SECURITY ANALYSIS AND THE COLLECTION OF HARD AND SOFT INFORMATION

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ABSTRACT

We use minute-by-minute Bloomberg online status microdata during 2017-2021 to directly study how hard and soft information collection affects equity analyst performance. Collection of hard information, proxied by office workday length, is positively associated with the quantity and timeliness of analyst reports. Soft information collection, as proxied by propensity to travel, is positively correlated with the market's reaction to recommendation changes and the likelihood of becoming a star analyst. Both hard and soft information collection improve forecast precision, a causal result that we confirm using the COVID lockdown as an instrument.

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1 Introduction

Calibrating the importance of hard and soft information in security analysis is typically challenging because its collection is inherently a hidden action. Surely, access to private information is valuable for financial analysts (Green, Jame, Markov, and Subasi, 2014)[1], but characterizing broad cross-sectional trends is typically challenging. Distance measures have been used successfully in a variety of settings, but are likely to be noisy proxies for information collection (Liberti and Petersen, 2019). Except for Malloy (2005), there is still a dearth of evidence that measures the link between the effort market participants employ to collect hard and soft information and the quantity and quality of their security analyses.

In this paper, we analyze the work habits of sell-side analysts *directly* by collecting minute-by-minute Bloomberg usage microdata from September 2017 through March 2021. We study 336 sell-side analysts employed by 42 brokerage firms, and estimate both the time that analysts spend in the office, as well as the time they spend away. This allows us to proxy for their hard and soft information collection and quantify the effect that both types of effort provision have on their ability to forecast earnings and value equities.

Equity analysts use Bloomberg extensively. In our sample, they logged into the platform on 72% of workdays, and on those days, they worked actively for more than 8 hours on average. Among other useful functions, Bloomberg allows analysts to explore financial data, utilize existing analytics and examine research by peer analysts.[2] In addition, it constitutes an online social network community. When individuals sign user agreements with Bloomberg, they are given the opportunity to communicate with each other using the messaging service. As a result, whether a user is actively using the software is publicly observable to all users.

A Bloomberg terminal user's profile page indicates the status of their activity on the platform. A green dot next to an analyst's name indicates that he/she is actively using his/her personal account. If the analyst were to become inactive for greater than 15 minutes,

[1] See also Soltes (2014), Brown, Call, Clement, and Sharp (2015), Cheng, Du, Wang, and Wang (2016), and Han, Kong, and Liu (2018).

[2] See https://www.bloomberg.com/professional/expertise/analyst

the dot would turn yellow. If a user is offline, the dot is red, and if a telephone icon appears, it indicates he/she is using the mobile application.

To analyze the effects of hard information collection, we use an expectation-maximization algorithm to quantify the length of their workday based on Bloomberg usage pattern (Ben-Rephael, Carlin, Da, and Israelsen, 2023). The quarterly measure Average Workday Length (*AWL*) proxies for each analyst's effort to collect and process hard information at work. The average *AWL* in our sample is 9.8 hours. Not surprisingly, *AWL* increased sharply starting during the COVID outbreak in the first quarter of 2020 to almost 11 hours. Note that we do not focus on the intensity or total time of Bloomberg usage in our tests, as we expect analysts to engage in other hard information processing activities at work, such as meetings, working on a spreadsheet, emailing, and reading. Nevertheless, given that analysts are heavy Bloomberg users, we find similar results using their time spent on the platform, as reported in the appendix.

We proxy for soft information collection by using the percentage of workdays when analysts are not on the Bloomberg platform at all (Percentage of Away Days, *PAD*). Each quarter, we define "traveling analysts" as those with a *PAD* above the sample median. Admittedly, there is a possibility that this measures the magnitude of soft information collection with some error. For example, an analyst might be traveling for leisure when they are not using the platform. The results speak against this being a problem. First, the percentage of days away are too high to be consistent with lack of work. Second, an anecdotal example using cellular geolocation data confirms that when an analyst is away from the office according to *PAD*, he travels to cities where his covered firms are headquartered. Last, and most interestingly, we use the COVID lockdown as an instrument, and show that when *PAD* decreased for "traveling" analysts, their forecast precision actually suffered.

We show that *AWL* and *PAD* are authentic and persistent analyst characteristics. Neither quarter, brokerage-firm, nor sector fixed effects explains more than 15% of their variation. Analyst fixed effects only explain 49.8% and 57.2% of variation in *AWL* and *PAD*. There is a negative correlation between AWL and PAD ($\rho = -0.23$), and both measures are positively correlated with the number of stocks that analysts cover. Analysts with more experience or who have a high-ranked title are associated with a lower AWL. In addition, star analysts or high-ranked analysts are associated with a higher PAD.

We find that AWL is positively associated with the number of earnings and price target forecasts issued, even after including analyst fixed effects. For example, with analyst fixed effects and other controls, a one-hour increase in AWL is associated with 3.4 more EPS forecsts and 0.54 more price target forecasts. In addition, AWL is positively related to both forecast timeliness and the trading commission generated. In contrast, compared to their peers, "traveling" analysts issue 9.0 fewer EPS forecasts and 1.29 fewer price target forecasts, though the timeliness of their forecasts are not statistically different from that of their peers. But, the market reacts more to recommendation changes issued by "traveling" analysts. Also, non-star-analysts who travel more during the first three quarters of the year are more likely to be voted as a star analyst in quarter 4 by the *Institutional Investor* magazine. This evidence suggests that soft information is highly valuable.

Next, we examine the effect of information collection on the accuracy of EPS forecasts. Following Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016), we compute a "Proportional Mean Absolute Forecast Error" ($PMAFE$), which compares each analyst's forecast error to those of their peers covering the same earnings announcement. The most accurate analyst will have a $PMAFE$ of -1. A zero $PMAFE$ indicates average accuracy. Even with analyst fixed effects and other controls, a one hour increase in AWL is associated with a significant reduction in $PMAFE$ (or improvement in accuracy) of 0.5%. We also find "traveling" analysts to produce more accurate forecasts than their peers. Specifically, even with analyst fixed effects and other controls, a $HIGH\_PAD$ dummy is associated with a significant reduction in $PMAFE$ (or improvement in accuracy) of 1.8%. Overall, the results suggest that both hard and soft information contribute to more accurate forecasts. We also confirm that these associations are robust to team effort, which is shown to be important in

Fang and Hope (2021).

To establish a causal effect of *AWL* and *PAD*, we use two instruments. The first is the COVID lockdown that exogenously curtailed travel during the first two quarters of 2020. This shock should hurt "traveling" analysts more than their peers. Indeed, we find that analysts whose *PAD*s exceed the sample median pre-COVID (during the last two quarters of 2019) experienced a significant increase in their *PMAFE*s (or reduction in accuracy) of 11.7%. In addition, the increased relative forecast error is concentrated among faraway firms whose headquarters are at least 300 miles from the "traveling" analyst.

The COVID lockdown is less effective as an instrument for *AWL* since there is no clear ex-ante separation, as is the case for *PAD*. A better instrument that offers such separation is the pre-lockdown commute time, which we estimate using the distance between each analyst's home and corporate address from Google maps. Analysts who spent a longer time commuting to work during the last two quarters of 2019 would ostensibly save more time by working from home. We find that one-hour commuting time pre-COVID predicts a 1.3 hour increase in *AWL* during the lockdown. Using commuting time as an instrument for increased *AWL*, we find that *AWL* significantly increased the total number of forecasts issued and improved the accuracy of the forecasts (a reduction of *PMAFE* of 8.5%).

The importance of hard and soft information in finance cannot be overstated, both for raising capital and the pricing of traded financial assets. While distance measures have been used extensively for the former (e.g., Lerner, 1995; Garmaise and Moskowitz, 2004; Butler, 2008)[3], they are less attractive as a proxy when studying security analysis[4]. This is because information collection is inherently a hidden action. Distance is likely to be a noisy proxy, especially for soft information collection. For example, a distance-based measure would

[3]See Liberti and Petersen (2019) for an excellent review. Distance measures have been used to distinguish hard and soft information collection in equity markets (Coval and Moskowitz, 1999; Ivkovic and Weisbenner, 2005; Loughran and Schultz, 2005), the municipal bond market (Butler, 2008), the venture capital market (Lerner, 1995), the real estate market (Garmaise and Moskowitz, 2004), and in the market for distressed assets (Granja, Matvos, and Seru, 2017). The thesis in these papers is that hard information can be transmitted across distance, whereas soft information cannot.

[4]One exception is Malloy (2005) who finds that analysts located closer to firm headquarters have more accurate forecasts

assume that two analysts in the same location have the same information, which may not be true based on their effort provision. So, our paper contributes to this literature in that we measure information collection more directly.

Our paper also adds to a series of papers that show that collecting soft information is valuable for security analysis. Green et al. (2014) show that access to management at broker-hosted investor conferences leads to analyst recommendation changes that have larger immediate price impacts. Brown et al. (2015) survey 365 analysts and find that private communication with management is a more useful to analysts than their own primary research, recent earnings performance, and recent 10-K and 10-Q reports. Cheng et al. (2016) show that analysts who visit corporate sites have better forecast accuracy than others. Han, Kong, and Liu (2018) show that visits to listed companies lead to improvements in forecast accuracy.

The rest of the paper is organized as follows. Section 2 provides information about our data and economic variables. Section 3 describes how our measures of hard and soft information affect the quantity and quality of analyst output. Section 4 describes use of the COVID lockdown and commuting data as instruments to deal with potential endogeneity. Section 5 concludes.

2 Sample Construction and Analyst Work Habit Measures

This section describes how we construct our sample of sell-side analysts and measures of their hard and soft information collection. Table A.1 provides variable definitions for all variables used in this paper.

2.1 Sample Construction

Bloomberg Usage Data:

When Bloomberg users are assigned accounts, the company records their "status" by default. Status is either designated as "online", "idle", "offline", or "mobile". When users first log on to the platform, their status changes from offline to online, and it remains that way while they use Bloomberg. However, if they stop using it for 15 minutes, the user's status automatically changes to "idle". Eventually, and depending on the users' settings, a user is logged off after a long period of inactivity. Also, when users are logged in via the "Bloomberg Anywhere" application on their mobile device, the status is listed as "mobile". While using the mobile app, access to an assigned desktop is restricted, so there is no possibility of double counting.

Other users of the platform can detect the status of any other Bloomberg user by employing the "PEOP" function, the "BIO" function, or by directly navigating to a user's profile. A green dot by a user's name indicates that he/she is online and active. Other status indicators are as follows: a red dot means that a user is offline, a yellow dot means that a user is idle, and a gray dot indicates that a user has chosen to be private. If a user is online via the mobile app, a mobile phone icon appears.

Analyst Data:

Since 2017, we have observed and recorded the profile status and the time spent on Bloomberg for a few thousand users who self-identified as "analysts." Some of them are credit analysts, analysts working for buy-side firms, or simply have the title "analyst" without actually being one. We identify 997 sell-side equity analysts among them by cross-referencing them to the IBES recommendation file. We verify that the individuals are the same based on their full names, the brokerage firms and locations.[5] Requiring non-missing IBES output further reduces the number of analysts to 710.

We restrict the sample to analysts who are active on Bloomberg. To be considered as an active Bloomberg user, an analyst needs to have at least one quarter with a quarterly average percent activity greater than 3%. Percent activity is the time in minutes that an analyst is actively logged on, scaled by the number of minutes within a day, so 3% means

[5] The alternative is to start with all IBES analysts and identify them on Bloomberg. This alternative procedure is less efficient and likely error-prone as the IBES recommendation file only provides the initials of analysts' first names.

around 40 minutes of Bloomberg usage per day. This cut-off removes the left tail of the login distribution, which is populated by inactive users. In addition, we require an analyst to be reasonably active on IBES, meaning that they issue at least two earnings forecasts per quarter and cover at least 3 stocks. These minimum Bloomberg and IBES activity filters result in a final sample of 336 analysts across 42 brokerage firms. We also collected all of their recommendations across all US stocks as well as their earnings per share forecasts, across all horizons, long term growth forecasts, and 12-month price target forecasts. Information on star analysts is obtained from *Institutional Investor* Magazine's All-America Research Team rankings.[6]

Overall, our sample includes about 15% of all active IBES analysts in these 42 brokerage firms. The sample attrition mostly comes from the fact that many sell-side analysts do not self identify as "analysts" on Bloomberg. We verify that analysts in our sample are similar to their peers from the same brokerage firm. In other words, this attrition should not impose any systematic bias in our analyses.

2.2 Analyst Work Habits Measures

Average Workday Length (*AWL*):

To measure *AWL*, we use an unsupervised machine learning algorithm - the Gaussian Mixture Model - to quantify analysts' time spent on hard information collection and processing in a given quarter based on their Bloomberg usage patterns. The same methodology was used in Ben-Rephael et al. (2023) and validated there using cellphone geolocation data.

Figure 1 illustrates the algorithm for a specific analyst-quarter observation. In the figure, the blue bars represent relative usage patterns throughout each workday during the quarter. The overall usage pattern resembles the mixture of two normal distributions: one in the morning and one after lunch. This pattern holds generally across most analysts. Clearly, the usage pattern is not derived from a distribution, per se, but we use this observation to construct our Average Workday Length (AWL) measure based on a mixture of normal

[6] We thank An-Ping Lin for sharing his data on star analysts.

distributions as follows.

For each analyst and quarter, we know the probability P^j_{min} that the analyst is actively using the platform every minute of the day $j \in J \equiv$\{12:00 am, 11:59 pm\}. We construct a pdf by computing $p^i_{min} = P^i_{min} / \sum_J P^j_{min}$. By construction, $\sum_J p^j_{min} = 1$. We then assume that the constructed distribution is a mixture of two normal distributions $k \in \{1, 2\}$, each with mean μ_k and variance σ^2_k, where $\mu_2 > \mu_1$. This captures the notion that analysts' work habits may differ before and after lunch. As mentioned, a dip in activity around lunchtime is very frequent in our sample.

For the mixed distribution, there is a probability q that any realization is drawn from distribution 1 and probability $(1 - q)$ that it was drawn from distribution 2. The mixed distribution has mean $\mu_{1,2}$ and variance $\sigma^2_{1,2}$, which can be measured for each analyst. We also have the following relationships:

$$\mu_{1,2} = q\mu_1 + (1 - q)\mu_2 \tag{1}$$

$$\sigma^2_{1,2} = q\sigma^2_1 + (1 - q)\sigma^2_2 + q(1 - q)(\mu_2 - \mu_1)^2 \tag{2}$$

Using these two equations, we perform an expectation-maximization (EM) algorithm to estimate all five parameters for each analyst $(q, \mu_1, \mu_2, \sigma^2_1, \sigma^2_2)$.

The EM algorithm consists of two steps: the estimation step (E-Step) and the maximization step (M-Step). In the E-Step, the expectation of the log-likelihood function is calculated for a given set of parameters. In the M-Step, the parameters are re-chosen in order to maximize the expectation. The process continues, iterating between the E-Step and the M-Step until the sequence converges. In our case, the likelihood function involves the likelihood of observing the data given that there are two unobservable Gaussian distributions generating the data. We implement the procedure using the skikit-learn libarary for Python.[7]

Returning to the example in Figure 1, we see the estimated Gaussian Mixture Model pdf in red as well as the two underlying Gaussian distributions in orange for this analyst-quarter

[7] We use the sklearn.mixture.GaussianMixture method with a convergence threshold of 0.001 and K-Means clustering to initialize the parameters.

observation. The dashed vertical bars are the estimated means of the two distributions. The two black lines represent the beginning and end of the AWL measure, or the interval $(\mu_1 - \sigma_1, \mu_2 + \sigma_2)$.[8] For this example, AWL is 9.12 hours.

Since *AWL* is measured using Bloomberg usage patterns, it naturally captures the average time spent on hard information collection and processing per day in that quarter (when the analyst is not traveling). Note that the measure does not require the analyst to be active on Bloomberg for the entire 9.12 hours. The analyst could also be collecting and processing hard information by reading periodicals, doing spreadsheet modeling, or meeting with colleagues. Assuming that the analyst gemerally logs in to Bloomberg near the start of their workday and logs off near the end, the *AWL* measure also captures these other non-Bloomberg work activities.

Percentage Away Day (*PAD*):

To quantify the extent of soft information collection that requires travel, we count the days when the analyst does not log in to Bloomberg at all. We first define a daily dummy variable that receives the value of one if an analyst is not logged in to Bloomberg during that day, and zero otherwise. Then, we average the dummy variable within a quarter to compute the Percentage Away Days (*PAD*).

Clearly, *PAD* measures analysts' work-related travel with some error. While analysts in our sample are heavy Bloomberg users, it is still possible that on some days, analysts may work in the office without using Bloomberg at all. In addition, even if they are away from the office, there is no guarantee that they are traveling for work-related reasons rather than vacationing. To the extent that analysts have similar total numbers of annual vacation days, the cross-sectional variation in *PAD* should still reveal differences across analysts in their soft information collection effort.

If anything, this bias works against our finding a benefit to being away from the office.

[8] An alternative *AWL* can be computed as the length of an interval that covers the middle 90% of the usage distribution. We confirm that such an alternative measure gives similar results.

But, as we show later in the paper, we use the travel restriction during the COVID lockdown as an instrument and show that fewer days away led to less accurate EPS forecasts for analysts who tend to be away from the office.

In what follows, we focus on a "traveling" analyst dummy variable in our main empirical analyses. We identify traveling analysts in a quarter as those whose PAD is above the median in that quarter. Traveling analysts are more likely to specialize in acquiring soft information from attending events organized by the firms, meeting management face-to-face, and visiting sites. In contrast, analysts with low PADs are more likely to rely on hard information when making forecasts.

Cellular Geolocation Data:

One way to investigate the validity of using Bloomberg activity is by identifying subjects' mobile phones in the geolocation database from the location-based analytics firm Reveal Mobile. The data include latitude, longitude, and timestamps for more than 100 million unique mobile devices in the United States for 2018-2020. While the identification number for each device is anonymized, Reveal Mobile provides the "home" latitude and longitude associated with each device. We attempt to combine this data with a residential address history for each subject in our sample from Mergent Intellect, and create a list of potential subject cellphones based on the home coordinates in the geolocation database.

Our initial intent was to identify when each subject was in their corporate office and correlate that with the Bloomberg data. Several disadvantages of the cell phone data precluded this exercise for many of our subjects and rendered our evidence anecdotal. First, many of the cellular devices in a particular household were not likely to be specific to the subject or consistently carried with him or her. Second, many of the subjects opted-out of location tracking, which meant that they only appeared sporadically or not at all in the geolocation data. Third, even though we used Google Places API to identify each corporate building footprint, many of the subjects live and work in tall buildings in metropolitan areas, and we were not able to uniquely identify their cellular device.

These limitations prevented us from carrying out cross-sectional tests to correlate Bloomberg usage with geolocation data.[9] Notwithstanding, there is anecdotal evidence of a good correlation between time in the office and *AWL*. Consider Figure 2. We were able to identify three devices belonging to one particular subject that show up a total of 92,893 times during the sample period. Using cellphone data to identify when he is at work, we estimate a *AWL* statistic and compare it to the *AWL* estimated using Bloomberg activity. The two measures are remarkably similar. The *AWL* based on Bloomberg usage is 8.0 hours, while it is 7.88 hours based on geolocation data. Admittedly, this is only one subject, but it does provide some reassurance that the *AWL* measure estimated with Bloomberg platform usage plausibly captures work habits.

We also found anecdotal evidence that *PAD* captures the time spent away from the office collecting soft information. For example, we identified a particular energy analyst from Denver who uses the Bloomberg platform 92% of the days that geolocation data indicates that he is at his office. However, on days that he is away from his office (at least 100 miles), he is never logged onto Bloomberg. Tracking his travel and identifying the companies this analyst covers shows that when he is away, he is in cities where the firms he covers are headquartered (New York and Houston). But again, this is only one example, but it does provide some reassurance that the *PAD* is plausibly capturing the collection of soft information.

2.3 Summary Statistics

Table 1 provides summary statistics of analyst output during the sample period. In Panel A we report statistics for the Bloomberg sample. The sample includes 2,874 analyst-quarter observations with 336 distinct analysts from 42 brokerage firms. In Panel B we contrast the Bloomberg sample with a comparable I/B/E/S analyst sample (the comparison sample). To be included in the comparison sample, we require an analyst to cover at least 3 stocks, to

[9] This exercise highlights the benefits of Bloomberg data over cell-phone data in studying effort provision. While geolocation data have potential advantages, the lack of cross-sectional coverage and the inability to cleanly identify the user of a device is a drawback relative to the use of Bloomberg data.

be on I/B/E/S for at least four quarters, and to belong to one of the 42 brokerage firms in our Bloomberg sample. The comparison sample includes 1,854 distinct analysts and 16,239 analyst-quarter observations.

Starting with Bloomberg analysts, we find that the average number of unique stocks covered over the previous four quarters is 17.85. The number of unique industries based on GICS 6-digit codes is 3. The average number of Q1 (Y1) forecasts in a given quarter is 23.1 (24.79). This is based on 16.07 unique stocks, where 77% of the forecasts are for common stocks (Share code 10 or 11). Other forecasts include long-term growth with an average of 5.67 forecasts, stock recommendations with an average of 3.28 recommendations, price targets with an average of 11.8, and all other forecasts with an average of 140.1 forecasts. The number of stock recommendations and price targets is lower than the number of earnings forecasts, with an average of 3.28 and 11.81, respectively.

Panel B reports each group averages together with their differences and associated p-values. Overall, the comparison reveals that Bloomberg analysts are more active than those in the comparison sample, but the differences are not large. For example, Bloomberg analysts cover 2 more stocks and issue 1.75 more quarterly forecasts, on average. Bloomberg analysts also issue 0.4 (1.36) more recommendations (price targets). Finally, both groups display better accuracy than analysts that are not in the same 42 brokerage firms.[10] This is consistent with the fact that larger brokerage firms have more resources leading to more accurate forecasts. Interestingly, the Bloomberg group displays higher portfolio accuracy relative to the comparison group on an equally weighted basis. However, these differences shrink and are no longer statistically significant on a value-weighted basis, based on stock market capitalization.

Next, Table 2 reports summary statistics of analysts log-in activity on Bloomberg (Panel A), together with the log-in based measures (Panel B), and their correlation matrix (Panel C). Panel A indicates that on average analysts are logged in to the terminal on 71.7% of the

[10]The forecast accuracy measure is defined in details in Section 3.3. It is normalized so the most accurate forecast takes the value of -1 while a median forecast takes the value of 0.

work days. Analysts are active on average 362 minutes (6 hours) per day, which amounts to 30.14 hours per week.

Providing more granular information, Figure 3 depicts the average time spent on Bloomberg by day-of-the-week and holidays. As in Panel A of Table 2, the daily time spent on the terminal is around 6 hours, but it drops to 5 hours on Fridays. The log-in activity is small during weekends and holidays. In addition, Graph A of Figure 4 plots the average daily minute activity across analysts in a given quarter over time. There is a sharp increase in the minutes spent on the platform starting the first quarter of 2020 (the COVID period).

Panel B of Table 2 provides statistics of the log-in based measures of analyst work habits (*AWL* and *PAD*). The average *AWL* during the sample period is around 9.8 hours with a tight distribution. Eighty percent of the time, *AWL*s range from 8 hours to 12 hours. The average *PAD* is 0.283. The distribution of *PAD* is wider, with the 10th percentile of 0.033 and 90th percentile of 0.656.

For emphasis, *AWL* is different from intensity of Bloomberg usage. Using intraday distribution of Bloomberg usage within a quarter, *AWL* aims to measure the typical length of analyst' workday in that quarter, without assuming Bloomberg usage throughout the day. We measure the intensity of Bloomberg usage using *LnCondActive*, defined as the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter. The correlation between *AWL* and *LnCondActive*, while positive, is only 0.25. The correlation between *AWL* and *PAD* is negative, but not huge ($\rho = -0.23$). This suggests that hard and soft information collection effort are not perfect substitutes for each other.

Graphs A-C of Figure 4 provide additional information at the quarterly level. Similar to the minutes spent on the terminal, *AWL* has increased from around 9.5 hours during the early part of the sample to more than 10.5 hours during the COVID period. In a similar manner, *PAD* dropped significantly from Q1 of 2020.

Finally, Figure 5 depicts the log-in measures averages based on stock coverage deciles.

In particular, we rank analyst-quarter observations based on the number of stocks that an analyst covered during the recent year. Decile 1 (10) refers to the lowest (highest) number of stocks covered. It is probably not surprising that *PAD* generally increases with the number of stocks covered. For *AWL*, we also observe a positive relation with the stock coverage beyond the first three coverage deciles. In our empirical tests, we control for such mechanical correlations with coverage $\times$ time fixed effects, whenever possible.

2.4 Determinants of AWL and PAD

2.4.1 Login Activity and Market Information

As mentioned, Bloomberg allows analysts to explore financial data, utilize existing analytics, and examine research by peer analysts. In this subsection, we provide evidence on this link by exploring Bloomberg analysts' login activity in response to market events concerning the stocks they cover (hard information). We show that analysts increase their login activity in response to public information about the stocks they cover. To study this link, we focus on login activity between 7-9 am (the pre-open period), which is more likely to reflect analysts' processing of overnight news. Table 3 reports the findings.

We find that analysts increase their login activity if stocks they cover are in the top decile based on abnormal trading volume over the previous day. Also, various measures of news (RavenPack News Analytics) indicate that analysts increase their login behavior if stocks they cover have fundamental news – either after-market-close of the previous day or before-market-open of the current day. This is particularly strong for earnings news, where analysts respond to both stock level news and industry news. For example, a one standard deviation increase in the number of stocks with before-market-open earnings news leads to a $(0.43 \times 0.079 =)$ 0.034 increase in abnormal login activity. Since the average login activity during 7-9 am is around 0.269, this means an increase of 12.6%. Finally, the pre-market login activity is positively correlated with *AWL* (a correlation of 0.24), which highlights the link between *AWL* and analyst effort to collect and process hard information.

2.4.2 AWL, PAD, and Other Analyst Characteristics

In this subsection, we first explore how much of the variation in *AWL* and *PAD* is explained by time (year-quarter), analyst, industry coverage, and broker fixed effects. We then regress *AWL* and *PAD* on a battery of analyst characteristics obtained from FINRA's BrokerCheck website, LinkedIn, and Facebook.

Almost every analyst in our sample is registered with FINRA BrokerCheck. These records include the full name (including middle name as well as other names used) of each analyst as well as their work histories, the locations of their branch offices, and which FINRA Qualification Exams the analysts have passed. The full name and work history from FINRA helps us locate LinkedIn accounts, which provide educational background, and Facebook accounts, which help identify whether analysts have children.

Panel A of Table 4 indicates that analyst fixed effects are the most important determinant in explaining the variation in both *AWL* and *PAD*, with an R-squared of 49.8% and 57.2%, respectively. So, *AWL* and *PAD* both appear to be independent and authentic analyst characteristics. Next, broker fixed-effects explain 9.5% and 12.7% of the variation in *AWL* and *PAD*, which is consistent with work place culture. Both analyst characteristics also change over time, with time fixed-effects explaining 5.5% and 9.5% of the variation in *AWL* and *PAD*. The time variation is in part due to the COVID lockdown as evident in Figure 4. Finally, industry fixed effects, based on the analyst's main covered GICS6 industry, explain around 10.5% and 8.7% of the variation in *AWL* and *PAD*, suggesting that information collection effort differs based on the type of stocks that the analysts are covering.

The analyst characteristics reported in Panel B of Table 4 reveal that analyst time on I/B/E/S (*IBES Years*) and seniority (*High Rank Indicator*) are two important determinants of *AWL* and *PAD*. In particular, an increase in years in the I/B/E/S sample leads to a reduction in *AWL*, but to an increase in *PAD*. In a similar manner, being greater seniority leads to a lower *AWL* and a higher *PAD*. Relatedly, we find that being a star analyst is positively associated with *PAD* but not *AWL*. This is consistent with the fact that analyst ranking depend on interactions with institutional investors, who are the ones ultimately voting on analysts.

Other work experience variables such as total work experience (*Work Experience*) and the number of jobs that an analyst had switched (*# Jobs FINRA*) are not statistically nor economically significant. In addition, variables such as NYC location, MBA degree, gender, children and qualifying exam do not load significantly or consistently across the *AWL* and *PAD* specifications. These variables only add around 0.003- 0.027 to the R-squared. Finally, including brokerage firm fixed effects does not alter these findings, but adds between 0.045-0.072 to the R-Squared.

3 Analysts' Information Collection and Performance

3.1 Analysts' Output

In this section, we examine how hard and soft information collection are related to analyst forecast outputs. Table 5 reports results from panel regressions of analyst output on *AWL*. We consider quarterly (Q1) and annually (Y1) earnings forecasts (Panel A), together with other earnings forecasts and price targets (Panel B). We control for lagged dependent variables (*AveDep t-4_t-1*), analyst experience (*IBES Years*), and the average number of industries covered (*Ave # of Industries t-4_t-1*). We include Coverage $\times$ Time fixed effects and analyst fixed effects. Standard errors are clustered by analysts.

The *AWL* coefficient estimates are positive and significant regardless of the specification used. Specifications 1 and 5 of Panel A indicate that an one hour increase in *AWL* is associated with an increase of around 0.25 in the number of quarterly forecasts and 0.364 in the number of annual forecasts. In contrast, the coefficients on the "traveling" analyst dummy are negative and significant. Specifications 2 and 4 suggest that relative to their peers, "traveling" analysts with above-median *PAD* produce 1.095 fewer quarterly forecasts and 1.082 fewer annual forecasts. The results are similar in Specifications 3 and 7 when *AWL* and *HIGH_PAD* are included simultaneously. Finally, specifications 4 and 8 include analyst fixed-effects which corresponds with larger absolute coefficients. For the same analyst, a one hour increase in *AWL* is associated with an increase of around 0.306 in the number of quarterly forecasts and 0.539 in the number of annual forecasts. When a given analyst travels much more than usual, she issues 1.554 (1.749) fewer quarterly (annual) forecasts during that quarter.

Panel B reports similar results for the number of other EPS forecasts and price target forecasts. Focusing on specifications 4 and 8 with all controls and analyst fixed-effects, a one hour increase in *AWL* is associated with an increase of around 2.538 in the number of other EPS forecasts and 0.54 in the number of price target forecasts. When the same analyst travels more, the number of other EPS (price target) forecasts decreases by 5.71 (1.29). Specifications with analyst fixed-effects are more likely to allow a causal interpretation. Overall, holding stock coverage constant, when an analyst works longer, she issues more forecasts. When she travels more, she issues fewer forecasts.

3.2 Analysts' Timeliness

Next, we explore another dimension of analysts' output, the timeliness of their forecasts. Timeliness is defined as "how quickly an analyst issues a forecast following an earnings announcement." Our timeliness measure is calculated as the natural logarithm of the average time in days between the earnings announcement and the subsequent forecast, across all stocks covered by the analyst. Table 6 reports the results. We control for analyst experience (*IBES Years*), the number of Q1 forecasts during the quarter (*# Q1 EPS Forecasts*), the number of industries covered (*Ave # of Industries t-4_t-1*), and analyst forecast accuracy (*Ave Q1 PMAFE t-4_t-1*).

The *AWL* coefficient estimates are all negative regardless of the specification used and are also significant except when analyst fixed-effects are included (Specification 6). For example in specification 5, a one hour increase in *AWL* is associated with a 5.9% decrease in *LnTFE*. As most earnings announcements occur before the market opens and after the market closes, a longer *AWL* means that the analyst is more likely to be working when the earnings announcement occurs, allowing her to respond to the announcement in a more timely fashion. With analyst fixed-effect in specification 6, the coefficient on *AWL* is still negative but no longer significant, suggesting the strong association between *AWL* and forecast timeliness comes mostly from cross-analyst variation. In contrast, the coefficient on *HIGH_PAD* dummy, while negative, is never significant. In other words, traveling analysts do not differ significantly from their peers in terms of their forecast timeliness.

3.3 Market Reaction to Analysts Stock Recommendations

In this subsection, we explore how the market reaction to analyst stock recommendations is affected by *AWL* and *PAD*. Following Loh and Stulz (2011), we focus on analyst recommendation changes that are not centered around earnings announcements, and end up with 8,712 recommendation changes. To have a meaningful comparison, we multiply the daily returns by -1 if the analyst's recommendation change is negative. Recommendations that are issued after the market close are shifted to the next trading day.

We find that *HIGH_PAD* is associated with a stronger market response. The effect is sizable, as recommendations issued by *HIGH_PAD* analysts are associated with 2.6% higher returns. The result supports the notion that soft information is value relevant. Including analyst fixed effects (columns 4 and 8) attenuates the effect, and suggest that this is driven by differences across analysts. This is consistent with the findings of Panel B of Table 4, which suggests that *HIGH_PAD* analysts are more senior and influential.

3.4 The Probability of Being a Star Analyst

In Table 8 we explore how *AWL* and *PAD* affect the probability of being ranked as a star analyst. Since the rankings are done in Q4 in each year, we explore the relation between being ranked as a star in year t and the averages of *AWL* and *HIGH_PAD* in Q1-Q3 of year t. We find that *HIGH_PAD* is associated with a higher probability of being ranked as a star analyst, especially if he/she was not ranked as a star analyst in the previous year. This evidence also suggests that institutional investors value soft information.

3.5 Brokerage Dollar Trading Volume

Another relevant outcome variable for an analyst is the dollar trading volume via his/her brokerage firm on a stock he or she covers. Analysts are often compensated on the trading commission generated by their research. More broadly, it is common for buy-side clients to evaluate a brokerage firm on a regular basis for the service it provides, which includes analyst research. The result of such a "broker vote" may then determine how much of their trading to be allocated to this broker.

Following Lehmer, Lourie, and Shanthikumar (2022) and Ben Lourie and Yoo (2023), we manually collect such trading volume data from Bloomberg. Bloomberg provides information on the total number of shares traded for each stock-day-broker, which we aggregate to a quarterly frequency. In Table 9, we regress these quarterly dollar trading volume measures (both contemporaneous and the subsequent three quarters) on *AWL* and *PAD* after controlling for the lagged volumes and a battery of stock characteristics.

We find significant and positive coefficients on *AWL* in the first three columns, suggesting that a longer workday length leads to more trading volume. A one hour increase in *AWL* is associated with a $8.7 million to $11.8 million increase in shares traded per quarter in the current and subsequent quarters. It is possible that *AWL* may proxy for the general availability of the analyst which institutional clients value. The coefficients on *PAD* are not significant. In other words, traveling analysts generate similar trading volumes compared with their peers.

When we include analyst fixed effects in the next four columns, the coefficients on *AWL* generally become insignificant with no specific pattern, suggesting that the trade allocation decisions are slow moving and do not react strongly to quarter-to-quarter variation in *AWL* for the same analyst.

The patterns are qualitatively similar when we include stock-quarter fixed effects to focus on *relative* dollar trading volumes across different brokerage firms for a given stock in a given quarter in our sample. The detailed results are reported in Table A.7. The number of observations is smaller as we require at least two brokerage firms in our sample for the same stock-quarter.

3.6 Analysts' Forecast Accuracy

Finally, we explore the relation between analyst hard and soft information collection efforts and forecast accuracy. We follow Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016), and calculate the "Proportional Mean Absolute Forecast Error" (*PMAFE*) defined as $(AFE_{i,j,t} - \overline{AFE_{j,t}})$ / $\overline{AFE_{j,t}}$. In particular, for each analyst i and firm j, we calculate the analyst's quarterly equally-weighted forecast errors average based on all earnings forecasts initiated during the quarter. We then calculate the absolute value of the average forecasts errors. We repeat the calculation for all analysts on I/B/E/S covering the stock during that quarter and calculate the stock's quarterly mean absolute forecasts errors. The measure has a minimum is at -1 (most accurate relative to peers) and a maximum around 3 (the least accurate analyst). At zero, the analyst's accuracy is similar to that of its peers. The measure has a standard deviation of 0.53. In absolute terms ($|PMAFE|$) the measure has a mean of 0.39.

We run regressions at the analyst-quarter-stock level. The regressions include firm fixed effects, Coverage $\times$ Time fixed effects, and with or without analyst fixed effects. In addition, we control for various analyst and firm characteristics. In particular, we include how early the analyst forecast is relative to its peers (*Early Forecast*), past analyst accuracy (*Ave Q1 PMAFE t-4_t-1*), number of quarterly forecasts and industries covered (*# Q1 EPS Forecasts*, and *# of GICS6 Industries*), firm size, firm book-to-market, return volatility and institutional holdings.

Table 10 reports the results. Coefficient estimates for both *AWL* and *HIGH_PAD* are negative and significant, regardless of the specification used. Both hard and soft information seem to contribute to forecast accuracy. In terms of economic significance, a one hour increase in *AWL* is associated with a reduction in *PMAFE* ranging from 0.5% to 0.7%, or 1.3% to 1.8% of its mean. Similarly, the *PMAFE* of a "traveling" analyst is 1.2% to 1.9%

lower than that of a peer, or 3.1% to 4.9% of its mean.

Fang and Hope (2021) show that equity research reports are often prepared by a team of analysts. We, as is standard in the analyst literature, focus on the lead analyst which is recorded in I/B/E/S. Nevertheless, in Table A.8, we repeat the analysis conducted in Table 10 after controlling for team effort. In the baseline version, we measure team effort using the average AWL of peer analysts from the same brokerage firm covering the same industry. For about 9.8% of the lead analysts stock-quarter observations, the team members (singed on the report) are also in our sample, so we can measure their team effort using the average AWL of their actual team members for a given stock in a given quarter, resulting in an augmented team effort measure. We confirm that our results are robust to controlling for team effort.

4 Causal Evidence from the COVID Lockdown

The COVID-19 pandemic changed the work habits of many people. During the first two quarters of 2020, much of the country (and the world) was under stay-at-home mandates. Many in-person conferences, meetings, and other events were canceled. Our minute-by-minute Bloomberg online status data uniquely allows us to examine how sell-side equity analysts changed their work habits during that period. In addition, to the extent that the shocks to their work habits are largely exogenous, we can establish a causal relation when studying the resulting changes in the quantity and quality of their outputs.

For this section, we focus on the period 2019Q3-2020Q2 and keep all analysts with 4 quarters of data. We match the analysts' names with records on FINRA BrokerCheck, LinkedIn, Facebook, and other sources. From their online profiles, we estimate personal characteristics such as age, gender, and whether they have young children.

Almost every analyst in our sample is registered with FINRA BrokerCheck. These records include the full name (including middle name as well as other names used) of each analyst, as well as their work histories and the locations of their branch offices. After we identify the full name and work history for each analyst, we manually search through the Mergent Intellect database, which includes address histories for hundreds of millions of people in the US. These address histories combined with the work/school histories in the FINRA and LinkedIn data allow us to uniquely identify individuals in the Mergent data, which ultimately helps us identify home addresses of almost every analyst in our data during our sample period.

We then calculate the typical commute time between home and work using Google Maps. Google Maps provides typical travel times between points at any hour of the day. We measure minimum travel times between home and work at 7:00 am on workdays. We keep the minimum time based on foot, car, public transport, and bicycle travel. Figure 6 illustrates how we collect this information using a fictitious home address (to preserve anonymity of the analysts in our sample). These filters leave us with 102 identified analysts with full information. Of these 102 analysts, 87 are from the New York area, 7 are from San Francisco, 6 are from Houston, and 2 are from Chicago.

The soft information production channel was effectively shut down during much of 2020Q1-2020Q2. The COVID-lockdown made it harder for analysts to travel. Even if they could travel, there was little soft information they could extract from in-person interactions as most conferences and meetings had been moved online. Intuitively, this negative information shock should be larger for traveling analysts, who we can uniquely identify using their *PAD* pre-COVID. In what follows, we use the pre-COVID *PAD* to instrument the shock to soft information production during the COVID lockdown.

4.1 Pre-COVID *PAD* Identification Strategy

Table 11 examines the causal impact of *PAD* on forecast outcomes in a standard difference-in-difference setting. The treatment group consists of analysts with above-median *PAD* pre-COVID (2019Q3-2019Q4). The control group contains the remaining analysts who rarely travelled pre-COVID. The POST dummy equals 1 for 2020Q1-2020Q2 and 0 for 2019Q3-2019Q4. The coefficient on the interaction term ($TREATMENT \times POST$) identifies the impact of *PAD* on forecast outcomes. We examine both the quantity (the number of quarterly, annual EPS forecasts and price target forecasts) and the quality (relative forecast accuracy measured by *PMAFE*) of the output.

Focusing on the treatment effect (*TREATMENT*), consistent with the full sample results in Tables 5 and 10, traveling analysts issue significantly fewer forecasts and the forecasts are slightly more accurate (though not significant). Focusing on the post effect (*POST*), with all analysts locked down at home, not surprisingly, their outputs increase significantly. The accuracy measure *PMAFE* is not significantly affected since it is a relative accuracy measures (which should not change over time on average). Finally, focusing on the interaction term (*TREATMENT* $\times$ *POST*), we find the traveling analyst to experience an increase in output (though insignificant) during the COVID lockdown.

More importantly, their accuracy (relative to their peers) decreases significantly, as reflected in a significant increase in *PMAFE* of 11.7%. Column 5 shows that the effect is driven by firms whose headquarters are located at least 300 miles away, and thus, are more affected by travel restrictions. The result provides causal evidence that soft information extracted by traveling analysts increase forecast accuracy.

4.2 Commute Time to Work Identification Strategy

We now turn our attention to *AWL*. Graph B of Figure 4 shows that the average analyst in our sample experiences a one hour increase in his *AWL* after the COVID lockdown. Unlike the reduction in *PAD* which is completely exogenous and beyond any analyst's control, the increase in *AWL* during the lockdown could reflect an analyst's conscientious choices, which may in turn affect their forecast outcomes.

In Panel A of Table 12, we run cross-sectional regressions of changes in *AWL* (from 2019Q3-2019Q4 and 2020Q1-2020Q2) on various analyst characteristics measured pre-COVID. Analyst characteristics include the pre-COVID analyst commute time, the analyst age, a female analyst indicator, an indicator for an analyst with kids under 18-years old, and a few other analyst characteristics reported in Panel B of Table 4 such as yeas in I/B/E/S, MBA degree, work experience, and analyst rank.

The average analyst age in the pre-COVID analyzed sample is 44, where the youngest analyst is 30 years old, and the oldest is 62 years old. The pre-COVID sample also includes 10 female analysts and 19 analysts with kids under 18 years old. Both Du (2021) and Li and Wang (2021) document that female analysts, especially those with young children are more negatively affected by the COVID lockdown. By observing their *AWL*s, we can precisely quantify the impact of analysts personal characteristics on changing workday length.

Table 12 Panel A presents clear evidence that the only significant predictor of analysts' changing *AWL* during COVID lockdown is their commuting time pre-COVID. The result is very intuitive. COVID lockdown makes commuting to office impossible, and analysts can spend the time saved from commuting on work. Indeed, Table 12 suggests that one hour saved from not commuting leads to a workday that is 1.3 to 1.4 hours longer. Such a strong and positive relation between pre-COVID commute time and change in *AWL* during the lockdown is evident in the decile bin scatter plot in Figure 7. Importantly, the commute time is measured pre-COVID and therefore cannot be affected by events during the COVID pandeimc, so it provides a nice instrument for the change in *AWL* during the lockdown.

Building on the relation between the COVID lockdown and commute-time-saved, in Table 12 Panel B we examine the causal impact of *AWL* on forecast outcomes in a difference-in-difference setting, very similar to that in Table 11. The treatment group (*TREATMENT*) consists of analysts with below-median commute time pre-COVID (2019Q3-2019Q4) who are predicted to have higher increase in *AWL* during COVID lockdown. The control group contains the remaining analysts with above-median commute time pre-COVID. The post dummy (*POST*) equals 1 for 2020Q1-2020Q2 and 0 for 2019Q3-2019Q4. The coefficient on the interaction term ($TREATMENT \times POST$) identifies the impact of *AWL* on forecast outcomes.

The treatment effect is not significant, suggesting that commuting time does not affect forecast outcomes pre-COVID. The post effect again suggests a significant increase in the amount of forecasts issued, as analysts are locked down at home. *PMAFE*, being a relative forecast accuracy measures, does not change for an average analyst. Finally, focusing on the interaction term, we find that analysts with a long commute time pre-COVID experience a further increase in output during the COVID lockdown. More importantly, their accuracy (relative to their peers) increases significantly, as reflected in a significant decrease in $PMAFE$ of 8.5%. This result provides causal evidence that a longer workday length increases both the quantity and quality of forecasts.

5 Conclusion

Despite the importance of equity analysts, we still know relatively little about how they spend their working hours. In this paper, we take advantage of their minute-by-minute Bloomberg usage data to quantify two dimensions of their work habits: their average workday length to measure hard information collection and processing; and the extent of their travels to measure their soft information acquisition. We find that hard and soft information collection improves analysts' output on several dimensions, including the accuracy of their earnings forecasts.

Our findings related to the COVID lockdown speak to the recent debate on the benefit and cost of working-from-home (WFH). At least in the case of equity analysts, we find WFH to increase effort provision by eliminating work commute, which in turn improves both the quantity and quality of the forecasts. On the downside, WFH hurts soft information production based on decreased in-person interaction and reduces forecast accuracy.

More broadly, we uncover the hidden effort problem which is ubiquitous in economics. We are able to characterize analysts' information collection without changing their behavior, and link their effort to outcomes that can be objectively and precisely measured.

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Figure 1: Average Workday Length Example

This figure provides an example of the AWL measure for an analyst-quarter observation. The blue bars represent the empirical probability density function based on activity on Bloomberg. The red curve is the estimated Gaussian Mixture Model pdf using the iterative Expectation-Maximization (EM) algorithm. The two orange curves are the two underlying Gaussian pdfs. The dashed vertical bars are the estimated means of the two distributions. The two black lines represent the beginning and end of the AWL measure, or the interval $(\mu_1 - \sigma_1, \mu_2 + \sigma_2)$.

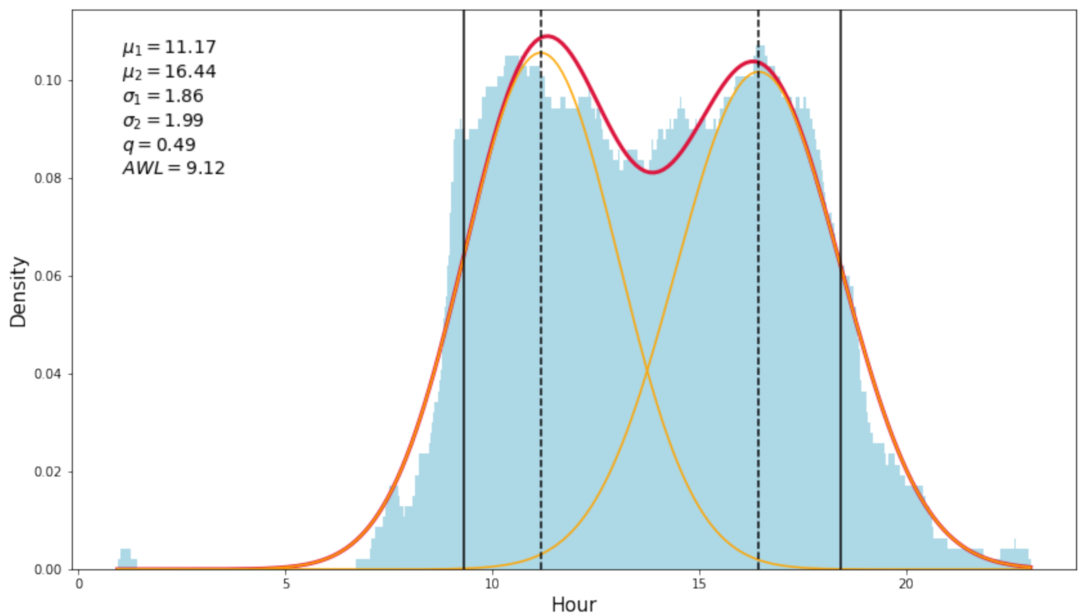


Figure 2: Comparing AWL using Bloomberg and Cell Phone Activity – Example

The figure provides an example of AWL measured using cell phone usage data and Bloomberg platform activity for an executive for 2018 – 2019. The blue and red curves are the estimated Gaussian Mixture Model pdf using the iterative Expectation-Maximization (EM) algorithm for the cell phone data and Bloomberg platform usage data, respectively. The sets of vertical lines represent the beginning and end of the AWL measures. The sample period is from September 2017 to March 2021.

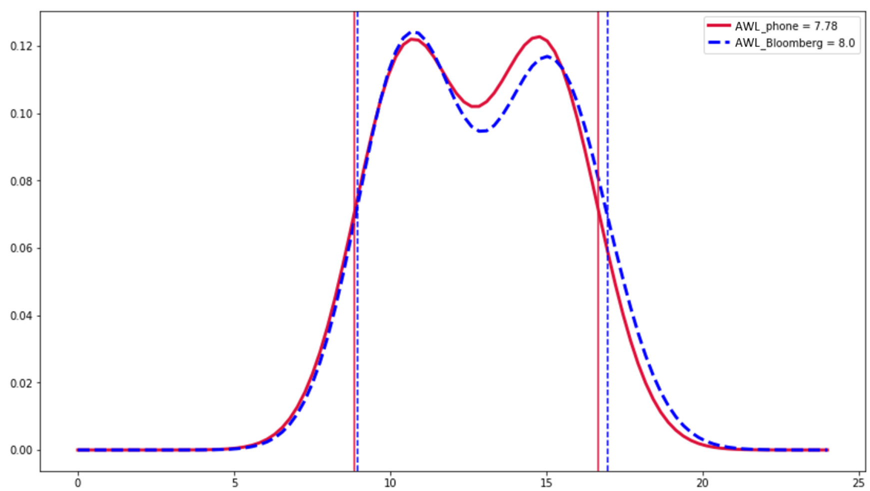


Figure 3: Minutes Active on Terminal based on Day-of-the-Week and Holidays

This figure depicts the average time spent on the Bloomberg terminal by day-of-the-week and Holidays. The sample period is from September 2017 to March 2021.

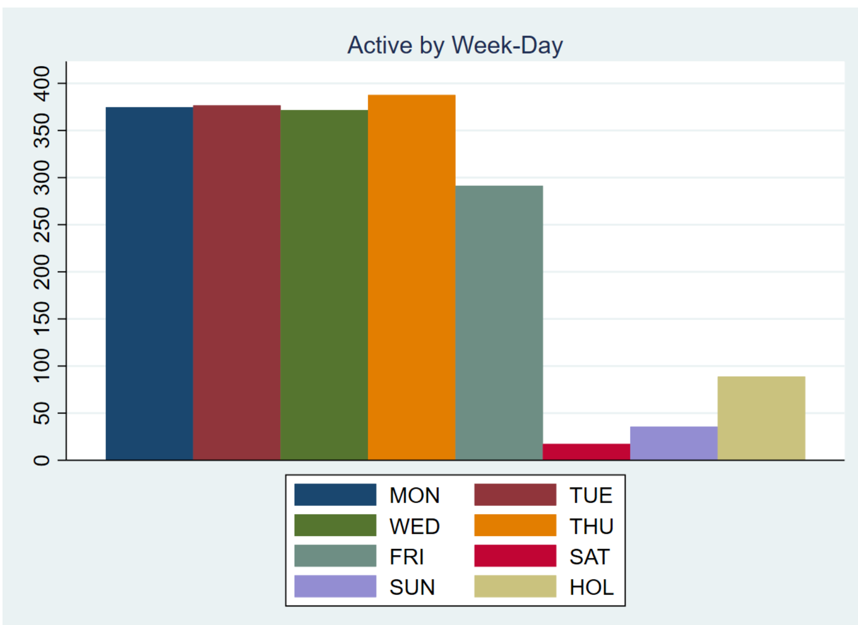
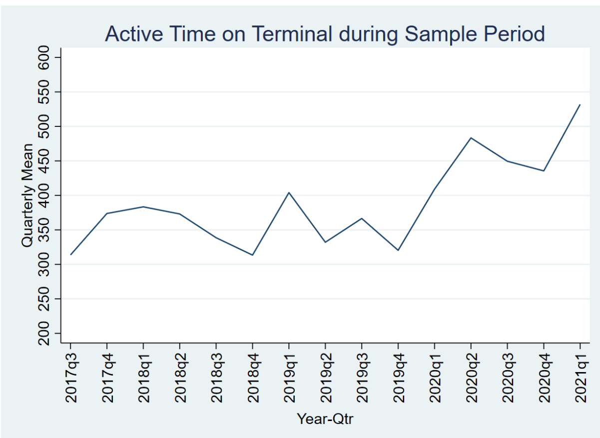


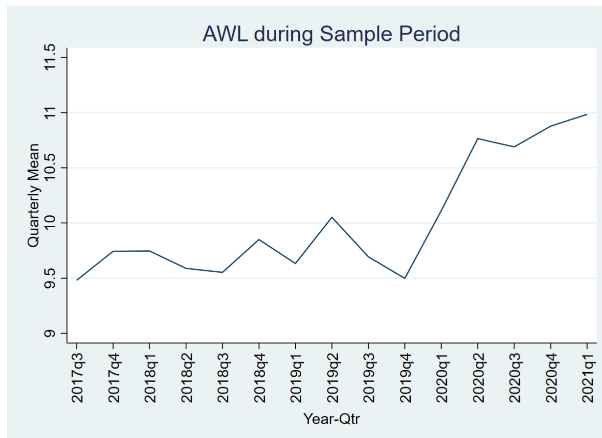
Figure 4: *AWL*, *Minutes Active*, and *PAD* during Sample Period

This figure depicts the quarterly cross-analyst averages of the various log-in measures over the sample period. The measure are: *Minutes Active*, *AWL*, and *PAD*. See Table A.1 and Table 1 for details about variable and sample definitions. The sample period is from September 2017 to March 2021.

Panel A: *Minutes Active*



Panel B: *AWL*



Panel C: *PAD*

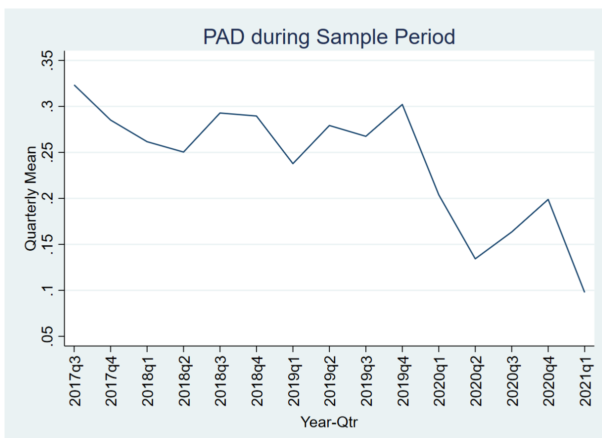
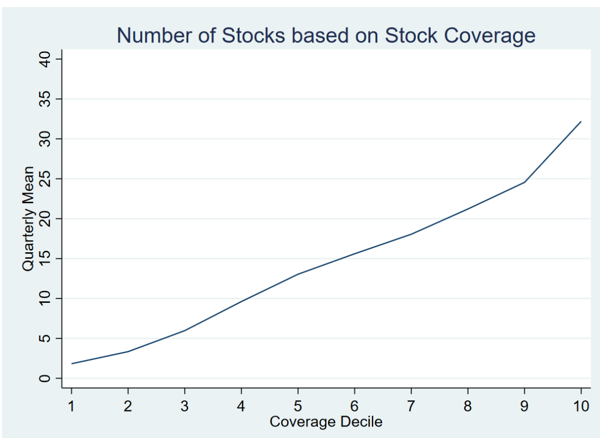


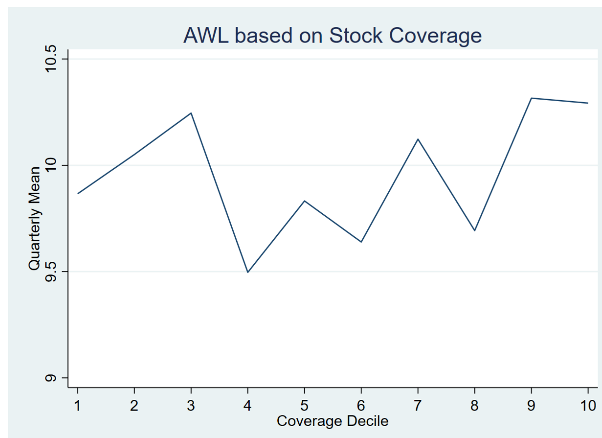
Figure 5: Stocks, *AWL*, *Minutes Active*, and *PAD* based on Coverage

This figure provides statistics based on stock-coverage deciles. The sample period is from September 2017 to March 2021. Each year and quarter we rank all analysts in our sample into deciles based on the number of stock they cover over the previous 4 quarters. Graph A plots the average number of stocks covered per decile. Graph B plots the average *AWL*. Graph C plots the average time on Bloomberg terminal conditioning on days with terminal activity ("Conditional Active"), and Graph D plots the average *PAD*.

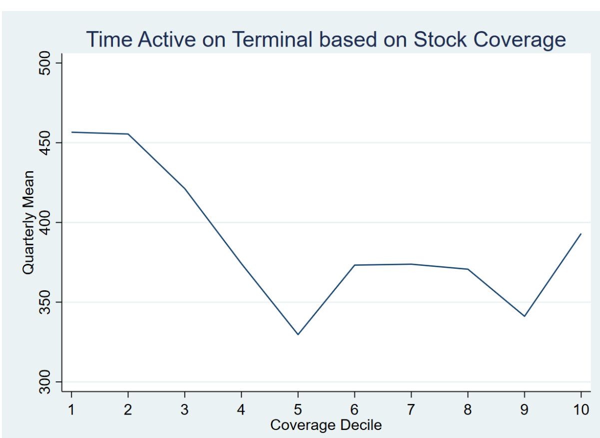
Panel A: Number of Stocks



Panel B: *AWL*



Panel C: Conditional Active Time on Terminal



Panel D: *PAD*

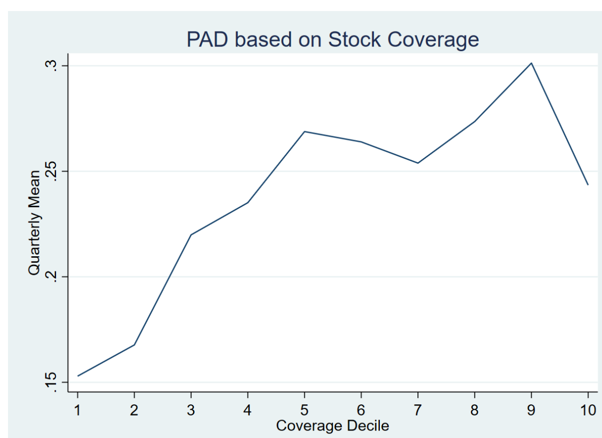


Figure 6: Measuring Commute Time - Example

This figure provides a fictitious (to preserve anonymity) example of how we measure commute time for a given analyst. Using Google Maps, we measure the minimum typical travel time between home and work at 7:00 am on a workday. The figure illustrates this for public transit – in this case 23 minutes – but we collect the same information for automobile, bicycle, and foot travel. Commute time is then the minimum travel time across these various options. We verify the home address and work address of the analysts using data from FINRA BrokerCheck, Mergent Intellect, and LinkedIn.

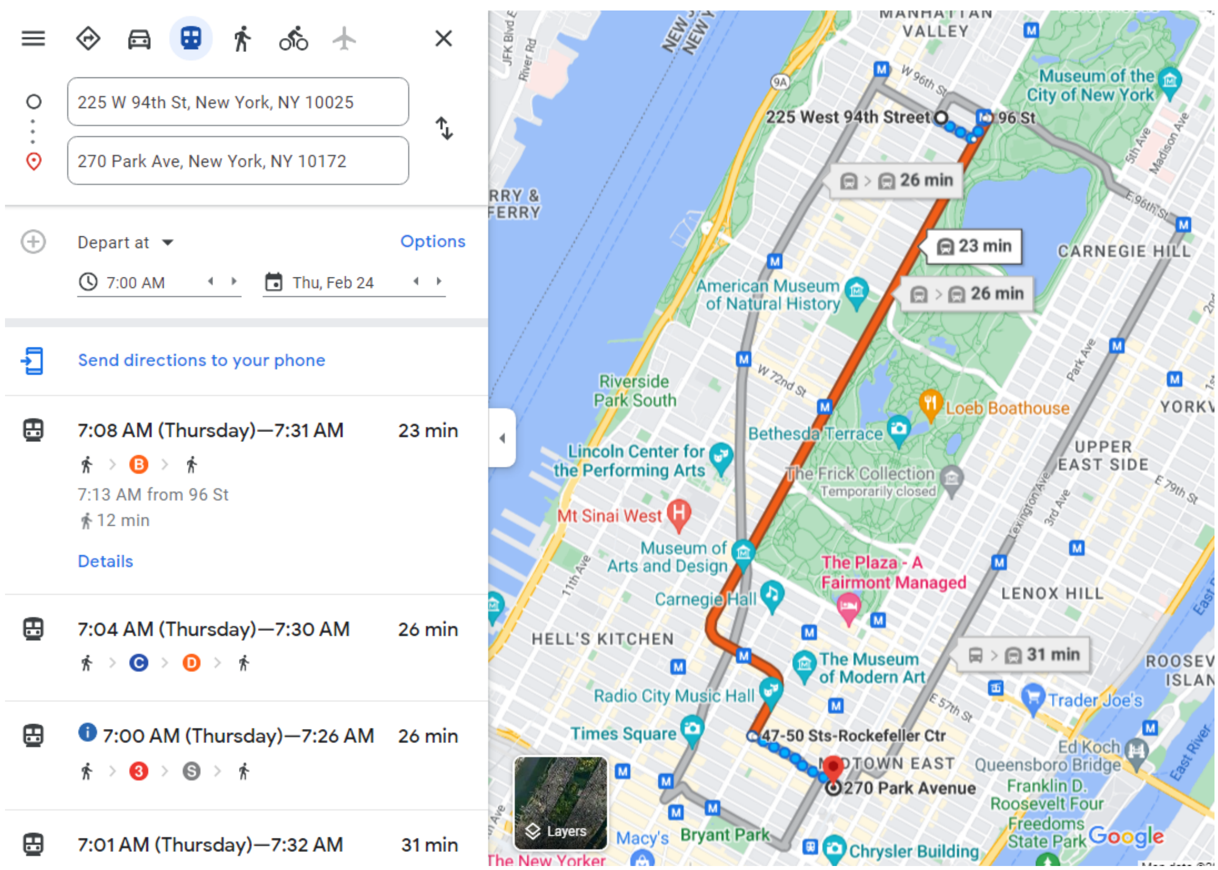


Figure 7: Changes in AWL and Commute Time Saved

This figure illustrates the relation between AWL and commute-time-saved reported in Table 12, where changes in AWL (Q1-Q2 of 2020 minus Q3-Q4 of 2019) are plotted against commute-time-saved deciles. The x-axis reports the average commute time saved for each decile, where the y-axis reports the corresponding average change in AWL.

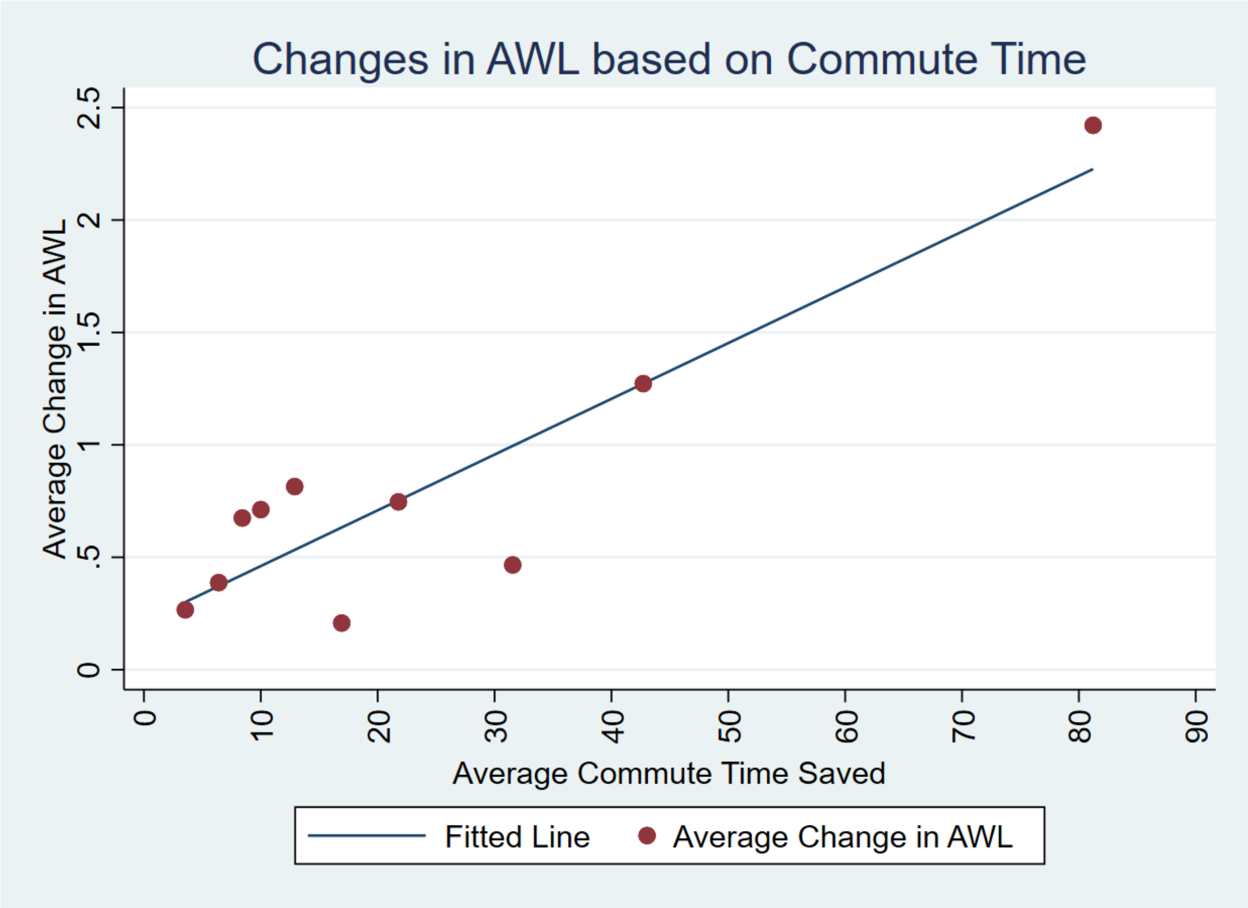


Table 1: Summary stats of analyst output

This table reports summary statistics of analyst output for the sample of Active Bloomberg analysts analyzed in this study (Bloomberg sample) and their comparison sample. The active analysts' sample includes 336 analysts and 42 brokerage firms, over 2,874 analyst-quarter observations. To be included in the comparison sample, we require an analyst to cover at least three stocks, to be on I/B/E/S for at least four quarters, and belong to one of the 42 brokerage firms in our Bloomberg sample. The comparison sample includes 1,854 analysts over 16,239 analyst-quarter observations. See Table A.1 for details about variable definitions. The sample period is from September 2017 to March 2021. To be considered as an active Bloomberg user, an analyst needs to have at least one quarter with a quarterly average percent activity greater than 3%. Percent activity is the time in minutes that an analyst is actively logged to the terminal scaled by the number of minutes within a day. This cut-off removes the left tail of the log-in distribution, which is populated by inactive users. In addition, we require an analyst to have at least two earnings forecasts per quarter, and to cover at least 3 stocks. Panel A reports the mean, median, standard deviation and other percentiles of the Bloomberg sample. Panel B compares the Bloomberg sample with the comparison sample. We report each group's averages, their differences, and associated p-values. Standard errors are clustered by analyst and year-quarter.

Panel A: The Bloomberg Sample Summary Statistics

	Mean	Std. Dev.	10%	25%	Median	75%	90%
# Unique Stocks t-4_t-1	17.848	10.529	4.000	10.000	17.000	25.000	31.000
Ave # Stocks t-4_t-1	15.696	9.384	3.000	7.500	15.500	22.250	27.000
# of GICS6 Industries	2.999	1.969	1.000	2.000	2.000	4.000	6.000
# of Stocks w Q1 EPS Forecasts	16.068	9.354	4.000	8.000	16.000	22.000	28.000
% of Common Stocks	77.070	27.997	28.125	69.231	88.000	96.154	100.000
# Q1 EPS Forecasts	23.079	16.194	5.000	10.000	21.000	32.000	43.000
# Y1 EPS Forecast	24.785	17.414	5.000	11.000	22.000	35.000	47.000
# Long Term Growth Forecasts	5.673	11.281	0.000	0.000	0.000	6.000	20.000
# of Other Forecasts	140.124	133.086	19.000	45.000	101.000	193.000	305.000
# of Stocks w Rec	3.276	3.269	1.000	1.000	2.000	4.000	7.000
# of Rec	2.468	3.343	0.000	0.000	2.000	3.000	6.000
# of non-stale Rec	2.225	3.025	0.000	0.000	1.000	3.000	5.000
# of Stocks w PTG	11.805	7.940	2.000	5.000	11.000	17.000	23.000
# of PTG	15.275	14.429	0.000	4.000	12.000	23.000	34.000
# of Analyst-Quarters	2,874						

Panel B: Mean Differences of the Bloomberg Sample and their Comparison Group

	Bloomberg	Comparison	Mean-Diff	P-value
# Unique Stocks t-4_t-1	17.848	15.7486	2.099	0.011
Ave # Stocks t-4_t-1	15.696	13.7563	1.940	0.008
# of GICS6 Industries	2.999	3.13178	-0.133	0.316
# of Stocks w Q1 EPS Forecasts	16.068	14.359	1.709	0.015
% of Common Stocks	77.07	69.2383	7.832	0.001
# Q1 EPS Forecasts	23.079	21.327	1.752	0.098
# Y1 EPS Forecast	24.785	21.1604	3.625	0.004
# Long Term Growth Forecasts	5.673	1.83447	3.839	0.000
# of Other Forecasts	140.124	125.927	14.197	0.105
# of Stocks w Rec	3.276	2.92485	0.351	0.024
# of Rec	2.468	2.03171	0.436	0.007
# of non-stale Rec	2.225	1.77345	0.452	0.003
# of Stocks w PTG	11.805	10.5826	1.222	0.029
# of PTG	15.275	13.9109	1.364	0.200
AveQtrAccuracy	-0.030	-0.017	-0.012	0.045
AveQtrAccuracy_VW	-0.025	-0.019	-0.006	0.322
# of Analysts	336	1,854		
# of Analyst-Quarters	2,874	16,239		

Table 2: Summary stats of analyst Bloomberg log-in activity and *AWL* measures

This table reports summary statistics of analysts log-in activity on the Bloomberg terminal (Panel A), together with the log-in based measures (Panel B), and their correlation martix (Panel C). See Table A.1 and Table 1 for details about variable and sample definitions.

Panel A: Log-in Statistics

	Mean	Std. Dev.	10%	25%	Median	75%	90%
% of Workdays with Bloomberg Activity	0.717	0.246	0.344	0.611	0.786	0.902	0.967
Active (minutes per day)	361.711	198.075	87.190	235.902	362.169	477.891	588.000
Conditional Active (on active days)	475.638	188.910	285.829	382.333	472.765	552.520	650.085
Active - hours per Week	30.143	16.506	7.266	19.658	30.181	39.824	49.000
# of Analyst-Quarters	2,874						

Panel B: *AWL* and *PAD* statistics

	Mean	Std. Dev.	10%	25%	Median	75%	90%
AWL	9.805	2.028	7.966	8.830	9.732	10.873	12.074
PAD	0.283	0.246	0.033	0.098	0.214	0.389	0.656
# of Analyst-Quarters	2,874						

Panel C: Correlation matrix

	(1)	(2)	(3)
(1) *AWL*	1.00		
(2) *PAD*	-0.23	1.00	
(3) *LnCondActive*	0.25	-0.37	1.00

Table 3: Analysts Pre-Open Daily Abnormal Login Activity

This table reports results from daily panel regressions of analysts' abnormal login activity during 7 am - 9 am on various market and information events variables. Specifically, for each analyst and half an hour during 7-9 am, we have an indicator that is equal to one if an analyst is logged in to the Bloomberg terminal. To capture an analyst's abnormal login activity, for each day and half an hour interval, we remove the analyst's day-interval average sample activity. This is comparable to including day and interval fixed effects in a regression. We then calculate the de-trended averages during the pre-open period. We further construct a battery of analyst-specific explanatory variables based on the set of stocks that an analyst cover in her portfolio during a given year-quarter. These variables include extreme market activity and news coverage. See Table A.1 and Table 1 for details about variable and sample definitions. Standard errors are double clustered by analyst and date reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Analysts Average LogIn Activity During 7-9 AM					
	(1)	(2)	(3)	(4)	(5)	(6)
# Stocks in AbnVOl Decile t-1	0.007***	0.007***	0.006***	0.006***	0.005***	0.005***
	(6.44)	(6.45)	(5.90)	(5.88)	(5.19)	(5.21)
# Stocks in AbsExtRet Decile t-1	0.001	0.001	0.001	0.001	0.001	0.001
	(1.03)	(1.04)	(0.82)	(0.82)	(0.95)	(0.96)
# Stock with AMC News t-1	0.005***			0.004***	0.002	
	(3.33)			(2.65)	(1.33)	
# Stock with AMC Earn News t-1		0.008***				0.001
		(2.80)				(0.22)
# Stock with AMC AR News t-1		-0.013				-0.012
		(-1.52)				(-1.30)
# Stock with BMO News t			0.013***	0.013***		
			(9.05)	(9.05)		
# Stock with BMO Earn News t					0.079***	0.079***
					(12.31)	(12.33)
# Stock with BMO AR News t					0.004***	0.004***
					(3.15)	(3.16)
# Max Industry Earn BMO News Pressure t					0.074***	0.074***
					(3.66)	(3.66)
Analyst FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Coverage FE	YES	YES	YES	YES	YES	YES
Date Cluster	YES	YES	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES
Observations	141,472	141,472	141,472	141,472	141,472	141,472
R^2	0.138	0.138	0.140	0.140	0.149	0.149

Table 4: *AWL* and *PAD* explained by Fixed-Effect and Analyst Characteristic

This table reports results from panel regressions of *AWL* and *PAD* on various fixed effects and analyst characteristics. Panel A reports the explained variation of our *AWL* and *PAD* measures by time, analyst, brokerage firm, and main GICS6 industry using fixed effect regressions. Panel B regresses the *AWL* and *PAD* measures on analyst characteristics obtained from various sources. *HIGH_PAD* is a dummy variable that receives the value of one if *PAD* is above the distribution median, and zero otherwise. See Table A.1 and Table 1 for details about variable and sample definitions. In Panel B the standard errors are clustered by analysts reported in parentheses below the coefficient estimates We keep analyst-quarter observations that meet the required quarterly login activity filter. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: *AWL* and *PAD* Variation Explained by Fixed Effects

	AWL				PAD			
	(1) TIME	(2) ANALYST	(3) BROKER	(4) INDUSTRY	(5) TIME	(6) ANALYST	(7) BROKER	(8) INDUSTRY
Constant	9.346***	10.940***	10.797***	10.069***	0.335***	0.145	0.801***	0.263***
	(68.06)	(12.40)	(12.43)	(65.05)	(21.37)	(1.53)	(8.05)	(14.40)
R^2	0.055	0.498	0.095	0.105	0.095	0.572	0.127	0.087
Observations	2,874	2,874	2,874	2,874	2,874	2,874	2,874	2,874

Panel B: *AWL*, *PAD* and Analyst Characteristics

	AWL				*HIGH_PAD*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IBES Years	-0.044***	-0.041***	-0.044***	-0.034**	0.005	0.004	0.005	0.004
	(-2.88)	(-2.65)	(-2.87)	(-1.99)	(1.27)	(1.20)	(1.25)	(1.15)
High Rank Indicator	-0.455**	-0.491***	-0.534***	-0.390**	0.139***	0.136***	0.139***	0.102**
	(-2.52)	(-2.77)	(-3.07)	(-2.20)	(3.07)	(2.95)	(3.02)	(2.20)
STAR	0.218	0.117	0.133	-0.163	0.116***	0.116**	0.114**	0.182***
	(1.23)	(0.65)	(0.73)	(-0.81)	(2.64)	(2.58)	(2.55)	(3.99)
Work Experience	0.007	-0.000	-0.000	-0.012	0.000	0.001	0.001	0.003
	(0.44)	(-0.01)	(-0.01)	(-0.67)	(0.03)	(0.17)	(0.17)	(0.70)
# Jobs FINRA	-0.026	-0.026	-0.036	-0.048	0.013	0.013	0.014	0.023*
	(-0.56)	(-0.56)	(-0.78)	(-0.93)	(1.11)	(1.16)	(1.22)	(1.90)
Ave Q1 PMAFE t-4_t-1	0.039	0.047	0.069	-0.094	-0.054	-0.031	-0.033	-0.034
	(0.08)	(0.10)	(0.15)	(-0.22)	(-0.49)	(-0.28)	(-0.29)	(-0.31)
NYC Indicator		0.311*	0.346*	0.192		0.008	0.005	-0.001
		(1.72)	(1.95)	(0.87)		(0.18)	(0.12)	(-0.01)
MBA Indicator		0.279	0.311	0.563		-0.119	-0.122	-0.168*
		(0.57)	(0.64)	(1.25)		(-1.50)	(-1.54)	(-1.97)
Female Indicator		0.081	0.090	-0.030		-0.001	-0.002	0.008
		(0.36)	(0.40)	(-0.13)		(-0.02)	(-0.04)	(0.15)
Children Indicator		0.373	0.392	0.145		-0.024	-0.026	0.013
		(0.72)	(0.75)	(0.27)		(-0.21)	(-0.23)	(0.10)
Principal Exam			0.385*	0.197			-0.033	-0.045
			(1.70)	(0.79)			(-0.58)	(-0.79)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Brokerage Firm FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,501	2,501	2,501	2,499	2,501	2,501	2,501	2,499
R^2	0.195	0.212	0.217	0.268	0.152	0.154	0.154	0.229

Table 5: Analyst Output Regressions

This table reports results from panel regressions of analyst output on *AWL*, *HIGH_PAD*, and other control variables. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *HIGH_PAD* is a dummy variable that receives the value of one if *PAD* is above the distribution median, and zero otherwise. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Earnings Forecasts

	Q1 EPS				Y1 EPS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AWL	0.250***		0.214**	0.306*	0.364***		0.330***	0.539***
	(2.67)		(2.24)	(1.76)	(3.73)		(3.34)	(2.97)
HIGH_PAD		-1.095***	-0.993***	-1.554***		-1.082***	-0.926**	-1.749***
		(-3.24)	(-2.94)	(-3.54)		(-3.02)	(-2.58)	(-3.69)
AveDep t-4_t-1	0.864***	0.865***	0.864***	0.120	0.865***	0.865***	0.864***	0.099
	(46.67)	(46.38)	(46.90)	(1.13)	(44.91)	(45.15)	(45.35)	(0.92)
IBES Years	-0.026	-0.028	-0.020	-4.711	-0.034	-0.042	-0.029	-6.604*
	(-1.10)	(-1.17)	(-0.83)	(-1.27)	(-1.38)	(-1.63)	(-1.15)	(-1.79)
Ave # of Industries t-4_t-1	-0.048	-0.050	-0.052	-0.252	-0.083	-0.086	-0.088	-0.476
	(-0.61)	(-0.61)	(-0.64)	(-0.39)	(-0.98)	(-0.98)	(-1.03)	(-0.69)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,591	2,591	2,591	2,559	2,593	2,593	2,593	2,561
R^2	0.793	0.794	0.794	0.841	0.797	0.797	0.798	0.845

Panel B: Other Forecasts

	Other EPS				PTG			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AWL	1.748**		1.579**	2.538**	0.462***		0.420***	0.540**
	(2.37)		(2.13)	(2.13)	(3.61)		(3.18)	(2.41)
HIGH_PAD		-5.315**	-4.550*	-5.710		-1.129**	-0.884*	-1.290**
		(-2.00)	(-1.71)	(-1.60)		(-2.58)	(-1.96)	(-1.99)
AveDep t-4_t-1	0.893***	0.891***	0.892***	0.234***	0.769***	0.777***	0.771***	-0.054
	(64.15)	(64.54)	(65.22)	(2.97)	(20.26)	(20.13)	(20.19)	(-0.78)
IBES Years	-0.417**	-0.457**	-0.391**	-36.341	0.007	-0.002	0.013	-7.852
	(-2.32)	(-2.55)	(-2.21)	(-1.33)	(0.23)	(-0.07)	(0.45)	(-0.51)
Ave # of Industries t-4_t-1	-0.136	-0.167	-0.159	-1.360	-0.059	-0.063	-0.064	0.510
	(-0.22)	(-0.27)	(-0.26)	(-0.26)	(-0.65)	(-0.67)	(-0.71)	(0.98)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,593	2,593	2,593	2,561	2,279	2,279	2,279	2,247
R^2	0.813	0.813	0.813	0.854	0.630	0.628	0.630	0.715

Table 6: Analyst Timeliness Regressions

This table reports results from panel regressions of analyst Q1 forecast timeliness on *AWL*, *HIGH_PAD*, and other control variables. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *HIGH_PAD* is a dummy variable that receives the value of one if *PAD* is above the distribution median, and zero otherwise. *LnTFE* is the natural logarithm of the analyst average timeliness. Analyst timelines in turn, is the number of days that takes an analyst to issue a forecast after the most recent earnings announcement. To reduce noise due to analysts who update their forecasts infrequently, we keep analysts with average timeliness not longer than 30 calendar days. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Time From Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
AWL	-0.059**		-0.062**	-0.061**	-0.059**	-0.019
	(-2.24)		(-2.40)	(-2.28)	(-2.22)	(-0.82)
HIGH_PAD		-0.074	-0.102	-0.108	-0.107	-0.101
		(-0.82)	(-1.18)	(-1.25)	(-1.23)	(-1.57)
IBES Years	-0.022**	-0.019**	-0.021**	-0.019*	-0.019**	-0.916***
	(-2.31)	(-1.98)	(-2.23)	(-1.96)	(-1.97)	(-2.72)
# Q1 EPS Forecasts	0.017***	0.017***	0.017***	0.015***	0.015***	-0.009**
	(4.27)	(4.08)	(4.25)	(3.63)	(3.68)	(-2.59)
Ave # of Industries t-4_t-1				-0.068**	-0.067**	0.033
				(-2.28)	(-2.26)	(0.56)
Ave Q1 PMAFE t-4_t-1					0.363	0.247
					(1.09)	(0.86)
Coverage x Time FE	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES
Observations	2,374	2,374	2,374	2,365	2,345	2,312
R^2	0.111	0.107	0.112	0.120	0.119	0.519

Table 7: Market Reaction to Analyst Recommendation Changes

This table reports results from daily panel regressions of market reaction to analyst recommendation changes on *AWL*, *HIGH_PAD*, and other control variables. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *HIGH_PAD* is a dummy variable that receives the value of one if *PAD* is above the distribution median, and zero otherwise. To have a meaningful comparison, we multiply the daily returns by -1 if the analyst's recommendation change is negative. Recommendations that are issued after market close are shifted to the next trading day. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AWL	-0.001		0.000	0.002	-0.001		0.000	0.002
	(-0.33)		(0.03)	(0.35)	(-0.34)		(0.04)	(0.32)
HIGH_PAD		0.026**	0.026**	0.010		0.028**	0.028**	0.011
		(2.02)	(2.08)	(0.80)		(2.12)	(2.17)	(0.88)
Ave Q1 PMAFE t-4_t-1	0.001	0.011	0.012	0.026	0.001	0.012	0.013	0.028
	(0.03)	(0.26)	(0.26)	(0.36)	(0.02)	(0.28)	(0.29)	(0.39)
Early Forecast	0.000**	0.000**	0.000**	0.000	0.000**	0.000**	0.000**	0.000
	(2.37)	(2.41)	(2.40)	(0.73)	(2.36)	(2.38)	(2.38)	(0.85)
IBES Years	0.000	0.000	0.000	-0.044	0.000	0.000	0.000	0.026
	(0.34)	(0.17)	(0.18)	(-0.24)	(0.38)	(0.22)	(0.24)	(0.14)
# Q1 EPS Forecasts	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001
	(-0.26)	(-0.22)	(-0.23)	(-1.05)	(-0.25)	(-0.22)	(-0.22)	(-1.01)
# of GICS6 Industries	-0.006	-0.007	-0.007	-0.006	-0.006	-0.007	-0.007	-0.005
	(-1.52)	(-1.61)	(-1.62)	(-0.53)	(-1.53)	(-1.62)	(-1.63)	(-0.46)
LnSize					-0.009	-0.013*	-0.013**	-0.015**
					(-1.43)	(-1.97)	(-2.00)	(-2.38)
LnBM					-0.002	-0.001	-0.001	-0.000
					(-0.65)	(-0.28)	(-0.29)	(-0.03)
StdDev.Ret					0.110	0.111	0.111	0.153
					(0.55)	(0.56)	(0.56)	(0.96)
InstHold					-0.026**	-0.026**	-0.026**	-0.023**
					(-2.46)	(-2.49)	(-2.50)	(-2.36)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,712	8,712	8,712	8,708	8,598	8,598	8,598	8,594
R^2	0.326	0.335	0.335	0.647	0.328	0.338	0.338	0.650

Table 8: Probability of Being a Star Analyst

This table reports results from panel regressions of a star analyst indicator on *AWL* and *PAD* controlling for various fixed effects and analyst characteristics. In particular, we employs a linear probability model where a dummy variable of being a star analysts in Q4 of year t is regressed on average *AWL* and average *HIGH_PAD* in Q1-Q3 of year t. Columns 1—4 include all observations. Columns 5–6 (7–8) focus on a sub sample where the analyst was not elected (elected) as a star analyst in the previous year. See Table A.1 and Table 1 for details about variable and sample definitions. Standard errors are clustered by analyst reported in parentheses below the coefficient estimates We keep analyst-quarter observations that meet the required quarterly login activity filter. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	ALL				Not a STAR in t-1		A STAR in t-1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ave AWL Q1-Q3	-0.008		-0.001	-0.003	-0.001	-0.001	-0.020	-0.012
	(-0.63)		(-0.09)	(-0.23)	(-0.13)	(-0.07)	(-1.21)	(-0.66)
Ave High_PAD Q1-Q3		0.107**	0.106**	0.121**	0.079**	0.085**	-0.050	-0.051
		(2.25)	(2.19)	(2.51)	(2.04)	(2.27)	(-0.97)	(-0.98)
Ave Q1 PMAFE t-4_t-1	0.070	0.067	0.067	0.028	0.031	0.027	0.094	0.082
	(0.58)	(0.56)	(0.56)	(0.23)	(0.39)	(0.32)	(0.38)	(0.30)
IBES Years	0.019***	0.018***	0.018***	0.021***	0.009**	0.010**	0.002	0.007
	(5.29)	(5.16)	(5.16)	(5.78)	(2.26)	(2.55)	(0.75)	(1.50)
High Rank Indicator	0.121**	0.114**	0.113**	0.120**	0.060	0.053	0.056	0.047
	(2.30)	(2.24)	(2.21)	(2.45)	(1.37)	(1.12)	(1.33)	(1.08)
Work Experience	-0.004	-0.004	-0.004	-0.008	-0.011***	-0.012***	0.003	0.003
	(-0.73)	(-0.74)	(-0.74)	(-1.52)	(-2.96)	(-3.39)	(1.02)	(0.62)
# Jobs FINRA				-0.042***		-0.016*		-0.027*
				(-3.26)		(-1.73)		(-1.84)
NYC Indicator				0.013		0.024		-0.033
				(0.22)		(0.50)		(-0.55)
MBA Indicator				0.145		0.002		-0.107
				(1.30)		(0.04)		(-0.88)
Female Indicator				-0.010		-0.010		0.038
				(-0.19)		(-0.22)		(0.74)
Children Indicator				-0.251*		-0.128*		-0.042
				(-1.96)		(-1.67)		(-0.82)
Principal Exam				-0.010		0.063		-0.149**
				(-0.14)		(0.90)		(-2.13)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Brokerage Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	690	690	690	690	457	457	227	227
R^2	0.529	0.535	0.535	0.556	0.289	0.299	0.291	0.335

Table 9: Stock Level Brokerage Firm Dollar Trading Volume Regressions

This table reports results from quarterly panel regressions of brokerage firm stock level dollar trading volume on *AWL*, *HIGH_PAD*, and other control variables. For each brokerage firm and stock in our sample, we collect the daily share trading volume processed by the brokerage firm. We then calculate the daily dollar trading volume and aggregate it at the quarter level. The sample period is from July 2018 to March 2021. In Table A.7, we extend the analysis by including Firm × Time fixed effects, which allow us to explore changes in a stock-quarter dollar trading volume share of a given brokerage firm *relative* to other brokerage firms in our sample. See Table A.1 and Table 1 for details about variable and sample definitions. *HIGH_PAD* is a dummy variable that receives the value of one if *PAD* is above the distribution median, and zero otherwise. To control for trading volume persistence, we include the one-quarter lagged dependent variable (*LagDEP*). We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Cross-Analysts				Within-Analyst			
	(1) q	(2) q+1	(3) q+2	(4) q+3	(5) q	(6) q+1	(7) q+2	(8) q+3
AWL	8.773**	8.859***	11.724**	11.884	-1.033	-4.975	1.095	-3.681
	(2.19)	(2.72)	(2.42)	(1.52)	(-0.19)	(-1.11)	(0.20)	(-0.38)
HIGH_PAD	5.853	11.674	22.013	41.540*	-6.873	4.200	2.526	22.875
	(0.36)	(0.77)	(1.16)	(1.84)	(-0.44)	(0.35)	(0.13)	(1.52)
LagDEP	0.863***	0.860***	0.863***	0.877***	0.770***	0.769***	0.768***	0.783***
	(18.57)	(18.40)	(18.42)	(17.28)	(12.02)	(12.02)	(11.83)	(11.40)
LnSize	-3.247	15.288	13.965	-15.181	25.200	39.438*	35.011	15.443
	(-0.17)	(0.87)	(0.63)	(-0.47)	(0.96)	(1.79)	(1.47)	(0.47)
LnBM	-20.467***	15.405*	-6.168	7.895	-16.628**	10.032	-6.185	4.903
	(-2.59)	(1.93)	(-0.68)	(0.56)	(-2.09)	(1.19)	(-0.60)	(0.34)
StdDev.Ret	-498.318**	-191.488	-327.767	1153.515	-549.314**	-311.527	-255.290	1151.554
	(-2.00)	(-0.72)	(-0.47)	(1.05)	(-2.22)	(-1.15)	(-0.35)	(1.08)
InstHold	13.801	-27.349	97.604**	168.790***	-7.239	-50.703*	71.718*	167.579***
	(0.54)	(-0.98)	(2.08)	(3.24)	(-0.26)	(-1.70)	(1.67)	(3.35)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	NO	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	17,844	17,845	12,856	10,070	17,843	17,844	12,849	10,067
R^2	0.905	0.904	0.913	0.923	0.911	0.911	0.920	0.930

Table 10: Analyst Stock Level Accuracy Regressions

This table reports results from panel regressions of analyst Q1 forecast accuracy on *AWL*, *HIGH_PAD*, and other control variables. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *HIGH_PAD* is a dummy variable that receives the value of one if *PAD* is above the distribution median, and zero otherwise. *PMAFE* is the Analyst quarterly forecast accuracy measure based on Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016). We require at least two analysts to issue earnings forecasts in a given quarter. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AWL	-0.006***		-0.007***	-0.005*	-0.006***		-0.007***	-0.005*
	(-2.71)		(-2.94)	(-1.71)	(-2.84)		(-3.06)	(-1.65)
HIGH_PAD		-0.013*	-0.016**	-0.019**		-0.012*	-0.015**	-0.018**
		(-1.89)	(-2.28)	(-2.09)		(-1.73)	(-2.15)	(-1.99)
Ave Q1 PMAFE t-4_t-1	0.236***	0.241***	0.234***	-0.230***	0.234***	0.239***	0.231***	-0.230***
	(6.11)	(6.14)	(6.05)	(-4.99)	(5.92)	(5.95)	(5.85)	(-4.89)
Early Forecast	0.001***	0.001***	0.001***	0.001**	0.001***	0.001***	0.001***	0.001**
	(2.75)	(2.78)	(2.72)	(2.13)	(2.82)	(2.86)	(2.79)	(2.19)
IBES Years	0.001	0.001**	0.001	-0.029	0.001	0.001*	0.001	-0.021
	(1.52)	(2.11)	(1.63)	(-0.38)	(1.31)	(1.90)	(1.41)	(-0.28)
# Q1 EPS Forecasts	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(4.56)	(4.47)	(4.51)	(3.50)	(4.72)	(4.65)	(4.68)	(3.67)
# of GICS6 Industries	0.003	0.002	0.002	0.001	0.003	0.002	0.003	0.002
	(0.90)	(0.70)	(0.85)	(0.30)	(0.91)	(0.71)	(0.86)	(0.32)
LnSize					-0.003	-0.003	-0.003	-0.006
					(-0.24)	(-0.24)	(-0.25)	(-0.45)
LnBM					0.004	0.004	0.004	0.002
					(0.59)	(0.51)	(0.56)	(0.20)
StdDev.Ret					0.170	0.164	0.165	0.066
					(0.47)	(0.46)	(0.46)	(0.18)
InstHold					0.025	0.025	0.025	0.027
					(1.04)	(1.05)	(1.04)	(1.09)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	37,373	37,373	37,373	37,372	36,795	36,795	36,795	36,794
R^2	0.090	0.090	0.090	0.106	0.090	0.090	0.090	0.107

Table 11: *PAD* and COVID Lockdown Identification Strategy

This table reports results from panel regressions of analyst output and accuracy measures on *PAD* and other control variables using a difference-in-difference identification strategy. We focus the period Q3-2019 to Q2-2020 and use the exogenous drop in *PAD* due to the COVID lockdown as a shock to analyst ability to travel. We keep all analysts with full 4-quarter data and information about the analysts' home and work locations. This results in 102 unique analysts. We then calculate the average *PAD* during Q3 and Q4 of 2019 as a measure for the potential drop in *PAD*. The treatment group includes analysts with *PAD* values above the median . The pre- (post) period includes Q3-Q4 (Q1-Q2) of 2019(2020). $TREATMENT \times POST$ captures the potential difference in the drop in *PAD* between the treatment and the control group. All observations are at the analyst-quarter level. Consequently, *PMAFE* is the value-weighted average of the analysts accuracy measure across all stocks covered based on the stock market cap. FAR and NEAR are *PMAFE* averages for sub groups on stocks that the analyst covers based on the distance between the analyst home address and the covered firm headquarter. FAR (NEAR) referrers to stocks that their headquarter is above (up to) 300 miles. See Table A.1 and Table 1 for details about variable and sample definitions. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Output			Accuracy		
	(1) Q1	(2) Y1	(3) PTG	(4) PMAFE	(5) FAR	(6) NEAR
TREATMENT	-4.830**	-4.387**	-0.681	-0.049	-0.070	-0.041
	(-2.47)	(-2.12)	(-0.30)	(-1.34)	(-1.64)	(-0.63)
POST	5.546***	6.818***	8.164***	-0.038	-0.046	0.067
	(3.15)	(3.48)	(4.15)	(-0.79)	(-0.87)	(0.89)
$TREATMENT \times POST$	2.410	1.511	2.631	0.117**	0.128**	-0.017
	(1.06)	(0.60)	(0.74)	(2.47)	(2.29)	(-0.19)
Ave # Stocks t-4_t-1	1.071***	1.072***	0.829**	0.006*	0.008**	-0.001
	(3.08)	(2.93)	(2.07)	(1.79)	(2.08)	(-0.09)
Ave # of Industries t-4_t-1	-0.447	-0.754	-1.207*	-0.008	-0.004	0.003
	(-0.63)	(-1.04)	(-1.65)	(-1.21)	(-0.61)	(0.24)
IBES Years	-0.370**	-0.298	0.100	-0.002	-0.004	0.001
	(-2.08)	(-1.55)	(0.36)	(-0.78)	(-1.44)	(0.42)
Ave Q1 PMAFE t-4_t-1	-1.151	0.052	-6.048	-0.015	-0.076	-0.040
	(-0.17)	(0.01)	(-0.70)	(-0.14)	(-0.61)	(-0.19)
Firm FE	YES	YES	YES	YES	YES	YES
Coverage FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES
Observations	408	408	305	407	380	327
AdjR^2	0.561	0.555	0.400	0.036	0.042	0.030

Table 12: *AWL* and Commute Time Saved Identification Strategy

This table reports results from panel regressions of analyst output and accuracy measures on *AWL* and other control variables using a difference-in-difference identification strategy. We focus the period Q3-2019 to Q2-2020 and use the COVID lockdown as a positive shock to analyst *AWL* due to saved commute time to work. We keep all analysts with full 4-quarter data and information about home and work locations. This results in 102 unique analysts. To reduce noise we remove the min and max values of analysts' commute time, which results in a final sample of 99 analysts. Panel A reports the relation between changes in *AWL*(in minutes) and commute time saved. In Panel B we build on this relation and report difference-in-difference analysis. The treatment (control) group includes the analysts with time saved above (below) the median. The pre- (post) period includes Q3-Q4 (Q1-Q2) of 2019(2020). All observations are at the analyst-quarter level. Consequently, *PMAFE* is the value-weighted average of the analysts accuracy measure across all stocks covered based on the stock market cap. See Table A.1 and Table 1 for details about variable and sample definitions. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: *AWL* and Commute Time

	Changes in *AWL* in Minutes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commute-Time-Saved	1.314***	1.318***	1.328***	1.394***	1.387***	1.309***	1.320***	1.315***
	(2.90)	(2.92)	(2.87)	(2.88)	(2.94)	(2.86)	(2.75)	(2.75)
AGE		-0.097	-0.064	-0.128	-0.049	-0.094	-0.164	-0.135
		(-0.16)	(-0.11)	(-0.21)	(-0.05)	(-0.11)	(-0.22)	(-0.18)
Young Kids Indicator			-17.834	-16.855	-16.806	-23.829	-24.399	-24.713
			(-1.00)	(-0.95)	(-0.94)	(-1.36)	(-1.32)	(-1.32)
Female Indicator				20.286	20.087	21.879	20.122	18.216
				(1.06)	(1.04)	(1.12)	(0.90)	(0.78)
IBES Years					-0.198	-1.250	-1.326	-1.266
					(-0.16)	(-0.70)	(-0.67)	(-0.65)
Work Experience						3.017	3.089	3.260
						(1.40)	(1.37)	(1.39)
MBA Indicator						59.568	60.919	59.671
						(1.08)	(1.12)	(1.09)
# Jobs FINRA						3.136	3.279	3.679
						(0.71)	(0.70)	(0.73)
High Rank Indicator							5.332	6.025
							(0.22)	(0.25)
Principal Exam								-13.248
								(-0.76)
White SE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	102	102	102	102	102	102	102	102
AdjR^2	0.136	0.128	0.126	0.123	0.114	0.132	0.123	0.116

Panel B: Output and Accuracy

	Output			Accuracy
	(1)	(2)	(3)	(4)
	Q1	Y1	PTG	MPAFE
TREATMENT	2.817	2.583	2.853	0.046
	(1.59)	(1.39)	(1.63)	(1.52)
POST	5.064***	5.490***	5.744***	0.060
	(3.32)	(3.48)	(2.95)	(1.36)
TREATMENT × *POST*	3.689	4.616*	9.326**	-0.085*
	(1.50)	(1.68)	(2.42)	(-1.75)
Ave # Stocks t-4_t-1	1.087***	1.064***	0.811**	0.006*
	(3.29)	(3.06)	(2.25)	(1.89)
Ave # of Industries t-4_t-1	-0.636	-0.928	-0.868	-0.009*
	(-0.86)	(-1.21)	(-1.58)	(-1.85)
IBES Years	-0.383**	-0.286	0.179	-0.002
	(-1.97)	(-1.36)	(0.74)	(-0.83)
Ave Q1 PMAFE t-4_t-1	-0.438	1.465	-2.086	-0.012
	(-0.06)	(0.20)	(-0.35)	(-0.11)
Firm FE	YES	YES	YES	YES
Coverage FE	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES
Observations	396	396	296	395
AdjR^2	0.571	0.570	0.471	0.032

A Appendix—Variable Definitions and Additional Tests

In our main tests, we use *AWL* to proxy for analysts' general effort provision or work ethics. The use of *AWL* is justified because analysts can engage in other productive activities at work rather than spending time on the Bloomberg terminal. Nevertheless, since analysts' terminal usage is not trivial, in this appendix, we repeat the main tests (Section 3) using an *intensive* usage measure that captures the analyst's minutes spent on the Bloomberg terminal. The measure, *LnCondActive*, is calculated as the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter (i.e., on days with *PAD*=0).

In Table A.2, we explore the relation between *LnCondActive* and analyst output, where the specifications are analogous to the ones reported in Table 5. All specifications indicate that an increase in time spent on the terminal is associated with higher output. For example, a one-unit increase in *LnCondActive*, results in 0.86-2.29 additional quarterly earnings forecasts and 1.59-4.55 additional price targets.

In Table A.3 we explore the analysts' timeliness dimension. *LnCondActive* coefficient estimates have the same sign as those reported in Table 6, but they are statistically insignificant, again, suggesting that *AWL* is a more comprehensive measure of the analyst workday activity.

In Table A.4, we repeat the analysis conducted in Table 7 and explore the relation between *LnCondActive* and the market response to analysts' recommendation. Similar to Table 7's *AWL* findings, we do not find a significant relation between *LnCondActive* and market reaction.

In Table A.5, we repeat the analysis conducted in Table 8 and explore the relation between *LnCondActive* in Q1-Q3 of year t and being selected as a star analyst in Q4 of year t. In contrast to Table 8, we find a somewhat positive relation between *LnCondActive* and the probability of being ranked as a start analyst at the end of the year, but the relation is not robust.

In Table A.6, we explore the relation between *LnCondActive* and analyst forecast accuracy similar to the analysis conducted in Table 10. Across all specifications, *LnCondActive* coefficient estimates are negative and statistically significant, suggesting an improvement in the forecast accuracy. Compared with Table 10, the results are somewhat weaker, suggesting that accuracy also depends on other effort provisions during the analyst workday captured by *AWL*.

In Table A.7, we repeat the analysis conducted in Table 9 including Firm × Time fixed effects. These fixed effects allow us to explore changes in a stock-quarter dollar trading volume share of a given brokerage firm *relative* to other brokerage firms in our sample.

Finally, in Table A.8, we repeat the analysis conducted in Table 10 controlling for Brokerage Firm Peers (team effort).

Table A.1: Variable definitions

Variable	Definition
Bloomberg User Data	
User Data	Bloomberg users with assigned accounts have an online "status" by default. This status is either designated as "online", "idle", "offline", or "mobile". When users first log on to the platform, their status changes from offline to online, and it remains that way while they use Bloomberg. However, if they stop using it for 15 minutes, the user's status automatically changes to "idle". Eventually, and depending on the users' settings, a user is logged off after a long period of inactivity. Using this information we construct various work habits measures.
Activity Measures based on Terminal Usage	
% of Workdays with Bloomberg Activity	The quarterly percent of working days with logged-in activity.
Active (minutes per day)	The quarterly average of the daily minutes that an analyst is actively logged-in to her Bloomberg terminal.
Conditional Active (on active days)	The quarterly average of the daily minutes that an analyst is actively logged-in to her Bloomberg terminal conditioning on days with Bloomberg activity.
LnCondActive	The natural logarithm of *Conditional Active*.
Active - hours per Week	The quarterly average of hours per week that the analyst is logged-in to the terminal.
AWL	NOT COMPLETE. For each executive and year, we know the probability that an analyst is logged on every minute of the day. Using this information we construct a pdf. We then assume that the constructed distribution is a mixture of two normal distributions. This captures the idea that an analyst may have different morning and afternoon work habits. The distance *AWL*measures the difference between the means of the two distributions and adds a standard deviation on each side.
PAD	The quarterly average of a daily dummy variable that receives the value of one if an analyst is not logged in to her Bloomberg terminal during that day, and zero otherwise.
HIGH_PAD	A dummy variable that recieved the value of one if *PAD* is above the median of the sample distribution.

Variable	Definition
Analyst Coverage and Output Measures	
# Unique Stocks t-4_t-1	The number of unique stocks that an analyst covered over the previous four quarters.
Ave # Stocks t-4_t-1	The average number of stocks in a given quarter that an analyst covered over the previous four quarters.
# of GICS6 Industries	The average number of industries that an analyst covered over the previous four quarters. The industries are defined by the GICS six digit codes.
% of Common Stocks	The % of common stocks from all stocks that an analyst covers.
# of Stocks w Q1 EPS Forecasts	The number of stocks that an analyst issued a quarterly forecast for during a given quarter.
# Q1 EPS Forecasts	The number of Q1 earnings forecasts that an analyst issued across all stocks covered in a given quarter.
# Y1 EPS Forecast	The number of Y1 earnings forecasts that an analyst issued across all stocks covered in a given quarter.
# Long Term Growth Forecasts	The number of long-term forecasts that an analyst issued across all stocks covered in a given quarter.
# of Other Forecasts	The number of other earnings forecasts that an analyst issued across all stocks covered in a given quarter.
# of Rec	The number of stock recommendations that an analyst issued across all stocks covered in a given quarter.
# of non-stale Rec	The number of stock recommendation changes that an analyst issued across all stocks covered in a given quarter.
# of PTG	The number of 12-month price target forecasts that an analyst issued across all stocks covered in a given quarter.
Analyst Earnings Forecast Accuracy Measure	
PMAFE	Analyst quarterly forecast accuracy measure based on Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016). The measure (Proportional Mean Absolute Forecast Error) is defined as $(AFE_{i,j,t} - \overline{AFE_{j,t}})\ /\ \overline{AFE_{j,t}}$, which is the absolute forecast error for analyst i's forecast of firm j minus the mean absolute forecast error for firm j in quarter t, divided by the mean absolute forecast error for firm j in quarter t. To calculate the measure, we require at least two analysts covering the stock on I/B/E/S in a given quarter. In particular, for each analyst i and firm j, we calculate the analyst's quarterly equally-weighted forecast errors average based on all earnings forecasts initiated during the quarter. We then calculate the absolute value of the analyst average forecasts errors. We repeat the calculation for all analysts on I/B/E/S covering the stock in that quarter and calculate the stock's quarterly mean absolute forecasts errors.
AveQtrAccuracy	The average of the analyst quarterly forecast accuracy measure ($PMAFE$) across all the stocks covered in a given quarter.
AveQtrAccuracy_VW	The value weighted average of the analyst quarterly forecast accuracy measure ($PMAFE$) across all the stocks covered in a given quarter. The weights are based on the stock's market capitalization.

Variable	Definition
Analyst Forecast Timeliness Measures	
LnTFE	The analyst earnings forecasts timeliness measure, based on the natural logarithm of the time in days from the earnings announcement and the analyst subsequent earnings forecast. Specifically, for each analyst i, stock j and quarter q, we calculate the number of days from the earnings announcement during quarter q and the subsequent analyst earnings forecast. We then calculate the equally-weighted average across all covered stocks.
Analyst Portfolio Based Measures	
# Stocks in AbnVOl Decile t-1	The number of stocks in the analyst's portfolio that are in the top decile of day t-1 abnormal trading volume of CRSP's cross-sectional ranking. Abnormal volume is calculated as the split adjusted daily stock volume divided by the the split adjusted average trading volume over the past 63 trading days.
# Stocks in AbsExtRet Decile t-1	The number of stocks in the analyst's portfolio that are in the top decile of day t-1 absolute return of CRSP's cross-sectional ranking
# Stock with AMC News t-1	The number of stocks in the analyst portfolio that had after-market-close news on day t-1. The news data is obtained from the Dow Jones Edition of RavenPack Analytics from 2017 to August 2020. To ensure that we capture relevant news, we identify news with a relevance score of 100, which ensures that the news is about the firm of interest, from the following news-types: news-flash, hot-news-flash, full article, and press release. To ensure we capture fundamental news we keep the following 13 news categories: acquisitions-mergers, analyst-ratings, assets, credit, credit-ratings, dividends, earnings, equity-actions, labor-issues, legal, marketing, products-services, and partnerships.
# Stock with AMC Earn News t-1	The number of stocks in the analyst portfolio that had after-market-close earnings news on day t-1.
# Stock with AMC AR News t-1	The number of stocks in the analyst portfolio that had after-market-close analyst rating news on day t-1.
# Stock with BMO News t	The number of stocks in the analyst portfolio that had before-market-open news on day t.
# Stock with BMO Earn News t	The number of stocks in the analyst portfolio that had before-market-open earnings news on day t.
# Stock with BMO AR News t	The number of stocks in the analyst portfolio that had before-market-open analyst rating news on day t.
# Max Industry Earn BMO News Pressure t	We construct an industry earnings news pressure variable, calculated as the market-cap value-weighted earnings news dummy across all CRSP's stocks in a specific Fama-French 48 industry. We then take the maximum across all the industries that are covered by the analyst.
Analyst Additional Characteristic Based Measures	
Data	We manually obtain analyst characteristics data from FINRA's BrokerCheck website, LinkedIn and Facebook.
High Rank Indicator	A dummy variable that received a value of one if the analyst specifies a managing director (high rank) title in his public profiles, and zero otherwise.
STAR	A dummy variable that received a value of one if the analyst is ranked as a star analysis in year t by Institutional Investor All-America Research Team, and zero otherwise.
Work Experience	The number of work experience in years, obtained from FINRA.
# Jobs FINRA	The number of jobs that an analyst had switched, obtained from FINRA.
NYC Indicator	A dummy variable that received a value of one if the analyst work in New York, and zero otherwise.
MBA Indicator	A dummy variable that received a value of one if the analyst specifies an MBA degree in his public profiles, and zero otherwise.

Variable	Definition
Analyst Additional Characteristic Based Measures (cont'd)	
Principal Exam	A dummy variable that received a value of one if the analyst has taken a principal exam and zero otherwise. Around 10% of the analysts in our sample have taken the principal exam. The information is obtained from FINRA.
AGE	The age of the analyst.
Female Indicator	A dummy variable that received a value of one if the analyst is a female and zero otherwise.
Children Indicator	A dummy variable that received a value of one if an analyst has children, and zero otherwise.
Young Kids Indicator	A dummy variable that received a value of one if an analyst has non-adult children, and zero otherwise.
Commute-Time-Saved	We verify the home address and work address of an analyst using data from FINRA BrokerCheck, Mergent Intellect, and LinkedIn. Using Google Maps, we then measure the minimum typical travel time between home and work at 7:00 am on a workday. Commute time is the minimum travel time across various options (public transit, automobile, bicycle, and foot travel). *Commute-Time-Saved*, is simply the commute time that an analyst saves due to working from home.
Additional Analyst Controls	
IBES Years	The analysts experience measured by the number of years in I/B/E/S.
AveQtrAccuracy	The analyst quarterly *PMAFE* average across all covered stocks.
Ave # Q1 EPS Forecasts t-4_t-1	The average of the quarterly number of earnings forecasts over the previous 12 months.
Ave # of Industries t-4_t-1	The average of the quarterly number of different industries that the analyst covers over the previous 12 months.
Stock Controls and fixed effects	
LnSize	The natural logarithm of the stock market capitalization.
LnBM	The natural logarithm of the stock book-to-market ratio.
BM_Dummy	A dummy variable that receives the value of one if book-to-market information is available, and zero otherwise. We augment book-to-market missing values with zeros.
StdDev.Ret	The standard deviation of stock daily stock returns.
InstHold	The stock quarterly percentage of institutional holdings.
Coverage fixed effects	To control for the number of stocks an analyst covers, every quarter we rank all analysts in our sample by the number of stocks they covered over the previous year into ten deciles. We then use the ranking to include coverage fixed effect.
Time fixed effects	We include time fixed effects in our regressions based on year-qtr pairs.

Table A.2: Analyst Output Regressions - *LnCondActive*

This table repeats the analysis conducted in Table 5, replacing *AWL* with *LnCondActive*. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *LnCondActive* is the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Earnings Forecasts

	Q1 EPS				Y1 EPS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnCondActive	0.856***		0.576*	2.287*	1.046***		0.781**	3.139**
	(2.64)		(1.74)	(1.68)	(2.83)		(2.08)	(2.23)
HIGH_PAD		-1.095***	-0.959***	-1.454***		-1.082***	-0.909**	-1.597***
		(-3.24)	(-2.76)	(-3.18)		(-3.02)	(-2.44)	(-3.26)
AveDep t-4_t-1	0.862***	0.865***	0.861***	0.097	0.862***	0.865***	0.861***	0.082
	(45.58)	(46.38)	(45.65)	(0.88)	(45.33)	(45.15)	(45.52)	(0.74)
IBES Years	-0.021	-0.028	-0.014	-5.317	-0.035	-0.042	-0.028	-7.426**
	(-0.93)	(-1.17)	(-0.60)	(-1.48)	(-1.42)	(-1.63)	(-1.13)	(-2.07)
Ave # of Industries t-4_t-1	-0.019	-0.050	-0.028	-0.169	-0.051	-0.086	-0.061	-0.333
	(-0.24)	(-0.61)	(-0.33)	(-0.26)	(-0.58)	(-0.98)	(-0.68)	(-0.47)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,535	2,591	2,535	2,502	2,537	2,593	2,537	2,504
R^2	0.794	0.794	0.794	0.839	0.797	0.797	0.797	0.843

Panel B: Other Forecasts

	Other EPS				PTG			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnCondActive	5.456**		4.093	21.916*	1.590***		1.351***	4.554***
	(2.03)		(1.54)	(1.69)	(3.43)		(2.80)	(2.66)
HIGH_PAD		-5.315**	-4.497	-4.899		-1.129**	-0.834*	-1.085
		(-2.00)	(-1.64)	(-1.34)		(-2.58)	(-1.77)	(-1.61)
AveDep t-4_t-1	0.898***	0.891***	0.896***	0.229***	0.762***	0.777***	0.766***	-0.071
	(71.21)	(64.54)	(71.62)	(2.90)	(19.01)	(20.13)	(19.03)	(-1.00)
IBES Years	-0.405**	-0.457**	-0.374**	-41.129	-0.006	-0.002	0.001	-10.820
	(-2.36)	(-2.55)	(-2.20)	(-1.53)	(-0.20)	(-0.07)	(0.05)	(-0.77)
Ave # of Industries t-4_t-1	0.087	-0.167	0.034	-0.738	-0.028	-0.063	-0.036	0.645
	(0.15)	(-0.27)	(0.06)	(-0.14)	(-0.29)	(-0.67)	(-0.38)	(1.19)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,537	2,593	2,537	2,504	2,231	2,279	2,231	2,198
R^2	0.814	0.813	0.814	0.854	0.626	0.628	0.627	0.713

Table A.3: Analyst Timeliness Regressions - *LnCondActive*

This table repeats the analysis conducted in Table 6, replacing *AWL* with *LnCondActive*. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *LnCondActive* is the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Time From Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
LnCondActive	-0.047		-0.077	-0.101	-0.104	-0.003
	(-0.40)		(-0.64)	(-0.86)	(-0.89)	(-0.02)
HIGH_PAD		-0.074	-0.109	-0.122	-0.122	-0.104
		(-0.82)	(-1.20)	(-1.36)	(-1.35)	(-1.57)
IBES Years	-0.020**	-0.019**	-0.020**	-0.017*	-0.017*	-0.941***
	(-2.14)	(-1.98)	(-2.04)	(-1.78)	(-1.79)	(-2.85)
# Q1 EPS Forecasts	0.017***	0.017***	0.017***	0.015***	0.015***	-0.009**
	(4.17)	(4.08)	(4.17)	(3.53)	(3.58)	(-2.47)
Ave # of Industries t-4_t-1				-0.073**	-0.072**	0.045
				(-2.48)	(-2.47)	(0.77)
Ave Q1 PMAFE t-4_t-1					0.370	0.325
					(1.06)	(1.09)
Coverage x Time FE	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES
Observations	2,323	2,374	2,323	2,314	2,295	2,262
R^2	0.110	0.107	0.111	0.120	0.119	0.522

Table A.4: Market Reaction to Analyst Recommendation Changes - *LnCondActive*

This table repeats the analysis conducted in Table 7, replacing *AWL* with *LnCondActive*. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnCondActive	-0.022		-0.015	-0.039	-0.022		-0.015	-0.037
	(-1.45)		(-1.12)	(-0.64)	(-1.41)		(-1.05)	(-0.62)
HIGH_PAD		0.026**	0.025**	0.010		0.028**	0.027**	0.011
		(2.05)	(2.02)	(0.81)		(2.13)	(2.11)	(0.88)
Ave Q1 PMAFE t-4_t-1	0.004	0.016	0.014	0.034	0.004	0.017	0.015	0.036
	(0.08)	(0.35)	(0.30)	(0.47)	(0.08)	(0.39)	(0.34)	(0.50)
Early Forecast	0.000**	0.000**	0.000**	0.000	0.000**	0.000**	0.000**	0.000
	(2.35)	(2.51)	(2.37)	(0.70)	(2.34)	(2.50)	(2.36)	(0.82)
IBES Years	0.000	0.000	-0.000	-0.026	0.000	0.000	-0.000	0.035
	(0.08)	(0.07)	(-0.07)	(-0.15)	(0.12)	(0.11)	(-0.02)	(0.20)
# Q1 EPS Forecasts	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001
	(-0.28)	(-0.25)	(-0.23)	(-0.97)	(-0.29)	(-0.26)	(-0.23)	(-0.94)
# of GICS6 Industries	-0.006	-0.007	-0.007	-0.005	-0.006	-0.007	-0.007	-0.004
	(-1.51)	(-1.61)	(-1.60)	(-0.41)	(-1.51)	(-1.62)	(-1.61)	(-0.34)
LnSize					-0.005	-0.009	-0.009	-0.011*
					(-0.85)	(-1.48)	(-1.45)	(-1.83)
LnBM					-0.002	-0.001	-0.001	-0.000
					(-0.80)	(-0.40)	(-0.36)	(-0.21)
StdDev.Ret					0.196	0.195	0.195	0.233**
					(1.12)	(1.15)	(1.14)	(2.16)
InstHold					-0.026**	-0.028***	-0.027***	-0.024**
					(-2.57)	(-2.77)	(-2.66)	(-2.60)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,633	8,712	8,633	8,630	8,521	8,598	8,521	8,518
R^2	0.330	0.335	0.339	0.655	0.333	0.339	0.342	0.658

Table A.5: Probability of Being a Star Analyst - *LnCondActive*

This table repeats the analysis conducted in Table 8, replacing *AWL* with *LnCondActive*. We keep analyst-quarter observations that meet the required quarterly login activity filter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	ALL				NO STAR y-1		STAR y-1	
	(1) star	(2) star	(3) star	(4) star	(5) star	(6) star	(7) star	(8) star
LnAveCondActive	0.075 (1.24)		0.117* (1.95)	0.114* (1.84)	-0.007 (-0.16)	-0.005 (-0.12)	0.072 (1.10)	0.100 (1.46)
Ave High_PAD Q1-Q3		0.107** (2.25)	0.131*** (2.71)	0.146*** (3.04)	0.079* (1.96)	0.085** (2.16)	-0.022 (-0.40)	-0.024 (-0.45)
Ave Q1 PMAFE t-4_t-1	0.078 (0.64)	0.067 (0.56)	0.077 (0.65)	0.038 (0.32)	0.031 (0.39)	0.027 (0.32)	0.149 (0.59)	0.136 (0.50)
IBES Years	0.019*** (5.39)	0.018*** (5.16)	0.018*** (5.19)	0.021*** (5.76)	0.009** (2.26)	0.010** (2.56)	0.004 (1.22)	0.008* (1.82)
High Rank Indicator	0.124** (2.38)	0.114** (2.24)	0.111** (2.19)	0.117** (2.41)	0.060 (1.37)	0.053 (1.13)	0.056 (1.31)	0.044 (0.99)
Work Experience	-0.004 (-0.68)	-0.004 (-0.74)	-0.004 (-0.67)	-0.008 (-1.38)	-0.011*** (-2.97)	-0.012*** (-3.39)	0.003 (1.15)	0.003 (0.75)
# Jobs FINRA				-0.042*** (-3.22)		-0.016* (-1.72)		-0.025 (-1.64)
NYC Indicator				-0.007 (-0.12)		0.024 (0.50)		-0.064 (-1.01)
MBA Indicator				0.139 (1.26)		0.002 (0.04)		-0.105 (-0.87)
Female Indicator				0.003 (0.07)		-0.010 (-0.23)		0.053 (1.10)
Children Indicator				-0.268** (-2.06)		-0.128* (-1.66)		-0.063 (-1.23)
Principal Exam				-0.007 (-0.11)		0.062 (0.90)		-0.167** (-2.62)
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Brokerage Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	690	690	690	690	457	457	227	227
R^2	0.530	0.535	0.539	0.560	0.289	0.299	0.287	0.340

Table A.6: Analyst Stock Level Accuracy Regressions - *LnCondActive*

This table repeats the analysis conducted in Table 10, replacing *AWL* with *LnCondActive*. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *LnCondActive* is the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnCondActive	-0.013		-0.017*	-0.045**	-0.015		-0.019*	-0.047**
	(-1.43)		(-1.82)	(-2.22)	(-1.60)		(-1.95)	(-2.33)
HIGH_PAD		-0.013*	-0.016**	-0.020**		-0.012*	-0.015**	-0.019**
		(-1.89)	(-2.29)	(-2.21)		(-1.73)	(-2.15)	(-2.09)
Ave Q1 PMAFE t-4_t-1	0.240***	0.241***	0.238***	-0.234***	0.239***	0.239***	0.237***	-0.235***
	(6.24)	(6.14)	(6.18)	(-4.95)	(6.09)	(5.95)	(6.04)	(-4.88)
Early Forecast	0.001***	0.001***	0.001***	0.001**	0.001***	0.001***	0.001***	0.001**
	(2.74)	(2.78)	(2.71)	(2.11)	(2.80)	(2.86)	(2.77)	(2.17)
IBES Years	0.001*	0.001**	0.001**	-0.011	0.001*	0.001*	0.001*	-0.003
	(1.95)	(2.11)	(2.08)	(-0.16)	(1.74)	(1.90)	(1.86)	(-0.04)
# Q1 EPS Forecasts	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(4.13)	(4.47)	(4.08)	(3.09)	(4.32)	(4.65)	(4.28)	(3.27)
# of GICS6 Industries	0.003	0.002	0.003	0.003	0.003	0.002	0.003	0.004
	(0.98)	(0.70)	(0.90)	(0.67)	(1.02)	(0.71)	(0.95)	(0.73)
LnSize					-0.001	-0.003	-0.001	-0.003
					(-0.07)	(-0.24)	(-0.08)	(-0.21)
LnBM					0.006	0.004	0.006	0.003
					(0.81)	(0.51)	(0.80)	(0.45)
StdDev.Ret					0.281	0.164	0.279	0.161
					(0.77)	(0.46)	(0.76)	(0.44)
InstHold					0.024	0.025	0.025	0.025
					(1.01)	(1.05)	(1.03)	(1.01)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Coverage x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	YES	NO	NO	NO	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	36,538	37,373	36,538	36,537	35,975	36,795	35,975	35,974
R^2	0.091	0.090	0.091	0.108	0.091	0.090	0.091	0.109

Table A.7: Stock Level Brokerage Firm Dollar Volume Regressions - Relative Share

This table repeats the analysis conducted in Table 9 including Firm × Time fixed effects. To be included in the analysis, a stock must be covered by at least two brokerage firms in our sample. These fixed effects allow us to explore changes in a stock-quarter dollar trading volume share of a given brokerage firm *relative* to other brokerage firms in our sample. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Cross-Analysts				Within-Analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	q	q+1	q+2	q+3	q	q+1	q+2	q+3
AWL	9.486**	7.353*	10.971*	14.936	-1.012	-7.754	3.207	-8.798
	(2.00)	(1.88)	(1.75)	(1.58)	(-0.12)	(-1.51)	(0.24)	(-0.88)
HIGH_PAD	-2.531	-1.795	18.519	33.539	-20.780	-9.757	4.407	22.079
	(-0.12)	(-0.11)	(0.81)	(1.03)	(-0.70)	(-0.46)	(0.16)	(0.85)
LagDEP	0.961***	0.962***	0.952***	0.979***	0.894***	0.894***	0.890***	0.916***
	(25.48)	(25.33)	(21.74)	(23.76)	(15.21)	(15.19)	(15.43)	(15.67)
Firm x Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Coverage FE	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FE	NO	NO	NO	NO	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	11,166	11,166	7,405	5,423	11,150	11,150	7,382	5,415
R^2	0.950	0.950	0.956	0.961	0.953	0.953	0.960	0.966

Table A.8: Analyst Stock Level Accuracy Regressions - Controlling for Brokerage Firm Peers

This table repeats the analysis conducted in Table 10 controlling for Brokerage Firm Peers' *AWL*. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *Brokerage-Firm PeerAWL* is the average *AWL* of the brokerage firm in a given year and quarter, excluding the analyst. Using Investext database, we also identified 3,672 stock-analyst-quarter observations for which we have team *AWL* data. *AUG Brokerage-Firm PeerAWL* then, is a variant of *Brokerage-Firm PeerAWL* where we augment *Brokerage-Firm PeerAWL* with the average *AWL* of the Investext identified Bloomberg team analysts that are cosigned on the firm reports. All specifications include brokerage-firm fixed effect. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
AWL	-0.006**	-0.006**	-0.006**	-0.006***	-0.006***	-0.006**
	(-2.53)	(-2.53)	(-2.47)	(-2.64)	(-2.63)	(-2.58)
HIGH_PAD	-0.014*	-0.013*	-0.014*	-0.013*	-0.012*	-0.012*
	(-1.85)	(-1.83)	(-1.82)	(-1.72)	(-1.69)	(-1.69)
Brokerage-Firm PeerAWL		-0.004			-0.003	
		(-0.67)			(-0.56)	
AUG Brokerage-Firm PeerAWL			-0.001			-0.001
			(-0.25)			(-0.17)
Ave Q1 PMAFE t-4_t-1	0.174***	0.176***	0.176***	0.170***	0.172***	0.172***
	(4.60)	(4.65)	(4.65)	(4.37)	(4.42)	(4.42)
Early Forecast	0.001**	0.001**	0.001**	0.001***	0.001***	0.001***
	(2.59)	(2.59)	(2.58)	(2.66)	(2.66)	(2.66)
IBES Years	0.001	0.001	0.001	0.001	0.001	0.001
	(1.60)	(1.54)	(1.58)	(1.33)	(1.27)	(1.30)
# Q1 EPS Forecasts	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(3.29)	(3.35)	(3.33)	(3.47)	(3.53)	(3.51)
# of GICS6 Industries	0.003	0.003	0.003	0.003	0.003	0.003
	(1.05)	(1.08)	(1.08)	(1.12)	(1.15)	(1.15)
LnSize				-0.004	-0.004	-0.004
				(-0.35)	(-0.36)	(-0.38)
LnBM				0.005	0.005	0.005
				(0.66)	(0.67)	(0.68)
StdDev.Ret				0.110	0.108	0.112
				(0.31)	(0.31)	(0.32)
InstHold				0.021	0.021	0.021
				(0.88)	(0.88)	(0.88)
Broker Firm FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Coverage x Time FE	YES	YES	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES
Observations	37,373	37,373	37,373	36,795	36,795	36,795
R^2	0.092	0.092	0.092	0.092	0.092	0.092