in 2009 and stopped providing

[13] Shekhar (2017) shows that the error rate that GPS coordinates of taxi trips are incorrectly recorded in the datasets is only 0.1%-0.5%. To ensure our taxi measures plausibly capture actual interactions in business contexts, we further require these taxi trips to occur during business days and business hours. Moreover, using *hand-collected* information on analysts' place of employment, we restrict our attention to analysts who work in the NYC branches of brokerages.

[14] Our empirical strategy is similar to Bradley, Finer, Gustafson, and Williams (2020) who find that taxi rides between the Federal Reserve Bank of New York and large financial institutions increase when the Fed or the banks possess negative information that has yet to be impounded into market prices.

[15] https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page. Taxi trip records do not provide information on passengers.

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latitude and longitude information in June of 2016 due to privacy concerns. Moreover, starting in 2015, the importance of ride-hailing services such as Uber and Lyft has increased. However, for these services, only information on pick-up *zones*, not that of drop-off, is provided, thus preventing the accurate identification of taxi rides between companies and brokerages that we employ.[16] Therefore, we exclude taxi trip records from 2015 onwards, resulting in a sample from 2009 to 2014.[17]

Second, we obtain company addresses from Compustat and those of brokers from FINRA's Broker Check website and Bloomberg Terminal. We restrict the sample of companies to those headquartered in NYC and covered in Compustat, and brokers to those having research offices in NYC and covered in I/B/E/S.[18] Then, we extract latitude and longitude coordinates of the addresses and match them to the NYC Census Block, a statistical area bounded by roads, to define areas against which to map pick-up and drop-off of each taxi trip.[19] If brokers have several offices in NYC, we include all of the offices to better capture the total amount of private communications and then aggregate taxi ride volumes across offices.[20]

As a result, we isolate all taxi trips that pick up and drop off in a pair of company-brokerage. We have 264 unique firms and 92 unique brokers in the sample. The sample firms are relatively large; the mean value of institutional ownership is 74% and analyst following is 14. The total market capitalization of our sample firms is $1.7 trillion. Thus, our sample is economically important. The sample brokerages are large, too; the mean brokerage size is 58 analysts. In all tests, the total number of taxi trips between firm *i* and brokerage *j* on date *t* is denoted as $Taxi_{i,j,t}$. By construction, $Taxi_{i,j,t}$

[16] The NYC zones are meant to approximate the neighborhood by aggregating the NYC blocks, which are discussed below. Specifically, there are only 263 zones, while there are 38,800 blocks in NYC. For example, a zone named Financial District North (zone ID 87), where Wall Street is located, spans more than 60 blocks.
[17] No inferences are affected if we include 2015 (untabulated).
[18] Because I/B/E/S no longer provides translation files, we hand-collect brokers' full names through Bloomberg Terminal, FINRA's Broker Check website, and LinkedIn. We then match them to broker IDs provided in I/B/E/S.
[19] Data on NYC Census Block are available at https://data.cityofnewyork.us/City-Government/2010-Census-Blocks/v2h8-6mxf. They are the smallest geographic area defined by the Bureau of the Census.
[20] In our sample, there are seven brokers having multiple offices in NYC; among them, six have two, and one has three. Taking the average of taxi ride volumes across offices does not alter our conclusions.

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is the sum of taxi trips that pick up at brokerage *j* and drop off at company *i* and those in the opposite direction. To further ensure that taxi rides capture actual interactions between analysts and management in business contexts, we include business days only and exclude taxi rides from 8 PM to 7 AM, which likely indicate rides for commuting or entertainment. Moreover, we restrict our sample to analysts working in NYC using *hand-collected* information on the place of employment, constructed from Bloomberg Terminal, FINRA's Broker Check, and LinkedIn. The sample firms are, on average, covered by 10.8 analysts working in NYC, reflecting the fact that the majority of analyst research outputs are generated in NYC.

In tests where a taxi measure is employed as a dependent variable, we use the log of raw counts for the taxi variables, and we include multiple fixed effects to control for seasonality of taxi rides or time-invariant characteristics associated with the location of the firm and broker. In all tests where a taxi measure is employed as our test variable, we consider *abnormal* ride volumes around the test window using ride volumes during the same length preceding the test window as a benchmark ($Ch\ Abnormal\ Taxi_{i,j,t}$). By construction, $Ch\ Abnormal\ Taxi_{i,j,t}$ adjusts for the seasonality of taxi rides specific to a given firm-broker pair and is positive when the number of taxi trips between firm *i* and brokerage *j* increases in the recent period.

4. Validating the Taxi Measures

Before examining the value of private communications via taxi trips, we validate our taxi measures in two different dimensions. First, we examine whether taxi rides plausibly capture increases in information demands triggered by firm-initiated news. Next, we provide evidence on whether taxi rides capture the activities of sell-side analysts.

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4.1. Ride Patterns around EAD

Analysts' research activities are clustered around EAD (Ivković and Jegadeesh 2004; Barron et al. 2008; Soltes 2014; Yezegel 2015), suggesting that analysts' incentive to acquire information is high at that time. Therefore, using earnings press releases as key events that create analysts' demands to meet with management, we provide evidence that taxi trips plausibly capture private communications between companies and analysts. To do so, we create a company-level measure by aggregating the company *i* – brokerage *j* level taxi measure for a given company *i* and all brokerages in the sample to capture general increases/decreases in traffic to and from company *i*. We then plot the quarterly patterns of mean weekly ride volumes in Panel A of Figure 1, on the left-hand side.[21] Consistent with the explanation that the needs for private communications increase around EAD, we find that the mean ride volumes in the week of EAD increase by 7.2% compared to those of four weeks prior to EAD.[22]

Next, on the right-hand side in Figure 1, Panel A, we compare taxi rides between two groups, where "Coverage = 1 (0)" is a subsample composed of all pairs of a company and broker that has (does not have) analyst coverage of the company.[23] The result shows that not only is the average taxi ride volume for "Coverage = 1" 47% higher than that of "Coverage = 0" throughout the quarter but also 64% of increases in taxi ride volumes on the week of EAD are explained by "Coverage = 1." These findings are consistent with firms interacting more with analysts from brokerages that cover them, supporting the notion that sell-side analysts act as information intermediaries who convey the company's message to the investment community (Brown et al. 2019). In this light, finding significant

[21] In our sample, the average time span between EADs is 12.78 weeks. Therefore, we aggregate daily ride volumes (business days and business hours only) by week and compute their means from the week of EAD to 12 weeks prior to EAD.

[22] We find similar patterns at the company-broker-level, with 5.7% increases in taxi ride volumes on the week of EAD (untabulated).

[23] There are 2,868 unique pairs of firm-brokerage in "Coverage = 1" and 2,764 unique pairs of firm-brokerage in "Coverage = 0."

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differences in terms of frequency of taxi rides around EAD and throughout a quarter depending upon coverage gives us greater confidence that our taxi measures capture sell-side analysts' activities.

Note that it is unlikely that our results are spuriously driven by the general trends in taxi ride patterns in NYC. In our sample, earnings announcement dates are concentrated in February, May, August, and November, as most of our sample firms have their fiscal year-end on December 31. In contrast, the average daily taxi usage in NYC is the highest in the spring months (April and May) and lowest in the summer (August) and winter months (November and December) (TLC Factbook 2014). Nevertheless, we provide additional evidence in Appendix 1 that taxi rides exhibit significant variations around EAD after controlling for *firm, broker, month*, and *year* fixed effects.

We also note that increases in ride volumes before EAD are *not* necessarily at odds with institutional policies. First, while firms can adopt quiet periods prohibiting private discussions with analysts and investors before EAD, they have considerable flexibility as to details of the implementation, such as the beginning period, scope of restrictions, etc. (Sharon Merrill Associates 2012).[24] Moreover, firms with quiet periods sometimes allow for exceptions at managers' discretion.[25] Second, analysts can visit firms multiple times and talk with different people on different days. As evidenced by survey results in Brown et al. (2019; p.71), it is common to ask a question several times a week. Firms typically designate authorized spokespersons who can communicate with the investment community, including the CEO, CFO, Chairman of Board, and IR directors. Upon

[24] Advisors often recommend that firms not shut down all communications prior to EAD. For example, Sharon Merrill Associates, an IR advisory firm, states, "The problem with this communications shutdown approach – particularly with small, underfollowed companies – is that it doesn't curry you any favor with the Street and clearly inhibits your visibility."
[25] Through a random search of firms' communication policies published on their IR websites, we were able to easily identify several cases where firms allow exceptions. For example, in Ciena's disclosure policy, it is articulated under the section "Limited End-of-Quarter Communications ("Quiet Period")" that "Ciena may participate in media/press and industry analyst interactions during this time at the discretion and in the presence of a member of the Corporate Communications Department, and participants will be appropriately apprised of the sensitivity of the period. See also Johnson & Johnson, Wills Towers Watson, Whirlpool Corporation, and Pinnacle West, among others.

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request, analysts are allowed to talk with others, such as employees and consultants, and in such cases, authorized spokespersons schedule another meeting with them.

4.2. Ride Patterns around Corporate Events

We provide additional validating evidence that taxi rides can plausibly capture analysts' activities by examining ride patterns around various corporate events. First, we focus on investor conferences and analyst/investor days. Firms typically hold such corporate events at their corporate facility or offsite near a major investment center in NYC (Kirk and Markov 2016). Thus, we expect taxi rides to increase on the days of such events. At the firm level (untabulated), daily taxi ride volumes increase on the days of corporate events by 21% compared to four weeks prior to those events, and we observe 25% (15%) increases for "Coverage = 1" ("Coverage = 0"). [26] In Column (1) of Table 1, we present regression results at the firm-brokerage-day level. Daily taxi ride volumes are regressed on daily indicators around the investor conferences and analyst/investor days.[27] After controlling for firm, broker, month, and year fixed effects, we find a significant increase on the days of such corporate events.

Second, for comparison, we examine ride patterns around annual shareholder meetings and board meetings, two major corporate events that are much less likely to involve the participation of analysts. In Table 1, Columns (2) and (3), in contrast to investor conferences and analyst/investor days, we find no evidence that ride volumes increase around shareholder meetings and board meetings. Overall, our validation results suggest that the taxi measures are likely to capture business contexts where analysts are meeting with managers.

[26] We exclude corporate events that occur within ten business days around EAD. We also find similar results at the firm-brokerage-level (20% increases for Coverage = 1 and 14% increases for Coverage = 0).
[27] The sample is restricted to 21 days surrounding corporate events. We exclude corporate events that occur within ten business days around EAD or have overlapping windows.

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5. Empirical Evidence on the Value of Private Communications

5.1. Private Communications via Taxi Trips and Forecast Errors

To test whether private communications around EAD are negatively related to analysts' forecast errors, we estimate the following OLS regression at the firm-quarter-analyst-forecast-level:

$$Forecast\ Error_{i,j,k,t+1} = \beta_1 Ch\ \ Abnormal\ \ Taxi_{i,j,t} + \sum_k \beta_k Controls_t + FE + e_{ijkt} \ldots (1)$$

where *i* indexes firm, *j* indexes broker, *k* indexes analyst, and *t* indexes quarter. We illustrate the timeline of our analysis in Figure 2. For every firm-quarter, all brokerages except for one case have only one analyst forecasting the firm's earnings.[28] Thus, to the extent that our taxi measures capture analysts' activities, our research designs allow us to examine the association between forecast accuracy and private communication of an individual analyst working at a particular brokerage.

As shown in the validation results in Section 4.1, taxi ride volumes increase primarily during the week of EAD. Therefore, to identify increases in ride volumes around the week of EAD relative to its preceding non-EAD periods, we first measure non-EAD ride volumes between firm *i* and broker *j* ($Taxi\ \ Benchmark_{i,j,t}$) by aggregating ride volumes between $EAD_{t-1} + 6$ (six business days past the EAD in the previous quarter) and $EAD_t - 6$ (six business days before the EAD in the current quarter). Then, we compute abnormal ride volumes by comparing aggregate ride volumes undertaken during the EAD window with $Taxi\ \ Benchmark_{i,j,t}$ normalized to have the length same as that of the EAD window. Last, we define changes in ride volumes around the EAD compared to the benchmark non-EAD ride volumes ($Ch\ \ Abnormal\ \ Taxi_{i,j,t}$).[29] To be consistent with our prediction that private communications will help analysts understand the implications of current earnings signals

[28] There is only one case where two analysts working at the same brokerage issue earnings forecasts for the same firm.
[29] To avoid zero denominators, we add one for all taxi rides.

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for future earnings, we focus on days on or right after EAD, [0, 5], for our primary EAD window.[30] For comparison, we also construct $Ch\ \ Abnormal\ \ Taxi_{i,j,t}$ for days before EAD, [-5, -1], to capture increases in ride volumes prior to EAD.

$Forecast\ Error_{i,j,k,t+1}$ is analyst k's forecast errors of earnings forecasts for firm i issued after the EAD window but no later than a month after the window.[31] If analysts issue forecasts for a given horizon multiple times during this period, we take the earliest forecasts among them. We define forecast errors as the absolute value of the difference in analysts' forecast values and actual earnings divided by the stock price at the beginning of the quarter.[32] The sample includes all quarterly and annual earnings forecasts issued by analysts.

We employ a variety of fixed-effect structures to facilitate the interpretation of multiple sources of variations. We include *analyst fixed effects* to exploit within-analyst variations and *firm fixed effects* to control for the unobservable time-invariant firm characteristics, such as corporate communication policies. We also include *year fixed effects* to control for trends in taxi rides volumes affecting all firms and brokers (e.g., the entry of Uber and Lyft). Thus, the interpretation becomes how, within a group of firms that an analyst covers, variations of changes in ride volumes shortly after EAD relate to variations in forecast accuracy. As an alternative specification, we include pairwise *firm-broker fixed effects* to subsume time-invariant characteristics at the firm-broker pair level, such as financial ties and closeness between a firm and broker. In all tests, standard errors are clustered by analysts.

[30] We find that 72.5% of abnormal ride volumes lie within one-to-two-unit decreases or increases, suggesting that our measures could capture one more or fewer private communications than would normally have been expected during non-EAD periods.

[31] Soltes (2014) finds that the average forecast is updated 26 days after interacting privately with management, suggesting that analysts are not, on average, immediately reacting to information provided by private communications with management. To be consistent with his observation, we allow one month for analysts to update their forecasts following taxi rides.

[32] Scaling by actual earnings instead does not alter our conclusions.

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In addition to the fixed effects, we include an extensive set of control variables that comprise analysts' information mosaic to test whether taxi trips convey private information orthogonal to analysts' pre-existing information set. All control variables are constructed from Thompson Reuters, Compustat, CRSP, I/B/E/S, Edgar, and Capital IQ. Appendix 2 provides detailed variable definitions.

First, we control for the information content of public information ($EADReturn_{i,t}$), which is defined as cumulative market-adjusted returns during the five-day window [-2,2] surrounding EAD, stock return volatility ($Volatility_{i,t}$), which proxies for the uncertainty related to earnings announcements, the log of the number of management earnings forecasts ($Guidance_{i,t}$), and the log of the number of 8-K items ($N8-KItems_{i,t}$) disclosed during the EAD window.[33] Second, studies that examine market reactions around public events allowing private communications with management (e.g., broker-sponsored investor conferences and analyst/investor days) (Kirk and Markov 2016) find that such private communications are informative (e.g., Bushee et al. 2017; Kirk and Markov 2016). Thus, we include an indicator variable that a firm holds an investor conference (analyst/investor day) during the EAD window, $InvestorConference_{i,t}$ ($Analyst/InvestorDay_{i,t}$), zero otherwise. Third, we control for the log of the number of analysts following the firm ($NFollow_{i,t}$), as analysts can learn from the earnings forecasts from other analysts. Last, for the analyst-firm-controls, we include $PriorForecastErrors_{i,j,k,t}$, which is defined as the realized forecast errors of analyst *k* for the most recent fiscal quarter for firm *i*, to directly control for the quality of analyst *k*'s existing information set on firm *i*.

For the firm-analyst-forecast-level control variables, we include $Horizon_{i,j,k,t+1}$, which is defined as the log of the differences in days between forecast announcement dates and actual EAD. The shorter the horizon, the more likely analysts issue more accurate forecasts. For other broker- or

[33] As an alternative to $EADReturn_{i,t}$, we control for realized earnings surprise ($Surprise_{i,t}$) measured against the analyst consensus available two days prior to EAD. No inferences are affected.

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analyst-level controls, we include broker size ($BrokerSize_{j,k,t}$), which is defined as the log of the number of analysts employed in the brokerage, the log of the number of firms that analysts cover ($NCoverage_{j,k,t}$), and the log of the analyst's working experience in years ($Experience_{j,k,t}$). For analyst-firm-level controls, we include the log of the analyst's coverage history of the firm in years ($CovHistory_{i,j,k,t}$).

5.1.1. Descriptive Statistics and Correlations

Panel A of Table 2 provides summary statistics of the variables used in the forecast error sample.[34] Panel B shows the Pearson correlation coefficients between variables. All continuous variables are winsorized at 1% and 99%.[35] On average, sample firms disclose 2.6 items through 8-K filings and provide 0.3 management earnings forecasts during the 11-day EAD window. While 28% of the sample firms have investor conferences during the EAD window, fewer than 1% of the firms have analyst/investor days, which is consistent with Kirk and Markov (2016)'s finding that analyst/investor days rarely overlap with earnings seasons. The average analyst covers 16 companies. The mean value of analyst experience is 8 years, while the average coverage history is 4.2 years.

5.1.2 Results

Panel A of Table 3 shows the regression results of analysts' forecast errors on taxi ride volumes during the six-day window [0,5] on or immediately following EAD. We first show the results without any controls (except fixed effects), then those with control variables that comprise the analysts' information mosaic, and last those with the extended control variables including other broker and analyst characteristics. Consistent with our expectation, the coefficient on

[34] The mean value of $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ is 0.01 (1%). We find that the distribution $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ is approximately normally distributed around zero (untabulated). Conditional on non-negative observations, the mean value is 0.073 (7.3%). Also note that the abnormal ride volumes are deflated by the aggregate ride volumes undertaken during the non-EAD periods to capture the relative importance of ride during the EAD periods compared to other periods.

[35] No inferences are affected by the choice to winsorize or not.

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$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ is negative and statistically significant from Columns (1) to (4), and the estimated coefficients are comparable across different fixed effects structures.[36] The effect is robust to controlling for potential confounding factors, suggesting that analysts obtain a private source of information that is not contained in their information set through taxi trips.[37] The effect is also economically meaningful; a one standard deviation increase in $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ is associated with a 7.3% reduction in forecast errors.[38] In Column (4), we find that our inferences hold after controlling for firm-broker fixed effects, ruling out a potential explanation that analysts working at a brokerage having financial ties with firms are more likely to issue accurate forecasts.

To ensure that our finding is not an artifact of how we construct the test variable, in additional analyses, we employ alternative definitions, each of which summarizes ride patterns around EAD differently: the log of aggregate ride volumes (Column 5), aggregate rides volumes scaled by all rides from and to a company (Column 6), aggregate ride volumes scaled by the sample mean ride volumes between a company and broker (Column 7), and the log of mean taxi ride volumes (Column 8). In all columns, the findings are robust, suggesting that, along with variations of the changes in ride volumes, variations in the level of ride volumes around EAD, within a group of firms covered by an analyst or within pairs of a firm and broker, explain variations in forecast accuracy.[39]

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[36] The extensive fixed-effects structure controls for unknown sources of heterogeneity at the firm, analyst, brokerage, and time period levels. In addition, the time-varying control variables further control for changes in firm characteristics, the information environment, and analyst-related factors. As a result, we consider the possibility of correlated omitted variables that could affect our inferences to be relatively low.

[37] The inferences are robust to a variety of additional controls and different sample selection. First, our conclusions do not change if we exclude a set of brokerages located in the same block and at the same time covering the same firm (N = 18,369). Specifically, the estimated coefficient is -0.022 with a t-statistic -2.27 in the most restrictive specification. Second, our findings are robust to controlling for either driving distance or driving time between a firm and a brokerage. Last, when we restrict the sample of brokerages and firms to those with driving distance greater than 1KM (driving time greater than 5 minutes), the estimated coefficient is -0.024 (-0.026) with t-statistic -2.52 (-2.63) (N = 15,550 and N = 15,909, respectively) in the most restrictive specification.

[38] While we cannot rule out the possibility that taxi measures could capture other brokerage firm employees' activities other than sell-side analysts (e.g., investment bankers having M&A deals with the sample firm), Hwang, Liberti, and Sturgess (2019) find that information and resources are shared among colleagues working at the same brokerage.

[39] In untabulated analyses, we explore whether the implications of private communications differ depending upon who initiates taxi trips. Specifically, we disaggregate taxi trips into those that pick up at brokerage j and drop off at company i ($Analyst\ to\ Manager_{i,j,t}$) and those in the opposite direction ($Manager\ to\ Analyst_{i,j,t}$). Conceptually,

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An alternative explanation for our results is that already well-informed analysts take taxi trips and issue more accurate forecasts. Because we control for $PriorForecastErrors_{i,j,k,t}$, which proxies for the quality of the pre-existing information set, it is unlikely that this alternative channel explains our results. Nevertheless, we provide additional evidence in Table 3, Panel B that $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ (measured again during the EAD period) does not explain forecast errors of earnings forecast issued *before* EAD (a "falsification test"). We include all the latest earnings forecasts for a given horizon outstanding right before EAD. While the associations between $ForecastErrors_{i,j,k,t}$ and the control variables are unaltered or become even stronger, the association between $ForecastErrors_{i,j,k,t}$ and $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ is insignificant. Therefore, our results are unlikely to be explained by reverse causality.

5.1.3 Cross-Sectional Analyses

In this section, we perform cross-sectional analyses to study when the benefits of private communications are particularly prominent. To the extent that face-to-face communication facilitates trust development, we expect the relationship built on repeated face-to-face interactions to increase the reciprocal sharing of information between managers and analysts and its perceived trustworthiness (Jarvenpaa and Leidner 1999). Thus, we conduct cross-sectional analyses focusing on the EAD setting to examine whether the value of private communications increases with the length of the coverage relationship. Panel C of Table 3 presents the results. We include firm and year fixed effects to exploit variations across analysts in Column (1) and additionally include analyst fixed effects in

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$Analyst\ to\ Manager_{i,j,t}$ captures private meetings that occur in the company's headquarter, such as corporate visits. In contrast, $Manager\ to\ Analyst_{i,j,t}$ captures private meetings that occur in the brokerage's office, such as in-house meetings and non-deal roadshows. We examine which direction is incrementally useful by horse racing them in the same model. We find that the variations in forecast errors are mainly explained by $Analyst\ to\ Manager_{i,j,t}$, suggesting that analysts traveling to the firm's headquarter are more likely to benefit from private communications than those having the firm's management travel to their office. One potential explanation is that $Manager\ to\ Analyst_{i,j,t}$ is more likely hosted by analysts to serve their buy-side clients' demands (Bushee et al. 2018) than to meet their own informational needs. However, given the relatively high correlation between $Analyst\ to\ Manager_{i,j,t}$ and $Manager\ to\ Analyst_{i,j,t}$ (Pearson correlation of 0.43), these results should be interpreted with caution.

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Column (2) or firm-broker fixed effects in Column (3). We find that the effects of private communications on forecast accuracy are more pronounced for analysts with a longer coverage history of the firm, suggesting that analysts who have established relatively solid relationships with managers are more likely to benefit from private communications. Thus, our cross-sectional results underscore the importance of *building* a good relationship with managers in promoting efficient communications between managers and analysts.

In untabulated analyses, we also conduct analyses that highlight potential tradeoffs between the benefits and costs of private communications using the driving time between a firm and brokerage (i.e., how long it takes to drive by car between two places) as a proxy for traveling costs. We predict that once analysts and managers are willing to embark on trips despite a longer traveling time, they will expect greater benefits from doing so. Consistent with the expectation, we find that the effects of private communications on forecast accuracy are more pronounced when it takes longer time to travel, suggesting that the value of in-person meetings is greater when the participants incur greater costs. Last, we find that the effects of taxi rides are stronger for more volatile stock returns around EAD, consistent with the notion that face-to-face meetings facilitate the transmission of complex and tacit information.

5.1.4 Further Exploration of Pre-EAD Meetings

Next, we investigate whether the implications of private communications vary by the timing of taxi trips, pre- versus post-EAD. In Table 3, Panel D, we horse-race $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ and $Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$ in the same model.[40] We find that the variations in forecast errors are mainly explained by $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$, suggesting that private meetings shortly on or after EAD, not before EAD, benefit analysts. The evidence that private communications

[40] The Pearson correlation between $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ and $Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$ is 0.16.

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immediately before EAD are not, on average, translated into information advantages of analysts suggests different motives for having meetings before EAD.

In Table 4, we consider a possibility that pre-EAD meetings relate to the well-known "walk-down" of earnings forecasts prior to earnings releases to create positive earnings surprises (e.g., Richardson, Teoh, and Wysocki 2004). It is worth noting that several Reg FD investigations are associated with firms' private communications *before EAD* to walk down the consensus (e.g., Office Depot 2010; AT&T 2021). For example, in its recent charge against AT&T, the SEC alleges that AT&T management made calls to about 20 analysts to walk the analysts down. Consequently, the day before AT&T released Q1 2016 earnings, the consensus estimate had fallen just below the revenues that the company would report. Based on these observations, we explore the possibility that increases in ride volumes prior to EAD (i.e., [-5, -1]) are associated with analysts' revision of current quarter earnings forecasts below the consensus.

We define the dependent variable, $Below\ Consensus\ Revision_{i,j,k,t}$, to equal one, if analysts adjust near-term earnings forecasts below the current consensus during the pre-EAD window [-5, -1]. Here, the current consensus is measured as the mean consensus earnings forecast at the time of *five business days* before the earnings announcement. The sample is at the firm-analyst-EAD-level. We additionally control for $AboveConsensus_{i,j,k,t}$, which is equal to one if analyst k's earnings forecasts before the revision were above the consensus. We expect a positive coefficient on $AboveConsensus_{i,j,k,t}$. In untabulated descriptive statistics, we find that ride volume during [-5,-1] between managers and analysts whose forecasts are *above* the current consensus are greater than the counterpart by 42%, suggesting that analysts above the consensus talk more with managers than those below the consensus during the pre-EAD periods.[41]

[41] The inferences do not depend on whether this control variable is included or not.

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In Table 4, we find that $Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$ is significantly, positively associated with the likelihood that analysts adjust near-term earnings forecasts below the current consensus during [-5, -1]. A one standard deviation increases in $Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$ is associated with 21% increases in $Below\ Consensus\ \ Revision_{i,j,k,t}$. The results suggest that the objective of private communications could be very different depending on the timing. Prior communications *before* EAD may be related to managers and analysts engaging in a "numbers game," which could be a potential reason we find limited evidence that prior communications before EAD are positively associated with forecast accuracy.

5.2. Private Communications via Taxi Trips and Recommendation Profitability

To better understand the value of private communications, we also investigate whether analysts with private communications around EAD subsequently issue more profitable stock recommendations. To conduct the analysis, we identify recommendations made after EAD, but no later than the next-quarter EAD and require that at least two analysts update their recommendations on the firm for each period.[42] Following prior literature (e.g., Barber, Lehavy, and Trueman 2007; Cohen, Frazzini, and Malloy 2010; Klein et al. 2020), we use the I/B/E/S numeric recommendation code to assign each recommendation change to one of two classifications: (1) a BUY recommendation if a stock is upgraded compared to the previous recommendation or of stocks for which coverage is initiated or reiterated with a buy or strong buy rating, and (2) a SELL recommendation if a stock is downgraded compared to the previous recommendation or of stocks for which coverage is initiated or reiterated with a hold, sell, or strong sell rating; or coverage is dropped. For BUY (SELL) recommendations, we invest (sell) $1 in the recommended stocks. We estimate the following equation for the pooled sample of all identified recommendations.

[42] Given the sticky nature of recommendations, we do not require that recommendation changes occur within one month following the EAD window as in the forecast error tests.

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$$Profitability_{i,j,k,t} = \beta_1 Ch\ Abnormal\ Taxi_{i,j,t} + \sum_k \beta_k Controls_t + FE + e_{ijkt} \ldots (2)$$

where i indexes firm, j broker, k analyst, t time. $Ch\ Abnormal\ Taxi_{i,j,t}$ is changes in ride volumes during the window [0, 5] surrounding EAD, relative to its preceding non-EAD periods. Following extant research (e.g., Mikhail, Walther, and Willis 2004; Cohen et al. 2010; Loh and Stulz 2011; Green et al. 2014), we compute the one-month buy-and-hold cumulative abnormal return subsequent to recommendation as follows:

$$Profitability_{i,j,k,t} = \prod_{t=1}(1 + R_{it}) - \prod_{t=1}\left(1 + R_{it}^{DGTW}\right)$$

where R_{it} is the raw return of stock *i* on day *t*, and R_{it}^{DGTW} is the return on day *t* of a 5 × 5 × 5 benchmark portfolio based on size, book-to-market, and momentum characteristics defined in Daniel et al. (1997).[43] The recommended stock is held for the period starting from the next trading day following the recommendation date until the earlier of the end of the holding period or one trading day before the analyst updates her recommendation. The sample contains 1,784 recommendations. Panel A of Table 5 presents summary statistics for the sample.

The results are presented in Panel B of Table 5. Across all columns including varying controls and alternative definitions of taxi variables, we find that taxi rides undertaken on or shortly after EAD (i.e., [0,5]) are associated with greater one-month buy-and-hold returns of recommendations issued after EAD. This finding indicates that analysts having interactions with the firm issue more profitable recommendations.[44]

[43] Inferences do not change if we instead use raw returns and include size, book-to-market, and momentum as controls.
[44] In terms of economic importance, a one standard deviation increase in taxi ride volumes is associated with an almost doubling in one-month buy-and-hold returns. For completeness, we also examine six-month buy-and-hold returns, and we no longer find a significant effect (untabulated), suggesting that the benefits of private communications are likely short-lived.

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5.3. Private Communications around Unanticipated Information Events

Our primary focus is on EAD, given that analysts' research activities are centered around these dates. In additional analyses, we also consider potential effects on unanticipated information events. Following Livnat and Zhang (2012) and Rubin, Segal, and Segal (2017), we examine the association between increases in ride volumes following unanticipated 8-K filings and the timeliness of analysts' earnings forecasts. We define unanticipated news as all 8-K filings except for those containing item 2.02 (Results of Operations), which are typically announcements of preliminary earnings. We further exclude 8-K disclosures filed within three days of EAD or having overlapping windows. Prior literature defines forecast revisions as timely if they are released between the event date and three days after the filing date (i.e., [0,3]). Thus, we investigate how changes in ride volumes four business days after 8-K filing dates ($Ch\ Abnormal\ \ Taxi[0,3]_{i,j,t}$) relate to the timeliness of earnings forecasts. To capture whether ridership between a company and broker during the 8-K window is high relative to the recent past, we use the window [-12,-5] (eight days preceding the 8-K filing window) as a benchmark period, which is then normalized to the same length of the 8-K window being considered. For these analyses, the sample is constructed at the firm-analyst-8-K filing level.

In Panel A of Table 6, we provide descriptive evidence on the association between 8-K items and $Ch\ Abnormal\ \ Taxi[0,3]_{i,j,t}$. Consistent with prior literature, items 9.01, 8.01, 5.02, 7.01, 1.01, and 1.02 are the most prevalent types of 8-K filings. We find that the mean value of $Ch\ Abnormal\ \ Taxi[0,3]_{i,j,t}$ is greater for items that trigger significant market reactions (e.g., delisting), but such filings are rare. On average, 12% of analysts react to unanticipated 8-Ks in a timely manner, and descriptive statistics of control variables are similar to the EAD sample (untabulated). Panel B presents OLS estimation results. We find that increases in ride volumes around 8-K filings are significantly associated with more timely revisions of earnings forecasts; a one standard deviation increase in taxi ride volumes is associated with 4% increases in the likelihood of

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analysts' reaction to unanticipated news.[45] Our results suggest that private communications facilitate the timely incorporation of unexpected news into analysts' earnings forecasts.

5.4. Access to Private Information during Private Communications (Exploratory Analysis)

While we find consistent results in Section 5 that point toward the informational value of private communications, we cannot tell which pieces of information ultimately fill in the information mosaic, as it is not feasible to observe what is discussed during the private meetings. As an *exploratory* analysis, we assess whether the information obtained through taxi trips could be material enough to create analysts' information advantages by establishing associations between Reg FD-specific 8-K items and taxi ride patterns. Specifically, we exploit the disclosure mandate under Reg FD that firms make any non-public material information shared during private meetings public within 24 hours through filing Form 8-K (Brown et al. 2015; 2019; Campbell et al. 2020; Gleason et al. 2020).[46] Therefore, if non-public information is shared during private communications and thus triggers 8-K filings, one should observe a positive association between taxi trips and Reg FD-*specific* 8-K filings.[47]

Similar to the research design in Appendix 1, we create indicators for three time-bins, $I[-5,-1]_{i,t}$, $I[0]_{i,t}$, and $I[1,5]_{i,t}$, where 0 indicates the 8-K filing dates, to capture whether taxi ride volumes during these time-bins are significantly greater than the baseline.[48] The sample includes 21-day windows surrounding 8-K filings dates for any firm-brokerage pairs, and we require that each

[45] We do not find that the association is more pronounced for certain types of 8-K filings.
[46] Specifically, firms should disclose the non-public material information under Item 7.01 "Regulation FD Disclosure" (SEC 2018). Firms that file an Item 7.01 Form 8-K are disclosing material information in order to comply with Reg FD (Campbell et al. 2020).
[47] Through manual reading of a small sample of Reg FD-specific 8-K filings, we confirm that Reg FD-specific 8-K filings are often triggered by a disclosure of material information during private meetings (potentially accidentally). For example, Barnes & Noble, Inc.'s Reg FD-specific 8-K filings on May 4, 2011 disclosed "In a meeting with investor analysts on May 4, 2011 Barnes & Noble inc. (the company) indicated it expects to make an announcement on May 24, 2011 regarding the launch of a new e-reader device." On the same day, we observe that ride volumes between the firm and one brokerage increased by four (both directions counted), compared to the previous day.
[48] These analyses differ from those in Section 5.3 in that they may include anticipated as well as unanticipated 8-K filings.

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window does not overlap with each other, as well as a 21-day window around EAD. We report the results in Table 7. In Column (2), we find significant increases on the 8-K filing dates (i.e., positive coefficients on $I[0]_{i,t}$) for Reg-FD-specific 8-K filings.[49] When we disaggregate $I[-5,-1]_{i,t}$, $I[0]_{i,t}$, and $I[1,5]_{i,t}$ into the eleven separate daily indicators, we find 1.8% and 3.3% increases in taxi ride volumes (t-statistic = 1.96 and 2.87) a day before and on the filing dates (consistent with the 24-hour window set by the SEC), while we do not find any significant increases on the other days (untabulated). Our findings may provide a lower bound on the effects that taxi rides have on analysts as private communications can still occur without triggering Reg FD-specific 8-K filings; that is, analysts may benefit substantially from selected access to non-public information during private communications.

6. Determinants of Private Communications via Taxi Trips: Why do Such Meetings Occur?

A question that naturally follows is why not all analysts seek private communications all the time if private communications can bring value to analysts. Therefore, we conduct determinant analyses to explore whom the managers (or analysts/brokerages) are more likely to interact with, given the limited resources available to managers (or analysts/brokerages) for holding private meetings. Drawing on prior literature on private meetings with analysts and institutional investors, in Appendix 3, we motivate variables that proxy for the incentives and resources that firms and analysts/brokerages have.

Table 8 shows the descriptive statistics of the determinant sample. In Table 9, we estimate a panel regression at the firm-broker-analyst-month level by regressing the natural logarithm of the taxi ride volumes between firm *i* and brokerage *j* of analysts *k* in month *t+1* on determinants measured in

[49] In our sample, out of 2,212 Reg FD-specific 8-K filings, 287 filings (13.5%) are made within two days of investor conferences or analyst/investor days. Excluding such filings does not alter our inferences (untabulated); we find 3.34% increases on the days of Reg FD-specific 8-K filings at the firm-brokerage-level (N = 158,947 and t-statistic = 2.86).

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month *t*.[50] Standard errors are clustered by firm and broker. We employ different sets of fixed effects to exploit cross-sectional variations within a firm or analyst. In the first column, we include *firm-month* and *year fixed effects* to explore whom the managers are more likely to interact with among analysts covering their firm in a given month. We find that managers are more likely to communicate with analysts from large brokerages (analysts from large brokerages having better access to the management). Interestingly, we find that managers are more likely to interact with analysts having *unfavorable* recommendations on their firm, consistent with managers' incentives to boost the firms' valuations (Brown et al. 2015; p. 19). Our findings are consistent with anecdotal evidence that managers want to "re-educate" analysts who have negative views on their firms (Brown et al. 2019).[51] We note that our findings can be contrasted with determinants of other *public* settings that include management discussions with analysts. For example, studies on public earnings conference calls document that the likelihood of analysts being called on increases with the favorableness of their recommendations (Mayew 2008; Cohen, Lou, and Malloy 2020). In the context of prior studies' findings, our results provide nuanced evidence that managers may use their discretion differently depending on the venues to control information flow in their favor. We further find that managers are less likely to communicate with analysts covering many other firms (analysts' limited resources to interact with an individual company) and analysts with greater forecast errors (managers' preferences toward analysts with industry knowledge). Moreover, we find that managers interact more when their stocks perform well in the market.

In the second column, we include *broker-month* and *year* fixed effects to explore whom the analysts/brokerages are more likely to communicate with among firms they cover in a given month.

[50] We identify the dates analysts *k* at brokerage *j* initiates or drops the coverage on firm *i* and then make a monthly panel at the firm-broker-analyst-level between these two dates.

[51] Brown et al. (2019) find survey evidence that investor relations officers are more likely to contact analysts if the recommendation revision is downgrade than upgrade.

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Consistent with the previous results, we find that analysts are more likely to interact with managers when the stocks perform well. We also find that analysts interact more with firms with shorter coverage history, consistent with analysts' incentives to develop a relationship with management. Along with the results in Section 5.1.3 that the benefits of private communications are greater for analysts with longer coverage history, the findings imply that face-to-face communications can play an important role in the development of trust between management and analysts, which facilitates the reciprocal sharing of information.

Overall, our determinant and cross-sectional analyses show that decisions to have taxi trips are jointly determined by time-varying and cross-sectionally different incentives that firms, brokers, and analysts face, reflecting that taxi rides are likely far from random. Therefore, as robustness checks, we repeat our analyses on the association between taxi rides and forecast errors and stock recommendation profitability after including all determinants of taxi rides as additional control variables. No inferences are affected (untabulated).

7. Conclusion

This study provides a novel way to capture face-to-face, unobservable private meetings between analysts and managers using taxi trip records. To identify such private meetings, we map the GPS coordinates of pick-up and drop-off records in New York City taxi datasets to those of companies and brokerages' addresses.

We first provide evidence on the construct validity of the taxi measures. We show that taxi rides significantly increase around earnings announcement dates (EAD) and that taxi ride patterns differ in terms of frequency conditional on whether brokerages publish research on the company. Collectively, the evidence shows that taxi rides explain sell-side analysts' increased information demands triggered by firm news.

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More importantly, employing multivariate regressions with strict fixed-effects structures, we find significant, negative (positive) associations between taxi ride volumes following EAD and analysts' forecast errors (analysts' stock recommendation profitability). Moreover, taxi ride volumes are positively significantly associated with the timeliness of analysts' earnings forecast following unanticipated 8-K disclosures. We also find that private communications can serve different purposes in different contexts. In particular, private communications immediately before EAD likely reflect managers' incentive to walk down the consensus. In determinant analyses, we further demonstrates that taxi rides between companies and brokers are positively associated with broker size and unfavorable recommendations, consistent with management's desire to reach out to a broad pool of institutional investors and increase stock valuation. Analysts are more likely to communicate with management when their coverage history is relatively short, consistent with analysts' incentives to develop relationships with management. Further, they interact more when the firm's stock performs well in the market.

A potential limitation of this study is that taxi rides may capture private communications with noise. Private communications can occur through various media, such as phone calls and emails, and taxi trips capture a subset of total private communications. However, it is worth noting that even this subset of private communications can explain the quality of analysts' research outputs in an economically meaningful way, implying that analysts and consumers of their research can benefit from private communications. The availability and granularity of taxi trip records also create opportunities for future research. By following a similar approach to this paper, future research can be extended to examine settings where private communications between key actors – managers, analysts, institutional investors, auditors, lenders, lawyers, rating agencies, regulators, standard setters, and others – are critical to understanding various business outcomes.

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Appendix 1: Multivariate Tests of Taxi Ride Patterns (Validity Test)

In this appendix, we provide additional evidence that taxi rides exhibit significant variations around EAD after controlling for seasonality in taxi rides by employing a linear model with multiple fixed effects at the day level. Model (3) is for firm-level analyses, and the model at the firm *i* and brokerage *j* level is defined similarly.

$$Log(Taxi_{it} + 1) = I[-5,-1]_{i,t} + I[0]_{i,t} + I[1,5]_{i,t} + \alpha NYC\ Taxi\ Rides_t + \alpha_{m(t)} + \alpha_{y(t)} + \alpha_i + e_{it} \quad \ldots (3)$$

To control for the nonlinearity of the count measure, $Taxi_{i,j,t}$, we take its natural log. Given that we previously observe that taxi rides increase in the week of EAD, we create indicator variables that capture variations in the week before EAD, on the day of earnings announcements, and the week after EAD; $I[-5,-1]_{i,t}$, $I[0]_{i,t}$, and $I[1,5]_{i,t}$, respectively.[52] We expect all coefficients of the window indicators to be positive. To control for the seasonality of taxi rides in NYC, we include *month* and *year fixed effects* in the model. We also include *firm* and *broker fixed effects* (*firm fixed effects*) for the firm-brokerage-level test (firm-level test) to control for time-invariant characteristics associated with the firm or broker location (e.g., high-traffic zones). Given this set of fixed effects, the interpretation of coefficients becomes whether taxi ride volumes in the 11-business day window surrounding the EAD deviate from the baseline for a given firm *i* or brokerage *j* within the same month and year. Last, we include $NYC\ Taxi\ Rides_t$, daily aggregate taxi ride volumes in the NYC borough, to control for daily supply and demand shocks that affect all taxi rides in NYC, such as weather. We cluster standard errors by firm and broker (firm) for the firm-brokerage-level test (firm-level test).

Table A1, Column (1) shows the regression results for the firm-level and Column (2) for the firm-brokerage-level. For brevity, we only present results for a subsample of brokerages having analyst coverage of the company and observe a 4.3% (2.1%) increase at the firm level (firm-broker level) in daily taxi ride volumes on EAD. Moreover, we find, in general, significant increases in taxi ride volumes a week before and after EAD.[53] Overall, our regression results show that it is unlikely that increases in taxi ride volumes around EAD are driven by general trends or a small set of firms and brokers.[54,55]

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[52] We map calendar business days to EADs by computing the difference in days from the nearest EADs. Therefore, all window variables are defined based on business days.

[53] While we do not find a significant coefficient for $I[1,5]_{i,t}$ for the firm-level analyses in Column (1), we find significant increases four and five business days after EAD when we disaggregate $I[1,5]_{i,t}$ into the five separate daily indicators (untabulated).

[54] Moreover, it is worth noting that the more modest increase in daily taxi ride volumes around EAD at the firm-brokerage-level compared to the increase at the firm level implies that firms interact with only a subset of brokerages around EAD. Thus, significant variations in taxi ride volumes within firm and broker provides an ideal setting to test the value of private communications.

[55] In untabulated tests, we examine taxi ride volumes undertaken during non-business hours, from 8 PM to 12 AM (Night) and from 12 AM to 7 AM (Morning). We generally find insignificant coefficients or negative coefficients

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Table A1. Daily Taxi Ride Patterns Around EAD

This table reports results of regressions of daily taxi ride volumes between companies and brokerages on the indicators mapped into the windows surrounding EAD. In Column (1), the firm-level dependent variable $Taxi_{i,t}$ aggregates the firm-broker-level taxi measures of brokerages that have the analyst coverage of company i. In Column (2), the firm-broker-level dependent variable, $Taxi_{i,j,t}$, is daily taxi ride volume between company i and brokerage j. $I[-5,-1]_{i,t}$, $I[0]_{i,t}$, and $I[1,5]_{i,t}$ are the indicators of whether date t falls in the specified EAD window $[lb, ub]$ of firm i, where a negative integer lb or ub indicates a day prior to the EAD, a positive integer indicating a day subsequent to the EAD, and 0 indicating EAD. The t-values, in parentheses, are based on two-tailed tests of significance. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are clustered by firm (firm and broker) for the firm-level (firm-brokerage-level) tests. All variable definitions can be found in Appendix 2.

Dependent Variable:	$Taxi_{i,t}$	$Taxi_{i,j,t}$
Unit of Observation	Firm-day	Firm-brokerage-day
Model:	(1)	(2)
Variables		
$I[-5,-1]_{i,t}$	0.008^{**}	0.006^{***}
	(2.21)	(2.30)
$I[0]_{i,t} = EAD$	0.043^{***}	0.021^{***}
	(5.53)	(4.70)
$I[1,5]_{i,t}$	0.003	0.007^{***}
	(.79)	(3.01)
$NYCTaxiRides_t$	0.044^{***}	0.012^{**}
	(4.70)	(2.47)
Fixed-effects		
$Firm$	Yes	Yes
$Broker$		Yes
$Year$	Yes	Yes
$Month$	Yes	Yes
Fit statistics		
Observations	256,988	2,204,817
R^2	0.839	0.393

using ride volumes during these hours, suggesting that most private communications between companies and brokers occur during working hours on business days.

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Appendix 2: Variable Descriptions

Variables	Variable Description
Taxi Variables – Validation and Determinant Tests	
$Taxi_{i,j,t}$	The log of the total number of taxi trips between firm *i* and brokerage *j* on date *t*.
Taxi Variables – Forecast Error and Recommendation Profitability Tests	
$Ch\ Abnormal\ Taxi_{i,j,t}$	The changes in ride volumes around the EAD compared to the benchmark ride volumes, where the benchmark period is defined as $EAD_{t-1} + 6$ (six business days past the EAD in the previous quarter) and $EAD_t - 6$ (six business days before the EAD in the current quarter).
$Taxi\ (Unscaled)_{\ i,j,t}$	The log of the total number of taxi trips between firm *i* and brokerage *j* during the EAD window.
$Taxi\ (Scaled\ -\ Company)_{\ i,j,t}$	The total number of taxi trips between firm *i* and brokerage *j* during the EAD window, deflated by the total number of taxi rides to or from firm *i*
$Taxi\ (Scaled\ -\ Company\ \times\ Broker)_{\ i,j,t}$	The total number of taxi trips between firm *i* and brokerage *j* during the EAD window, deflated by the sample mean number of taxi rides between firm *i* and brokerage *j*
$Taxi\ (Mean\ Unscaled)_{\ i,j,t}$	The log of the mean number of daily taxi trips between firm *i* and brokerage *j* during the EAD window.
Taxi Variables – Forecast Timeliness Tests	
$Ch\ Abnormal\ Taxi_{i,j,t}$	The changes in ride volumes around the unanticipated 8-K filings compared to the benchmark ride volumes, where the benchmark period is defined as [-12,-5] (eight days preceding the 8-K filing window).
Forecast Variables (Analyst-Firm-Forecast-Level)	
$Forecast\ Error_{i,j,k,t}$	The absolute value of the difference in analyst *k*' forecast values and actual earnings divided by the price at the beginning of period *t*.
$Horizon_{i,j,k,t+1}$	The log of the differences in days between forecast announcement dates and actual EAD
Recommendation Variables (Analyst-Firm-Recommendation-Level)	
$Profitability_{i,j,k,t+1}$	One-month buy-and-hold characteristic-adjusted returns constructed as in Daniel et al. (1997). The characteristic-adjusted returns are defined as raw returns minus the returns on a value-weighted portfolio of all CRSP firms in the same size, industry-adjusted market-to-book, and 1-year momentum quintiles.
Forecast Timeliness Variables (Analyst-Firm-Unanticipated 8-K Filings-Level)	
$Timely\ Revision_{i,j,k,t}$	An indicator that analyst *k* updates forecasts for firm *i* between the event date and three days after the filing date (i.e., [0,3])
Walk-down Forecast Variables (Analyst-Firm-EAD-Level)	

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$Below\ Consensus\ Revision_{i,j,k,t}$	An indicator that analyst k adjusts near-term earnings forecasts below the current consensus during the pre-EAD window [-5, -1].
Explanatory Variables (Firm-Level)	
$NYC\ Taxi\ Rides_t$	The log of the total taxi rides volumes in the NYC boroughs that firm *i* belongs on date *t*.
$I[lb, ub]_{i,t}$	An indicator that date *t* falls in an event window [lb, ub] of firm *i*.
$N8-KItems_{i,t}$	The log of the total number of firm *i*'s 8-K items disclosed during period *t*.
$Guidance_{i,t}$	The log of the total number of firm *i*'s management earnings forecasts issued during period *t*.
$InvestorConference_{i,t}$	An indicator that the firm holds an investor conference during period *t*.
$Analyst/InvestorDay_{i,t}$	An indicator that the firm holds an analyst/investor day during period *t*.
$Size_{i,t}$	The log of firm *i*' market value.
$Volatility_{i,t}$	The standard deviation of firm *i*'s stock returns during period *t*.
$EADReturn_{i,t}$	The cumulative market-adjusted returns during the window [-2,2] surrounding EAD.
$Return_{i,t}$	The accumulated market-adjusted returns of firm *i* during period *t*.
$NFollow_{i,t}$	The log of the total number of analysts issuing earnings forecasts on firm *i* during period *t*.
$InstitutionalOwnership_{i,t}$	The percentage of institutional holdings of firm *i* during period *t*.
$Turnover_{i,t}$	The median value of trading volume divided by shares outstanding during period *t*.
$Intangible_{i,t}$	Recognized intangibles plus goodwill divided by total assets at the end of the prior fiscal period.
$R\&D_{i,t}$	Research and development expenses divided by total assets at the end of the prior fiscal period.
Explanatory Variables (Analyst-Firm-Level)	
$PriorForecastErrors_{i,j,k,t}$	Analyst *k*'s realized forecast errors for the latest fiscal quarter of firm *i*.
$UnfavRecommendation_{i,j,k,t}$	An indicator that the outstanding recommendation on firm *i* by analyst *k* is "HOLD," "SELL," or "STRONG SELL."
$CovHistory_{i,j,k,t}$	The log number of days that analyst *k* covers firm *i*
Explanatory Variables (Broker- or Analyst-Level)	
$BrokerSize_{j,k,t}$	The log number of analysts employed by brokerage *j*.
$NCoverage_{j,k,t}$	The log number of firms analyst *k* are covering.
$Experience_{j,k,t}$	The log number of the working experience of analyst *k*.

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Appendix 3: Predictions for Determinants Analyses

Drawing on prior literature on private meetings with analysts and institutional investors, we motivate variables that proxy for the incentives and resources that firms and analysts have. First, we expect that firms with a higher percentage of shares held by institutions, $InstitutionalOwnership_{i,t}$, will have fewer in-person private meetings with analysts. Such firms likely allocate more time to interacting with their institutional investors to meet their demands (Bushee and Miller 2012; Kirk and Vincent 2014).[56] In a similar vein, we expect firms with a higher level of analyst following ($NFollow_{i,t}$) to have fewer interactions with individual analysts, as the greater number of analysts following crowds out managers' available time for private meetings with individual analysts. Likewise, we expect that the more firms analysts cover ($NCoverage_{j,k,t}$), the less time they will spend on communicating with an individual firm they are covering.

Second, firms that are performing well in the stock market likely attract more attention from the members of the investment community, which in turn may increase their demands to meet with managers. Therefore, we expect a positive association between $Return_{i,t}$ (accumulated market-adjusted returns) and $Taxi_{i,j,t+1}$.[57] We also expect the information demand to increase for hard-to-value firms. Thus, we predict positive effects for $R\&D_{i,t}$ and $Intangible_{i,t}$. Furthermore, we expect managers' incentives to privately communicate to increase when firm returns are volatile ($Volatility_{i,t}$).

Third, analysts likely prefer to have private meetings with managers when there are changes in the firm's information environment (e.g., Soltes 2014). We include two proxies for firm-initiated information events: the log of the number of management earnings forecasts ($Guidance_{i,t}$) and the log of the number of 8-K items ($N8-KItems_{i,t}$). We expect all these variables to be positively associated with $Taxi_{i,j,t+1}$.[58] In contrast, we predict negative associations between public events that may allow for private communications, such as $Analyst/InvestorDay_{i,t}$ and $InvestorConference_{i,t}$, and $Taxi_{i,j,t+1}$, as such public events could satisfy analysts' demands to privately communicate with management.

Fourth, developing a good relationship with management is critical to success as a sell-side analyst (Brown et al. 2015). Accordingly, we expect analysts' incentives to privately communicate with managers to increase when the length of the coverage relationship between analysts and the company, $CovHistory_{i,j,k,t}$, is relatively short. Studies also show that analysts are more likely to cover firms with

[56] This prediction is not without tension. It is possible that analysts may try harder to hold private meetings with firms with high $InstitutionalOwnership_{i,t}$, as they have economic incentives to meet buy-side clients' information demands.

[57] However, it is also possible that poorer performing firms in the stock market may face more questions about their performance (Cohen et al. 2020), resulting in a negative association.

[58] However, the opposite direction is also possible; that is, a greater number of public disclosures could crowd out the available time for private meetings and analysts' needs to privately communicate with managers (Bushee et al. 2018).

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high share turnover to maximize turnover-based commission. Therefore, we expect analysts to interact more with firms with high turnover ($Turnover_{i,t}$). Moreover, managers prefer to communicate with analysts who possess considerable industry knowledge (Brown et al. 2019). To proxy for analysts' industry knowledge, we include $Experience_{j,k,t}$, which is the log number of the working experience of analyst k, and $PriorForecastErrors_{i,j,k,t}$, which is the analyst's realized forecast errors for the firm's latest fiscal period.

Fifth, we examine whether analysts with unfavorable recommendations on firms have more interactions with management. One investor relations office Brown et al. (2019, p. 70) interviewed described how to deal with analysts who have a negative view of the company, saying, "When an analyst has a 'sell' on us, I view that as an opportunity to re-educate that person on us."[59] In a similar vein, an analyst in Brown et al. (2015, p. 19) noted, "Management will call the analysts who are at the low end of their valuation if they want the stock to move up." Therefore, we expect managers' incentives to communicate with the analysts with unfavorable recommendations on their companies to increase. This expectation is not without tension. One stream of the literature suggests that analysts with unfavorable stock recommendations have information disadvantages due to their limited access to management (Chen and Matsumoto 2006; Mayew 2008; Brown et al. 2015).[60] For example, an analyst in Brown et al. (2015; p.37) described an experience in which company management canceled an already-scheduled roadshow with the analyst immediately after the analyst lowered his stock recommendation for the company. We include an indicator variable, $UnfavRecommendation_{i,j,k,t}$, which is equal to one if outstanding recommendation on firm i by analyst k is "HOLD," "SELL," or "STRONG SELL."

Finally, we include two variables to control for the resources available to managers and analysts for holding private meetings. We include firm size, measured as the log of the firms' market value ($Size_{i,t}$), because firm size is related to the establishment of a professional IR department (Kirk and Vincent 2014). Similarly, we include $BrokerSize_{j,t}$, the log number of analysts employed by brokerage j. Broker-hosted investor conferences are more likely to be hosted by larger brokerage houses (Green et al. 2014), suggesting that analysts from larger brokerage have better access to management. Therefore, we predict a positive relation between $BrokerSize_{j,t}$ and $Taxi_{i,j,t+1}$.

[59] Consistent with this view, Brown et al. (2019) find that following a stock recommendation revision, investor relations officers are more likely to contact analysts if the revision is downgrade than upgrade.

[60] However, Chen and Matsumoto (2006) find limited evidence in the post-Reg FD period that analysts with favorable recommendation enjoy information advantages. Moreover, Mayew (2008)'s setting is different from our setting in that he examines whether analysts with favorable recommendations are more likely to ask questions during *public* earnings conference calls.

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Figures and Tables

Figure 1. Taxi Ride Patterns around EAD and Corporate Events

The graphs in Panel A show the quarterly pattern of the weekly mean taxi ride volume at the firm level. Window = 0 on the x-axis is the week that a company releases its earnings. Lines indicate smooth local regression. Coverage = 1 (Coverage = 0) indicates taxi rides between companies and brokers that (do not) publish reports on the companies.

Panel A: Weekly Taxi Ride Patterns around EAD

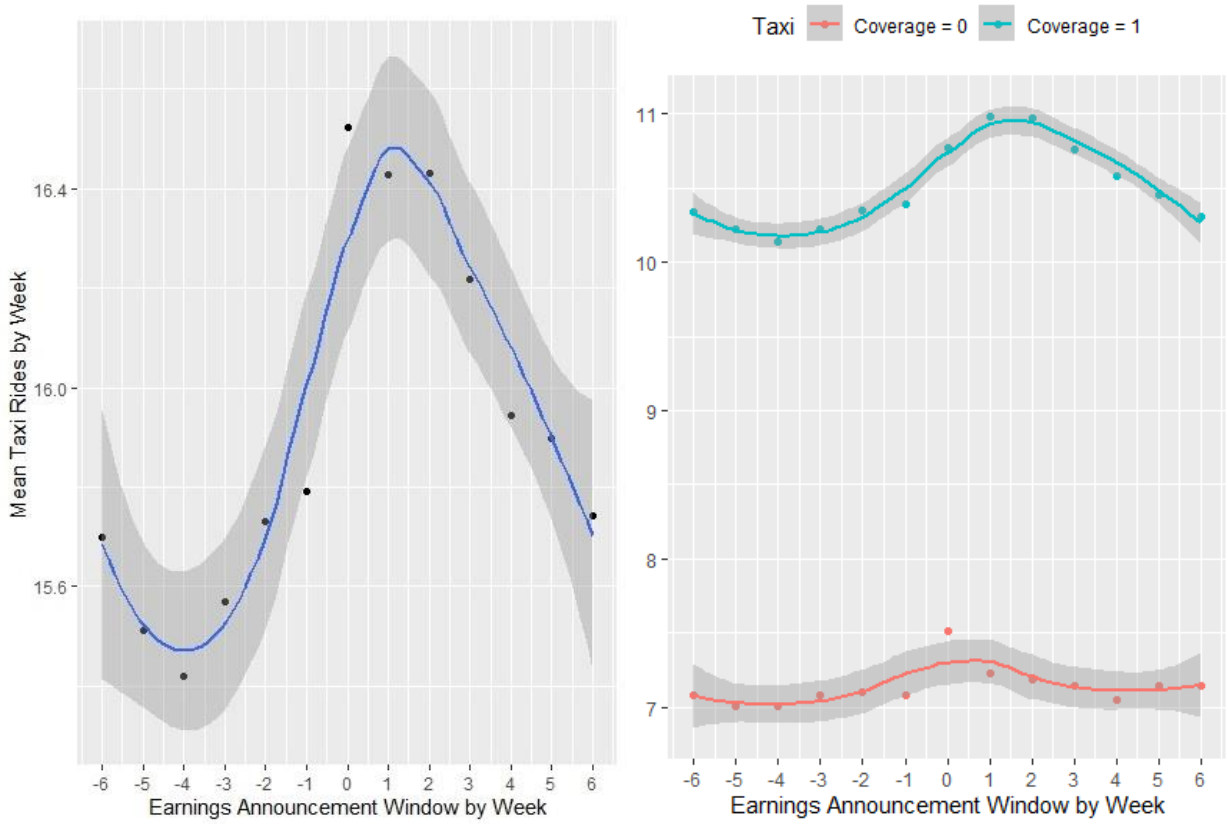

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Figure 2. Timeline of Tests

This figure plots the relevant time periods for the forecast accuracy tests. For the analyses on the [0, 5] window surrounding EAD, we aggregate taxi ride volumes from EAD event day to EAD event day +5 ($Taxi_{i,j,t}$), where we restrict the taxi rides to those occurring during business days and business hours. To capture abnormal ride volumes around EAD, we compare $Taxi_{i,j,t}$ with normalized ride volumes during the benchmark non-EAD period ($Taxi\ Benchmark_{i,j,t}$), which spans days from $EAD_{t-1} + 6$ (six business days past the EAD in the previous quarter) to $EAD_t - 6$ (six business days before the EAD in the current quarter). $Ch\ Abnormal\ Taxi_{i,j,t}$ is then defined as changes in ride volumes compared to aggregate ride volumes undertaken during the benchmark non-EAD periods. We take analysts' earliest forecasts that are issued following the EAD window for a given firm but are issued no later than a month subsequent to the window. We define forecast errors as the absolute value of the difference in analysts' forecast values and actual earnings divided by the price at the beginning of the quarter. The timeline for the analyses on the [-5, -1] windows surrounding EAD is defined similarly.

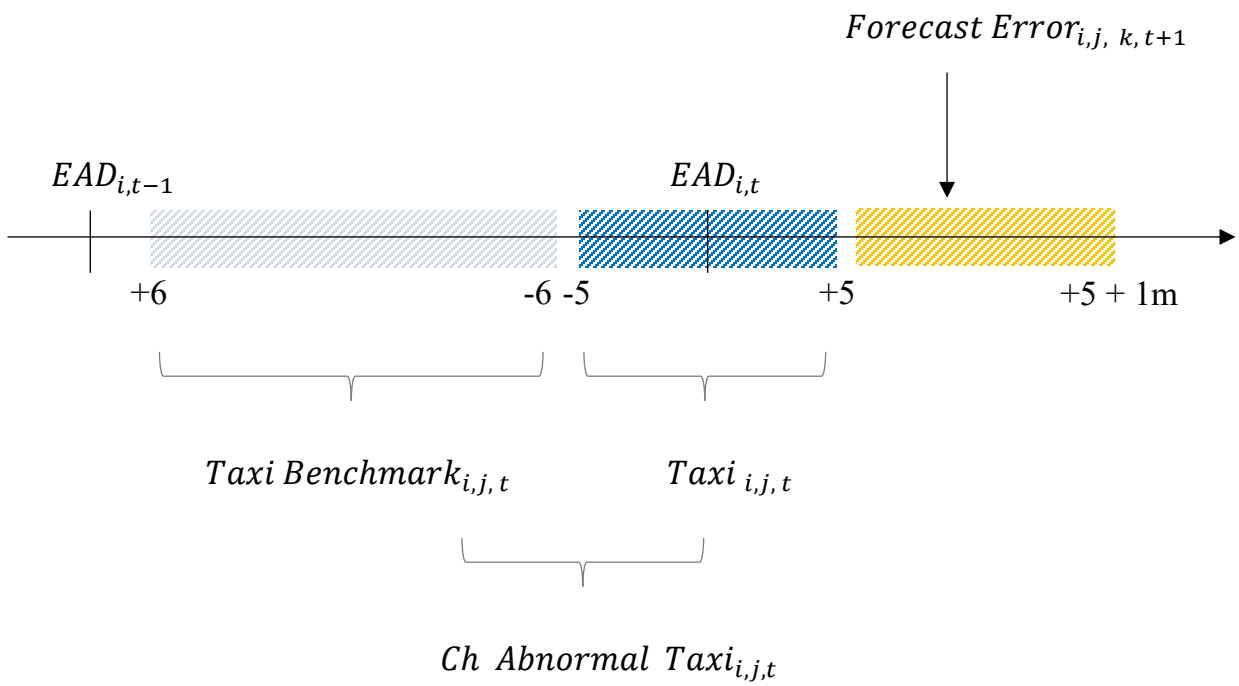

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Table 1. Daily Taxi Ride Patterns Around Corporate Events

This table reports results of regressions of daily taxi ride volumes between companies and brokerages on the indicators mapped into the windows surrounding corporate events. The dependent variable, $Taxi_{i,j,t}$, is daily taxi ride volume between company i and brokerage j. $I[-5,-1]_{i,t}$, $I[0]_{i,t}$, and $I[1,5]_{i,t}$ are the indicators of whether date t falls in the specified window $[lb, ub]$ of firm i, where a negative integer lb or ub indicates a day prior to the event, a positive integer indicating a day subsequent to the event, and 0 indicating EAD. In Columns (1) to (3), the sample include 21 days around investor conferences and analyst/investor days, annual shareholder meetings, and board meetings respectively. The t-values, in parentheses, are based on two-tailed tests of significance. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are clustered by firm and broker. All variable definitions can be found in Appendix 1.

Dependent Variable:		$Taxi_{i,j,t}$	
Corporate Events:	Investor Conferences & Analyst/Investor Days	Shareholder Meeting	Board Meeting
Model:	(1)	(2)	(3)
$I[-5,-1]_{i,t}$	-0.002	0.012	0.016
	(-0.588)	(1.093)	(0.520)
$I[0]_{i,t} = EventDate$	0.028 ***	0.019	-0.044 **
	(4.823)	(1.393)	(-2.421)
$I[1,5]_{i,t}$	0.018 ***	-0.000	0.020
	(5.013)	(-0.037)	(0.615)
Controls and Fixed-effects			
$NYCTaxiRides_t$	Yes	Yes	Yes
$Firm$ FE	Yes	Yes	Yes
$Broker$ FE	Yes	Yes	Yes
$Month$ FE	Yes	Yes	Yes
$Year$ FE	Yes	Yes	Yes
Fit statistics			
Observations	310,451	43,587	1,619
Adjusted R^2	0.409	0.414	0.311

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Table 2. Descriptive Statistics

Panel A reports descriptive statistics for the forecast error tests. The unit of observation is firm-quarter-analyst-forecast. Variables are shown after logs are taken. Panel B reports Pearson correlations between variables used in the forecast error tests. Asterisks denote significance levels at 5% or higher. All variable definitions are in Appendix 2.

Panel A: Summary Statistics for the Forecast Error Tests

Variables	Valid N	Mean	Median	25th	75th	St. Deviation
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$	18564	0.0097	0.0000	-0.0403	0.0337	0.0920
$Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$	18564	0.0076	-0.0002	-0.0370	0.0310	0.0811
$ForecastErrors_{i,j,k,t+1}$	18564	0.0276	0.0053	0.0017	0.0167	0.0848
$Horizon_{i,j,k,t+1}$	18564	5.6791	5.8141	5.0999	6.3351	0.8511
$PriorForecastErrors_{i,j,k,t}$	18564	0.2387	0.0020	0.0007	0.0056	9.9568
$EADReturn_{i,t}$	18564	0.0000	-0.0020	-0.0350	0.0321	0.0678
$Volatility_{i,t}$	18564	0.0252	0.0192	0.0134	0.0298	0.0184
$Guidance_{i,t}$	18564	0.1849	0.0000	0.0000	0.0000	0.3590
$N8-KItems_{i,t}$	18564	1.1105	1.0986	1.0986	1.6094	0.6387
$InvestorConference_{i,t}$	18564	0.2806	0.0000	0.0000	1.0000	0.4493
$Analyst/InvestorDay_{i,t}$	18564	0.0044	0.0000	0.0000	0.0000	0.0659
$NFollow_{i,t}$	18564	2.5745	2.7081	2.1972	3.0445	0.5966
$NCoverage_{k,t}$	18564	2.7562	2.8332	2.4849	3.0910	0.4535
$Experience_{k,t}$	18564	2.0600	2.2957	1.7237	2.5075	0.5914
$CovHistory_{i,j,k,t}$	18564	1.4267	1.4113	0.8418	1.9944	0.6888
$BrokerSize_{j,t}$	18564	3.8400	4.1589	3.3673	4.3820	0.7966

Panel B: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$															
(2)$Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$	0.16*														
(3)$ForecastErrors_{i,j,k,t+1}$	-0.02*	0.01													
(4)$Horizon_{i,j,k,t+1}$	0.02*	0.01	0.13*												
(5)$PriorForecastErrors_{i,j,k,t}$	0.00	-0.01	0.15*	-0.01											
(6)$EADReturn_{i,t}$	0.00	0.01	-0.03*	0.01*	0.05*										
(7)$Volatility_{i,t}$	0.06*	0.01	0.29*	-0.01	0.08*	0.04*									
(8)$Guidance_{i,t}$	0.02*	0.00	-0.11*	0.03*	-0.01	0.01	-0.10*								
(9)$N8-KItems_{i,t}$	0.02*	0.00	0.05*	-0.03*	0.01	0.02*	0.09*	-0.56*							
(10)$InvestorConference_{i,t}$	-0.01	-0.01	-0.04*	-0.01	-0.01	0.00	-0.11*	-0.03*	0.13*						
(11)$Analyst/InvestorDay_{i,t}$	0.01	-0.02*	-0.01	-0.01	0.00	-0.04*	0.05*	-0.02*	-0.05*	-0.02*					
(12)$NFollow_{i,t}$	-0.03*	0.00	-0.16*	0.00	-0.02*	0.01	-0.20*	0.14*	-0.14*	0.16*	0.01				
(13)$NCoverage_{k,t}$	-0.03*	0.00	0.08*	-0.02*	0.00	-0.03*	0.04*	-0.11*	0.09*	0.00	0.00	-0.06*			
(14)$Experience_{k,t}$	0.00	-0.01	-0.01	-0.02*	0.01	-0.06*	-0.07*	0.05*	-0.03*	0.06*	0.00	0.11*	0.29*		
(15)$CovHistory_{i,j,k,t}$	0.00	-0.01	-0.04*	-0.02*	0.02*	-0.05*	-0.09*	0.05*	0.00	0.07*	0.01	0.21*	0.17*	0.56*	
(16)$BrokerSize_{j,t}$	-0.02*	0.01	-0.02*	0.02*	0.00	0.00	-0.06*	-0.01	0.06*	0.03*	-0.01	-0.04*	0.03*	-0.10*	-0.04*

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Table 3. Forecast Errors and Taxi Ride Volumes around EAD

This table reports the results of regressions of analysts' forecast errors on taxi ride volumes around EAD between companies and brokerages. The unit observation is firm-quarter-analyst-forecast. The dependent and independent variables are defined based on the timeline provided in Figure 2. In Panel A, C, and D, forecast errors are defined based on the earliest forecasts issued following the EAD window, whereas in Panel B, the sample includes forecast errors of all the latest earnings forecasts for a given horizon that are outstanding right before EAD. $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ ($Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$) is changes in ride volumes during the window [0, 5] ([-5, -1]) surrounding EAD, relative to its preceding non-EAD periods. In Panel A, Columns (1) to (4) report results using $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ as a test variable, whereas Columns (5) to (8) report results using alternative definitions of taxi variables. Panel B reports the results of regressions of analysts' forecast errors before EAD on taxi ride volumes around EAD. Panel C reports the cross-sectional results. The continuous variables in the interaction terms are mean-centered (Aiken, West, and Reno 1991). Panel D examines taxi rides that are further decomposed into those undertaken before EAD and after EAD. The t-values in parentheses are based on two-tailed tests of significance. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are clustered by analysts. All variable definitions are in Appendix 2.

Panel A: Forecast Errors and Taxi Ride Volumes during the [0,5] EAD Window

Dependent Variable:	$ForecastErrors_{i,j,k,t+1}$							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$	-0.018 *	-0.022 **	-0.022 **	-0.020 *				
	(-1.862)	(-2.177)	(-2.225)	(-1.834)				
$Taxi[0,5]_{i,j,t}(Unscaled)$					-0.004 ***			
					(-2.617)			
$Taxi[0,5]_{i,j,t}(Scaled - Company)$						-1.423 **		
						(-2.491)		
$Taxi[0,5]_{i,j,t}(Scaled - Company \times Broker)$							-0.002 **	
							(-1.971)	
$Taxi[0,5]_{i,j,t}(Mean\ Unscaled)$								-0.010 ***
								(-2.906)
$Horizon_{i,j,k,t+1}$		0.015 ***	0.015 ***	0.015 ***	0.015 ***	0.015 ***	0.015 ***	0.015 ***
		(11.424)	(11.566)	(11.052)	(11.533)	(11.534)	(11.541)	(11.533)
$PastForecastErrors_{i,j,k,t}$		0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***
		(3.773)	(3.776)	(4.646)	(3.770)	(3.765)	(3.792)	(3.764)
$EADReturn_{i,t}$		-0.027	-0.025	-0.015	-0.025	-0.024	-0.024	-0.024
		(-1.437)	(-1.358)	(-0.719)	(-1.338)	(-1.313)	(-1.331)	(-1.333)
$Volatility_{i,t}$		0.702 ***	0.701 ***	0.676 ***	0.699 ***	0.697 ***	0.698 ***	0.699 ***
		(4.753)	(4.768)	(4.139)	(4.757)	(4.746)	(4.754)	(4.761)
$Guidance_{i,t}$		0.001	0.002	0.000	0.001	0.001	0.001	0.002
		(0.278)	(0.472)	(0.058)	(0.372)	(0.315)	(0.344)	(0.441)
$N8-KItems_{i,t}$		0.002	0.003	-0.000	0.002	0.002	0.002	0.002
		(1.121)	(1.163)	(-0.158)	(1.102)	(1.081)	(1.142)	(1.111)
$InvestorConference_{i,t}$		-0.003	-0.003	-0.004	-0.003	-0.003	-0.003	-0.003
		(-1.287)	(-1.288)	(-1.463)	(-1.167)	(-1.226)	(-1.233)	(-1.159)
$Analyst/InvestorDay_{i,t}$		-0.049 ***	-0.048 ***	-0.041 ***	-0.048 ***	-0.047 ***	-0.048 ***	-0.047 ***
		(-3.528)	(-3.480)	(-2.620)	(-3.554)	(-3.351)	(-3.434)	(-3.567)
$NFollow_{i,t}$		-0.021 ***	-0.020 ***	-0.019 ***	-0.020 ***	-0.020 ***	-0.020 ***	-0.020 ***
		(-3.983)	(-3.779)	(-2.683)	(-3.724)	(-3.736)	(-3.770)	(-3.695)
$NCoverage_{k,t}$			0.006	0.007	0.006	0.006	0.006	0.006
			(1.235)	(1.581)	(1.270)	(1.243)	(1.244)	(1.294)
$Experience_{k,t}$			-0.003	-0.012 **	-0.004	-0.003	-0.003	-0.004
			(-0.344)	(-2.176)	(-0.367)	(-0.341)	(-0.293)	(-0.410)
$CovHistory_{i,j,k,t}$			0.007 **	0.011 **	0.007 *	0.007 *	0.007 *	0.007 *

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			(1.981)	(2.184)	(1.910)	(1.948)	(1.942)	(1.935)
$BrokerSize_{j,t}$			0.006 **	0.007	0.007 **	0.006 **	0.006 **	0.007 **
			(2.034)	(0.911)	(2.346)	(2.251)	(2.060)	(2.361)
Fixed-effects								
$Firm$	Yes	Yes	Yes		Yes	Yes	Yes	Yes
$Analyst$	Yes	Yes	Yes		Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Firm \times Broker$				Yes				
Fit statistics								
Observations	18,564	18,564	18,564	18,564	18,564	18,564	18,564	18,564
Adjusted R^2	0.471	0.515	0.516	0.541	0.516	0.515	0.515	0.516

Panel B: Test for Potential Reverse Causality

Dependent Variable:	$ForecastErrors_{i,j,k,t+1}$ Before EAD			
Model:	(1)	(2)	(3)	(4)
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$	0.877	-0.038	-0.032	-0.064
	(1.152)	(-0.148)	(-0.126)	(-0.255)
$Horizon_{i,j,k,t}$		-0.017	-0.017	-0.016
		(-0.913)	(-0.905)	(-0.879)
$PastForecastErrors_{i,j,k,t}$		0.306 ***	0.306 ***	0.306 ***
		(8.977)	(8.977)	(8.727)
$EADReturn_{i,t}$		0.497 **	0.500 **	0.542 **
		(2.032)	(2.059)	(2.303)
$Volatility_{i,t}$		6.680 ***	6.704 ***	6.869 ***
		(3.049)	(3.055)	(3.088)
$Guidance_{i,t}$		-0.021	-0.022	0.040
		(-0.672)	(-0.686)	(1.554)
$N8-KItems_{i,t}$		0.020	0.020	0.015
		(0.744)	(0.762)	(0.698)
$InvestorConference_{i,t}$		-0.005	-0.003	-0.004
		(-0.426)	(-0.274)	(-0.283)
$Analyst/InvestorDay_{i,t}$		-0.109 ***	-0.107 ***	-0.125 ***
		(-3.761)	(-3.632)	(-3.076)
$NFollow_{i,t}$		-0.471 ***	-0.472 ***	-0.714 ***
		(-4.049)	(-4.052)	(-3.290)
$NCoverage_{k,t}$			0.075	0.057
			(1.304)	(1.204)
$Experience_{k,t}$			0.064	-0.117
			(0.572)	(-1.594)
$CovHistory_{i,j,k,t}$			0.008	0.081 *
			(0.283)	(1.736)
$BrokerSize_{j,t}$			0.027	0.180 *
			(0.816)	(1.756)
Fixed-effects				
$Firm$	Yes	Yes	Yes	
$Analyst$	Yes	Yes	Yes	
$Year$	Yes	Yes	Yes	Yes
$Firm \times Broker$				Yes
Fit statistics				
Observations	180,138	180,138	180,138	180,138
Adjusted R^2	0.068	0.361	0.361	0.360

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Table 3. Forecast Errors and Taxi Ride Volumes around EAD (Continued)

Panel C: Cross-Sectional Analyses (Coverage History)

Dependent Variable:	$ForecastErrors_{i,j,k,t+1}$		
Model:	(1)	(2)	(3)
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t} \times CovHistory_{i,j,k,t}$	-0.033 ***	-0.034 ***	-0.026 **
	(-2.845)	(-2.751)	(-2.025)
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$	-0.019 **	-0.018 **	-0.018 *
	(-2.011)	(-1.996)	(-1.675)
$CovHistory_{i,j,k,t}$	0.003	0.007 **	0.012 **
	(1.573)	(2.003)	(2.204)
$Horizon_{i,j,k,t+1}$	0.015 ***	0.015 ***	0.015 ***
	(11.510)	(11.548)	(11.043)
$PastForecastErrors_{i,j,k,t}$	0.001 ***	0.001 ***	0.001 ***
	(2.759)	(3.807)	(4.646)
$EADReturn_{i,t}$	-0.022	-0.024	-0.015
	(-1.184)	(-1.297)	(-0.695)
$Volatility_{i,t}$	0.782 ***	0.698 ***	0.673 ***
	(5.682)	(4.774)	(4.140)
$Guidance_{i,t}$	0.003	0.002	0.000
	(0.917)	(0.527)	(0.084)
$N8-KItems_{i,t}$	-0.000	0.003	-0.001
	(-0.119)	(1.175)	(-0.166)
$InvestorConference_{i,t}$	-0.003	-0.003	-0.004
	(-1.457)	(-1.395)	(-1.525)
$Analyst/InvestorDay_{i,t}$	-0.047 ***	-0.048 ***	-0.041 ***
	(-3.721)	(-3.542)	(-2.616)
$NFollow_{i,t}$	-0.021 ***	-0.021 ***	-0.019 ***
	(-3.828)	(-3.837)	(-2.715)
$NCoverage_{k,t}$	0.003	0.006	0.008 *
	(1.150)	(1.312)	(1.677)
$Experience_{k,t}$	-0.002	-0.004	-0.012 **
	(-1.045)	(-0.367)	(-2.205)
$BrokerSize_{j,t}$	0.003 **	0.005 *	0.007
	(2.308)	(1.938)	(0.931)
Fixed-effects			
$Firm$	Yes	Yes	
$Year$	Yes	Yes	Yes
$Analyst$		Yes	
$Firm \times Broker$			Yes
Fit statistics			
Observations	18,564	18,564	18,564
Adjusted R^2	0.473	0.516	0.541

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Table 3. Forecast Errors and Taxi Ride Volumes around EAD (Continued)

Panel D: Post-EAD Meetings vs. Pre-EAD Meetings

Dependent Variable:	$ForecastErrors_{i,j,k,t+1}$			
Model:	(1)	(2)	(3)	(4)
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$	-0.017 *	-0.021 **	-0.021 **	-0.019 *
	(-1.781)	(-2.153)	(-2.218)	(-1.846)
$Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$	-0.005	-0.004	-0.003	-0.006
	(-0.338)	(-0.348)	(-0.261)	(-0.553)
$Horizon_{i,j,k,t+1}$		0.015 ***	0.015 ***	0.015 ***
		(11.423)	(11.564)	(11.058)
$PastForecastErrors_{i,j,k,t}$		0.001 ***	0.001 ***	0.001 ***
		(3.741)	(3.746)	(4.588)
$EADReturn_{i,t}$		-0.027	-0.025	-0.015
		(-1.441)	(-1.362)	(-0.721)
$Volatility_{i,t}$		0.702 ***	0.701 ***	0.676 ***
		(4.749)	(4.764)	(4.132)
$Guidance_{i,t}$		0.001	0.002	0.000
		(0.293)	(0.485)	(0.067)
$N8-KItems_{i,t}$		0.002	0.003	-0.000
		(1.136)	(1.175)	(-0.152)
$InvestorConference_{i,t}$		-0.003	-0.003	-0.004
		(-1.286)	(-1.286)	(-1.461)
$Analyst/InvestorDay_{i,t}$		-0.049 ***	-0.048 ***	-0.041 ***
		(-3.559)	(-3.507)	(-2.632)
$NFollow_{i,t}$		-0.021 ***	-0.020 ***	-0.019 ***
		(-3.988)	(-3.783)	(-2.702)
$NCoverage_{k,t}$			0.006	0.007
			(1.231)	(1.575)
$Experience_{k,t}$			-0.004	-0.012 **
			(-0.354)	(-2.174)
$CovHistory_{i,j,k,t}$			0.007 **	0.011 **
			(1.978)	(2.173)
$BrokerSize_{j,t}$			0.006 **	0.007
			(2.037)	(0.907)
Fixed-effects				
$Firm$	Yes	Yes	Yes	
$Analyst$	Yes	Yes	Yes	
$Year$	Yes	Yes	Yes	Yes
$Firm \times Broker$				Yes
Fit statistics				
Observations	18,564	18,564	18,564	18,564
Adjusted R^2	0.471	0.515	0.516	0.541

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Table 4. Forecast Walk-Down and Pre-EAD Taxi Ride Volumes

This table reports the regressions of analysts' adjustment of near-term earnings forecasts below consensus on taxi ride volumes before EAD between companies and brokerages. The unit observation is firm-quarter-analyst. $Below\ Consensus\ Revision_{i,j,k,t}$ is equal to one if analysts adjust near-term earnings forecasts below the current consensus during the pre-EAD window [-5, -1]. $Ch\ Abnormal\ Taxi[-5,-1]_{i,j,t}$ is changes in ride volumes during the window [-5, -1] surrounding EAD, relative to its preceding non-EAD periods (see Figure 2 for its construction). The t-values in parentheses are based on two-tailed tests of significance. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are clustered by analysts. All variable definitions are in Appendix 2.

Dependent Variable:	$Below\ Consensus\ Revision_{i,j,k,t}$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$ChAbnormalTaxi[-5,-1]_{i,j,t}$	0.032 *	0.031 *	0.031 *	0.039 **	0.038 **	0.038 **
	(1.806)	(1.747)	(1.744)	(2.029)	(1.975)	(1.988)
$Above\ Consensus_{i,j,k,t}$		0.012 ***	0.012 ***		0.011 ***	0.011 ***
		(3.514)	(3.504)		(3.341)	(3.321)
$EADReturn_{i,t}$		-0.005	-0.005		-0.009	-0.009
		(-0.286)	(-0.295)		(-0.509)	(-0.497)
$Volatility_{i,t}$		0.352 ***	0.352 ***		0.373 ***	0.373 ***
		(3.193)	(3.191)		(3.177)	(3.190)
$Guidance_{i,t}$		0.007	0.008		0.008	0.008
		(0.844)	(0.875)		(0.826)	(0.843)
$N8-KItems_{i,t}$		0.008 **	0.008 **		0.008 **	0.008 **
		(2.187)	(2.181)		(2.002)	(2.014)
$InvestorConference_{i,t}$		-0.002	-0.002		-0.003	-0.003
		(-0.560)	(-0.573)		(-0.718)	(-0.697)
$Analyst/InvestorDay_{i,t}$		0.103 **	0.103 **		0.106 **	0.106 **
		(2.474)	(2.488)		(2.409)	(2.416)
$NFollow_{i,t}$		-0.003	-0.003		-0.001	-0.001
		(-0.331)	(-0.338)		(-0.112)	(-0.129)
$NCoverage_{k,t}$			0.008			0.007
			(1.506)			(1.234)
$Experience_{k,t}$			-0.021			-0.006
			(-1.223)			(-0.779)
$CovHistory_{i,j,k,t}$			-0.000			-0.003
			(-0.143)			(-0.478)
$BrokerSize_{j,t}$			-0.010 *			-0.005
			(-1.676)			(-0.314)
Fixed-effects						
$Firm$	Yes	Yes	Yes			
$Analyst$	Yes	Yes	Yes			
$Year$	Yes	Yes	Yes	Yes	Yes	Yes
$Firm \times Broker$				Yes	Yes	Yes
Fit statistics						
Observations	18,912	18,912	18,912	18,912	18,912	18,912
Adjusted R^2	0.052	0.054	0.055	0.046	0.049	0.049

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Table 5. Recommendation Profitability and Taxi Ride Volumes around EAD

Panel A reports descriptive statistics for the recommendation profitability tests. The unit of observation is firm-quarter-analyst-recommendation change. Variables are shown after logs are taken. Panel B reports the results of regressions of analysts' recommendation profitability on taxi ride volumes around EAD between companies and brokerages. The EAD window is defined as [0,5] surrounding EAD. $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ is changes in ride volumes during the window [0, 5] surrounding EAD, relative to its preceding non-EAD periods. In Panel A, Columns (1) to (4) report results using $Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$ as a test variable, whereas Columns (5) to (8) report results using alternative definitions of taxi variables. The dependent variable is $Profitability_{i,j,k,t+1}$, which is one-month buy-and-hold characteristic-adjusted returns constructed as in Daniel et al. (1997). Standard errors are clustered by analysts. All variable definitions are in Appendix 2.

Panel A: Summary Statistics for the Recommendation Profitability Tests

Variables	Valid N	Mean	Median	25th	75th	St. Deviation
$ChAbnormalTaxi[0,5]_{i,j,t}$	1784	0.0106	0.0000	-0.0451	0.0374	0.1008
$Profitability_{i,j,k,t+1}$	1784	0.0060	0.0037	-0.0337	0.0428	0.0836
$EADReturn_{i,t}$	1784	-0.0049	-0.0052	-0.0434	0.0352	0.0811
$Volatility_{i,t}$	1784	0.0276	0.0227	0.0147	0.0337	0.0193
$Guidance_{i,t}$	1784	0.2238	0.0000	0.0000	0.6931	0.3833
$N8-KItems_{i,t}$	1784	1.0897	1.0986	1.0986	1.6094	0.6450
$InvestorConference_{i,t}$	1784	0.2713	0.0000	0.0000	1.0000	0.4448
$Analyst/InvestorDay_{i,t}$	1784	0.0034	0.0000	0.0000	0.0000	0.0579
$NFollow_{i,t}$	1784	2.7999	2.8904	2.5649	3.1355	0.4663
$NCoverage_{j,k,t}$	1784	2.7796	2.8332	2.4849	3.0910	0.4584
$Experience_{j,k,t}$	1784	2.0444	2.3224	1.7064	2.5272	0.6630
$CoverageHistory_{i,j,k,t}$	1784	1.4386	1.4964	0.7753	2.1031	0.7640
$BrokerSize_{i,j,t}$	1784	3.7292	4.0431	3.1781	4.3694	0.8820
$PastForecastErrors_{i,j,k,t}$	1784	0.1289	0.0063	0.0027	0.0141	1.9409

Panel B: Recommendation Profitability and Taxi Ride Volumes during the [0, 5] EAD Window

Dependent Variable:	$Profitability_{i,j,k,t+1}$							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ch\ Abnormal\ Taxi[0,5]_{i,j,t}$	0.065 ***	0.066 ***	0.065 ***	0.085 **				
	(2.890)	(2.927)	(2.902)	(2.000)				
$Taxi[0,5]_{i,j,t}(Unscaled)$					0.010 **			
					(2.515)			
$Taxi[0,5]_{i,j,t}(Scaled - Company)$						4.821 ***		
						(2.825)		
$Taxi[0,5]_{i,j,t}(Scaled - Company \times Broker)$							0.007 *	
							(1.904)	
$Taxi[0,5]_{i,j,t}(Mean\ Unscaled)$								0.019 **
								(2.397)
$EADReturn_{i,t}$		-0.014	-0.013	0.005	-0.016	-0.016	-0.016	-0.014
		(-0.287)	(-0.277)	(0.070)	(-0.331)	(-0.320)	(-0.332)	(-0.297)
$Volatility_{i,t}$		0.106	0.104	0.209	0.134	0.113	0.122	0.138
		(0.470)	(0.462)	(0.568)	(0.602)	(0.508)	(0.543)	(0.620)
$Guidance_{i,t}$		0.009	0.008	0.000	0.007	0.007	0.008	0.007
		(0.581)	(0.496)	(0.004)	(0.457)	(0.441)	(0.534)	(0.448)
$N8-KItems_{i,t}$		0.022 ***	0.022 ***	0.016 **	0.022 ***	0.022 ***	0.022 ***	0.022 ***
		(3.563)	(3.528)	(1.970)	(3.560)	(3.548)	(3.569)	(3.573)

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$InvestorConference_{i,t}$		0.016 **	0.015 **	0.015	0.014 **	0.015 **	0.015 **	0.014 **
		(2.412)	(2.37)	(1.418)	(2.169)	(2.248)	(2.224)	(2.126)
$Analyst/InvestorDay_{i,t}$		-0.041	-0.040	-0.088 **	-0.039	-0.044 *	-0.041 *	-0.039
		(-1.575)	(-1.532)	(-2.116)	(-1.574)	(-1.651)	(-1.662)	(-1.641)
$NFollow_{i,t}$		0.029 **	0.031 **	0.029	0.031 **	0.031 **	0.031 **	0.031 **
		(2.335)	(2.409)	(1.205)	(2.435)	(2.416)	(2.401)	(2.409)
$PriorForecastErrors_{i,j,k,t}$		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(-0.592)	(-0.533)	(-1.179)	(-0.686)	(-0.573)	(-0.581)	(-0.704)
$NCoverage_{k,t}$			-0.011	-0.010	-0.010	-0.011	-0.011	-0.010
			(-1.119)	(-0.858)	(-1.029)	(-1.059)	(-1.110)	(-1.053)
$Experience_{k,t}$			-0.012	0.008	-0.009	-0.012	-0.010	-0.010
			(-0.752)	(0.649)	(-0.592)	(-0.786)	(-0.654)	(-0.663)
$CovHistory_{i,j,k,t}$			-0.002	0.001	-0.002	-0.002	-0.003	-0.002
			(-0.343)	(0.141)	(-0.382)	(-0.368)	(-0.457)	(-0.338)
$BrokerSize_{j,t}$			0.005	-0.11	0.003	0.004	0.005	0.004
			(0.583)	(-.330)	(0.433)	(0.480)	(0.637)	(0.528)
Fixed-effects								
$Firm$	Yes	Yes	Yes		Yes	Yes	Yes	Yes
$Analyst$	Yes	Yes	Yes		Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Firm \times Broker$				Yes				
Fit statistics								
Observations	1,784	1,784	1,784	1,784	1,784	1,784	1,784	1,784
Adjusted R^2	0.065	0.078	0.077	0.130	0.075	0.076	0.074	0.075

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Table 6. Forecast Timeliness and Taxi Ride Volumes around Unanticipated Events

Panel A reports descriptive statistics for the forecast timeliness tests. The unit of observation is firm-analyst-unanticipated 8-K filings. Panel B reports the results of regressions of analysts' timely updates on taxi ride volumes around unanticipated 8-K filings between companies and brokerages. $Ch\ \ Abnormal\ \ Taxi[0,3]_{i,j,t}$ is changes in ride volumes during the window [0, 3] surrounding 8-K filing date, relative to its recent periods. The dependent variable is $Timely\ \ Revision_{i,j,k,t}$, which is equal to one if analysts update their forecasts between the event date and three days after the filing date (i.e., [0,3]). Standard errors are clustered by analysts. All variable definitions are in Appendix 2.

Panel A: Summary Statistics for the Forecast Timeliness

8-K Items	$\%Sample$	$Ch\ \ Abnormal\ \ Taxi[0,3]$	$\%Timely\ \ Revision$
9.01 Financial Statements and Exhibits	0.382	0.334	0.123
8.01 Other Events	0.193	0.338	0.113
5.02 Departure of Directors or Certain Officers; Election of Directors; Appointment of Certain Officers; Compensatory Arrangements of Certain Officers	0.122	0.317	0.078
7.01 Regulation FD Disclosure	0.103	0.371	0.206
1.01 & 1.02 Entry into or Termination of Material Definitive Agreement	0.070	0.296	0.111
5.07 Submission of Matters to a Vote of Security Holders	0.043	0.294	0.070
2.03 Creation of a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement of a Registrant	0.028	0.316	0.089
5.03 Amendments to Articles of Incorporation or Bylaws; Change in Fiscal Year	0.026	0.312	0.100
3.03 Material Modification to Rights of Security Holders	0.009	0.316	0.105
3.02 Unregistered Sales of Equity Securities	0.008	0.382	0.121
2.01 Completion of Acquisition or Disposition of Assets	0.007	0.376	0.115
2.05 Costs Associated with Exit or Disposal Activities	0.003	0.299	0.329
5.04 Temporary Suspension of Trading Under Registrant's Employee Benefit Plans	0.002	0.336	0.107
2.06 Material Impairments	0.002	0.341	0.272
3.01 Notice of Delisting or Failure to Satisfy a Continued Listing Rule or Standard; Transfer of Listing	0.001	0.416	0.061
5.01 Changes in Control of Registrant	0.001	0.327	0.150
4.01 Changes in Registrant's Certifying Accountant	0.001	0.301	0.046
2.04 Triggering Events That Accelerate or Increase a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement	0.001	0.366	0.053
4.02 Non-Reliance on Previously Issued Financial Statements or a Related Audit Report or Completed Interim Review	0.000	0.306	0.161
5.05 Amendment to Registrant's Code of Ethics, or Waiver of a Provision of the Code of Ethics	0.000	0.363	0.000

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Panel B: Forecast Timeliness and Taxi Ride Volumes during the [0, 3] 8-K filing Window

Dependent Variable:		$Timely\ Revision_{i,j,k,t}$	
Model:	(1)	(2)	(3)
$Ch\ Abnormal\ Taxi[0,3]_{i,j,t}$	0.006 ***	0.006 **	0.005 **
	(2.658)	(2.521)	(2.114)
$N8-KItems_{i,t}$		0.031 ***	0.030 ***
		(5.072)	(4.881)
$Guidance_{i,t}$		-0.041 ***	-0.040 ***
		(-5.165)	(-4.912)
$Analyst/InvestorDay_{i,t}$		0.143 ***	0.143 ***
		(5.875)	(5.789)
$InvestorConference_{i,t}$		-0.007	-0.007 *
		(-1.638)	(-1.672)
$Volatility_{i,t}$		-0.728 ***	-0.846 ***
		(-4.131)	(-4.781)
$CAR[-1,1]_{i,t}$		-0.081	-0.081
		(-1.431)	(-1.381)
$NFollow_{i,t}$		-0.001	-0.003
		(-0.099)	(-0.312)
$PastForecastErrors_{i,j,k,t}$		-0.013	-0.024
		(-0.976)	(-1.631)
$BrokerSize_{i,j,t}$		0.005	-0.005
		(0.602)	(-0.368)
$NCoverage_{j,k,t}$		-0.024 ***	-0.019 ***
		(-4.495)	(-3.509)
$Experience_{j,k,t}$		0.028	-0.001
		(1.249)	(-0.158)
$CovHistory_{i,j,k,t}$		-0.004	0.010
		(-0.773)	(1.257)
Fixed-effects			
$Firm$	Yes	Yes	
$Analyst$	Yes	Yes	
$Year$	Yes	Yes	Yes
$Firm \times Broker$			Yes
Fit statistics			
Observations	50,511	50,511	50,511
Adjusted R^2	0.068	0.072	0.077

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Table 7. Reg FD-Specific 8-K Filings and Taxi Rides

This table reports results of regressions of daily taxi ride volumes between companies and brokerages on the indicators mapped into the windows surrounding 8-K filings. The unit observation is firm-broker-day. $I[-5,-1]_{i,t}$ ($I[1,5]_{i,t}$) is an indicator variable that is equal to one if day *t* falls on the window $[-5,-1]_{i,t}$ ($[1,5]_{i,t}$), where the event day is defined as $0_{i,t} = 8 - KFilingDate$. The t-values in parentheses are based on two-tailed tests of significance. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are clustered by firm and broker. All variable definitions are in Appendix 2.

Dependent Variable:	$Taxi_{i,j,t}$	
	All	Reg FD
Model:	(1)	(2)
$I[-5,-1]_{i,t}$	0.005	0.009
	(1.58)	(1.10)
$I[0]_{i,t} = 8 - KFilingDate$	-0.003	0.025 **
	(-0.71)	(2.45)
$I[1,5]_{i,t}$	0.003	0.010
	(1.11)	(1.13)
$NYCTaxiRides_t$	0.009 **	0.019 ***
	(1.99)	(2.70)
Fixed-effects		
$Firm$	Yes	Yes
$Broker$	Yes	Yes
$Month$	Yes	Yes
$Year$	Yes	Yes
Fit statistics		
Observations	1,037,914	182,402
Adjusted R^2	0.396	0.360

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Table 8. Descriptive Statistics – Determinants

Panel A reports descriptive statistics for the determinant tests. The unit observation is at the firm-analyst month. Variables are shown after logs are taken. Panel B reports Pearson correlations between variables used in the forecast error tests. Asterisks denote significance levels at 5% or higher. All variable definitions are in Appendix 2.

Panel A: Summary Statistics

Variables	Valid N	Mean	Median	25th	75th	St. Deviation
$Taxi_{i,j,t+1}$	51,416	2.5577	2.7726	1.7918	3.4657	1.2655
$N8-KItems_{i,t}$	51,416	0.8777	1.0986	0.0000	1.3863	0.7699
$Guidance_{i,t}$	51,416	0.0921	0.0000	0.0000	0.0000	0.2695
$Size_{i,t}$	51,416	8.8451	8.9801	7.3964	10.3835	1.8652
$InstitionalOwnership_{i,t}$	51,416	0.7396	0.7766	0.6401	0.8972	0.2235
$Analyst/InvestorDay_{i,t}$	51,416	0.0135	0.0000	0.0000	0.0000	0.1152
$InvestorConference_{i,t}$	51,416	0.4562	0.0000	0.0000	1.0000	0.4981
$Turnover_{i,t}$	51,416	0.0097	0.0075	0.0051	0.0120	0.0073
$Intangible_{i,t}$	51,416	0.3464	0.1857	0.0181	0.5983	0.3745
$R\&D_{i,t}$	51,416	0.0104	0.0053	0.0000	0.0133	0.0146
$Volatility_{i,t}$	51,416	0.0201	0.0161	0.0114	0.0238	0.0136
$Return_{i,t}$	51,416	0.0173	0.0165	-0.0347	0.0658	0.0943
$NFollow_{i,t}$	51,416	2.7734	2.9444	2.3979	3.2189	0.5744
$UnfavRecommendation_{i,j,k,t}$	51,416	0.5083	1.0000	0.0000	1.0000	0.4999
$PriorForecastErrors_{i,j,k,t}$	51,416	0.0129	0.0027	0.0011	0.0071	0.0595
$BrokerSize_{j,t}$	51,416	3.7291	4.0073	3.1781	4.3041	0.8268
$NCoverage_{k,t}$	51,416	2.3123	2.3979	2.0794	2.7081	0.5466
$Experience_{k,t}$	51,416	2.1231	2.3397	1.8524	2.5320	0.5761
$CovHistory_{i,j,k,t}$	51,416	1.5038	1.5542	0.9385	2.1101	0.7179

Panel B: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)$Taxi_{i,j,t+1}$																		
(2)$N8-KItems_{i,t}$	0.05*																	
(3)$Guidance_{i,t}$	0.04*	-0.12*																
(4)$Size_{i,t}$	0.09*	0.09*	0.05*															
(5)$InstitionalOwnership_{i,t}$	-0.07*	-0.12*	0.05*	0.11*														
(6)$Analyst/InvestorDay_{i,t}$	0.00	0.05*	0.04*	0.05*	0.01*													
(7)$InvestorConference_{i,t}$	0.02*	0.07*	-0.02*	0.27*	0.00	0.06*												
(8)$Turnover_{i,t}$	-0.01	0.06*	0.12*	-0.19*	-0.02*	-0.01	-0.08*											
(9)$Intangible_{i,t}$	-0.05*	-0.14*	0.07*	0.14*	0.18*	-0.01	0.05*	-0.17*										
(10)$R\&D_{i,t}$	-0.02*	-0.11*	0.09*	-0.04*	0.05*	-0.02*	0.01*	-0.15*	0.16*									
(11)$Volatility_{i,t}$	-0.02*	0.10*	0.03*	-0.40*	-0.13*	-0.01*	-0.11*	0.45*	-0.12*	0.01*								
(12)$Return_{i,t}$	0.01*	0.00	0.00	-0.02*	0.03*	-0.01*	-0.02*	-0.02*	0.02*	0.02*	0.02*							
(13)$NFollow_{i,t}$	0.06*	0.00	0.10*	0.72*	0.15*	0.03*	0.21*	0.11*	0.14*	-0.06*	-0.28*	-0.01						
(14)$UnfavRecommendation_{i,j,k,t}$	0.03*	-0.01*	0.00	-0.11*	-0.06*	-0.02*	-0.05*	0.06*	-0.06*	-0.02*	0.05*	0.00	-0.07*					
(15)$PriorForecastErrors_{i,j,k,t}$	-0.02*	0.05*	-0.05*	-0.18*	-0.13*	-0.01*	-0.05*	0.24*	-0.12*	0.00	0.33*	0.01	-0.13*	0.07*				
(16)$BrokerSize_{j,t}$	0.16*	0.00	0.01	0.01*	0.00	0.00	-0.01*	-0.04*	0.01*	-0.04*	-0.03*	0.01	-0.03*	0.11*	-0.01*			
(17)$NCoverage_{k,t}$	0.00	0.02*	-0.04*	-0.03*	-0.03*	-0.04*	0.00	0.03*	-0.11*	-0.07*	0.01*	-0.01*	0.03*	0.06*	0.04*	0.17*		
(18)$Experience_{k,t}$	0.02*	0.00	0.01*	0.14*	0.01*	0.00	0.07*	-0.05*	0.03*	0.05*	-0.08*	-0.01*	0.13*	-0.03*	-0.01*	-0.05*	0.21*	
(19)$CovHistory_{i,j,k,t}$	0.00	0.03*	0.02*	0.24*	-0.01*	0.02*	0.07*	-0.02*	-0.03*	-0.02*	-0.09*	-0.02*	0.20*	0.01*	0.02*	-0.03*	0.14*	0.58*

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Table 9. Regression Results of Determinant Tests

This table reports the results of regressions of monthly taxi ride volumes between companies and brokerages on their determinants. The unit of observation is at the firm-analyst-month. The dependent variable, $Taxi_{i,j,t+1}$, is the log of aggregate monthly taxi ride volumes between company *i* and brokerage *j*. Column 1 (2) report results including firm-month (broker-month) and year fixed effects. The t-values, in parentheses, are based on two-tailed tests of significance. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are clustered by firm and broker. All variable definitions are in Appendix 2.

Dependent Variable:	$Taxi_{i,j,t+1}$	
Model:	(1)	(2)
$N8-KItems_{i,t}$	0.004	0.056
	(0.57)	(0.78)
$Guidance_{i,t}$	-0.025	0.220
	(-1.43)	(1.20)
$Size_{i,t}$	0.041	0.081
	(1.28)	(1.25)
$InstitutionalOwnership_{i,t}$	-0.139	-0.453
	(-1.40)	(-1.53)
$Analyst/InvestorDay_{i,t}$	0.012	-0.101
	(0.30)	(-0.66)
$InvestorConference_{i,t}$	-0.004	-0.022
	(-0.41)	(-0.27)
$Turnover_{i,t}$	0.868	-0.986
	(0.35)	(-0.11)
$Intangible_{i,t}$	-0.096	-0.200
	(-1.17)	(-0.68)
$R\&D_{i,t}$	1.03	0.079
	(0.50)	(0.02)
$Volatility_{i,t}$	-1.11	-0.469
	(-1.36)	(-0.16)
$Return_{i,t}$	0.181 ***	0.191 **
	(7.50)	(1.99)
$NFollow_{i,t}$	0.029	0.060
	(0.62)	(0.32)
$UnfavRecommendation_{i,j,k,t}$	0.116 ***	-0.032
	(3.54)	(-0.48)
$PriorForecastErrors_{i,j,k,t}$	-0.761 **	0.242
	(-2.35)	(0.33)
$BrokerSize_{i,j,t}$	0.290 ***	-0.041
	(2.93)	(-0.96)
$NCoverage_{j,k,t}$	-0.137 **	-0.016
	(-2.15)	(-0.26)
$Experience_{j,k,t}$	0.072	0.091
	(0.92)	(1.23)
$CovHistory_{i,j,k,t}$	0.019	-0.144 **
	(0.30)	(-2.23)
Fixed-effects		
$Firm \times Month$	Yes	
$Broker \times Month$		Yes
$Year$	Yes	Yes
Fit statistics		
Observations	51,416	51,416
Adjusted R^2	0.544	0.313

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