Mobile Internet and Analyst Forecast Performance †

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Abstract: We study the impact of mobile internet technology on analyst forecast performance. Mobile internet facilitates uninterrupted access to various types of information and provides productivity tools for professionals. As such, it can help financial analysts gain immediate access to information and integrate it into their forecasts, leading to improved forecast timeliness. Mobile internet may also allow analysts to gather or receive additional information more promptly, improving forecast accuracy. Our tests utilize the rollout of 3G mobile internet in the U.S. and include both continuous treatment and sharp-increase differences-in-differences models, comparing forecast characteristics for a given firm-year across analysts with varying degrees of access to mobile internet. Results indicate that enhanced access to mobile internet results in significant improvements in analysts' forecast timeliness and accuracy. We link these improvements empirically to the rollout of productivity apps, and confirm their effect with a tool particularly pertinent for analysts, the Bloomberg app.

Keywords: mobile internet; financial analysts; forecast accuracy; forecast timelines.

JEL Classification: G17, O33

1. Introduction

Mobile internet access has altered professional and personal lives and blurred the lines between the two. A well-documented distinguishing feature of the technology is that it serves as a critical tool facilitating dissemination of various kinds of information (Manacorda and Tesei 2020; Guriev, Melnikov and Zhuravskaya 2021). As such, mobile internet can put relevant and valuable information at the fingertips of working professionals, improving their productivity and output quality. At the same time, it also has the power to hinder professional performance, an outcome that can result from two sources. First, information overload together with bounded information processing capability can impair a professional's ability to discern relevant from irrelevant information. Second, mobile technology also makes readily available information that individuals consume for personal needs, such as their latest medical test results, sports scores, or even entertainment and games. A critical feature of mobile technology is that all information is available all the time, blurring the distinction between work and personal hours. Thus, it can facilitate a professional's desire to be productive when away from the office, or it can encourage the same individual to pursue information for personal consumption when physically at the workplace or "on the clock" at other venues (such as professional conferences). Our goal is to provide evidence on the net effect of mobile technology on the productivity of a specific category of professionals, financial analysts, who are deemed critical for the smooth functioning of capital markets and whose careers rely heavily on access to information.

The trade-off resulting from constant and uninterrupted access to both business and personal information is particularly relevant for financial analysts. Analysts compete on providing timely and accurate forecasts and thus value uninhibited and swift access to information (Bradshaw 2011; Brown, Call, Clement and Sharp 2015; Ben-Rephael, Carlin, Da, and Israelsen 2022), but research shows financial analysts can also be prone to distractions that adversely affect the quality of their output (DeHaan, Madsen and Piotroski 2017; Bourveau, Garel, Joos, and Petit-Romeck 2022; Du 2023). In this paper, we examine how mobile internet technology affects the timeliness and accuracy of analysts' forecasts, and thus, more generally, the quality of forward-looking financial information.

Financial analysts can benefit professionally from mobile internet because it serves as a helpful work-tool that lowers information awareness and acquisition costs, as well as information integration costs (Blankespoor, DeHaan and Marinovic 2020). One of the flagship features of mobile technology is granting its users improved and uninterrupted access to information (Guriev et al. 2021). As direct beneficiaries of mobile internet's news dissemination, analysts immediately become aware of and incorporate new information into their forecasts. Mobile technology also enhances communication, improving analysts' ability to stay in touch with their respective teams and allowing for refinements of forecasts on a timely basis even when the analyst and their team members are in different locations. Finally, analysts' career prospects and compensation rely critically on their accessibility and responsiveness (Brown, Call, Clement and Sharp 2015). Mobile internet allows for connectivity beyond phone calls, including faster replies to email and other messages, and improving clients' and company management's access to analysts, as well as vice versa. We expect these features of mobile technology to help analysts acquire and integrate new information on a timelier basis, which should result in improvements in forecast timeliness. If analysts incorporate the same information into their forecasts, albeit in a timelier fashion, we would expect no change in forecast accuracy with access to mobile internet. But to the extent mobile technology makes information searches more efficient, and analysts choose to use some of the time advantage for additional research, forecast accuracy may improve.

Analysts are continuously processing information, and often work long hours including weekends (DeHaan, Shevlin and Thornock 2015). To remain competitive, they engage in frequent meetings and conversations with clients, visit sites of firms they follow, and participate in various broker-hosted investor conferences (Bushee, Jung and Miller 2011; Green; Jame, Markov and Subasi 2014; Bradshaw, Ertimur, and O'Brien 2017). Moreover, they have to be available and ready to receive and process information arriving after-hours. The lack of mobile access would disadvantage analysts in two possible ways. First, analysts' ability to access and process information continuously would be impaired, forcing them to delay some of their outputs such as forecast releases, thus sacrificing timeliness. Alternatively, unaware or simply unable to process all available information in a timely manner, they may proceed to release less accurate forecasts.

It is, however, conceivable that mobile internet has a detrimental effect on analysts' forecast quality because it distracts analysts from their professional tasks or leads to information overload. For example, Bourveau et al. (2022) provide evidence that cognitive distraction arising from industries experiencing extreme returns and commanding analysts' attention leads to such analysts making less accurate forecasts and revising them less frequently on other unaffected stocks. More generally, a rich literature on limited attention shows that the presence of competing events or stimuli slows down or alters human response to information (Hirshleifer and Teoh 2003; Corwin and Coughenour 2008; Hirshleifer, Lim and Teoh 2009; Drake, Gee and Thornock 2016). Analysts are no exception to experiencing limited attention, and the quality of their forecasts can be negatively affected by alternative attention-grabbing events, weather, and personal responsibilities (DeHaan et al. 2017; Bourveau et al. 2022; Du 2023). Further, entertainment, gaming and personal communication applications enabled by mobile internet provide constant sources of distraction, potentially inhibiting information acquisition and integration (Strayer and Johnston 2001; Jacobsen and Forste 2011; Thompson, Rivara, Ayyagari, and Ebel 2013). Consistent with this, there is evidence that mobile internet distractions impede sophisticated investors' information-gathering and stock-market participation (Brown, Elliott, Wermers, and White, 2022). In summary, analyst forecast quality can suffer as a result of information overload and/or distractions arising from mobile technology, and we would then expect analysts with mobile internet access to make less accurate and less timely forecasts. Overall, the observed effect of mobile internet access on analyst forecast quality represents the net effect of mobile internet providing a new work resource and any potential detrimental effects of information overload and distraction.

In our predictions and empirical tests, we focus on timeliness and accuracy of analysts' forecasts. The directional effect of mobile internet access on these two characteristics is relatively clear and intuitive both under the work resource and under the distraction perspective. In addition, these two characteristics have been studied extensively by prior literature as they are clear indicators of the quality of analyst performance (Bradshaw 2011; Bourveau et al. 2022; Bradley, Gokkaya and Liu 2017; Fang and Hope 2021). Finally, analysts consider these attributes essential to their career outcomes and compete on these dimensions (Mikhail, Walther and Willis 1999; Brown, Call, Clement and Sharp 2015; DeHaan et al. 2017; Harford, Jiang, Wang, and Xie 2019). While clients value forecast accuracy, it is also necessary for analysts' output to be timely for clients to rely on it and monetize it.

To examine whether mobile internet access enhances or hinders the timeliness and accuracy of analyst forecasts, we take advantage of the staggered expansion of the 3G mobile internet across the United States. The staggered rollout affects analysts in different locations and years to varying degrees and thus provides variation in technology that is largely exogenous with respect to analyst forecasts. Our main analyses utilize a continuous treatment differences-in-differences (DID) design and enable us to compare changes in outcomes across analysts, conditional on their exposure to the expansion of the 3G network in the county in which they operate.[1] We include firm-year fixed effects. The comparison is thus for a given firm-year across analysts with varying degrees of access to mobile internet. This element of our research design controls for various events and financial reporting choices that may affect a firm's earnings and conceivably forecasts in a given year. County and analyst fixed effects further control for time-invariant geographical location and analyst characteristics. We measure accuracy with the absolute forecast error and timeliness with the leader-follower ratio, both of which have been commonly employed in prior literature (e.g., Mikhail et al. 1999; Cooper et al. 2001; Green et al. 2014; Shroff et al. 2014).[2] Our sample for this analysis includes 286,163 forecasts issued between 2007 and 2017.[3]

We find that enhanced access to 3G mobile internet results in significant improvements in analysts' forecast timeliness and accuracy. The overall improvement in average local access to 3G internet (approximately 21 percent points over 2007-2017) leads to a 2.2% increase in timeliness, and a similar 2.9% increase in forecast accuracy relative to their respective means.[4]

[1] Our analyses use digital maps of 3G coverage from Collins Bartholomew's Mobile Coverage Explorer for years 2007 to 2017 to determine the percentage of each county with 3G internet access. We obtain county location of each financial analyst from FINRA's Brokerage Check. Jointly the data allow us to measure the extent to which a given analyst has access to 3G internet within their county of location in a given year. This location measurement relies on the assumption that analysts spend a significant amount of time at and around their workplace and use their mobile phones during that time. That is likely to be the case, because, in addition to the time they spend in the office, analysts meet with clients and managers of local firms they follow (Malloy 2005; O'Brien and Tan 2015). Analysts may also attend local conferences and live in proximity to their offices. To the extent analysts travel outside of their local area, this measure fails to capture part of their mobile activity.

[2] The leader-follower ratio captures the extent to which a given analyst is a leader rather than a follower in issuing their forecast. It relies on the timing of the focal analyst's forecast conditional on forecasts from other analysts versus the timing of other analysts updating relative to a forecast from the focal analyst. In robustness analysis, we also use an alternative measure of timeliness, i.e. whether an analyst issued a forecast on the day of or the day after the earnings announcement.

[3] While in the main analyses we retain each analyst's last annual EPS forecast from all annual forecasts with one- to twelve-month horizon, we confirm that our results are robust to retaining the first annual forecast instead. Focusing consistently on either last or first forecasts has the benefit of making forecast horizon more comparable (Mikhail et al. 1999).

[4] The economic magnitudes are comparable to those documented in prior studies examining analyst forecasts. For example, prior industry experience improves forecast accuracy by 1.6% (Bradley et al. 2017), forecasts with acute career concern implications for the analyst are approximately 1.9% more accurate (Harford et al. 2019), analyst teams are approximately 2.6% more accurate than individual analysts (Fang and Hope 2021), and forecast accuracy suffers by 1.4% when analysts' attention is diverted away from a particular stock in a given quarter (Bourveau et al. 2022).

Having established that mobile internet access has a positive net effect on analyst forecast quality, we subject this finding to a number of robustness tests. First, following Guriev et al. (2022), we conduct an alternative differences-in-differences test where the treatment relies on sharp increases (i.e., a 50 percent points or higher increase) in county-level 3G coverage. Consistent with our main results, forecast timeliness and accuracy improve significantly following sharp increases in local 3G coverage. The coefficients imply that forecasts issued by treated analysts experienced an increase in timeliness and accuracy equal to 7.3% and 13.6% of their corresponding means, respectively. Further, based on this discrete treatment specification, we are able to validate the parallel trend assumption, i.e., we find no significant differences in forecast timeliness or accuracy between treated and control observations in the pre-treatment years. Finally, to address the empirical challenges associated with a staggered treatment design when there are heterogeneous treatment effects, we follow a stacked difference-in-differences estimation approach. This approach involves aligning and stacking different treatment instances (i.e., sharp increases in 3G coverage) in event time where only those observations that are never treated within the sample window serve as controls in each event dataset (Cengiz, Dube, Lindner, Zipperer 2019; Baker, Larcker and Wang 2021). Again, these tests indicate significant improvements in forecast timeliness and accuracy in response to 3G network expansion.

To further alleviate concerns that omitted variables may influence both the local rollout of the 3G network and analyst forecast quality, we estimate an instrumental variables regression where we use the frequency of lightning strikes as an instrument for 3G coverage. The expansion of the 3G network was much slower in counties with higher frequency of lightning strikes. Lightning strikes cause electrostatic surges, increasing the costs of providing service and negatively affecting the quality (e.g., speed) of the transmission signal (Manacorda and Tesei 2020; Guriev et al. 2021). A county's average lightning strike frequency is plausibly exogenous with respect to analyst forecast attributes, other than via its impact on the expansion of 3G networks. Our results from these instrumental variables regressions support the causal interpretation that 3G expansion led to a significant increase in the timeliness of analyst forecasts, as well as an improvement in forecast accuracy.

The advent of 3G networks motivated the introduction of numerous smartphone-friendly applications targeted at improving both workplace productivity and personal entertainment. Our next set of tests focuses on the role of productivity applications (apps) in enhancing analyst forecast performance. We expect productivity apps (i.e., news and business apps) to play a significant role because they aid information awareness and acquisition, as well as information integration. Immediate access to breaking news and other information, which news apps provide, is likely to be critical for analyst forecast timeliness and accuracy. A prominent example of an application that is helpful in this respect is Bloomberg. Bloomberg is widely used by equity analysts to receive timely news updates, extract relevant financial information, and examine research by peer analysts (Ben-Rephael et al. 2022). Before the rollout of the Bloomberg app on July 16th 2008, analysts had access to Bloomberg terminals in their respective offices but access was limited to time spent at their desk, making it challenging to access information in a timely fashion elsewhere. Consequently, the availability of Bloomberg and similar news apps likely improved analysts' information awareness and acquisition.

In addition, various other business apps can also lower information processing costs. For example, mobile access to email and other communication applications allows analysts to connect swiftly with their clients, and with managers of companies they follow, which can increase information awareness and acquisition. More efficient communication about new information with their respective teams can facilitate timelier and better incorporation of analysts' information and insights into prediction models for earnings and prices, thus lowering integration costs as well.

We gauge whether productivity applications play a significant role in improving analyst forecast performance in two different analyses. First, we adopt a general approach and conduct cross-sectional tests based on the popularity of productivity apps. Specifically, we expand our main specification to add an interaction between 3G coverage and an indicator variable capturing the popularity of productivity apps in a given year.[5] Our results suggest that forecast accuracy and timeliness improves significantly more for analysts with greater 3G access in years with more than usual popularity of productivity apps. In our second analysis, we conduct a differences-in-differences test using the launch of the Bloomberg App, as a plausibly exogenous shock that differentially affects analysts with varying degrees of 3G access. We classify as treated those analysts that are located in counties with at least fifty percent 3G coverage in 2007, the year before the app was launched. Consistent with our prediction, we find that the launch of the Bloomberg App improves forecast timeliness and accuracy significantly more for analysts with greater access to the 3G network. The result indicates that mobile technology can affect analyst performance by offering on-demand access to information.

In additional tests we find that analysts with greater 3G access have better career outcomes, pointing to career-driven incentives to exploit mobile internet to improve productivity. Analysts with expanded exposure to 3G internet experience an increased likelihood of obtaining an All-Star status from institutional investors and a reduced likelihood of demotion from a top-10 broker to a lower-tier brokerage firm. We find evidence that in addition to becoming more accurate in forecasting EPS, analysts with greater 3G access also

[5] Specifically, the indicator variable takes the value of one in a given year when downloads of productivity apps as a percentage of top 200 apps exceed the sample median.

improve the accuracy of their target price forecasts. Finally, we confirm that our results are not driven solely by financial analysts employed by brokerage houses in New York. Even though removing these analysts from our sample results in a significant reduction in sample size, we still observe significant improvements in forecast accuracy and timeliness for analysts with better access to 3G mobile internet.

Our paper contributes to the growing literature on how mobile technology affects information acquisition and sharing, as well as the real effects of various parties utilizing this information. Guriev et al. (2021) document that the global expansion of 3G mobile networks helps expose government corruption and lowers trust in government, especially when the traditional media are censored. Their findings underscore the important role mobile internet plays in information awareness, acquisition and sharing. In a similar vein, Manacorda and Tesei (2020) report that mobile technology enhanced information about economic downturns and helped with coordination of mass protests in Africa. In the context of capital markets, Brown, Stice and White (2015) find that reduced access to mobile devices due to statewide distracted-driving restrictions limits individuals' financial information search activity, and lowers local trading volume. Finally, improved information acquisition, and sharing on mobile devices via social media apps, such as Twitter, has been shown to deter corporate misconduct (Hesse and Pacelli 2023).

We expand prior work in this research area by speaking to mobile internet's effect on financial analysts, who not only acquire information but also use it to generate new forward-looking information. Finding that greater access to mobile internet improves forecast timeliness and accuracy highlights the technology's role in engendering a positive information feedback loop, with improved access to information begetting additional valuable information.

Our evidence is particularly pertinent in the context of Brown et al. (2022), who exploit short-lived Blackberry usage disruptions to provide evidence that access to mobile internet inhibits investors' information gathering and trading activities. They report that the distraction effect is more pronounced in the presence of sophisticated investors. In our paper, we ask a significantly different question: if the same technology has both the power to improve a professional's productivity, and also the power to impair the quality of that individual's professional output, which effect dominates on average? We study this trade-off for financial analysts, linking the availability of mobile technology directly to their observable professional outputs. Our evidence indicates that the improved productivity effect dominates, presumably because producing accurate and timely forecasts is essential to analysts' career outcomes (Mikhail et al. 1999; Brown, Call, Clement and Sharp 2015; DeHaan et al. 2017; Harford et al. 2019).

Finally, our findings add to prior literature that attempts to understand factors affecting analyst forecast performance. Research has linked forecast quality to an analyst's firm-specific experience, industry expertise, portfolio complexity, innate ability, professional designations, and geographical proximity to the covered firm. There is also evidence that competition among analysts, as well as brokerage house prestige, and availability of a support team matter for analysts' performance.[6] We contribute to this literature by providing evidence that mobile internet access leads to improvements in forecast accuracy and timeliness. Our research suggests that better connectivity and uninterrupted access to information improve analysts' outputs and, more generally, the timeliness and quality of information available in capital markets.

[6] See, for example, Mikhail, Walther and Willis (1997), Clement (1999), Jacob, Lys and Neale (1999), Malloy (2005), Clement, Koonce and Lopez (2007), Bae, Stulz, and Tan (2008), Brown and Hugon (2009), De Franco and Zhou (2009), Kadan, Madureira, Wang, and Zach (2012), Bradley et al. (2017), Merkley, Michaely and Pacelli (2017), and Fang and Hope (2022).

2. Variable Measurement and Research Design

2.1. Measurement of 3G Mobile Technology Network

3G, the third generation of high-speed mobile networks, revolutionized the accessibility of online content on mobile phones, enabling users to actively browse the web with greater speed and convenience. Introduced to the public in 2001, the initial growth of the 3G network was slow due to the significant capital required for investing in network transmission towers. According to the International Telecommunication Union (ITU, 2019), the global average of active mobile broadband subscriptions per capita was only 0.04 in 2007. However, by 2018, this figure had increased to 0.70, indicating a substantial growth in mobile broadband adoption worldwide. 3G was a significant improvement over 2G, not only in terms of the speed of data transmission, but also the functions it enabled. In particular, 3G technology enabled seamless email communication, website browsing, simultaneously accessing voice and data, and resulted in the development of many applications (aps).

To study the expansion and coverage of 3G networks, we obtained digital maps from Collins Bartholomew's Mobile Coverage Explorer for the years 2007 to 2017.[7] These maps compile coverage data submitted by mobile network operators to the GSM Association.[8] The dataset provides valuable information on the adoption of mobile phone technology at a granular level (GSMA, 2012). We geographically map this data to each county in the United States for each year of our study.

Figure 1 illustrates a "heat map" of 3G coverage at three-year intervals during our sample period. Counties are color-coded in blue if they have any 3G coverage within the year. In 2007, 3G coverage was sporadic, with approximately 7.5% of counties having access to the

[7] 2007 is the first year Collin Bartholomew collects information on 3G coverage.

[8] Due to a change in the entity responsible for collecting mobile network coverage data in 2010, the data for that year remained static, and no data was collected for 2011. As a result, to fill this gap in the dataset, we perform interpolation using the most recently available coverage data. This allows us to estimate and approximate the 3G network coverage for the missing years, ensuring a more complete and continuous representation of the coverage trends over time.

3G network. However, starting around 2010, the expansion of the network accelerated significantly to 39.8%. By 2013, 95.5% of counties were covered by 3G technology, and this number further increased to 97.9% by 2016, indicating a remarkable growth and widespread coverage of the 3G network across the United States.

2.2. Measurement of Analyst Location

To track analysts' current and past employment and their exposure to 3G technology over time, we rely on data obtained from the Financial Industry Regulatory Authority (FINRA) registry. Specifically, we utilize information on employment location to determine analysts' exposure to 3G technology. FINRA's BrokerCheck serves as an online database accessible to investors, providing comprehensive professional background information on brokers, brokerage firms, investment adviser firms, and advisers. The data contained within BrokerCheck is sourced from the Central Registration Depository (CRD), which functions as the online registration and licensing database for the securities industry.

The CRD gathers information through various forms completed by brokers, brokerage firms, and regulators as part of the registration and licensing process within the securities industry. These forms contribute to CRD’s dataset, which is subsequently utilized as a source for BrokerCheck’s data. Figure 2 provides an illustrative example of an analyst's registration information displayed on the BrokerCheck platform. For our study, we focus on analysts’ historical employment information and the specific office locations where they have worked, according to their respective BrokerCheck forms. This information, in turn, allows us to trace analysts’ exposure to 3G technology over time. The data thus collectively enables us to examine how the availability and coverage of 3G networks influences the performance and career trajectories of financial analysts.

Embedded in our use of this data is an assumption that analysts spend a significant amount of time at and around their workplace and use their mobile phones during that time. Analysts are likely to benefit from mobile technology when they take lunch and coffee breaks, but also when they engage in professional activities, such as meetings with clients and managers of local firms they follow (Malloy 2005; O'Brien and Tan 2015). Moreover, some analysts may also attend conferences and/or live in close proximity to their offices and use mobile technology then. Nevertheless, analysts also travel outside of their local area, so measuring 3G coverage based on their employment likely fails to capture analysts' total mobile activity.

In Panel A of Table 1, we present the annual count of unique U.S.-based analysts throughout our sample period. Our analysis reveals a consistent upward trend in the number of analyst forecasts over the years, starting from 19,380 in 2007, and reaching 27,691 in 2017. Within our sample, the count of unique analysts experiences an increase from 1,781 in 2007 to 2,368 in 2013, followed by a subsequent decrease to 2,153 in 2017. Panel B provides a breakdown of forecasts and unique analysts by location, aggregated at the state level. Overall, across all years, there are 3,947 unique analysts in our sample. Unsurprisingly, the majority of analysts (2,397) are located in New York State, primarily concentrated in New York City. California accounts for 9% of the analyst forecasts, amounting to 434 individuals, with their distribution spanning across areas such as Los Angeles and San Francisco. Texas, and Illinois respectively attract the third and fourth highest number of analysts, predominantly located in and around Houston and Chicago. The number of analysts' forecasts exhibits a similar distribution across different states.

2.3. Measurement of Analyst Forecasts Attributes

We employ two measures to capture analysts' performance, earnings forecast accuracy and forecast timeliness, which have been widely used in the literature (e.g., Mikhail et al. 1999; Cooper et al. 2001). We define forecast *Accuracy* as the absolute value of the difference between the analyst's earnings forecast and the actual value of earnings, scaled by the stock price and multiplied by -100. A higher value of forecast *Accuracy* implies more accurate forecasts. To capture forecast timeliness, we follow prior work and calculate the leader-follower ratio for each analyst forecast in our sample (e.g., see Cooper et al. 2001; Green et al. 2014; Shroff et al. 2014). Specifically, we first compute the cumulative number of days by which two prior forecasts issued by other analysts precede the focal forecast (i.e., lead time). The longer the period without preceding forecasts by other analysts, the more likely it is that the focal forecast was not issued simply as a follow-up to other analysts' forecasts but rather by an analyst who is a leader. Next, we compute the cumulative number of days by which two subsequent forecasts issued by other analysts follow the focal forecast (i.e., lag time). A shorter lag time implies that other analysts issue forecasts as a follow-up to the forecast issued by the focal analyst. *Timeliness* is the ratio of the lead time to the lag time. Thus, a higher value of *Timeliness* (greater lead time and shorter lag time) indicates that the analyst is more likely to be at the forefront in revising forecasts ahead of other analysts, i.e., a leader, rather than acting as a follower with respect to forecasts from other analysts.

2.4. Research Design

We utilize the staggered expansion of the 3G mobile network, which affects analysts in different locations and years to varying degrees, in order to investigate the impact of the advent of this new technology on the quality of analyst research. This research setting provides a significant advantage by offering a source of exogenous variation in technology that is largely independent of specific brokerage houses and analyst forecast quality. Using this expansion, we attempt to establish causal relationships between the introduction of 3G technology and observed changes in analyst performance.

To estimate the effects, we employ a differences-in-differences (DID) design that relies on a continuous treatment. The research design enables us to measure changes in the forecast outputs of analysts who were exposed to the expansion of the 3G network from before to after the expansion occurred, relative to the corresponding differences for analysts who were not exposed to a similar expansion. Consequently, we can attribute the observed differences in outcomes to the introduction/expansion of 3G technology, providing valuable insights into its effects on the analyst community. Specifically, we estimate the following difference-in-differences specification:

$$Forecast_{ijt} = \beta_0 + \beta_1 3G\ Coverage_{it} + \gamma' X_{ijt} + Firm{*}YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \quad (1)$$

where i indexes analysts, j indexes firms, and t indexes times, respectively. *Forecast* referes to forecast attributes we study: *Timeliness* and *Accuracy*. *3G Coverage* measures treatment intensity and is defined as the proportion of the county that is covered by 3G network in year t. *X* represents a vector of control variables, which we discuss in more detail below. *Firm*YearFE* denotes interacted firm-year fixed effects, which allow the regression to capture variation in forecast attributes across analysts within a specific firm-year. Using firm-year fixed effects controls for financial reporting and disclosure choices that can affect a firm's earnings and thus forecasts in a given year. *AnalystFE* denotes analyst fixed effects, which ensure that our results are not biased by time-invariant attributes of analysts (e.g., education or risk attitude). *CountyFE* captures county fixed effects, accounting for time-invariant characteristics of the local economy that may influence the rollout of the 3G network. We cluster the standard errors at the county level. The coefficient, β1, captures the effect of mobile technology on forecast attributes.

To control for other factors that may influence forecast quality, we incorporate additional control variables identified in prior research (e.g., Green et al. 2014; Bradley et al. 2017). *Firm Experience* captures an analyst's experience with a specific firm, measured as the number of years since the analyst issued the first forecast for the firm. *General Experience* measures an analyst's experience in the profession, calculated as the number of years since the analyst first appears in IBES. *# Covered Firms* is the number of unique firms covered by the analyst during the year, and *# Covered Industries* is the number of unique 2-digit SIC industries covered by the analyst. *Broker Size* is defined as the number of unique analysts employed by the brokerage firm during the year. We winsorize all continuous variables at the top and bottom one percentile. Detailed definitions of variables are available in the Appendix.

3. Sample Selection and Descriptive Statistics

We collect comprehensive data on analysts' fiscal year-end earnings-per-share (EPS) forecasts from the I/B/E/S (Institutional Brokers' Estimate System) database for the period spanning 2007 to 2017. To ensure the accuracy and reliability of the data, we specifically focus on analysts with non-missing employment history and location information obtained from BrokerCheck. Additionally, we manually gather analysts' All-Star Status from the October issues of Institutional Investor magazine on an annual basis. Our data collection process also requires the availability of I/B/E/S data necessary for constructing our control variables. Following established research practices (e.g., Bradley et al., 2017), we start with all annual forecasts with one- to twelve-month horizon, and select the last annual earnings forecast (FPI=1) issued by each analyst.[9]

[9] Our inferences remain if we use the first forecast issued by analysts. The results are tabulated in Table 7 Panel C.

Table 2 indicates that mean 3G coverage is 96%, which reflects the wide coverage of 3G internet in counties with analysts during our sample period. Mean coverage increased steadily, especially over the earlier part of the sample period. For example, mean 3G coverage in 2007 was 78%, which gradually increases to 97% in 2010. Table 2 further provides descriptive statistics for forecast accuracy and timeliness measures, and for the control variables in our tests. The average forecast accuracy amounts to 0.36% of the stock price, indicating a relatively small margin of error in analysts' forecasts, at least as percentage of stock price. The average value of the *Timeliness* measure is 2.83, implying that, on average, the time by which an average forecast lags other forecasts in our sample is approximately 2.83 times longer than the subsequent forecasts that follow. Within our sample, approximately 14% of the analysts hold the prestigious designation of being All-Star analysts. On average, analysts cover around 17 firms from three different industries, with an average of four years of experience with the specific firms they follow and twelve years of overall professional experience. Moreover, they work alongside an average of 61 sell-side analysts within the same brokerage. These descriptive statistics offer insights into the characteristics and performance measures of the analysts included in our study.

4. Results

4.1. Main Results

We employ multivariate regression analysis to investigate the impact of the staggered rollout of 3G mobile technology on analysts' forecast accuracy and timeliness. In each test, we utilize the maximum number of observations available for the respective dependent variable. For our primary analysis examining the effect of 3G expansion on forecast timeliness and accuracy, we have a sample of 3,947 analysts and 286,163 forecast-firm-year observations, spanning the period from 2007 to 2017.

In Columns (1) and (2) of Table 3, we estimate Equation (1) and report the findings. In column (1), we find a statistically significant positive relationship between analysts' access to 3G technology and forecast timeliness (p-value less than 0.01). The coefficient estimate indicates that the mean increase in local 3G coverage in our sample (equal to about 21 percent point) would correspond to a 2.2% increase in timeliness relative to its mean.[10]

Moving to Column (2), we present the results regarding the impact of 3G technology expansion on forecast accuracy. The findings reveal a significant improvement in forecast accuracy with greater access to mobile technology (p-value less than 0.01). Specifically, an average increase in local 3G coverage results in a 2.9% increase in forecast accuracy relative to its mean.

To supplement our main analyses, which rely on a continuous treatment, with tests that also examine a discrete treatment effect, we conduct an event study focusing on sharp increases in local 3G coverage. We identify a discrete treatment event, a 50-percent point or higher increase in 3G coverage ("Sharp Increase"), and assign the value of one to counties with a sharp increase in the years following the increase.[11] Among the counties in our sample, 176 meet this criterion, with an average increase in 3G coverage of 86 percent point. Our pre-event period spans 2 years before the shock and the year of the shock, while our post-event window includes three years after the event, resulting in 217,664 observations.[12]

Columns (3) and (4) present the forecast timeliness and accuracy results using the sharp differences-in-differences research design. Consistent with our main findings, we find that *Timeliness* and *Accuracy* exhibit statistically significant increases following sharp rises in local

[10] The average increase in 3G coverage is 21 percent point from 2007 to 2017 for an average county in our sample (from 78% coverage in 2007 to 99% coverage in 2017). The 2.2% increase in timeliness is calculated as 2.2%=0.21*0.288/2.83

[11] We follow Guriev et al. (2021) in defining sharp increases in 3G coverage. In their words, a significant advantage of this treatment is as follows: "*By definition, this could happen only once per region, if it happens at all, provided that regional 3G coverage never falls substantially.*"

[12] Our control group includes counties that have a 3G coverage higher than 50% prior to 2007 and counties that are not treated yet. We include the event year in the pre-event window but our inferences are robust when excluding the event year from the analysis.

3G coverage. In terms of economic magnitudes, a sharp increase in 3G coverage is associated with a 7.3% improvement in timeliness, and 13.6% increase in forecast accuracy relative to their respective unconditional means.[13]

Relying on a sharp increases in 3G coverage also allows us to assess the validity of the parallel trend assumption in event time. Specifically, we examine whether forecasts of analysts who experienced sharp increases in 3G coverage in their county and forecasts of those analysts who did not experience such increases demonstrate parallel trends in the pre-period. We estimate a specification analogous to the sharp differences-in-differences model, replacing the post-event indicator with separate indicators for each of the two years preceding the sharp increase in 3G coverage, and for the three years after the increase. We use the event year as the benchmark year. The results of this specification are presented in Columns (5) and (6). None of the pre-event indicator variables are significant at conventional levels, indicating that the parallel trend assumption is unlikely to be violated in our setting.

Baker et al. (2021) discuss the empirical challenges associated with a staggered treatment design when there are heterogeneous treatment effects. To overcome this challenge, they propose a stacked difference-in-differences estimation approach, which involves aligning and stacking different events in event time. This approach helps address estimation issues that may arise when using previously treated units of observation in the control sample. In our study, we follow this recommendation and re-estimate the main results using a stacked differences-in-differences design, and present the results in Columns (7) and (8) of Table 3. For each treatment year in our sample, we select the counties that experience a sharp increase in 3G coverage as the treatment group, and use counties that are never treated as the control group. We stack the samples of each treatment event together and align them based on the treatment

[13] The economic magnitude of the increases in timeliness and accuracy are computed as 0.206/2.83 or 7.3% and 0.049/0.36 or 13.6%, respectively.

year.[14] Importantly, our results remain robust to this alternative specification, further supporting our conclusion that the expansion of the 3G network lead to significant increases in forecast timeliness and accuracy following.

In summary, our findings withstand various alternative specifications and consistently indicate substantial improvements in forecast timeliness and accuracy subsequent to the expansion of the 3G network.

4.2. Frequency of Lightning Strikes as an Instrument

Our next set of analyses aims to further alleviate concerns that systematic differences across counties, correlated with analyst forecast characteristics, drive differential speeds of 3G rollout. Following Manacorda and Tesei (2020), we estimate an instrumental variables regression where we use the frequency of lightning strikes as an instrument for 3G coverage. The test relies on exogenous variation in the local frequency of lightning strikes to predict the speed of expansion of local mobile 3G coverage. Our identification assumption is that frequent lightning strikes hinder the rollout of mobile technologies by causing electrostatic surges, which substantially increase the costs of providing service and maintaining the infrastructure. By doing so, they also negatively affect the quality (e.g., speed) of the transmission signal. Hence, telecom companies are typically slower to roll out or expand 3G networks in counties with more lightning strikes (Manacorda and Tesei 2020; Guriev et al. 2021), satisfying the relevance condition. Further, to the extent the propensity of a county to experience lightning strikes is plausibly exogenous to a local analyst's forecast attributes other than through its impact on 3G expansion, this test also satisfies the exclusion restriction.

[14] In total, we have three treatment years in the sample, 2008, 2009, and 2012. The number of observations becomes larger in the stacked DID regressions because of the duplication of observations in the control group under the approach.

We obtain the lightning strike frequency data from the World Wide Lightning Location Network (WWLLN) dataset. These data provide the exact coordinates and time of all detected cloud-to-ground lightning strikes. We then calculate the average annual number of lightning strikes for each county. Following Guriev et al. (2021), we weigh each lightning strike by population density in the county to reflect the number and likelihood of individuals potentially affected by lightning strikes.

To implement this instrumental variable regression design, we estimate the following two-stage specification:

$$3G\ Coverage_{ijt} = \beta_0 + \beta_1 HighLightning*Year_{it} + \gamma' X_{ijt} + Firm*YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \tag{2a}$$

$$Forecast_{ijt} = \beta_0 + \beta_1\ Pred\ 3G\ Coverage_{it} + \gamma' X_{ijt} + Firm*YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \tag{2b}$$

where *HighLightning* is an indicator equal to one if a county's population-weighted lighting frequency per county is higher than the sample median and zero otherwise. Following Guriev et al. (2021), we interact lightning strikes with a time trend as the prediction variable to capture the monotonic growth feature of 3G coverage. In the second stage, we regress forecast timeliness and accuracy on the predicted 3G coverage from the first stage.

We report the first-stage estimation results for forecast timeliness and accuracy in Columns (1) and (3) of Table 4, respectively. We find strong evidence that the frequency of lightning strikes is negatively associated with 3G coverage in the region. The estimated Cragg-Donald Wald F-statistics for both regressions are above 50, much higher than the 1% significance critical value of the Stock-Yogo weak instrument test. Columns (2) and (4) report the results of the second-stage estimation. Positive significant coefficients on predicted 3G coverage support a causal interpretation that 3G expansion leads to a significant increase in the timeliness of analyst forecasts as well as an improvement in forecast accuracy.

4.3. Launch of Productivity Apps on Mobile Devices

Our findings support the hypothesis that the emergence of mobile internet access improves analyst forecast performance. To shed more light on the underlying channels, our next set of tests examines the moderating impact of the launch of productivity apps for mobile devices on the relation between mobile technology and forecast performance. We hypothesize that the availability of work productivity apps (e.g., push notifications of breakout news from media apps) facilitates timely access to news and its incorporation into analyst forecasts.

Our first set of tests correlates analyst forecast performance with the availability of various productivity apps for mobile devices. We obtain the Top 200 Apps (paid and free) from Qimai.com over 2010 to 2017. Our sample period for this analysis starts in 2010 because this is the first year when app download data is available. We expand our main specification to include the interaction between 3G coverage and the availability of productivity apps for mobile devices. We define productivity apps as those apps classified under "Business" (e.g., Microsoft Office) and "News" (e.g., CNBC) by the App Store.[15] Specifically, we estimate the following cross-sectional regression:

$$Forecast_{ijt} = \beta_0 + \beta_1 3G\ Coverage_{it} * MoreProdApps_t + \beta_2 3G\ Coverage_{it} + \gamma' X_{ijt} + Firm*YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \qquad (3)$$

MoreProdApps is an indicator that takes a value of one if the percentage of productivity apps in the Top 200 App Ranking in year t is higher than the sample median and zero otherwise. We do not include *MoreProdApps* indicator separately because its effect is absorbed in the year fixed effects. We are particularly interested in the sign of the interaction term between *3G* Coverage and *MoreProdApps*.

[15] Other examples of Business apps include Adobe PDF Reader, LinkedIn, and Meta Business Suite. Examples of News apps include Twitter, CNN, and Fox.

We present the estimation results in Panel A of Table 5. The coefficients on *3G Coverage*MoreProdApps* are significant and positive for forecast *Timeliness* and *Accuracy*. These results are consistent with the interpretation that analysts leverage faster mobile network to improve work productivity, and one channel is the greater availability of more productivity apps that puts information and analysis tools in analysts' hands irrespective of their location and time.

Our next analysis focuses on the launch of a specific productivity app, the Bloomberg app, in 2008. Bloomberg terminals are widely used by equity analysts to extract relevant financial information, receive timely news updates, and examine peer analysts' research (Rephael, Carlin, Da, and Israelsen, 2022). Bloomberg aimed to extend its users' terminal experience to mobile devices by launching its first mobile application on July 16, 2008. The app provides users with real-time financial information, market data, news, and portfolio tracking on their mobile devices, and is thus particularly pertinent for the productivity of financial analysts. As noted by Business Insider, "*Bloomberg immediately became one of the most popular apps in the market, revered for its clean design and seamless integration with Apple's OS software… It created excitement in the financial industry, and is relied on by millions of users each week*".[16]

We estimate a differences-in-differences specification using the launch of the Bloomberg App as an arguably exogenous shock that differentially affects analysts with varying 3G access. We expect the launch of the app to benefit analysts with greater access to the 3G network. Specifically, we estimate the following regression:

$$Forecast_{ijt} = \beta_0 + \beta_1 Treat{*}Post_{it} + \gamma' X_{ijt} + Firm{*}YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \quad (4)$$

[16] https://www.businessinsider.com/bloombergs-new-app-2013-10

where i indexes analysts, j indexes firms, and t indexes times, respectively. Our test compares forecast performance after the launch of the app to that during the pre-event period across analysts with high versus low 3G access before the app's launch. We restrict our analyses to three years around the launch of the Bloomberg app to limit the potential effect of confounding events over longer horizons. The *Post* indicator takes the value of one from 2009 to 2011, and zero from 2006 to 2008, while the *Treat* indicator takes the value of one in all sample years if the county's 3G coverage is higher than 50% in 2007 (one year immediately before the app launch) and zero otherwise. We do not include *Treat* and *Post* indicators separately because these indicators are absorbed in the county fixed effects and year fixed effects, respectively. We cluster standard errors by county.

Panel B of Table 5 presents the results for this differences-in-differences estimation. Consistent with our prediction, we find that the launch of the Bloomberg app improves forecast accuracy and timeliness more for analysts with greater access to the 3G network, suggesting that one of the main channels through which mobile technology affects analysts' performance is by providing on-demand access to relevant information. In an untabulated test, we assess the validity of the parallel trend assumption, and our findings confirm that the parallel trend requirement is not violated in the pre-period.

4.4. Career Outcomes

Our findings indicate that the expansion of the 3G network improves analysts' forecast timeliness and accuracy. We next examine analysts' career outcomes as alternative indicators of their performance to see if 3G coverage influences investor perceptions of research quality. We use three measures: All-Star status from Institutional Investor (II), demotion from a top-10 broker to a lower-tier brokerage firm, and promotion to a top-10 broker. Survey evidence indicates that All-Star rankings and employment at prominent brokerage firms significantly influence analysts' compensation, thus serving as motivation to produce superior research (Brown, Call, Clement, and Sharp 2015).

We present the regression results in Table 6, examining data at the analyst-year level. In Column (1), the dependent variable, *Future All Star*, indicates whether an analyst achieves All-Star status in year t+1. In Columns (2) and (3), the dependent variables capture whether in year t+1 an analyst is demoted to non-top-10 or promoted to a top-10 brokerage firm, respectively. We account for the analyst's All-Star status in year t and include brokerage fixed effects. Other controls are based on the average values across the analyst's portfolio in year t. The coefficient on *3G Coverage* is positive (negative) and statistically significant in Column 1 (Column 2), indicating that 3G network expansion correlates with improved analyst career trajectories with a higher likelihood of winning all-star status and lower chances of demotion. While we observe a positive coefficient on *3G Coverage* in Column (3) where the dependent variables is *Promotion*, it is not statistically significant. In terms of economic significance, based on the coefficient in column (1), an increase in *3G Coverage* by 21 percent points is associated with a 2.56% increase in the likelihood of becoming an All-Star analyst relative to the unconditional mean.

4.5. Additional Analyses

In this section, we report the results of additional analyses that test the robustness of our results to some alternative specifications.

First, we investigate the 3G network's impact on another key research output of financial analysts, i.e., the accuracy of forecasts of target prices. Adopting the method from Bradshaw, Brown, and Huang (2012), we compute the accuracy of analyst target prices (*TP Accuracy*) as the absolute difference between the 12-month-ahead closing stock price and the predicted target price, scaled by the initial target price and multiplied by -1. Panel A of Table

7 shows the results of our estimation of the effect of 3G Internet on the accuracy of forecasts of target prices. The coefficient for *3G Coverage* is positive and significant at the 10% level, aligning with our earlier conclusion of the 3G network bolstering analysts' forecast accuracy.

Panel B of Table 7 reports results after excluding the county of New York, which is home to the highest concentration of financial analysts. The coefficients on *3G Coverage* remain positive and statistically significant, which demonstrate that our findings are not limited to the New York region. Panel C of Table 7 revisits our primary results using analysts' first, instead of last, forecasts for each fiscal year. The coefficient on *3G Coverage* remains consistently positive and statistically significant for both *Timeliness* and *Accuracy*, echoing our earlier findings in Table 3.

In Panel D of Table 7, we use an alternative measure of forecast timeliness. The dependent variable is an average of four indicator variables which are equal to one if the analyst revises a forecast on the day of or the day after an earnings announcement, and zero otherwise. Averaging these indicators across quarterly earnings announcements gives us an alternate annual measure of forecast timeliness. This metric gauges how promptly analysts respond to earnings news, mirroring methodologies from some prior studies (e.g., Jennings, Lee, and Matsumoto 2017). Our results are robust to this alternative measure of forecast timeliness: the coefficient on 3G Coverage is positive and statistically significant at the 1% level.

5. Conclusion

Mobile internet has permanently altered various professional and personal activities, blurring the line between traditionally distinct parts of a professional's life. A key feature of the technology is granting individuals perpetual access to information, both professional and personal. In this paper, we provide evidence on how increased availability of mobile internet affected the performance of financial analysts – professionals whose career outcomes depend on access to timely information, but who, nevertheless, can be subject to information overload or distracted by personal responsibilities.

Our tests rely on the 3G mobile internet rollout in the U.S., allowing us to evaluate how differential access to this technology across financial analysts affects their forecast performance. With the inclusion of firm-year fixed effects, our regressions pinpoint the effect of an analyst's access to mobile internet on their forecast timeliness and accuracy for a given firm-year. We estimate continuous treatment, sharp-increase, and stacked differences-in-differences models and find that our inferences are the same across these models: increased access to mobile internet improves forecast accuracy and timeliness. In addition, we use the local frequency of lightning strikes (i.e., a plausibly exogenous factor that slowed down the expansion of the 3G network) as an instrument for 3G coverage in instrumental variables regressions to further alleviate endogeneity concerns. Our results from these regressions support the causal interpretation that 3G expansion led to a significant increase in the timeliness of analyst forecasts, as well as an improvement in forecast accuracy.

In additional tests, we find that improvements in forecast timeliness and accuracy are linked to the availability of mobile productivity applications. The launch of the Bloomberg App, an essential work tool for financial analysts previously available only at designated terminals, improved forecast timeliness and accuracy significantly more for analysts with greater access to the 3G network. More generally, improvements in analyst forecast performance are concentrated in years with greater productivity (i.e., news and business) app downloads. The results indicate that mobile technology can aid analyst performance by offering on-demand access to information via Bloomberg, and other news and communication apps.

Overall, our research suggests that better connectivity and uninterrupted access to information improve analysts' outputs and, more generally, the timeliness and quality of information available in capital markets. Prior research finds that mobile internet plays a critical role in information dissemination (Manacorda and Tesei 2020; Guriev et al. 2021). This study advances prior research, indicating that mobile technology engenders a positive information feedback loop, with improved access to information begetting additional valuable information.

Our findings are not without tension as constant interruptions of personal and professional nature, which are inevitably associated with mobile technology, can exact a toll on financial analysts. We conclude that swift access to additional information granted by 3G mobile internet exceeds potential distraction or information overload costs for financial analysts for whom uninterrupted access to information is crucial and leads to better career outcomes. Importantly, our results do not imply that analysts necessarily sacrifice their personal needs for information to make productivity gains at work. Indeed, mobile technology may have provided individuals with better ability to process information for personal consumption as well. Rather, our results are better interpreted as highlighting that the nature of mobile internet as a work tool and an entertainment tool is constantly evolving, and gains in analysts' productivity critically depend on access to mobile internet providing valuable work tools.

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Appendix: Variable Definitions

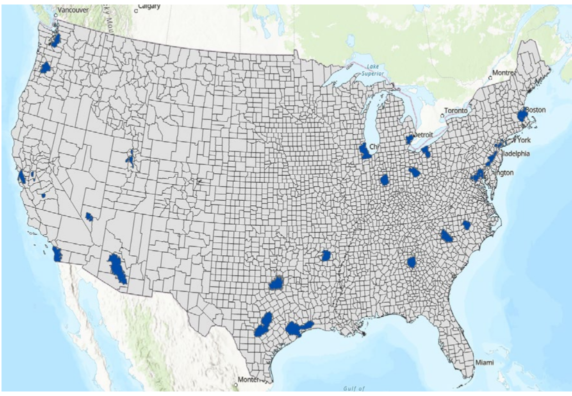
Variable	Definition	Source
3G Coverage	Percentage of the county of the analyst's work address covered by the 3G network.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck
Timeliness	Leader-follower ratio based on an analyst's last annual EPS analyst forecasts issued during the year. We calculate the lead (lag) time of an earnings forecast as the number of days between the focal forecast and two prior (following) forecasts and define leader-follower ratio as the lead time divided by the lag time.	IBES
Accuracy	Absolute difference between the analyst's last forecast and actual value of EPS, scaled by stock price and multiplied by -100.	IBES, CRSP
All Star	Indicator variable equal to one if the analyst is selected as an All-Star analyst by Institutional Investor in the year.	Institutional Investor
Firm Experience	Number of years since the analyst started covering the firm.	IBES
Future All Star	Indicator variable equal to one if the analyst is selected as an All-Star analyst by Institutional Investor in year t+1.	Institutional Investor
General Experience	Number of years since the analysts' first appearance in IBES.	IBES
Horizon	Number of days between the forecast announcement date and earnings announcement date.	IBES
Effort	Number of forecasts issued by the analyst for the firm in the year.	IBES
# Covered Firms	Number of unique firms covered by the analyst in the year.	IBES
# Covered Industries	Number of unique SIC2 industries covered by the analyst in the year.	IBES, Compustat
Broker Size	Number of unique analysts employed by the analyst's broker firm in the year.	IBES
Sharp Increase	Indicator equal to one if the county's 3G coverage increases by more than 50 percent points during a year in our sample period, and year t is after the sharp increase. The analyst's location is defined as the county of the analyst's work address.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck
Treat	Indicator equal to one if the county's 3G coverage is higher than 50% in 2007, and zero otherwise.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck
D(t=-x)	Indicator equal to one for x years preceding the sharp increase in 3G coverage, and zero otherwise.	
D(t=x)	Indicator equal to one for x years post the sharp increase in 3G coverage, and zero otherwise.	
High Lightning	Indicator variable equal to one if the population-density-weighted number of lightning strikes is higher than the sample median, and zero otherwise.	World Wide Lightning Location Network
Log Population	Logarithm of the analyst's county's population in 2007.	Census Bureau
Log County GDP	Logarithm of the analyst's county's GDP in year t.	
Log County Income	Logarithm of the analyst's county's average personal income in year t.	
3G Coverage in 2007	Value of the analyst's county's 3G coverage in year 2007.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck

MoreProdApps	Indicator variable equal to one if in year t the percentage of downloaded productivity apps (e.g., business & news) in the Top200 list is higher than the sample median.	QIMAI
Demoted	Indicator variable equal to one if the analyst is demoted from a top-10 broker to a non-top-10 broker in year t+1. Top-10 brokers are determined by the number of unique analysts employed in year t.	IBES
Promoted	Indicator variable equal to one if the analyst is promoted from a non-top-10 broker to a top-10 broker in year t+1. Top-10 brokers are determined by the number of unique analysts employed in year t.	IBES
TP Accuracy	Absolute difference between the 12-month-ahead closing stock price and the forecasted target price, scaled by beginning target price and multiplied by -1.	IBES, CRSP
Timeliness (Average of Dummies)	Average of the four dummy variables that equal to one if the analyst issues a revision on the day or the day after the quarterly earnings announcement.	IBES, Compustat

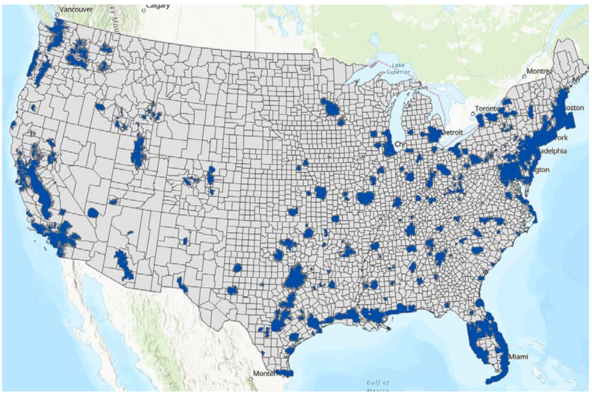
Figure 1 3G Rollout

This figure plots 3G rollout across counties every three years during our sample period.

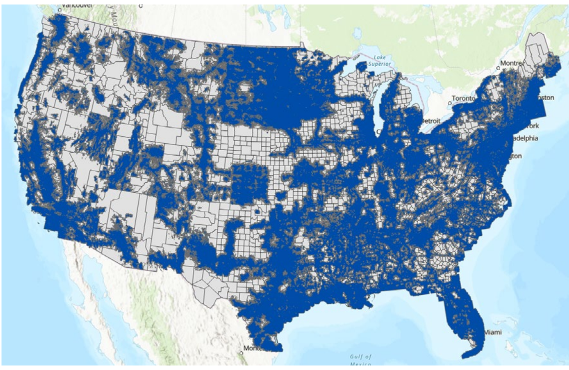
2007



2010



2013



2016

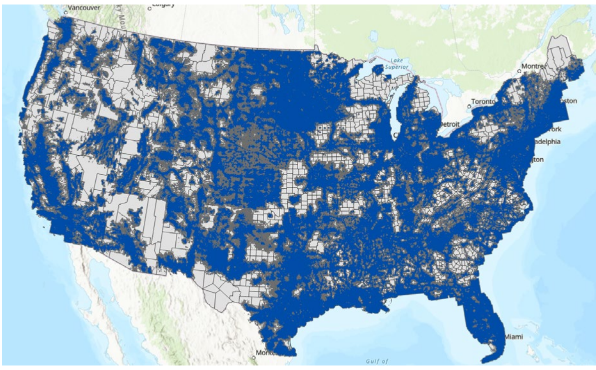


Figure 2 Illustrative Example of Analyst Profile on BrokerCheck

This figure provides an example of an analyst profile on BrokerCheck.

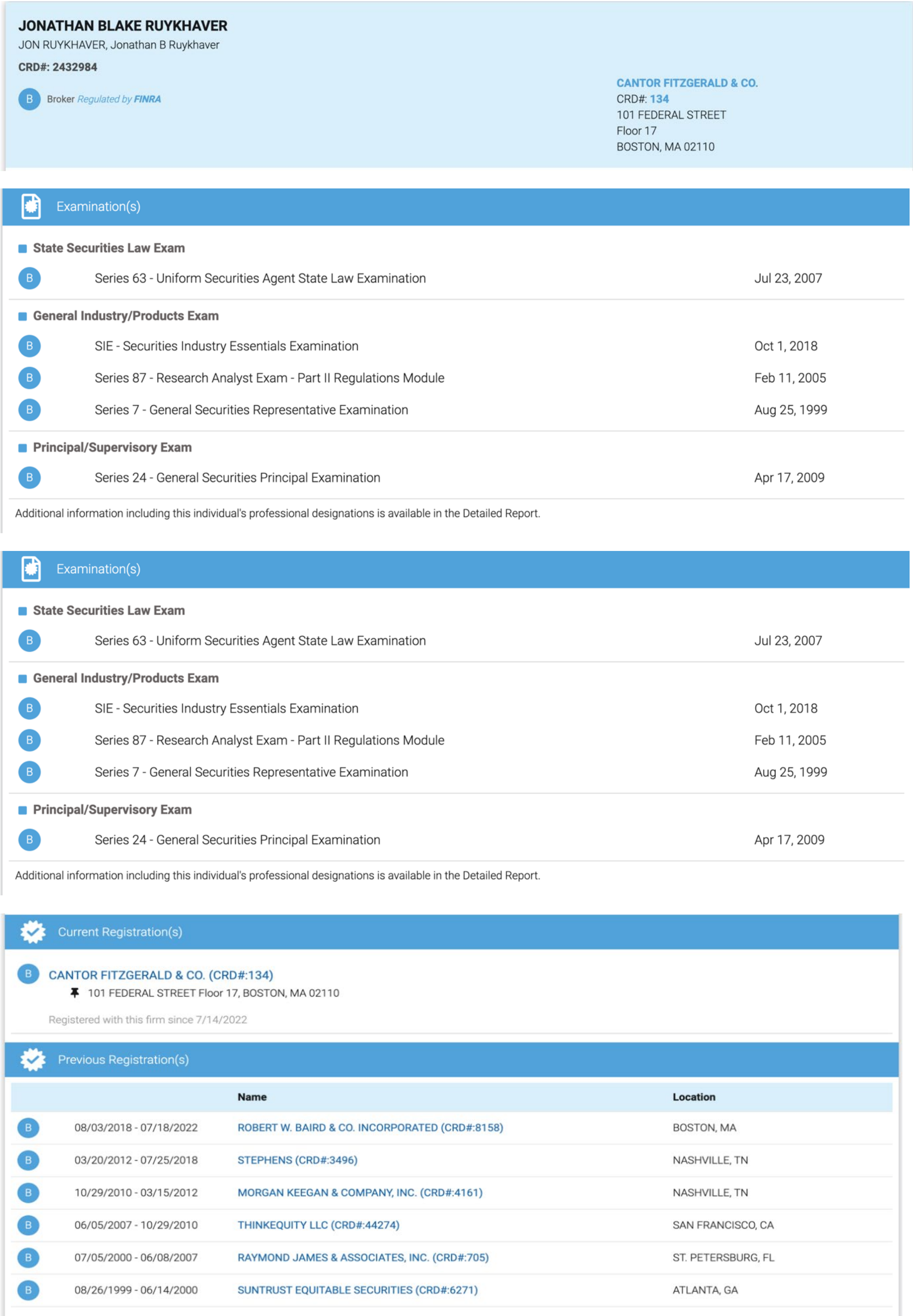


Table 1 Analyst Forecast Distribution

This table reports the number of unique analysts by year in Panel A and the number of unique analysts by state in Panel B.

Panel A: Distribution by Year			
Year	Freq. of Forecasts	Pct.	Unique Analysts
2007	19,380	6.77	1,781
2008	20,709	7.24	1,827
2009	21,361	7.46	1,852
2010	24,070	8.41	2,041
2011	26,490	9.26	2,223
2012	28,132	9.83	2,326
2013	28,900	10.10	2,368
2014	30,101	10.52	2,358
2015	30,414	10.63	2,341
2016	28,915	10.10	2,274
2017	27,691	9.68	2,153
Total	286,163	100	3,947

Panel B: Distribution by State			
State	Freq.	Percent	Unique Analysts
AL	25	0.01	3
AR	2,230	0.78	33
AZ	4	0.00	1
CA	25,824	9.02	434
CO	3,029	1.06	45
CT	4,091	1.43	101
DC	2,029	0.71	42
DE	70	0.02	4
FL	6,098	2.13	115
GA	5,164	1.80	69
IL	11,319	3.96	142
IN	123	0.04	1
KS	16	0.01	3
KY	1,079	0.38	13
LA	3,248	1.14	45
MA	9,619	3.36	145
MD	4,706	1.64	71
ME	783	0.27	7
MI	363	0.13	3
MN	8,618	3.01	139
MO	3,228	1.13	50
MS	194	0.07	4
MT	204	0.07	5
NC	590	0.21	14
NE	46	0.02	1
NH	35	0.01	2
NJ	1,983	0.69	41
NV	258	0.09	10
NY	147,177	51.43	2,397
OH	7,770	2.72	97
OK	2	0.00	1
OR	3,848	1.34	54
PA	2,719	0.95	59
RI	37	0.01	1
SC	140	0.05	6
TN	6,858	2.40	81
TX	13,942	4.87	194
UT	121	0.04	4
VA	8,038	2.81	112
VT	1	0.00	1
WA	402	0.14	10
WI	78	0.03	7
WV	54	0.02	1
Total	286,163	100	

Table 2 Descriptive Statistics

This table presents the descriptive statistics over the sample period 2007 to 2017. All variables are defined in the Appendix.

	N	Mean	SD	Median
3G Coverage	286,163	0.96	0.16	1.00
Timeliness	286,163	2.83	3.66	1.60
Accuracy	286,163	-0.36	5.93	-0.04
All Star	286,163	0.14	0.34	0.00
Horizon	286,163	116.61	66.66	99.00
Effort	286,163	4.45	2.28	4.00
Firm Experience	286,163	4.08	4.56	3.00
General Experience	286,163	12.24	8.80	12.50
# Covered Firms	286,163	17.77	7.38	17.00
# Covered Industries	286,163	3.69	2.42	3.00
Broker Size	286,163	61.55	50.37	46.00
Lightning (Raw)	286,163	1237.73	4309.13	25.00
Log Population	286,094	13.70	1.10	14.44
Log County GDP	286,094	19.20	1.09	19.91
Log County Income	286,094	11.40	0.48	11.64
ProdApps (Raw)	221,300	2.54	0.44	2.38
Demotion	25,319	0.29	0.00	0.00
Promotion	25,319	0.15	0.00	0.00
TP Accuracy	836,396	0.38	0.41	0.26
Timeliness (Average of Dummies)	286,163	0.18	0.27	0.00

Table 3 Effect of Mobile Internet Technology on Forecast Timeliness and Accuracy

This table presents the effects of 3G coverage on analyst forecasting performance. The dependent variable is forecast timeliness in odd-number columns, and forecast accuracy in even-number columns. Columns (1) and (2) are based on continuous treatment OLS specifications. Columns (3) and (4) employ a differences-in-differences (DID) research design and use a sharp increase in 3G coverage as the treatment event. Columns (5) and (6) test the parallel trend assumption for the DID analyses. Columns (7) and (8) use the stacked DID approach as suggested by Baker et al. (2020). The sample period is from 2007 to 2017. All variables are defined in the Appendix. Intercepts are included but their estimates are untabulated. t-statistics are presented below the coefficients in parentheses. ***, **, and * denote statistical significance (two-sided) at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroscedasticity and clustered by county.

	Continuous Treatment		**Sharp DID**		**Parallel Trend**		**Stacked DID**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Timeliness	*Accuracy*	*Timeliness*	*Accuracy*	*Timeliness*	*Accuracy*	*Timeliness*	*Accuracy*
3G Coverage	**0.288*****	**0.136*****						
	(2.64)	**(2.68)**						
Sharp Increase			**0.206*****	**0.049*****			**0.222*****	**0.049****
			(2.67)	**(2.95)**			**(2.62)**	**(2.58)**
D(t=-2)					-0.016	0.044		
					(-0.12)	(0.62)		
D(t=-1)					0.036	-0.035		
					(0.42)	(-1.03)		
D(t=1)					0.141	**0.059****		
					(1.46)	**(2.15)**		
D(t=2)					**0.253*****	0.032		
					(2.76)	(1.49)		
D(t=3)					**0.273****	**0.037****		
					(2.58)	**(2.58)**		
All Star	-0.142***	-0.080***	-0.167***	-0.036***	-0.168***	-0.036***	-0.178***	-0.044***
	(-5.19)	(-3.23)	(-4.57)	(-5.13)	(-4.57)	(-5.05)	(-5.73)	(-3.49)
Horizon		-0.002***		-0.001***		-0.001***		-0.002***
		(-6.48)		(-29.28)		(-29.29)		(-13.74)
Effort		-0.001		0.002		0.002		0.005
		(-0.20)		(0.66)		(0.66)		(1.40)
Firm Experience	0.020*	0.005	0.018*	0.010***	0.018*	0.010***	0.024**	-0.005
	(1.96)	(0.39)	(1.92)	(3.64)	(1.92)	(3.64)	(2.37)	(-0.30)
General Experience	1.199***	0.343	1.211***	-0.075**	1.212***	-0.075**	1.102***	-0.028
	(14.02)	(1.09)	(12.70)	(-2.26)	(12.75)	(-2.27)	(12.42)	(-0.19)
# Covered Firms	-0.001	0.003**	-0.004	-0.000	-0.004	-0.000	-0.005*	0.000
	(-0.42)	(2.24)	(-1.63)	(-0.28)	(-1.64)	(-0.33)	(-1.91)	(0.40)
# Covered Industries	-0.011	0.006	-0.006	0.010*	-0.006	0.010*	-0.010	0.011
	(-1.39)	(0.63)	(-0.50)	(1.90)	(-0.49)	(1.91)	(-0.84)	(1.39)
Broker Size	0.003***	0.000**	0.002***	0.000	0.002***	0.000	0.002***	0.000
	(9.84)	(2.15)	(7.20)	(0.74)	(7.17)	(0.75)	(6.53)	(1.61)
Observations	286,163	286,163	217,664	217,664	217,664	217,664	420,259	420,259
Adj. R-squared	0.338	0.567	0.341	0.555	0.341	0.555	0.342	0.568
Firm*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analysts FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 Instrumental Variable Regression

This table presents the Instrumental Variable (IV) regression results using lightning strikes as an IV. Columns (1) and (3) present the first-stage regression results. Columns (2) and (4) present the second-stage regression results for forecast timeliness and forecast accuracy. The sample period is from 2007 to 2017. All variables are defined in the Appendix. Intercepts are included but their estimates are untabulated. t-statistics are presented below the coefficients in parentheses. ***, **, and * denote statistical significance (two-sided) at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroscedasticity and clustered by county.

	(1) First-Stage *3G Coverage*	(2) Second-Stage *Timeliness*	(3) First-Stage *3G Coverage*	(4) Second-Stage *Accuracy*
3G Coverage		**0.072****		**0.163****
		(2.09)		**(2.52)**
High Lightning*Year	**-0.011*****		**-0.147*****	
	(-9.21)		**(-10.08)**	
All Star	0.701***	-0.187***	0.151	-0.103*
	(6.37)	(-4.39)	(1.61)	(-1.67)
Effort			0.000	-0.003***
			(1.56)	(-13.97)
Horizon			-0.043***	0.010
			(-4.35)	(1.49)
Firm Experience	-0.021	0.022***	0.001	0.003
	(-0.88)	(2.81)	(0.07)	(0.20)
General Experience	0.703**	1.150***	0.567**	-0.011
	(2.37)	(11.81)	(2.16)	(-0.07)
# Covered Firms	-0.101***	0.006	-0.021***	0.005
	(-16.42)	(1.58)	(-4.05)	(1.37)
# Covered Industries	-0.040	-0.008	0.003	0.004
	(-1.63)	(-1.01)	(0.12)	(0.30)
Broker Size	0.014***	0.002***	0.009***	-0.001
	(14.40)	(3.43)	(10.90)	(-1.12)
Log Population	48.263***	-2.680*	2,475.761***	-374.713**
	(52.46)	(-1.79)	(105.90)	(-2.41)
Log County GDP	-77.851***	4.710*	-33.838***	4.615**
	(-128.24)	(1.76)	(-63.15)	(2.11)
Log County Income	17.928***	-1.005	43.866***	-4.385
	(22.29)	(-1.50)	(64.80)	(-1.53)
3G Coverage in 2007	-0.029***	0.001	-5.719***	0.902**
	(-28.35)	(1.31)	(-286.45)	(2.42)
Observations	286,163	286,163	286,163	286,163
Cragg-Donald Wald F statistic	84.91		101.51	
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Analysts FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Table 5 Role of Productivity Apps on Mobile Devices

Panel A presents the results of estimating the regressions given by Eq. (3). The sample period is from 2010 to 2017. Panel B presents the results of estimating the regressions given by Eq. (4). The sample period is from 2006 to 2011. All variables are defined in the Appendix. Intercepts are included but their estimates are untabulated. t-statistics are presented below the coefficients in parentheses. ***, **, and * denote statistical significance (two-sided) at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroscedasticity and clustered by county.

Panel A:Popularity of Productivity Apps

	(1) *Timeliness*	(2) *Accuracy*
3G Coverage*MoreProdApps	**0.018*** **	**0.100** **
	(6.00)	**(2.02)**
3G Coverage	-0.005	0.126
	(-0.23)	(1.06)
All Star	0.014***	-0.100***
	(3.84)	(-3.02)
Horizon		-0.002***
		(-5.60)
Effort		-0.006
		(-0.87)
Firm Experience	0.006***	0.013
	(10.69)	(1.24)
General Experience	0.084***	0.372
	(11.99)	(1.00)
# Covered Firms	0.002***	0.005***
	(5.22)	(3.10)
# Covered Industries	-0.002	0.004
	(-1.49)	(0.37)
Broker Size	0.000***	-0.000
	(3.58)	(-0.61)
Observations	221,300	221,300
Adj. R-squared	0.464	0.587
Firm*Year FE	Yes	Yes
Analysts FE	Yes	Yes
County FE	Yes	Yes

Panel B: Launch of Bloomberg App as a Shock

	(1) *Timeliness*	(2) *Accuracy*
Treat*Post	**0.165*** **	**0.049** **
	(4.49)	**(2.39)**
All Star	-0.035	0.014
	(-0.84)	(0.98)
Horizon		-0.002***
		(-8.21)
Effort		0.009**
		(2.08)
Firm Experience	0.021**	-0.005
	(2.06)	(-0.19)
General Experience	0.005	-0.016***
	(0.32)	(-6.58)
# Covered Firms	0.001	-0.011**
	(0.33)	(-2.29)
# Covered Industries	-0.005	0.029***
	(-0.58)	(3.38)
Broker Size	0.007***	0.001**
	(3.96)	(2.39)

Observations	123,680	123,680
Adj. R-squared	0.292	0.469
Firm*Year FE	Yes	Yes
Analysts FE	Yes	Yes
County FE	Yes	Yes

Table 6 Career Outcomes

This table presents the regression results on analyst career outcomes. The sample period is from 2007 to 2017. All variables are defined in the Appendix. Intercepts are included but their estimates are untabulated. t-statistics are presented below the coefficients in parentheses. ***, **, and * denote statistical significance (two-sided) at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroscedasticity and clustered by analysts.

	(1) Future All Star	(2) Demotion	(3) Promotion
3G Coverage	**0.017*****	**-0.014*****	**0.007**
	(3.04)	**(-2.73)**	**(1.18)**
All Star	0.658***	-0.003	-0.006**
	(62.15)	(-0.99)	(-2.10)
Horizon	-0.000***	0.000***	0.000
	(-3.49)	(3.55)	(0.07)
Effort	0.003***	-0.000	-0.000
	(3.16)	(-0.59)	(-0.48)
Firm Experience	0.002	-0.001	0.001
	(1.07)	(-0.81)	(0.48)
General Experience	0.002**	0.000	0.001
	(2.18)	(0.77)	(1.64)
# Covered Firms	0.002***	0.000	0.000
	(9.07)	(0.83)	(0.95)
# Covered Industries	0.001	-0.000	-0.000
	(0.97)	(-1.24)	(-0.13)
Broker Size	0.000	0.003***	-0.000
	(1.61)	(17.16)	(-0.07)
NY	0.005	-0.002	0.001
	(1.41)	(-1.26)	(0.40)
Observations	25,319	25,319	25,319
Adj. R-squared	0.615	0.185	0.111
Year FE	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes

Table 7 Additional Analyses

Panel A presents the regression results on analyst target price forecast accuracy. Panel B presents the main regression results after excluding analysts based in New York. Panel C tabulates the results of robustness analyses using analysts' first forecast. Panel D presents the regression results using *Timeliness (Average of Dummies)* as an alternative dependent variable. The sample period is from 2007 to 2017. All variables are defined in the Appendix. Intercepts are included but their estimates are untabulated. t-statistics are presented below the coefficients in parentheses. ***, **, and * denote statistical significance (two-sided) at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroscedasticity and clustered by county.

Panel A: The Accuracy of Target Prices

	(1) *TP Accuracy*
3G Coverage	**0.035***
	(1.95)
All Star	-0.027*
	(-1.94)
Firm Experience	-0.003
	(-1.23)
General Experience	-0.103
	(-1.40)
# Covered Firms	0.004*
	(1.83)
# Covered Industries	-0.001
	(-0.11)
Broker Size	0.000
	(1.48)
Observations	836,396
Adj. R-squared	0.711
Firm*Year FE	Yes
Analysts FE	Yes
County FE	Yes

Panel B: Exclude NY		
	(1)	(2)
	Timeliness	*Accuracy*
	Excluding NY	Excluding NY
3G Coverage	**0.224***	**0.098*****
	(1.71)	**(3.00)**
All Star	0.033	0.031
	(0.38)	(1.03)
Horizon		-0.002***
		(-3.49)
Effort		-0.003
		(-0.30)
Firm Experience	0.035**	0.006
	(2.08)	(0.19)
General Experience	1.257***	0.946
	(6.96)	(1.30)
# Covered Firms	-0.001	0.002
	(-0.22)	(1.00)
# Covered Industries	-0.005	0.020
	(-0.34)	(1.14)
Broker Size	0.002**	-0.000
	(2.00)	(-0.45)
Observations	140,718	140,718
Adj. R-squared	0.353	0.556
Firm*Year FE	Yes	Yes
Analysts FE	Yes	Yes
County FE	Yes	Yes

Panel C: First Forecasts Sample		
	(1)	(2)
	Timeliness	*Accuracy*
	Full Sample	Full Sample
3G Coverage	**0.581*** **	**0.136*** **
	(2.71)	**(2.68)**
All Star	-0.280***	0.080***
	(-6.48)	(3.23)
Horizon		0.002***
		(6.48)
Effort		0.001
		(0.20)
Firm Experience	0.006	-0.005
	(0.58)	(-0.39)
General Experience	6.702***	-0.343
	(21.98)	(-1.09)
# Covered Firms	0.001	-0.003**
	(0.14)	(-2.24)
# Covered Industries	-0.009	-0.006
	(-0.79)	(-0.63)
Broker Size	0.005***	-0.000**
	(7.64)	(-2.15)
Observations	216,404	286,163
Adj. R-squared	0.4983	0.6219
Firm*Year FE	Yes	Yes
Analysts FE	Yes	Yes
County FE	Yes	Yes

Panel D: Alternative Measure of Timeliness	
	(1)
	Timeliness (Average of Dummies)
	Full Sample
3G Coverage	**0.027*****
	(2.78)
All Star	0.007
	(0.95)
Firm Experience	0.006***
	(7.01)
General Experience	0.099***
	(11.18)
# Covered Firms	0.001***
	(4.04)
# Covered Industries	-0.001
	(-0.86)
Broker Size	0.000***
	(7.05)
Observations	286,163
Adj. R-squared	0.439
Firm*Year FE	Yes
Analysts FE	Yes
County FE	Yes