Information at Your Fingertips: Mobile Internet and Analyst Forecast Performance †

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Abstract: This paper focuses on mobile internet technology as a technological innovation in the ability to access information and communicate more easily and evaluates its impact on analyst forecast performance. We examine the access to mobile internet around the analyst's workplace, where the analyst already has multiple alternative avenues for accessing and communicating information, and mobile internet thus possesses the power to reduce analysts' output quality by serving as a source of distraction. Our tests utilize the rollout of 3G mobile internet in the U.S. and include both continuous treatment and sharp-increase difference-in-differences models, comparing forecast characteristics for a given firm-year across analysts with varying degrees of access to mobile internet. Results indicate that the net effect of the enhanced access to mobile internet is a significant improvement in analysts' forecast timeliness and accuracy. We link this improvement empirically to the rollout of productivity apps and confirm the effect with an innovation particularly pertinent for analysts, the Bloomberg app. Access to mobile internet is especially crucial for the timeliness of forecast revisions spurred by unanticipated news releases, particularly those announced after hours. We also find evidence that such internet access can provide new sources or exacerbate the effect of existing sources of distraction. Overall, our results indicate that although mobile technology has the power to distract, its first-order effect is to significantly enhance the output quality of financial analysts, a key information intermediary in capital markets.

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

JEL Classification: G17, O33

1. 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 the 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 output quality. At the same time, it also has the power to hinder professional performance. After all, mobile technology 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 boundaries between professional and personal lives. Thus, it can facilitate a professional's desire to improve the quality of output at the workplace, and at the same time, it can encourage individuals to pursue information for personal consumption. 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 impactful reports 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).

The quality of each analyst's output can be fairly accurately measured with forecast timeliness and accuracy (Bradley, Gokkaya, and Liu 2017; Fang and Hope 2021; Bourveau et al. 2022). Forecasts are more continuous and more frequently revised than recommendations, allowing for a more granular assessment of output quality (Bradshaw 2011). Moreover, timely and accurate inputs used to formulate forecasts are also relevant in setting recommendations, even after controlling for expertise and conflict of interest (Ertimur, Sunder, and Sunder 2007; Bradshaw, Flake, Piorkowski 2023). It is thus not surprising that forecast timeliness and accuracy are linked to analysts' career outcomes.[1]

Mobile internet can serve as a valuable work resource expediting or even expanding the access to professionally relevant information, for example, through apps with push notifications. It can also improve analysts' ability to coordinate with their teams, and quickly respond to information. 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 mobile technology makes information searches more efficient, and analysts choose to use some of the time advantage for additional research, forecast accuracy may improve as well. We would interpret an improvement in any one of these forecast attributes, timeliness and/or accuracy, without any deterioration in the other, as increased output quality.

Another potential effect of mobile technology arises from its ability to distract. A rich literature on limited attention shows that the presence of competing events or stimuli slows down or alters human response to information[2]. 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

[1] See, for example, Mikhail, Walther and Willis (1999), Brown, Call, Clement and Sharp (2015), deHaan et al. (2017), and Harford, Jiang, Wang, and Xie (2019).
[2] See Hirshleifer and Teoh (2003), Corwin and Coughenour (2008), Hirshleifer, Lim and Teoh (2009), and Drake, Gee and Thornock (2016).

inhibiting information acquisition and integration.[3] Both the work-resource and the distraction effect are likely at play simultaneously.

Of particular interest is the net effect of the availability of mobile technology in the area surrounding an analyst's workplace. Analysts spend a significant amount of time either at work or in the surrounding area: commuting, attending official meals, and meetings with clients and managers of local companies they follow (Malloy 2005; O'Brien and Tan 2015). On the one hand, analysts already have access to desktops and the internet at their workplace, raising the possibility that mobile internet primarily serves to distract. On the other hand, mobile technology can act as a complement to other work tools by attracting analysts' attention to developing news (for example, through push notifications) and enabling them to acquire and process it more swiftly, leading to more timely reports (Blankespoor, deHaan, and Marinovic 2020).[4]

To examine the on-average impact of mobile internet access on the timeliness and accuracy of analyst forecasts, we take advantage of the staggered expansion of 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 difference-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

[3] See Strayer and Johnston (2001), Jacobsen and Forste (2011), and Thompson, Rivara, Ayyagari, and Ebel (2013).

[4] It is possible that mobile internet is valuable to analysts as a work tool when they travel to conferences, visit companies they cover or even travel on vacations. Unfortunately, the combination of the exact timing and the location of analysts when impactful corporate news is released is not observable. Further, the potential news content and informativeness of conferences may be in part be determined by mobile internet availability at the conference's location. Our research design is thus centered on the availability of mobile internet around the analyst's workplace.

which they operate.[5] The inclusion of firm-year fixed effects in the estimation implies that the comparison is 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, Jame, Markov, and Subasi 2014; Shroff, Venkataraman, and Xie 2014).[6] Our sample for this analysis includes 286,163 analyst-firm-years between 2007 and 2017.[7]

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 percentage points over 2007-2017) leads to a 2.2% increase in timeliness, and an 8.1% increase in forecast accuracy relative to their respective means.

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. Following Guriev et al. (2021), we conduct an alternative difference-in-differences test where the treatment relies on sharp increases in county-level 3G coverage and find that sharp coverage increases lead to

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[5] 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's workplace 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.

[6] 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 additional 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.

[7] We compute timeliness based on the leader-follower ratio averaged across all annual EPS forecasts issued by an analyst in a given year for a given firm. When computing accuracy, we retain each analyst's last annual EPS forecast from all annual forecasts with one- to twelve-month horizon. Focusing consistently on either last or first forecasts has the benefit of making forecast horizon more comparable (Mikhail et al. 1999). We also confirm that our results are robust to retaining the first annual forecast instead.

both attributes of analysts' forecasts improving significantly.[8] Forecasts issued by treated analysts experience an increase in timeliness and accuracy equal to 6% and 13.6% of their corresponding means, respectively. Based on the discrete treatment specification using sharp coverage increases, we validate the parallel trend assumption. We find no significant differences in forecast timeliness or accuracy between treated and control observations in the pre-treatment years. To address potential empirical issues with a staggered treatment design, we confirm that our results are robust to using a stacked difference-in-differences estimation. We also observe that our results are not driven solely by financial analysts employed by brokerage houses in New York.

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 prone to a higher frequency of lightning strikes, which is arguably exogenous to analysts' forecast attributes.[9] Our results from these instrumental variables regressions support the plausibly causal interpretation that 3G expansion led to a significant increase in the timeliness and accuracy of analyst forecasts.

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 analysts' forecast performance. A prominent example of an application that is likely helpful to analysts 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 2008 rollout of the app, analysts' access to Bloomberg

[8] A sharp increase is defined as a 50 percentage points or higher increase in 3G coverage.
[9] 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).

was limited to the desktop terminals in their offices. The mobile 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 analysts. 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, acquisition, and integration.

In our empirical analyses, we first conduct a difference-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. 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 second part of this test expands the analysis to all productivity apps. Our results suggest that forecast timeliness and accuracy improve significantly more for analysts with greater 3G access in years with more than usual downloads of productivity apps. We next test the power of mobile internet to distract analysts via easy access to entertainment and personal-use apps (as opposed to productivity apps). We find that, in years with more than usual downloads of entertainment apps, greater 3G coverage has no effect on forecast accuracy but significantly reduces timeliness. The evidence implies that distraction from entertainment apps can at times impair the quality of analysts' output.

Our next set of analyses focuses on whether mobile internet increases analysts' responsiveness to salient corporate events. Specifically, we examine whether following the release of earnings announcements and other less-anticipated but high-impact corporate news, the likelihood of issuing a timely forecast revision (i.e., on the same or next day) increases with an analyst's access to 3G. We observe this is indeed the case. We next turn to whether 3G access mitigates or aggravates the impact of events with the potential to distract analysts. We show that when the most popular college sports events (i.e., college football and March

Madness) coincide with the arrival of unanticipated corporate news, the likelihood of a timely revision declines (irrespective of 3G access). More importantly, analysts with greater 3G access are incrementally less likely to revise their forecasts in a timely manner when unanticipated corporate news is released on days of these sports events, indicative of 3G access heightening distraction.

An additional test that directly focuses on the blurring of the distinction between professional and personal hours examines whether 3G access facilitates timely analysts' responses to higher-impact corporate news released after working hours. This test is in part motivated by literature that analysts are continuously processing information, and often work long hours (deHaan, Shevlin, and Thornock 2015). We find that analysts are generally less likely to issue timely forecast revisions in response to unanticipated corporate news released after traditional office hours. However, greater access to 3G internet moderates this effect. This is consistent with the argument that mobile internet can decrease information awareness and acquisition costs, especially when analysts are around the workplace but less likely to be at their desk.[10]

Our evidence thus far has been based on the most frequently revised and thus most suitable form of analyst output for our study, i.e., earnings forecasts. In additional tests we find that analysts with greater 3G access improve the accuracy of their target price forecasts as well. These results speak more directly to analysts' forecasting abilities in general, and to the equity market implications of 3G access.

A natural question is whether the improvements in analyst output quality with access to mobile internet are beneficial for the analyst's career. Our analyses indicate that analysts

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[10] Interestingly, the economic magnitude of this moderating effect of access to 3G internet increases monotonically as we shift the definition of "after hours" to a later time of the day, making it more likely that analysts are away from their desk. Without mobile internet, analysts become aware of the information with a significant delay.

with expanded exposure to 3G internet experience an increased likelihood of obtaining an All-Star status from institutional investors and promotion to a top-10 broker from a lower-tier brokerage firm. This evidence suggests that analysts have career-driven incentives to exploit mobile internet to improve output quality.

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. These effects have been shown in the context of exposing government corruption, spreading information about economic downturns, and coordinating mass protests (Manacorda and Tesei 2020; Guriev et al. 2021). There is also evidence in the corporate setting, with mobile internet affecting investors' information searches (Brown, Stice and White 2015; Brown, Elliott, Wermers, and White, 2022), and deterring 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 underscores this 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 two recent papers that have investigated the influence of mobile technology on information flow in 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. Brown et al. (2015) interpret their results as evidence of access to mobile technology facilitating the flow of local information into stock prices. In contrast, Brown et al. (2022) exploit short-lived Blackberry usage disruptions to provide evidence that access to mobile internet can also inhibit investors' information gathering and trading activities. In the context of this evidence that mobile technology can both facilitate and inhibit information flows, our paper focuses directly on the outputs of crucial information intermediaries in capital markets, financial analysts. We find evidence of mobile internet's power to distract analysts, for example, during popular sports events. However, our evidence indicates that on average, this type of internet access improves analysts' output quality, implying improved information flows to capital markets from analysts.

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.[11] Further, in-person interactions between managers and analysts can serve as an important information channel in spite of advances in technology (Green et al. 2014; Durney, Kyung, Markov, Park 2024). We contribute to this literature by providing evidence that mobile internet access leads to improvements in forecast accuracy and timeliness. Our research highlights the role that technology plays in elevating the quality of analysts' outputs and more generally, the quality of information available in capital markets.

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.

[11] 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).

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 (apps).

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.[12] These maps compile coverage data submitted by mobile network operators to the GSM Association.[13] 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 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.

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[12] 2007 is the first year Collin Bartholomew collects information on 3G coverage.

[13] 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.

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 influence the performance and career trajectories of financial analysts.

Embedded in our use of this data is an assumption that analysts' daily activities center around the location of their workplace, whose 3G coverage would be a good approximation for analysts' exposure to such technology. We posit that analysts are likely to benefit from mobile technology when they take lunch breaks, communicate with clients or managers of their local portfolio firms, and get access to news information on their daily commute (Malloy 2005; O'Brien and Tan 2015). Nevertheless, analysts also travel outside of their local area, so measuring 3G coverage based on their workplace location likely introduces errors in measuring their total mobile technology exposure.

2.3. Measurement of Analyst Forecasts Attributes

We employ two measures to capture analysts' performance, earnings forecast timeliness and forecast accuracy, which have been widely used in the literature (e.g., Mikhail et al. 1999; Cooper et al. 2001). 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. We take the average value of *Timeliness* across forecasts issued in the year by a given analyst for a given firm to construct the measure at the analyst-firm-year level. We define forecast *Accuracy* as the absolute value of the difference between the analyst's last annual EPS 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.

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 difference-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:

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

where i indexes analysts, j indexes firms, and t indexes times, respectively. *Forecast* refers 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 and the differences in analysts' performance driven by their locations. 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 when calculating forecasting accuracy.[14] Therefore, our analyses are at the analyst-firm-year level.

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.

Table 2 indicates that the 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 timeliness and accuracy measures, and for the control variables in our tests. 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

[14] Our inferences remain the same if we use the first forecast issued by each analyst. The results are tabulated in Panel A of Table 4.

approximately 2.83 times longer than the subsequent forecasts that follow. 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 a percentage of stock price. 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 timeliness and accuracy. 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.[15]

[15] 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*0.293/2.83.

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 an 8.1% increase in forecast accuracy relative to its mean.[16]

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-percentage 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.[17] 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.[18]

Columns (3) and (4) present the forecast timeliness and accuracy results using the sharp difference-in-differences research design. Consistent with our main findings, we find that *Timeliness* and *Accuracy* exhibit statistically significant increases following sharp rises in local 3G coverage. In terms of economic magnitudes, a sharp increase in 3G coverage is associated with a 6% improvement in timeliness, and a 13.6% increase in forecast accuracy relative to their respective unconditional means.[19]

Relying on a sharp increase 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

[16] 8.1% is calculated as 0.21*0.139/0.36.
[17] 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.*"
[18] 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.
[19] The economic magnitude of the increases in timeliness and accuracy is computed as 0.170/2.83 or 6% and 0.049/0.36 or 13.6%, respectively.

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 difference-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 not violated in our setting.

To overcome the empirical challenges associated with a staggered treatment design when there are heterogeneous treatment effects, we employ a stacked difference-in-differences estimation approach (Cengiz, Dube, Lindner, Zipperer 2019; Baker, Larcker, and Wang 2021; Barrios 2022). 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. This approach helps address estimation issues that may arise when using previously treated units of observation in the control sample. 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 year.[20] The results of this estimation are presented in Columns (7) and (8) of Table 3. Our inferences are unchanged based on this alternative specification, further supporting the conclusion that the expansion of the 3G network leads to significant increases in forecast timeliness and accuracy.

[20] 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 this approach.

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. Robustness Tests

We conduct several additional analyses to evaluate the robustness of our findings. Panel A of Table 4 re-estimates our primary results using each analyst's first forecast for a given firm, instead of using the last forecast in computing accuracy, and the average of forecasts in computing timeliness for each fiscal year. The coefficient on *3G Coverage* remains consistently positive and statistically significant for both *Timeliness* and *Accuracy*, consistent with our findings in Table 3.

To mitigate the concerns that our results might be affected by a disproportionate number of analysts working in New York, Panel B of Table 4 reports results after excluding analysts in New York. The coefficients on *3G Coverage* remain positive and statistically significant, suggesting that our findings are not limited to the New York region.

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 variable 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, thereby substantially increasing the costs of providing service and maintaining the infrastructure. In addition, 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. Furthermore, 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.[21]

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 across our sample period. 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:

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

$$Forecast_{ijt} = \beta_0 + \beta_1\ Pred\ 3G\ Coverage_{it} + \gamma' X_{ijt} + FirmFE + YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \quad (2b)$$

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 Panel C of Table 4, respectively. We find strong evidence that the

[21] Consistent with previous studies (e.g., Guriev et al., 2021), our instrument variable gauges the average occurrences of lightning strikes in specific areas. This instrument differs from temporal weather fluctuations which can affect analysts' output, as noted by deHaan, Madsen, and Piotroski (2017). Moreover, any potential influence of long-term lightning conditions on analysts' mood and forecasting performance would be accounted for by including county-fixed effects in our regression analyses.

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. 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 mechanisms, our next set of tests examines the moderating impact of productivity and entertainment apps for mobile devices on the relationship between mobile technology and forecast performance. We hypothesize that the availability of work productivity (entertainment) apps facilitates (diminishes) timely access to news and its incorporation into analyst forecasts.

4.3.1. Launch of Bloomberg App

Our first set of tests 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 (Ben-Rephael et al. 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*".[22]

We estimate a difference-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:

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

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 A of Table 5 presents the results of this difference-in-differences estimation. We find that the launch of the Bloomberg app improves forecast timeliness and accuracy 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

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

assumption, and our findings confirm that the parallel trend requirement is not violated in the pre-period.

4.3.2. Availability of Productivity Apps

Our next set of tests correlates analyst forecast performance with the availability of various productivity apps for mobile devices, conditional on the analysts' mobile internet access. We obtain the Top 200 Apps (paid and free) from Qimai.com from 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) or "News" (e.g., CNBC) by the App Store. Specifically, we estimate the following cross-sectional regression:

$$Forecast_{ijt} = \beta_0 + \beta_1 3G\ Coverage_{it} * MoreProdApps_t + \beta_2 3G\ Coverage_{it} + \gamma' X_{ijt} + Firm*YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \qquad (4)$$

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 by the year fixed effects. We are particularly interested in the sign of the interaction term between *3G* Coverage and *MoreProdApps*.

We present the estimation results in Panel B 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 networks to improve work productivity, facilitated by the increased accessibility of productivity apps that provide analysts with information and analysis tools.

4.3.3. Availability of Entertainment Apps

We also assess the effects of mobile Apps that could distract analysts from their professional tasks and potentially affect their performance negatively. We estimate the following cross-sectional regression:

$$Forecast_{ijt} = \beta_0 + \beta_1 3G\ Coverage_{it} * MoreEntertainApps_t + \beta_2 3G\ Coverage_{it} + \gamma' X_{ijt} + Firm*YearFE + AnalystsFE + CountyFE + \varepsilon_{ijt} \qquad (5)$$

Entertainment Apps are those apps classified under "Entertainment" (e.g., Netflix), "Game", or "Social Media" (e.g., Facebook) by the App Store. Our measure *MoreEntertainApps* takes the value of one if the percentage of entertainment app downloads in the Top 200 App Ranking in year t is higher than the sample median and zero otherwise. We present the regression results in Panel C of Table 5. The coefficients on *3G Coverage*MoreEntertainApps* are negative for forecast *Timeliness* and *Accuracy*, though we only observe statistical significance at a 5% level for forecast *Timeliness*. The results suggest that mobile technology can also sometimes have a detrimental effect on analysts' forecast timeliness by distracting analysts from their professional tasks.

4.4. Analyst Timeliness in Responding to Corporate Events

In this section, we further explore the impact of the 3G network on analysts' performance by examining the timeliness of their responses to anticipated and unanticipated corporate news events. Prior studies find that analysts are incentivized to issue timely forecasts following a news event, as it is highly valued by investors and influences analysts' compensation (Guttman, 2010; Keskek, Tse, and Tucker, 2014). However, analysts need to become aware of news to integrate it into their reports and respond by issuing a timely revision. Mobile technology, along with push notifications and breaking news access, can be particularly helpful in this respect. We expect this time advantage to be valuable with respect to salient news events such as earnings announcements and other less anticipated corporate developments, as well as when news is released after traditional work hours. In additional analyses, we also examine how, during college sports events, access to on-demand scores and game updates affects analyst responsiveness to corporate events. Such events have been shown to distract investors (Drake et al. 2016). We re-examine these events in the context of their effect on financial analysts and ask if access to mobile technology influences any potential distraction effect.

4.4.1. Analysts' Reactions to Earnings Announcements

As a first step, we examine analysts' responses to quarterly earnings announcements. Consistent with previous research (Keskek et al., 2014; Jennings, Lee, and Matsumoto, 2017), we create an indicator variable that equals one if the analyst issues a forecast on the day of or the day following the earnings announcement. To construct a measure at the analyst-firm-year level, we average these indicator variables across the four quarters, providing insight into how promptly analysts react to earnings news within the firm-year, conditional on their access to 3G technology. Table 6 presents the regression results. The coefficient on *3G Coverage* is positive and statistically significant at the 5% level, which aligns with our earlier findings on timeliness based on the leader-follower ratio.

4.4.2 Analysts' Reactions to Corporate News Events

Next, we broaden our analysis to encompass various corporate news events (e.g., M&A, restructuring, layoffs, etc.) to provide a comprehensive understanding of the impact of 3G technology on analysts' forecast timeliness based on news that is often less anticipated than earnings announcements. We collect a sample of news events from Ravenpack's Dow Jones News database, retaining those with an impact score exceeding the average threshold of 0.5 as determined by Ravenpack. A high impact score allows us to filter out the most significant corporate news likely to affect analyst forecasts. We retain firm-analyst pairs where the analyst issues at least one annual earnings forecast for the firm in the year, and then merge analysts' earnings forecasts with the firm's news events. This dataset is structured at the analyst-firm-event level, comprising approximately 1.6 million observations. Our dependent variable (*Revision*) is an indicator variable that equals one if the analyst issues a forecast on the day of or the day following the firm's news event. The mean value of the *Revision* is 0.11, indicating that 11% of analysts issue a forecast within the two-day window following a high-impact corporate news event. In our model, we control for earnings announcements which allows us to focus on other sources of news. In Column (1) of Table 7, we observe a positive association between *3G Coverage* and timeliness of forecast revision to corporate news events, implying that access to mobile technology expedites analysts' response to high-impact but often unanticipated corporate news.

Next, we investigate potential factors that could amplify or attenuate the impact of 3G technology on analysts' forecast timeliness. In Columns (2) and (3) of Table 7, we examine the influence of a potential distraction source: sports events. Such events have been documented to affect the attention of capital market participants and consequently their responsiveness to information events (e.g., Drake et al., 2016). We focus on college football and March Madness basketball games due to their widespread popularity and the attention they garner from the public (e.g., Drake et al., 2016; Jones, 2017). We create an indicator variable, *Sports Events*, which equals one if the analyst's county hosts a college football game or if there is a March Madness basketball match occurring on the news day or the day after the corporate news event. In our sample, 4% of corporate news events coincide with a local sports event.

In Column (2), the coefficient on *Sports Events* is negative and statistically significant at the 1% level, suggesting that sports events adversely impact analysts' responsiveness to news events. This finding aligns with the distraction effect among investors documented in previous research (Drake et al. 2016). In Column (3), we further interact *Sports Events* with *3G*

Coverage and find a negative coefficient on this interaction effect, significant at the 10% level. These results indicate that the distraction resulting from sports events is exacerbated with better access to on-demand updates, providing further evidence of the potential distraction effect of mobile technology.

In Table 8, we examine the timeliness of forecast revisions following corporate news announcements occurring after office hours. The spontaneous occurrence of these news events, combined with their timing when analysts are likely away from their desk, offers a particularly interesting setting to analyze the impact of mobile technology on forecast timeliness. We link the zip code of the analyst's address to their local time zone and define an indicator variable, *After Hours*, which equals one if the news event occurs after 8 pm local time. As analysts are located across counties in different time zones (e.g., 8 pm EST in New York vs. 5 pm PST in Los Angeles), *After Hours* varies at the analyst level for the same news event.

In Column (1) of Table 8, we observe a significant negative coefficient on *After Hours*, indicating that analysts are less likely to respond to after-hours corporate news events. In Column ((2), we introduce an interaction term between *3G Coverage* and *After Hours* and find that this interaction is positively related to the likelihood of issuing a timely revision. This result supports the notion that analysts benefit from mobile technology when reacting to after-hours news events, when they are more likely to be away from their office and have limited access to broadband internet, thus relying more on mobile technology to become aware of relevant news and act on it.[23]

[23]Our results are robust to defining *After Hours* using other cutoffs, such as 6pm or 7pm. Interestingly, the economic magnitude of the coefficient on the interaction term between *3G Coverage* and *After Hours* increases monotonically as *After Hours* is defined using later cutoffs when analysts are more likely to be away from their desks.

4.5. Additional Analyses

In this section, we report the results of additional analyses, including the relationship between analysts' mobile internet access and (1) accuracy of target price forecasts, and (2) career outcomes.

4.5.1. Target Prices

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 9 shows the results of our estimation of the effect of 3G access 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.

4.5.2. Career Outcomes

Our findings thus far suggest that the expansion of the 3G network enhances analysts' research performance. We reason that analysts are motivated to exploit 3G availability to reduce their information processing costs (instead of becoming distracted), because they expect higher output quality to lead to better career outcomes. In our final series of analyses, we examine whether access to 3G is associated with analysts' career outcomes. We employ two measures: All-Star status from Institutional Investor (II) and employment at a prominent brokerage firm. Prior survey evidence suggests that All-Star rankings and employment at prestigious brokerage firms significantly impact analysts' compensation, serving as a motivator to produce superior research (Brown, Call, Clement, and Sharp, 2015).

We present the regression results in Table 10. The analyses are conducted 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 Column (2), the dependent variable, *Future Top10 Broker*, indicates whether an analyst is employed at a top-10 brokerage firm in year t+1, measured by broker size. We control for the analyst's All-Star and employment 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 and statistically significant in both columns, suggesting that 3G network expansion correlates with improved analyst career trajectories, with a higher likelihood of achieving All-Star status and being employed at a prominent brokerage firm. The economic magnitude indicates that a 21-percentage point increase in *3G Coverage* is associated with a 2.8% (3.7%) increase in the likelihood of becoming an All-Star analyst (being employed at a Top10 Broker) relative to the unconditional mean.[24] This evidence is consistent with analysts' career-driven incentives that motivate them to exploit mobile internet to improve output quality.

5. Conclusion

A key feature of mobile technology is granting individuals perpetual access to information, both professional and personal. In this paper, we provide evidence on how the increased availability of mobile internet affected the performance of financial analysts – professionals whose career outcomes depend on access to timely information, but whose productivity, nevertheless, can be negatively affected by entertainment and personal distractions on their mobile phones.

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

[24] For All-Star status, the economic significance is calculated as 0.21 * 0.012 / 0.09 = 2.8%. For employment at a Top10 Broker, the calculation is 0.21 * 0.049 / 0.28 = 3.7%.

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 difference-in-differences models and find that our inferences are the same across these models: increased access to mobile internet improves forecast timeliness and accuracy. 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. Analysts benefit from mobile internet access especially when unanticipated impactful corporate news is released after hours, revising their forecasts in a more timely fashion than analysts without such access do.

While the net effect of mobile technology is to improve the quality of analysts' output, the technology can also distract analysts, reducing their forecast timeliness in some circumstances. We find evidence of distraction in years with greater downloads of entertainment apps, and during popular college sports events.

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 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 a 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

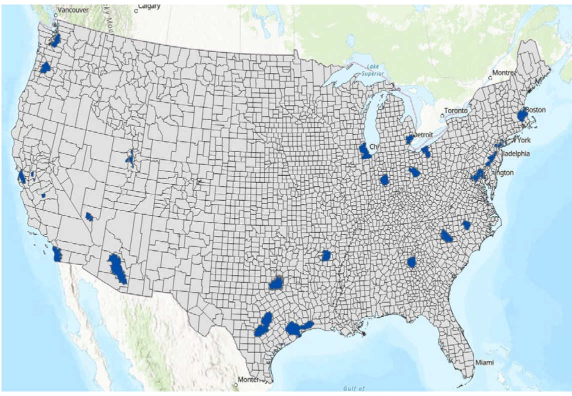
Variable	Definition	Source
3G Coverage	Percentage of the county where the analyst's workplace is located covered by the 3G network	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck
Timeliness	Leader-follower ratio based on an analyst's annual EPS forecasts issued during the year. We calculate the lead (lag) time of an earnings forecast as the number of days between the focal forecast and two prior (following) forecasts for a given firm-year and define leader-follower ratio as the lead time divided by the lag time. We take the average value across all forecasts for each analyst-year.	IBES
Accuracy	The absolute value of the difference between the analyst's last annual EPS forecast and the actual value of EPS, scaled by stock price and multiplied by -100.	IBES, CRSP
All-Star	An indicator variable that equals one if the analyst is selected as an All-Star analyst by Institutional Investor in the year, and zero otherwise.	Institutional Investor
Firm Experience	Number of years since the analyst started covering the firm.	IBES
Future All-Star	An indicator variable that equals one if the analyst is selected as an All-Star analyst by Institutional Investor in year t+1 and zero otherwise.	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	The log of the number of unique analysts employed by the analyst's broker firm in the year.	IBES
Sharp Increase	An indicator variable that equals one if there is a 50-percentage point or higher increase in 3G coverage, and zero otherwise.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck
D(t=-x)	An indicator variable that equals one for x years preceding the sharp increase in 3G coverage, and zero otherwise.	
D(t=x)	An indicator variable that equals one for x years post the sharp increase in 3G coverage, and zero otherwise.	
High Lightning	An indicator variable that equals 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	The logarithm of the analyst's county's population in 2007.	Census Bureau
Log County GDP	The logarithm of the analyst's county's GDP in year t.	
Log County Income	The logarithm of the analyst's county's average personal income in year t.	
3G Coverage in 2007	Percentage of the analyst's county with 3G coverage in the year 2007.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck

MoreProdApps	An indicator variable that equals one if the percentage of downloaded productivity apps (classified as business or news by the App Store) in the Top200 list in year t is higher than the sample median and zero otherwise.	QIMAI
MoreEntertainApps	An indicator variable that equals one if the percentage of downloaded entertainment apps (classified as entertainment, games, or social media by App Store) in the Top200 list in year t is higher than the sample median and zero otherwise.	QIMAI
Treat (Table 5 Panel A)	An indicator variable that equals 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.	Collins Bartholomew's Mobile Coverage Explorer, IBES, BrokerCheck
Post (Table 5 Panel A)	An indicator variable that equals one from 2009 to 2011, and zero from 2006 to 2008.	Compustat
Timeliness (Average of Indicators)	The average of the four indicator variables that take the value of one if the analyst issues a revision on the day of or the day after the quarterly earnings announcement.	IBES, Compustat
Revision	An indicator variable that equals one if the analyst issues a forecast on the day of or the day after a corporate news event, and zero otherwise.	IBES, Ravenpack
Sports Events	An indicator variable that equals one if the analyst's county hosts a college football event or if there is a March Madness college basketball event on the news day or the day after.	Google Search
After Hours	An indicator variable that equals one if the news is released on or after 8 PM as per analyst's county's local time, and zero otherwise.	Ravenpack
Top10Broker	An indicator variable that equals one if the analyst works at a Top 10 broker based on size in the year and zero otherwise.	IBES
TP Accuracy	The absolute value of the difference between the 12-month-ahead closing stock price and the forecasted target price, scaled by the beginning target price and multiplied by -1.	IBES, CRSP
Size	The logarithm of total assets.	Compustat
M/B Ratio	Market to book equity ratio.	Compustat, CRSP
ROA	Return on assets, calculated as net incomes scaled by total assets.	Compustat
Std of ROA	The standard deviation of quarterly ROA in the last five years.	Compustat
Leverage	Book leverage, calculated as total debt scaled by total assets.	Compustat

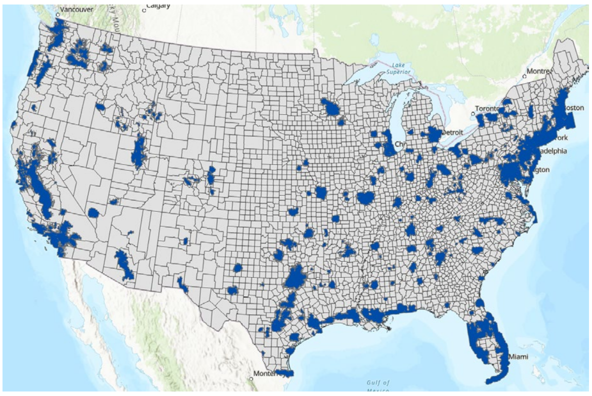
Figure 1 3G Rollout

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

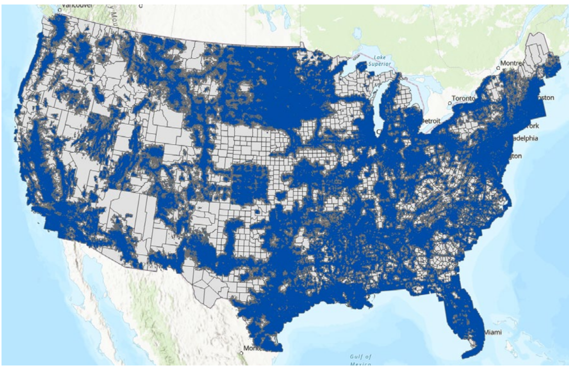
2007



2010



2013



2016

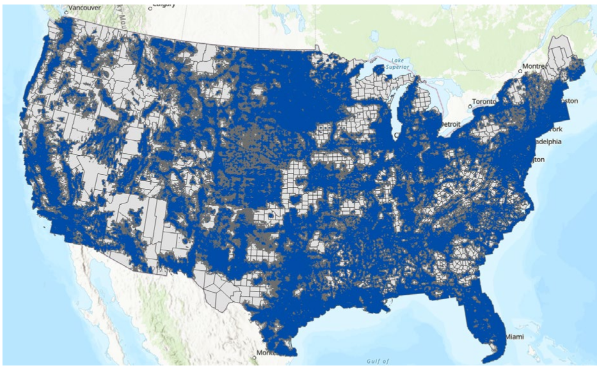


Figure 2 Illustrative Example of Analyst Profile on BrokerCheck

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

JONATHAN BLAKE RUYKHAVER

JON RUYKHAVER, Jonathan B Ruykhaver

CRD#: 2432984

B Broker *Regulated by* ***FINRA***

CANTOR FITZGERALD & CO.
CRD#: 134
101 FEDERAL STREET
Floor 17
BOSTON, MA 02110

Examination(s)

State Securities Law Exam

B	Series 63 - Uniform Securities Agent State Law Examination	Jul 23, 2007

General Industry/Products Exam

B	SIE - Securities Industry Essentials Examination	Oct 1, 2018
B	Series 87 - Research Analyst Exam - Part II Regulations Module	Feb 11, 2005
B	Series 7 - General Securities Representative Examination	Aug 25, 1999

Principal/Supervisory Exam

B	Series 24 - General Securities Principal Examination	Apr 17, 2009

Additional information including this individual's professional designations is available in the Detailed Report.

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Current Registration(s)

B **CANTOR FITZGERALD & CO. (CRD#:134)**

101 FEDERAL STREET Floor 17, BOSTON, MA 02110

Registered with this firm since 7/14/2022

Previous Registration(s)

		Name	Location
B	08/03/2018 - 07/18/2022	ROBERT W. BAIRD & CO. INCORPORATED (CRD#:8158)	BOSTON, MA
B	03/20/2012 - 07/25/2018	STEPHENS (CRD#:3496)	NASHVILLE, TN
B	10/29/2010 - 03/15/2012	MORGAN KEEGAN & COMPANY, INC. (CRD#:4161)	NASHVILLE, TN
B	06/05/2007 - 10/29/2010	THINKEQUITY LLC (CRD#:44274)	SAN FRANCISCO, CA
B	07/05/2000 - 06/08/2007	RAYMOND JAMES & ASSOCIATES, INC. (CRD#:705)	ST. PETERSBURG, FL
B	08/26/1999 - 06/14/2000	SUNTRUST EQUITABLE SECURITIES (CRD#:6271)	ATLANTA, GA

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
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 (Raw)	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
EntertainApps (Raw)	221,300	0.23	0.02	0.23
Timeliness (Average of Indicators)	286,163	0.18	0.27	0.00
Revision Indicator	1,595,890	0.11	0.32	0.00
Sports Event	1,595,890	0.04	0.20	0.00
EA Event	1,595,890	0.16	0.37	0.00
After Hours	1,595,890	0.14	0.35	0.00
TP Accuracy	836,396	-0.38	0.41	-0.26
CAR (Buy)	49,042	1.72	5.79	1.15
CAR (Sell)	7,372	-3.43	7.80	-1.99
All-Star	23,125	0.09	0.29	0.00
Top10 Broker	23,125	0.28	0.45	0.00

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

This table presents the results of our tests on 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 difference-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	**0.293*** **	**0.139*** **						
	(2.64)	**(2.71)**						
Sharp Increase			**0.170*** **	**0.049*** **			**0.222** **	**0.050*** **
			(4.66)	**(2.99)**			**(2.56)**	**(2.64)**
D(t=-2)					-0.002	0.048		
					(-0.02)	(0.70)		
D(t=-1)					0.041	-0.033		
					(0.48)	(-0.99)		
D(t=1)					0.143	**0.059** **		
					(1.48)	**(2.19)**		
D(t=2)					**0.256*** **	0.035		
					(2.74)	(1.61)		
D(t=3)					**0.277** **	**0.039*** **		
					(2.56)	**(2.80)**		
Horizon		-0.002***		-0.001***		-0.001***		-0.002***
		(-5.72)		(-31.91)		(-31.94)		(-12.87)
Effort		-0.001		0.002		0.003		0.005
		(-0.24)		(0.70)		(0.71)		(1.45)
Firm Experience	0.005**	0.001	0.005**	0.002***	0.004**	0.002***	0.006**	-0.001
	(2.07)	(0.41)	(2.01)	(3.46)	(2.04)	(3.46)	(2.50)	(-0.29)
General Experience	0.308***	0.052	0.001	-0.031***	0.320***	-0.031***	0.300***	-0.022
	(13.74)	(0.94)	(0.27)	(-3.10)	(13.16)	(-3.13)	(12.30)	(-0.62)
# Covered Firms	-0.002	0.003*	0.000	-0.000	-0.005*	-0.000	-0.006**	0.000
	(-0.84)	(1.95)	(0.17)	(-0.40)	(-1.96)	(-0.45)	(-2.27)	(0.29)
# Covered Industries	-0.011	0.006	-0.006	0.010*	-0.006	0.010*	-0.010	0.011
	(-1.36)	(0.64)	(-0.59)	(1.96)	(-0.51)	(1.96)	(-0.84)	(1.40)
Broker Size	0.153***	-0.001	0.311***	-0.002	0.115***	-0.002	0.105***	0.011
	(9.98)	(-0.09)	(3.98)	(-0.11)	(5.83)	(-0.12)	(5.57)	(0.84)
Observations	286,163	286,163	217,664	217,664	217,664	217,664	420,259	420,259
Adj. R-squared	0.338	0.567	0.292	0.526	0.341	0.555	0.341	0.53
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 Robustness Tests

This table presents the results of robustness analyses. Panel A presents regression results using the first forecast issued by analysts in the firm-year. Panel B presents regression results without analysts residing in New York. Panel C presents instrumental variable (IV) regression results using lightning strikes as an IV. The sample period is from 2007 to 2017 for all three panels. 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 First Forecasts Sample

	(1) *Timeliness* Full Sample	(2) *Accuracy* Full Sample
3G Coverage	**0.571*****	**0.136*****
	(2.62)	**(2.68)**
Horizon		0.002***
		(6.48)
Effort		0.001
		(0.20)
Firm Experience	0.001	-0.005
	(0.50)	(-0.39)
General Experience	1.735***	-0.343
	(16.37)	(-1.09)
# Covered Firms	-0.000	-0.003**
	(-0.08)	(-2.24)
# Covered Industries	-0.009	-0.006
	(-0.78)	(-0.63)
Broker Size	0.004***	-0.000**
	(7.10)	(-2.15)
Observations	216,404	286,163
Adj. R-squared	0.409	0.727
Firm*Year FE	Yes	Yes
Analysts FE	Yes	Yes
County FE	Yes	Yes

Panel B Exclude NY

	(1) *Timeliness* Excluding NY	(2) *Accuracy* Excluding NY
3G Coverage	**0.220***	**0.093*****
	(1.70)	**(3.13)**
Horizon		-0.002***
		(-3.16)
Effort		-0.001
		(-0.09)
Firm Experience	0.009**	0.001
	(2.12)	(0.14)
General Experience	0.305***	0.157
	(6.10)	(1.23)
# Covered Firms	0.000	0.002
	(0.07)	(1.15)
# Covered Industries	-0.008	0.023
	(-0.56)	(1.32)
Broker Size	0.113***	-0.015
	(3.05)	(-0.87)
Observations	144,949	144,949

Adj. R-squared	0.350	0.567
Firm*Year FE	Yes	Yes
Analysts FE	Yes	Yes
County FE	Yes	Yes

Panel C Instrumental Variable Analyses

	(1) First-Stage *3G Coverage*	(2) Second-Stage *Timeliness*	(3) First-Stage *3G Coverage*	(4) Second-Stage *Accuracy*
3G Coverage		**0.175***** **(3.47)**		**0.219**** **(2.51)**
High Lightning*Year	**-0.125***** **(-8.36)**		**-0.114***** **(-7.65)**	
Effort			0.001** (2.01)	-0.003*** (-13.71)
Horizon			-0.044*** (-4.42)	0.012 (1.63)
Firm Experience	-0.002 (-0.44)	0.009*** (4.1)	-0.001 (-0.14)	0.001 (0.35)
General Experience	0.140** (2.28)	0.202*** (7.53)	0.253*** (3.83)	-0.018 (-0.37)
# Covered Firms	-0.022*** (-4.31)	0.008*** (3.28)	-0.020*** (-3.87)	0.006 (1.44)
# Covered Industries	0.004 (0.21)	-0.017** (-1.97)	0.002 (0.09)	0.004 (0.31)
Broker Size	0.009*** (11.27)	0.001** (2.39)	0.009*** (11.18)	-0.001 (-1.54)
Log Population	4,398.399*** (111.38)	-738.144*** (-3.39)	2,990.014*** (79.91)	-606.089** (-2.43)
Log County GDP	-33.194*** (-61.85)	5.301*** (3.17)	-33.391*** (-62.37)	6.414** (2.2)
Log County Income	43.145*** (63.68)	-7.259*** (-3.31)	44.002*** (65.07)	-6.900* (-1.79)
3G Coverage in 2007	-5.697*** (-284.12)	0.988*** (3.4)	-5.774*** (-287.32)	1.238** (2.44)
Observations	286,163	286,163	286,163	286,163
Cragg-Donald Wald F statistic	69.83		60.52	
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 Apps on Mobile Devices

Panel A presents the results of estimating the regression in Eq. (3), testing the effects of the launch of the Bloomberg App. The sample period is from 2006 to 2011 (three years around the launch of the Bloomberg app) for analysis in Panel A. Panels B and C present the results of estimating the regressions in Eq. (4) and (5), examining the role of productivity Apps and entertainment Apps, respectively. The sample period is from 2010 to 2017 for analyses in Panel B and C because 2010 is the first year when app download data is available. 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 Launch of Bloomberg App as a Shock

	(1) *Timeliness*	(2) *Accuracy*
Treat*Post	**0.170***** **(4.66)**	**0.050**** **(2.37)**
Horizon		-0.002*** (-8.30)
Effort		0.009** (2.11)
Firm Experience	0.005** (2.01)	-0.001 (-0.18)
General Experience	0.001 (0.27)	-0.004*** (-7.22)
# Covered Firms	0.000 (0.17)	-0.011** (-2.32)
# Covered Industries	-0.006 (-0.59)	0.029*** (3.38)
Broker Size	0.311*** (3.98)	0.045** (2.11)
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

Panel B Availability of Productivity Apps

	(1) *Timeliness*	(2) *Accuracy*
3G Coverage*MoreProdApps	**0.019***** **(5.74)**	**0.096**** **(1.97)**
3G Coverage	-0.005 (-0.22)	0.126 (1.06)
Horizon		-0.002*** (-5.57)
Effort		-0.006 (-0.93)
Firm Experience	0.006*** (12.30)	0.013 (1.21)
General Experience	0.084*** (12.15)	0.372 (1.00)
# Covered Firms	0.002*** (4.95)	0.004*** (2.83)
# Covered Industries	-0.002 (-1.46)	0.004 (0.38)
Broker Size	0.020*** (6.78)	-0.018* (-1.87)

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 C Availability of Entertainment Apps

	(1) *Timeliness*	(2) *Accuracy*
3G Coverage*MoreEntertainApps	**-0.032****	**-0.556**
	(-2.20)	**(-1.34)**
3G Coverage	0.022	0.730*
	(0.83)	(1.74)
Horizon		-0.002***
		(-4.53)
Effort		-0.006
		(-0.82)
Firm Experience	0.006***	0.013
	(10.49)	(1.06)
General Experience	0.084***	0.372
	(12.14)	(0.70)
# Covered Firms	0.002***	0.005**
	(4.97)	(2.55)
# Covered Industries	-0.002	0.004
	(-1.46)	(0.38)
Broker Size	0.020***	-0.018*
	(7.24)	(-1.95)
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

Table 6 Revision Timeliness – Earnings Announcements

This table presents the results of our analysis of the timeliness of analysts' forecast revisions in response to earnings announcements. *Timeliness (Average of Indicators)* is the average of indicator variables that equal one if the analyst issues a forecast revision on the day of or the day after a quarterly earnings announcement. 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) *Timeliness (Average of Indicators)*
3G Coverage	**0.028****
	(2.22)
Firm Experience	0.001***
	(6.58)
General Experience	0.025***
	(8.58)
# Covered Firms	0.001***
	(3.42)
# Covered Industries	-0.001
	(-0.85)
Broker Size	0.024***
	(12.38)
Observations	286,163
Adj. R-squared	0.439
Firm*Year FE	Yes
Analysts FE	Yes
County FE	Yes

Table 7 Revision Timeliness - Corporate News Events and Sports Events

This table presents the regression results of our analysis of the timeliness of analysts' forecast revisions in response to corporate news events, and the effect of mobile technology when the news coincides with sports events. 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)	(2)	(3)
	Revision	*Revision*	*Revision*
3G Coverage	**0.005*****	**0.005***	**0.006****
	(2.64)	**(1.96)**	**(2.11)**
Sports Events		-0.023***	-0.011
		(-13.72)	(-1.47)
3G * Sports Events			**-0.013***
			(-1.73)
Firm Experience	0.001***	0.001***	0.001***
	(13.83)	(13.82)	(13.82)
Gen Experience	0.020***	0.020***	0.020***
	(16.47)	(16.48)	(16.49)
# Covered Firms	0.001***	0.001***	0.001***
	(9.12)	(9.15)	(9.14)
# Covered Industries	0.000	0.000	0.000
	(0.69)	(0.69)	(0.69)
Broker Size	0.005***	0.005***	0.005***
	(8.91)	(8.91)	(8.92)
EA Event	0.464***	0.464***	0.464***
	(35.11)	(35.00)	(35.00)
Observations	1,595,890	1,595,890	1,595,890
Adj. R-squared	0.341	0.341	0.341
Firm*Year FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Table 8 Revision Timeliness - After-hours Corporate News Events

This table presents the regression results of our analysis of the timeliness of analysts' forecast revisions in response to after-hours corporate news events. 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) *Revision*	(2) *Revision*
3G Coverage	**0.006****	**0.005****
	(2.40)	**(2.09)**
After Hour	-0.013***	-0.032***
	(-4.16)	(-3.30)
3G * After Hours		**0.020****
		(2.00)
Firm Experience	0.001***	0.001***
	(10.77)	(10.76)
Gen Experience	0.020***	0.020***
	(16.14)	(16.14)
Portfolio Size	0.001***	0.001***
	(8.52)	(8.53)
Number of Industries	0.000	0.000
	(0.81)	(0.81)
Broker Size	0.005***	0.005***
	(8.22)	(8.20)
EA Event	0.463***	0.463***
	(35.76)	(35.77)
Observations	1,595,890	1,595,890
Adj. R-squared	0.339	0.339
Firm*Year FE	Yes	Yes
Analyst FE	Yes	Yes
County FE	Yes	Yes

Table 9 The Accuracy of Target Prices

This table presents the regression results on analyst target price 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.

	TP Accuracy
3G Coverage	**0.031***
	(1.78)
Firm Experience	-0.001
	(-1.44)
General Experience	-0.024
	(-1.16)
# Covered Firms	0.004*
	(1.74)
# Covered Industries	-0.001
	(-0.10)
Broker Size	0.008
	(1.27)
Observations	836,396
Adj. R-squared	0.711
Firm*Year FE	Yes
Analysts FE	Yes
County FE	Yes

Table 10 Career Outcomes

This table presents the regression results of our analysis of 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) *Future Top10 Broker*
3G Coverage	**0.012***	**0.049*****
	(1.68)	**(4.36)**
All-Star	0.380***	0.037***
	(19.36)	(3.46)
Horizon	-0.000***	-0.000***
	(-3.33)	(-3.97)
Effort	0.006***	-0.001
	(5.02)	(-0.95)
Firm Experience	-0.001	0.001
	(-0.61)	(0.68)
General Experience	-0.006	0.005
	(-1.13)	(0.68)
# Covered Firms	0.002***	-0.000
	(4.55)	(-0.60)
# Covered Industries	-0.002*	-0.002
	(-1.82)	(-1.00)
Broker Size	0.011***	0.129***
	(3.43)	(23.27)
NY	0.009	-0.005
	(1.07)	(-0.42)
Top 10 Broker		0.419***
		(28.33)
Observations	23,125	23,125
Adj. R-squared	0.692	0.799
Year FE	Yes	Yes
Broker FE	Yes	Yes