# All in a Day's Work: What Do We Learn from Analysts' Bloomberg Usage?*

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Current version: February 2026

**Abstract**

We use minute-by-minute Bloomberg online status data to characterize two important dimensions of sell-side equity analysts' work habits: we estimate the average workday length (*AWL*) to proxy for analysts' general effort provision, and we use the percentage of away days (*PAD*) to proxy for their private information collection. Both *AWL* and *PAD* improve forecast precision, a causal result that we confirm using the COVID lockdown as an instrument. Frequent traveling not directly related to firm events is positively correlated with the likelihood of becoming an All-Star analyst, suggesting that institutional investors also value private information transmitted through in-person interactions.

**Keywords**: Analyst, Effort Provision, Forecast Accuracy
**JEL Classification**: G12

*We thank Bingxu Fang, Diego Garcia, Rawley Heimer, Ron Kaniel, Stephannie Larocque, Marcus Painter, Devin Shanthikumar, Eric So, David Solomon, Andrew Van Buskirk and seminar participants at Alliance Manchester Business School, Boston College, Brigham Young University, HEC Lausanne / EPFL, Hong Kong PolyU, Iowa State University, Lancaster University, MIT, McMaster University, Michigan State University, Nottingham University, Oklahoma State University, Peking University, Renmin University, Rutgers University, Tsinghua University, Washington State University, Western University, York University, Finance Conference at Chapman University, Asian Bureau of Finance and Economic Research 2023 Annual Conference, the 2024 Bretton Woods Accounting and Finance Ski Conference, the 35th Conference on Financial Economics and Accounting, 5th Future of Financial Information Conference, for helpful comments and suggestions. We also appreciate the advice and counsel from Richard Zansitis (Vice President and General Counsel for Rice University). This study was approved by the IRB at Rice University and use of the data was approved by Bloomberg Finance L.P. A previous version of the paper has been circulated under the title "Security Analysis and the Collection of Hard and Soft Information"

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## 1 Introduction

Sell-side analysts, by virtue of their recommendations, earnings, and price target forecasts, serve as important sources of information production in the financial market. Early work by Stickel (1992) and Sinha, Brown, and Das (1997) documents systematic differences in analysts' forecast accuracy. Since then, a long strand of literature has documented various analyst characteristics that are associated with their forecast accuracy, including prior experience, employer resources, industry specialization, portfolio complexity, peer competition, and decision fatigue, among others.[1] Yet, very basic characteristics related to analysts' work habits remain understudied, primarily because researchers do not observe how analysts spend their working hours on a day-to-day basis.

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 general effort provision and private information collection and quantify the effect that both types of work habits have on their ability to forecast earnings and value equities, and other dimensions analysts care about (Brown, Call, Clement, and Sharp, 2015).

Equity analysts use Bloomberg extensively. In our sample, they logged into the platform on 72% of workdays. On those days, they worked actively for more than 8 hours on average, and their pre-market login activities strongly react to overnight information. 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.

[1]See Clement (1999), Jacob, Lys, and Neale (1999), Merkley, Michaely, and Pacelli (2017), Hirshleifer, Levi, Lourie, and Teo (2019) among others.

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

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, 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.

We use an expectation-maximization algorithm to quantify the length of their workday based on Bloomberg usage pattern (Ben-Rephael, Carlin, Da, and Israelsen, 2025). The quarterly measure Average Workday Length (*AWL*) proxies for each analyst's general effort provision. 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 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 internet appendix.

We proxy for private information collection by using the percentage of workdays when analysts are not on the Bloomberg platform at all (Percentage of Away Days, *PAD*). Admittedly, there is a possibility that this measures the magnitude of private 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 away days is too high to be consistent with the lack of work. The majority of the analysts in our sample come from the top five brokerage firms, and given the typical work culture of these firms, it seems unlikely that the magnitude of *PAD* is driven purely by leisure. Second, we decompose *PAD* into two components: (1) *EvPAD* where we only count an "away day" if it can be justified by actual events organized by the firm the analyst covers, and (2) *OtherPAD*. We find that each of these proxies improves different aspects of analysts' performance and other career concerns. 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. In contrast, analysts who benefited from saving on their commute time exhibited modestly improved accuracy.

We show that *AWL* and *PAD* are authentic and persistent analyst characteristics. Neither quarter, brokerage-firm, nor sector fixed effects explains more than 12% of their variation. In contrast, analyst fixed effects explain 43.8% and 51.5% of the 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 higher *PAD* cover more growth stocks, which may require more private information, while analysts with higher *AWL* tend to cover larger and mature firms. 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 control for experience and include a seniority indicator in our regressions, in order to isolate the effect coming from analyst effort. Including an analyst fixed effect in our analyses further controls for other persistent analyst characteristics.

We study the relationship between analyst effort and dimensions important to their career concerns using three metrics. The first is the accuracy of EPS forecasts. Brown et al. (2015) report that 35% of the surveyed analysts view accuracy as an important determinant of their compensation. Using proprietary salary data, Groysberg, Healy, and Maber (2011) show that poor forecasts are important for termination. In addition, earnings forecast accuracy is probably the most widely studied analyst output in the finance and accounting literature.

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. We find *AWL* to be significantly related to improved accuracy. A one standard deviation increase in *AWL* is associated with a reduction of about 2% in *PMAFE*'s standard deviation units. While *PAD* is not significantly related to accuracy, its *EvPAD* component is, even when analyst fixed effects are included. In other words, when analysts travel to collect private information by attending events organized by firms they cover, their forecast accuracy improves. These patterns appear to be robust to team effort, which is shown to be important in Fang and Hope (2021).

The second metric we examine is the timeliness of the forecasts. Since institutional investors rely on information for their trading decisions, timeliness of the forecasts is also an important dimension of analysts' career outcomes (Bradshaw, 2011; Chiu, Lourie, Nekrasov, and Teoh, 2021). Indeed, surveyed analysts state that accessibility and responsiveness are important for their compensation (Brown et al., 2015). We find both *AWL* and *EvPAD* to improve the timeliness of the forecasts. A longer *AWL* means that the analyst is more likely to be working when the earnings announcement occurs. A higher *EvPAD* indicates that the analyst is more attentive to firms' events, including the earnings announcements.

Last but not least, we examine whether an analyst becomes an Institutional-Investor (II) All-Star. According to Groysberg, Healy, and Maber (2011), All-Star analysts earned 61% higher compensation on average and gaining/losing All-Star status was associated with a 16% increase/decrease in pay. Similarly, Brown et al. (2015) report that 67% of their survey respondents rate analysts' standing in rankings/broker votes to be very important. We find that *AWL* is not significantly related to All-Star status. In contrast, 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. A one standard deviation increase in *PAD* is associated with an 8.1-9.9% increase in that probability. This positive relation between *PAD* and the probability of being ranked as star analysts is driven by the *OtherPAD* component. Put differently, while event-related traveling is associated with higher accuracy and timeliness, other traveling activities contribute to an analyst's career concerns via the interactions with institutional investors. The finding suggests that institutional investors also value the private information transmitted through in-person interactions with the analyst.

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 improves the accuracy of the forecasts (a reduction of *PMAFE* of 8.5%).

Our paper contributes to a long strand of literature that links characteristics of sell-side equity analysts to their performance (see a recent survey by Coleman, Coleman, Larocque, and Markov, 2025). Since equity analysts are frequent users of Bloomberg terminals, we can take advantage of their minute-by-minute Bloomberg usage data to quantify two important yet previously unexplored dimensions of their work habits. We use the average workday length (*AWL*) to proxy for analysts' general effort provision and we use the percentage away day (*PAD*) to proxy for their private information collection. We find both measures are reliably related to important metrics of their performance. In addition, we present causal evidence that both dimensions of their work habit lead to improvement in their forecast accuracy.

The importance of information collection cannot be overstated, both for raising capital and the pricing of traded financial assets. While distance measures have been used extensively for private information collection (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 private information collection. For example, a distance-based measure would 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 private information collection more directly.

Our paper therefore adds to a series of papers that show that collecting private information is valuable for security analysis. Green, Jame, Markov, and Subasi (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 more useful to analysts than their own primary research, recent earnings performance, and recent 10-K and 10-Q reports. Cheng, Du, Wang, and Wang (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.

Finally, our paper also speaks to the important emerging literature on the impact of working-from-home (WFH). Early work by Bloom, Liang, Roberts, and Ying (2015) documents that WFH improves productivity though the employees in their studies are self-selected to WFH. In contrast, the COVID lockdown forces all analysts to WFH and the performance of analysts can be easily quantified, thus creating a nice setting to study the impact of WFH on productivity. While recent works by Du (2023) and Li and Wang (2024)

[3]See Liberti and Petersen (2019) for an excellent review on "hard" and "soft" information, related to the acquisition of "public" and "private" information. Distance measures have been used to distinguish public and private 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 public information can be transmitted across distance, whereas private information cannot.

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

document that the productivity of female analysts was negatively affected by the COVID lockdown, especially when they have young children, our Bloomberg usage data uniquely allow us to quantify their changing work habits directly before examining their changing outputs. In the case of sell-side equity analysts, we find WFH to have both a negative and a positive impact on their performance. On one hand, WFH prevents them from collecting private information and hurts their forecast accuracy, especially among analysts who traveled a lot pre-COVID, consistent with the recent findings by Bai and Massa (2021) using fund managers. On the other hand, we present strong and novel evidence that WFH increases analysts' average workday length (*AWL*) by eliminating the need for work commute. The longer *AWL*s increase both the quantity and accuracy of their forecasts.

The rest of the paper is organized as follows. Section 2 provides information about our data and economic variables. Section 3 characterizes the determinants of *AWL* and *PAD*. Section 4 describes how our measures of public and private information affect the performance and other dimensions of analysts' career concerns. Section 5 describes the use of the COVID lockdown and commuting data as instruments to deal with potential endogeneity. Section 6 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 work habits. 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 around 40 minutes of Bloomberg usage per day. This cut-off removes the left tail of the

[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.

login distribution, which is populated by inactive users. In addition, we require an analyst to be reasonably active in 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 collect 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 public information collection and processing in a given quarter based on their Bloomberg usage patterns. The same methodology was used in Ben-Rephael et al. (2025) and validated there using cellphone geolocation data. In that paper, we measured *AWL* for top executives (e.g., CEO's and CFO's) in U.S. firms and used it as a proxy for work effort. We showed that *AWL* is associated with higher firm value and that long-short portfolios using computed *AWL* earned abnormal risk-adjusted returns.

In Ben-Rephael et al. (2025), we showed that our results were robust to using other distributional measures, but that *AWL* proxies for effort provision in a very intuitive way. Figure 1 illustrates the algorithm for a specific analyst-quarter observation. In the figure,

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

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 distributions as follows.

For each analyst and quarter, we calculate the probability $P^j_{min}$ as the percentage of the time that an analyst is actively using the platform during all workdays in that specific quarter, where $j \in J \equiv$\{12:00 am, 11:59 pm\}. Then, using these relative frequencies, we construct a pdf by computing $p^i_{min} = P^i_{min}/\sum_J P^j_{min}$. By construction, $\sum_J p^j_{min} = 1$. This pdf captures the likelihood of the time of the analyst's terminal activity during the quarter. We then assume that the constructed distribution is a mixture of two normal distributions $k \in \{1,2\}$, each with mean $\mu_k$ and variance $\sigma^2_k$, 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 a 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 scikit-learn library 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 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 public 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 public information by reading periodicals, doing spreadsheet modeling, or meeting with colleagues. Assuming that the analyst generally 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.

Since analysts in our sample spend a non-trivial amount of time on Bloomberg, we also consider an *intensive* usage measure. The measure, *LnCondActive*, is calculated as the natural logarithm of the average daily minutes of active Bloomberg usage in a quarter, conditioning on days with Bloomberg activity in a quarter. Table IA.3 in the Internet Appendix confirms that the main results are qualitatively similar if we replace *AWL* with *LnCondActive*.

**Percentage Away Day (*PAD*):**

To quantify the extent of private information collection that requires travel, we count the

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

[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.

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 private information collection effort.

If anything, this bias works against our finding a benefit to being away from the office. But, as we show later in the paper, high levels of $PAD$ are associated with a higher probability of becoming a star analyst, indicating that this does not capture systematic noise or leisure. More importantly, 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.

### 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 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's 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). These differences come from the fact that active Bloomberg analysts in our sample are more likely to come from larger brokerage firms. Indeed, 55% of them come from the largest 5 brokerage firms. These firms have more resources to assign Bloomberg accounts to individual analysts so our effort measures are less likely to reflect shared Bloomberg terminal usage by a team of analysts.

Finally, both groups display better accuracy than analysts who are not in the same 42 brokerage firms.[9] 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).

[9]The forecast accuracy measure is defined in detail 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.

Panel A indicates that, on average, analysts are logged in to the terminal on 71.7% of the 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 2 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 3 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. We can see a shift in the distribution during the COVID period, which was affected by work-from-home. As for *PAD*, the average is 0.283. Compared to *AWL*, the distribution of *PAD* is wider, with the 10th percentile of 0.033 and the 90th percentile of 0.656. In a similar manner, we document a shift in the distribution of *PAD* during the COVID period, when traveling was restricted. We utilize the differences in *AWL* and *PAD* during the pre-COVID and COVID periods in our analysis and identification strategies.

For emphasis, *AWL* is different from the 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. As discussed above, 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. Alternatively, one can focus on the average daily usage of Bloomberg during the quarter as a measure of gathering information. Thus, we also define *LnActive*, as the natural logarithm of the average daily minutes of active

Bloomberg usage across all days during the quarter. The correlation between *AWL* and *LnActive* is 0.27, which is not different from the one reported with *LnCondActive*. Finally, the correlation between *AWL* and *PAD* is negative, but not huge ($\rho = -0.23$). This suggests that public and private information collection efforts are not perfect substitutes for each other.

Graphs A-C of Figure 3 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 4 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.

## 3 Determinants of *AWL* and *PAD*

### 3.1 Login Activity and Market Information

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 (public 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 public information.

### 3.2 Coverage Decisions

Next, we are interested to learn if *AWL* and *PAD* are associated with different stock coverage decisions. To this end, each quarter, we rank all the stocks in our sample into quintiles based on selected firm characteristics. Then, for each analyst and quarter, we calculate the stock market cap-weighted average of each ranking across all the stocks covered by the analyst. We then run quarterly panel regressions that capture the cross-sectional differences in coverage decisions.

Table 4 reports the results where we Z-score both the dependent and independent variables of interest. We find that *AWL* loads positively on firm age, market cap, and price, and negatively on illiquidity and idiosyncratic volatility. Thus, analysts with higher *AWL* prefer to cover larger, mature firms that are more liquid and less volatile. This may suggest that mature and large firms may rely less on private information. We further find that *PAD* also loads positively on size and negatively on illiquidity, but also loads positively on growth (inverse of BM) and momentum. This suggests that analysts with higher *PAD* tilt their coverage toward growth stocks, which may require more private information. The positive relation between *PAD* and stocks whose value recently appreciated may be driven by institutional demand for momentum stocks, which traveling analysts with presumably better institutional relations accommodate.

### 3.3 Explained Variation 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 help us locate LinkedIn accounts, which provide educational background, and Facebook accounts, which help identify whether analysts have children.

Panel A of Table 5 indicates that analyst fixed effects are the most important determinant in explaining the variation in both *AWL* and *PAD*, with an adjusted R-squared of 43.8% and 51.5%, respectively. So, *AWL* and *PAD* both appear to be independent and authentic analyst characteristics. Next, broker fixed-effects explain 8.5% and 11.5% of the variation in *AWL* and *PAD*, which is consistent with workplace culture. Both analyst characteristics also change over time, with time fixed-effects explaining 5.0% and 9.1% of the variation in *AWL* and *PAD*. The time variation is in part due to the COVID lockdown as evident in Figure 3. Finally, industry fixed effects, based on the analyst's main covered GICS6 industry, explain around 8.6% and 6.7% 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 5 reveal that analyst time on I/B/E/S (*IBES Years*), seniority (*High Rank Indicator*), and being a star analyst are three important determinants of *AWL* and *PAD*. An increase in years in the I/B/E/S sample leads to a significant reduction in *AWL*. *PAD* on the other hand, exhibits a positive sign, but the effect is not statistically significant. Second, greater seniority leads to a lower *AWL* and a higher *PAD*. We, therefore, control for both *IBES Years* and *High Rank Indicator* in subsequent analyses when we relate *AWL* and *PAD* to analyst performance. Finally, we find that being a star analyst is positively associated with *PAD* but not *AWL*. This is consistent with the fact that analyst ranking depends 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 or 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 0.002- 0.005 to the R-squared. Finally, including brokerage firm fixed effects does not alter these findings, but adds between 0.054-0.113 to the R-Squared.

## 4 Analysts' Work Habits and Analyst Career Concerns

Career concerns play an important role, and there are multiple dimensions analysts care about (Brown et al., 2015). One important dimension that affects compensation is accuracy, where Harford, Jiang, Wang, and Xie (2019) show that career concerns shape effort allocation and stock accuracy. Brown et al. (2015) report that 35% of the surveyed analysts view accuracy as an important determinant of their compensation. Using proprietary salary data, Groysberg, Healy, and Maber (2011) show that poor forecasts are important for termination. Motivated by these studies, we examine analysts' forecast accuracy, which is also the most widely studied analyst performance metric in the finance and accounting literature.

The timeliness of the forecasts is another important factor, as institutional investors rely on information for their trading decisions. Analysts' responsiveness to institutional information needs influences analysts' career outcomes (Bradshaw, 2011; Chiu et al., 2021). Indeed, surveyed analysts state that accessibility and responsiveness are important for their compensation (Brown et al., 2015).

Finally, being ranked as a top analyst is an important dimension that affects compensation. For example, according to Groysberg, Healy, and Maber (2011), All-Star analysts earned 61% higher compensation on average and gaining/losing All-Star status was associated with a 16% increase/decrease in pay. Similarly, Brown et al. (2015) report that 67% of their survey respondents rate analysts' standing in rankings/broker votes to be very important. We therefore examine Institutional-Investor (II) All-Star status as an important outcome variable. The All-Star status is individual analyst specific.

Motivated by these career concerns, in this section, we explore how *AWL* and *PAD* are associated with both the accuracy and timeliness of analysts' quarterly forecasts and the probability of being ranked as a star analyst. We acknowledge that analysts optimize across these dimensions to achieve their career goals.

To gain more economic insight related to analysts' traveling activity, in this section, we consider a decomposition of *PAD*. Specifically, we decompose *PAD* into two components, *EvPAD* and *OtherPAD*. *EvPAD* is calculated using away days that coincide with brokerage and firm events for stocks the analyst covers. The data is obtained from two sources: the Bloomberg Terminal's Corporate Events Calendar function (EVTS) and records of analyst and investor days from the Refinitiv StreetEvents Transcripts database. By construction, *EvPAD* aims to capture information-gathering activities that are related to the analyst's research and output. Consequently, it does not capture other interactions with institutional investors or other firm site visits. These Non-*EvPAD* away days are captured by the difference between *PAD* and *EvPAD* (denoted as "*OtherPAD*") and aim to capture other traveling activities that are important for analysts' career concerns. Details about the selection of firm-event series and the *EvPAD* construction are relegated to Section IA.1 of the Internet Appendix.

### 4.1 Analysts' Forecast Accuracy

We start with exploring the relation between analysts' public and private information collection efforts and forecast accuracy. We employ the accuracy measure suggested by 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 forecast 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 forecast errors. The measure has a minimum of -1 (most accurate relative to peers) and a maximum of 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 × 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*), experience and seniority as captured by *IBES Years* and *High Rank Indicator*, number of quarterly forecasts and industries covered (*# Q1 EPS Forecasts*, and *# of GICS6 Industries*), firm size, firm book-to-market, return volatility, institutional holdings, and liquidity.

Table 6 reports the results. We Z-score both the dependent and independent variables of interest. We report the results using *AWL* and *PAD* (Columns 1–4), and *AWL* and *PAD* components (Columns 5–8). Even columns include the full set of control variables. Focusing on Columns 1–4, *AWL* exhibits a significant negative relation with accuracy, suggesting that higher levels of *AWL* are associated with improved accuracy. In terms of economic significance, a one standard deviation increase in *AWL* is associated with a reduction of about 2% in *PMAFE*'s standard deviation units. *AWL* coefficient estimates are attenuated once analyst fixed effects are included (Columns 3–4). In contrast, *PAD*'s does not exhibit any relation with accuracy. This stands in contrast to all of our other tests, where *PAD* is a significant factor in explaining analysts' behavior. Given the evidence on career concerns, we conjecture that this is driven by the different aspects of *PAD*.

Consequently, in Columns 5–8, we replace *PAD* with *EvPAD* and *OtherPAD*. Consistent with the conjecture that *EvPAD* is related to information gathering activities, we find that *EvPAD* presents a significant negative relation with forecast accuracy, suggesting that increased participation in brokerage and company events is associated with improved accuracy. Opposed to *AWL*, *EvPAD* findings hold with and without the inclusion of analyst fixed effects. In contrast, *OtherPAD* coefficient estimates are insignificant, consistent with the overall findings of *PAD*. This suggests that other non-information gathering activities that analysts engage in are not necessarily important for accuracy, but can affect other career concerns. We explore that in detail when we analyze the relation between *OtherPAD* and the probability of becoming a star analyst.

Finally, 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, who is recorded in I/B/E/S. Nevertheless, in Table IA.4, we repeat the analysis conducted in Table 6 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 (signed 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.

Overall, the collective results indicate that both public and private information seem to contribute to forecast accuracy.

### 4.2 The Timeliness of Analysts' Forecasts

Next, we explore the timeliness of analysts' 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 7 reports the results. We follow the same specification structure of Table 6, where *AWL* and *PAD* (*EvPAD*and *OtherPAD*) are included in Columns 1–4 (5–8). We control for analyst experience and seniority (*IBES Years*and *High Rank Indicator*), 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 negative and statistically significant once controls are included. For example, in specification 2, a one standard deviation increase in *AWL* is associated with an 8.4% decrease in *LnTFE* standard deviation units. 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. As in Table 6 with analyst fixed-effects, the coefficients on *AWL* are still negative but no longer significant, suggesting the strong association between *AWL* and forecast timeliness comes mostly from cross-analyst variation.

Turning to *PAD* and its components, we find that the relation between *PAD* and timeliness is driven by *EvPAD*. A one standard deviation increase in *EvPAD* is associated with a 7.7% decrease in *LnTFE* standard deviation units. Similar to *AWL*, *EvPAD*'s coefficient estimates are insignificant once analyst fixed effects are included. Thus, in contrast to accuracy, timeliness seems to stem from cross-analyst variation. Finally, while *OtherPAD* exhibits a negative relation with *LnTFE*, none of the coefficient estimates is statistically significant.

### 4.3 The Probability of Being a Star Analyst

After establishing the relation between *AWL*, *PAD* (and its components) and analyst earnings forecast dimensions, we explore how *AWL* and *PAD* affect the probability of being ranked as a star analyst. Recall that our conjecture is that *OtherPAD* captures other interactions analysts have with institutional investors and other non-event activities. Thus, we expect *OtherPAD* to affect analysts' career concerns as captured by 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 *PAD* in Q1-Q3 of year $t$.

Table 8 reports the results. Even columns include the full set of controls, and all specifications include brokerage-firm fixed effects. Since we employ a linear probability model, the dependent variable has a natural economic interpretation. Thus, we only Z-score adjust *AWL*, *PAD*, and its components.

Columns 1 and 2 reveal that average *PAD* is associated with a higher probability of being ranked as a star analyst. A one standard deviation increase in *PAD* is associated with an 8.1-9.9% increase in that probability. Importantly, these specifications capture two possibilities: the probability of *becoming* a star analyst and the probability of *staying* a star analyst. To add more evidence, in Columns 3–4, we repeat the analysis for the sub-sample of analysts who are not a star analyst in year $t$-1. The analysis confirms that an increase in *PAD* is indeed associated with a higher probability of becoming a star analyst, with probability magnitudes between 5.5 to 5.7%. More strikingly, Columns 5–8 indicate that a positive relation between *PAD* and the probability of being ranked as star analysts is driven by *OtherPAD*. In contrast to *PAD*, average *AWL* is insignificant across all specifications. This contrast suggests that institutional investors value private information transmitted through face-to-face interactions.

More broadly, the collective findings across Tables 6–8 reveal an important distinction between the analyst's "away" activities. While event-related traveling is associated with higher accuracy and responsiveness, other activities (captured by *OtherPAD*) contribute to an analyst's career concerns via the interactions with institutional investors. Thus, while *OtherPAD* does not contribute to accuracy or timeliness, it is a relevant part of the analyst's optimization problem. Our direct measures enable us to unmask these trade-offs and contribute to this long standing literature.

## 5 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 of 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 5 illustrates how we collect this information using a fictitious home address (to preserve the 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 private information collection 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 private 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 private information collection during the COVID lockdown.

### 5.1 Pre-COVID *PAD* Identification Strategy and Analyst Accuracy

Table 9 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 traveled 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. As in Table 6, we examine the relative forecast accuracy of analysts' quarterly forecasts as measured by *PMAFE*.

Focusing on the treatment effect (*TREATMENT*), traveling analysts' forecasts are slightly more accurate (though not significant). Focusing on the post effect (*POST*), with all analysts locked down at home, the accuracy measure *PMAFE* is not significantly affected since it is a relative accuracy measure (which should not change over time on average). Finally, focusing on the interaction term ($TREATMENT \times POST$), we find that the accuracy of the treatment group (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 private information extracted by traveling analysts increases forecast accuracy.

### 5.2 Commute Time to Work Identification Strategy

We now turn our attention to *AWL*. Graph B of Figure 3 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 10, 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 5 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 (2023) and Li and Wang (2024) 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 10 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 the office impossible, and analysts can spend the time saved from commuting on work. Indeed, Table 10 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 6. Importantly, the commute time is measured pre-COVID and, therefore, cannot be affected by events during the COVID pandemic, 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 10 Panel B we examine the causal impact of *AWL* on forecast outcomes in a difference-in-difference setting, very similar to that in Table 9. The treatment group (*TREATMENT*) consists of analysts with below-median commute time pre-COVID (2019Q3-2019Q4) who are predicted to have a 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. *PMAFE*, being a relative forecast accuracy measure, 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 an improvement in their accuracy. Specifically, 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. Finally, as a placebo test, we repeat the analysis for far and near firms. This should not be relevant for *AWL*, which doesn't rely on private information gathering. Consistent with this conjecture and in contrast to Table 9, we do not find any differences between firms whose headquarters are located far or near and analyst locations.

## 6 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 general effort provision; and the extent of their travels to measure their private information acquisition. We find that both work habits improve analysts' output on several dimensions, including the accuracy and timeliness of their earnings forecasts, and the likelihood of becoming star analysts.

Our findings related to the COVID lockdown speak to the recent debate on the benefits and costs 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 the quality of the forecasts. On the downside, WFH hurts private information collection based on decreased in-person interaction and reduces forecast accuracy.

More broadly, we uncover another 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 $(\mu_1 - \sigma_1, \mu_2 + \sigma_2)$.

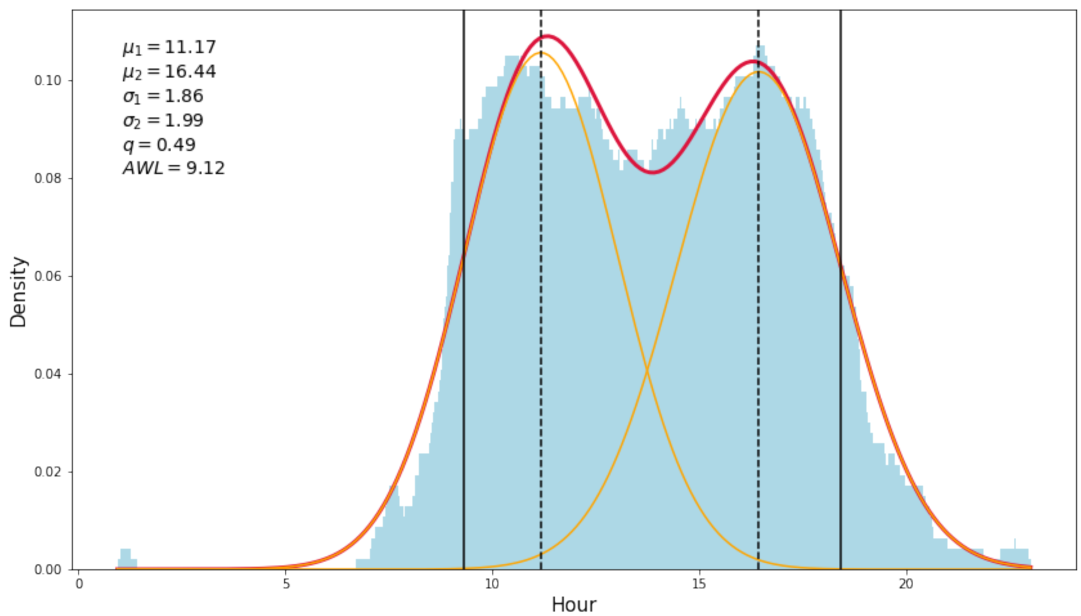


Figure 2: Minutes Active on Terminal based on Day-of-the-Week and Holidays

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.

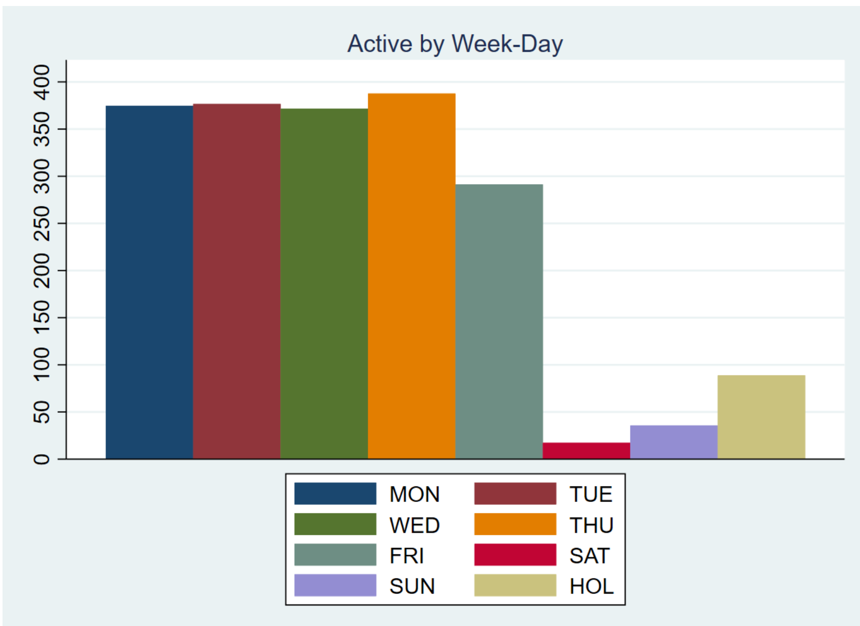
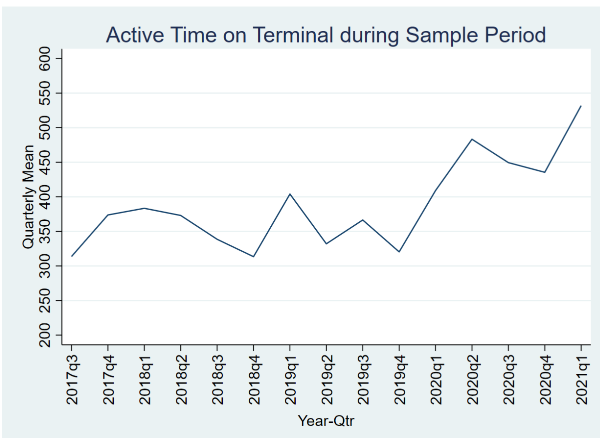


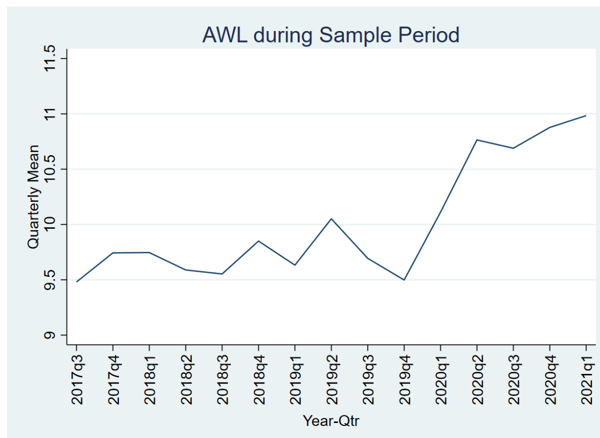
Figure 3: *AWL*, *Minutes Active*, and *PAD* during Sample Period

This figure depicts the quarterly cross-analyst averages of the various log-in measures over the sample period. The measures 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*

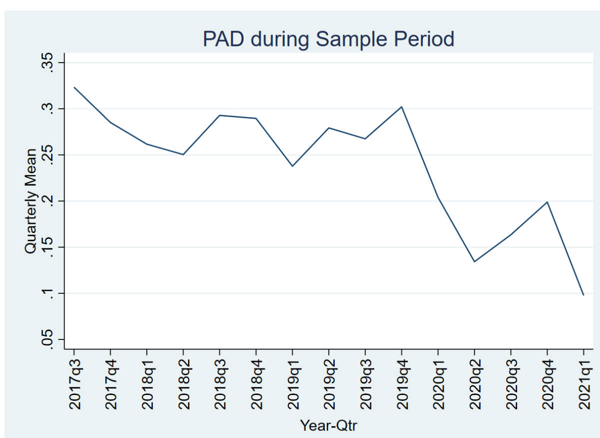
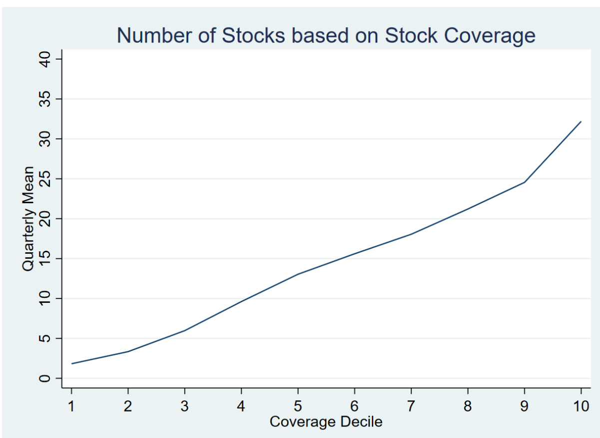


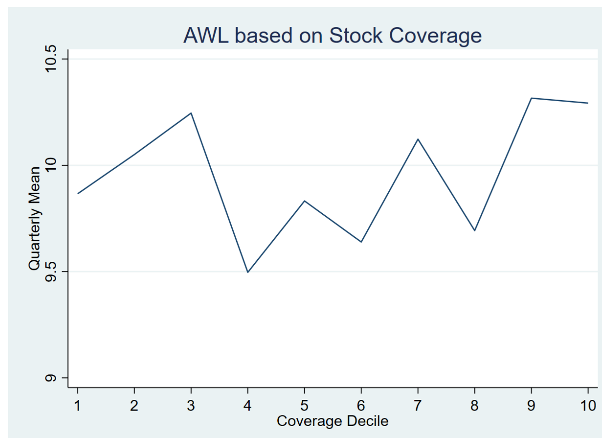
Figure 4: Stocks, *AWL*, *Minutes Active*, and *PAD* based on Coverage

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 stocks 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*.

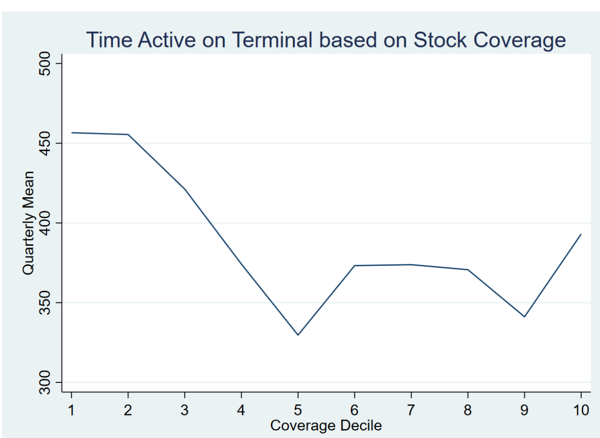
Panel A: Number of Stocks




Panel B: *AWL*




Panel C: Conditional Active Time on Terminal




Panel D: *PAD*

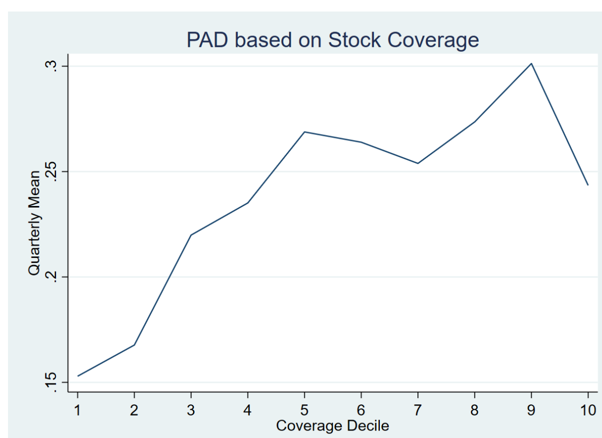


Figure 5: Measuring Commute Time - Example

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.

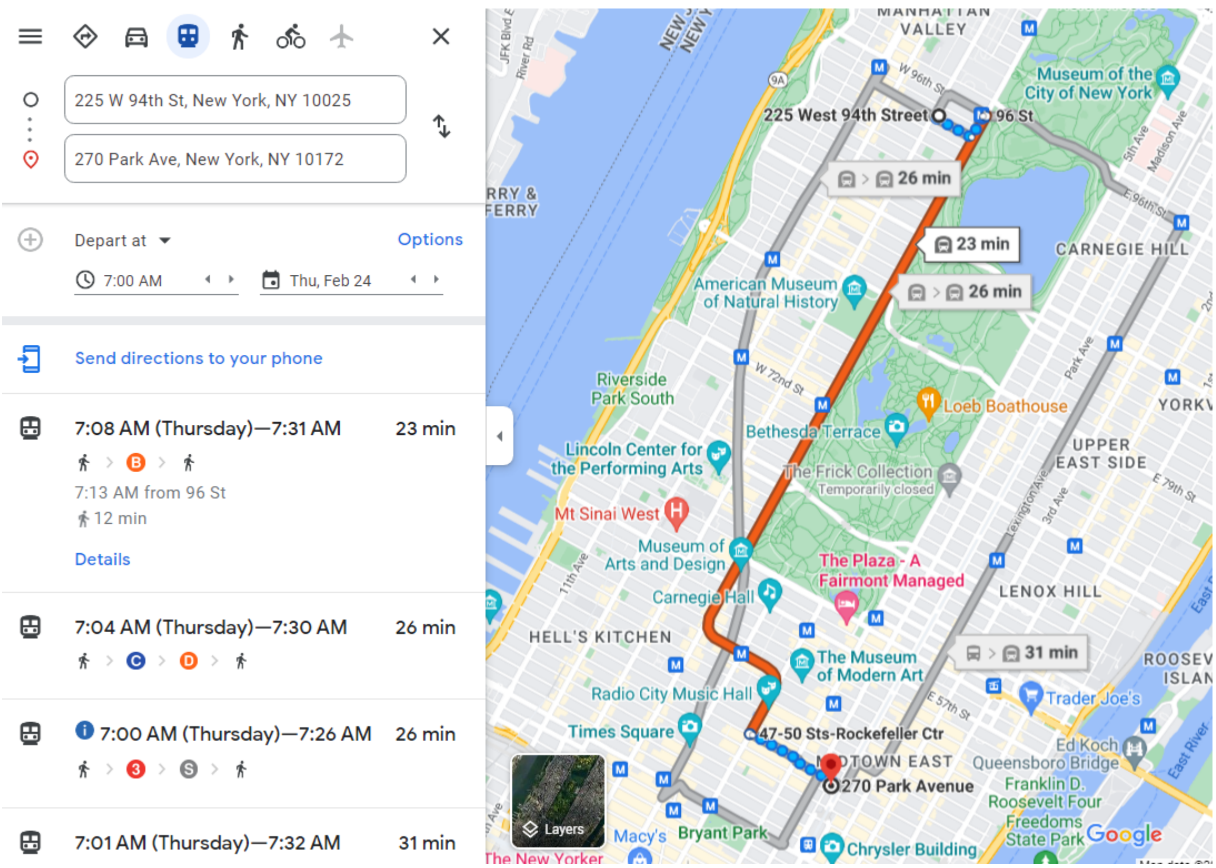


Figure 6: Changes in $AWL$ and Commute Time Saved

This figure illustrates the relation between $AWL$ and commute-time-saved reported in Table 10, 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, whereas the y-axis reports the corresponding average change in $AWL$.

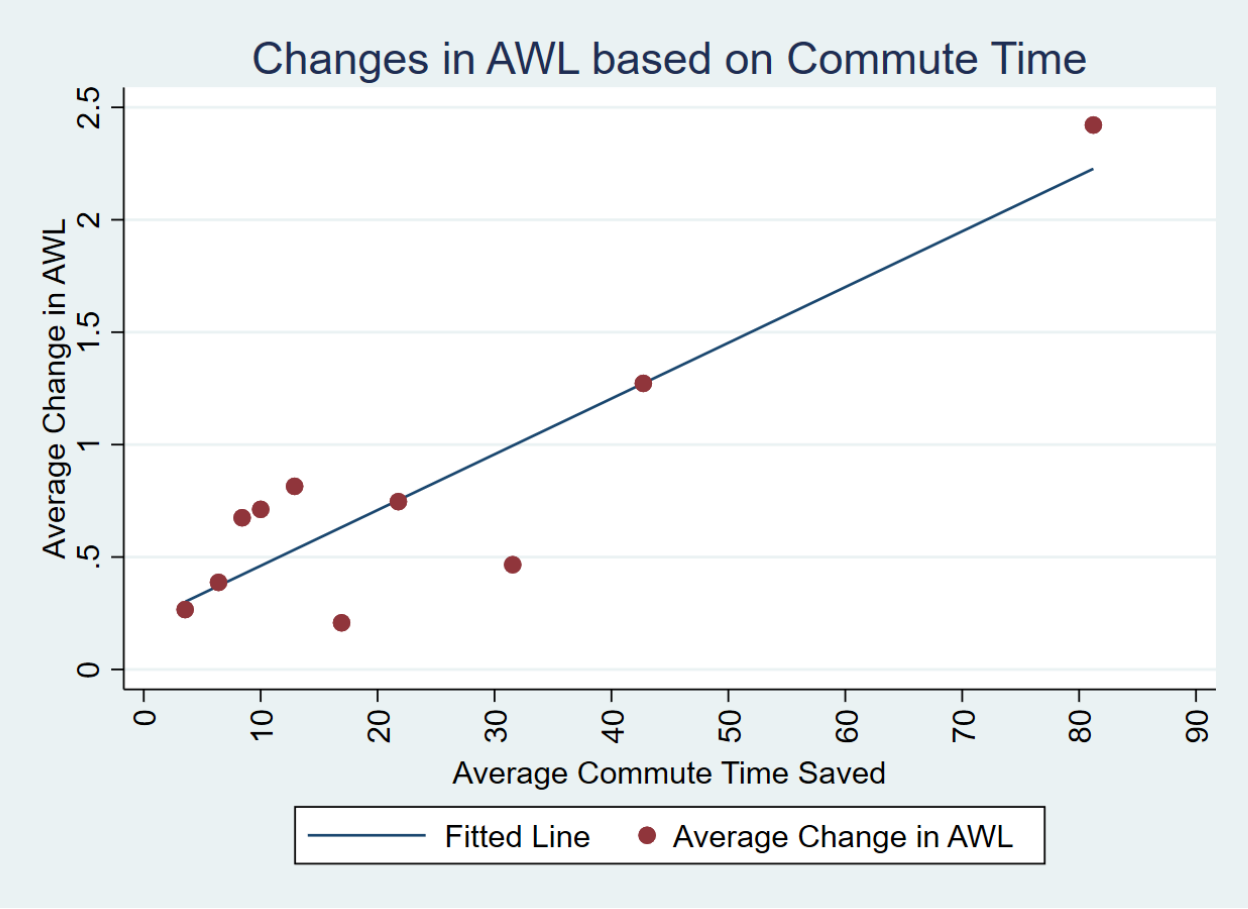


Table 1: Summary stats of analyst output

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, with 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 to 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% |
|---|---|---|---|---|---|---|---|
| ALL | | | | | | | |
| *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 |
| Pre-COVID | | | | | | | |
| *AWL* | 9.532 | 1.913 | 7.840 | 8.662 | 9.421 | 10.462 | 11.678 |
| *PAD* | 0.316 | 0.234 | 0.067 | 0.145 | 0.256 | 0.419 | 0.654 |
| COVID | | | | | | | |
| *AWL* | 10.461 | 2.142 | 8.527 | 9.421 | 10.480 | 11.586 | 12.763 |
| *PAD* | 0.205 | 0.254 | 0.016 | 0.033 | 0.100 | 0.246 | 0.667 |
| # of Analyst-Quarters | 2,874 | 2,029 | 845 | | | | |

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 from 7 am to 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 covers 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. The sample period is from September 2017 to March 2021. We keep analyst-quarter observations that meet the required quarterly login activity filter. 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*** |
| | (6.52) | (6.54) | (5.97) | (5.94) | (5.24) | (5.27) |
| *# Stocks in AbsExtRet Decile t-1* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (1.04) | (1.04) | (0.82) | (0.82) | (0.96) | (0.96) |
| *# Stock with AMC News t-1* | 0.005*** | | | 0.004*** | 0.002 | |
| | (3.37) | | | (2.68) | (1.34) | |
| *# Stock with AMC Earn News t-1* | | 0.008*** | | | | 0.001 |
| | | (2.81) | | | | (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*** | | |
| | | | (9.11) | (9.10) | | |
| *# Stock with BMO Earn News t* | | | | | 0.079*** | 0.079*** |
| | | | | | (12.31) | (12.34) |
| *# Stock with BMO AR News t* | | | | | 0.004*** | 0.004*** |
| | | | | | (3.17) | (3.17) |
| *# Max Industry Earn BMO News Pressure t* | | | | | 0.074*** | 0.074*** |
| | | | | | (3.67) | (3.67) |
| 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*, *PAD*, and Stock Coverage Decisions

This table reports results from quarterly panel regressions of analysts' average firm characteristic portfolio ranking on *AWL*, and *PAD*. Each quarter, we rank all the stocks in our sample into quintiles based on selected firm characteristics. Then for each analyst and quarter, we calculate the stock market cap weighted average of each ranking across all the stocks covered by the analyst. AGE is the firm number of years on CRSP, SIZE is the stock market cap, PRC is the stock price, ILLIQ is the stock AMIHUD illiquidity measure, BM is the stock book-to-market ratio, MOM is the stock return momentum over the past 12 months, IDIOVOL is the stock daily idiosyncratic volatility measured over the past 252 days, and SKEW is the stock daily skewness measured over the past 252 days. (Z) stands for a Z-Score adjustment (a mean of zero and a standard deviation of one). We Z-Score adjust both the dependent variable and independent variables of interest. See Table A.1 and Table 1 for details about variable and sample definitions. The sample period is from September 2017 to March 2021. We keep analyst-quarter observations that meet the required quarterly login activity filter. To reduce the effect of outliers, *AWL* and *PAD* are winsorized at their 99% level. 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.

| | AGE | SIZE | PRC | ILLIQ | BM | MOM | IDIOVOL | SKEW |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *AWL(Z)* | 0.089* | 0.083* | 0.160*** | -0.091** | -0.019 | 0.029 | -0.073* | -0.002 |
| | (1.81) | (1.96) | (3.21) | (-2.25) | (-0.34) | (0.81) | (-1.78) | (-0.06) |
| *PAD(Z)* | 0.001 | 0.086** | 0.069 | -0.073* | -0.082* | 0.113*** | -0.039 | 0.041 |
| | (0.02) | (2.02) | (1.46) | (-1.71) | (-1.67) | (3.03) | (-0.87) | (1.25) |
| *IBES Years* | 0.035*** | 0.051*** | 0.027*** | -0.054*** | -0.001 | -0.000 | -0.042*** | -0.007 |
| | (3.98) | (5.87) | (3.17) | (-6.08) | (-0.10) | (-0.03) | (-4.67) | (-1.05) |
| *High Rank Indicator* | 0.055 | 0.053 | 0.094 | -0.055 | -0.125 | 0.090 | -0.081 | 0.020 |
| | (0.46) | (0.48) | (0.81) | (-0.50) | (-0.94) | (1.04) | (-0.67) | (0.29) |
| *Ave # of Industries t-4_t-1* | -0.062** | -0.001 | 0.084*** | -0.007 | -0.166*** | 0.170*** | -0.066** | 0.030 |
| | (-2.09) | (-0.05) | (3.24) | (-0.30) | (-5.80) | (7.59) | (-2.18) | (1.64) |
| *Ave Q1 PMAFE t-4_t-1* | -0.063 | -0.325 | -0.780** | 0.845** | -0.204 | -0.283 | 0.690** | -0.149 |
| | (-0.16) | (-0.84) | (-2.14) | (2.19) | (-0.51) | (-0.96) | (2.10) | (-0.41) |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,563 | 2,563 | 2,563 | 2,563 | 2,317 | 2,559 | 2,561 | 2,561 |
| $R^2$ | 0.145 | 0.258 | 0.159 | 0.274 | 0.136 | 0.145 | 0.146 | 0.081 |

Table 5: *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. In Panel B, the standard errors are clustered by analysts reported in parentheses below the coefficient estimates See Table A.1 and Table 1 for details about variable and sample definitions. The sample period is from September 2017 to March 2021. We keep analyst-quarter observations that meet the required quarterly login activity filter. To reduce the effect of outliers, *AWL* and *PAD* are winsorized at their 99% level. 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*** | 10.520*** | 10.069*** | 0.335*** | 0.145 | 0.801*** | 0.263*** |
| | (69.63) | (12.76) | (12.41) | (66.57) | (21.38) | (1.53) | (8.05) | (14.40) |
| *Adj.* $R^2$ | 0.050 | 0.438 | 0.085 | 0.086 | 0.091 | 0.515 | 0.115 | 0.067 |
| Observations | 2,874 | 2,874 | 2,874 | 2,872 | 2,874 | 2,874 | 2,874 | 2,872 |

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

| | *AWL* | | | | *PAD* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *IBES Years* | -0.042*** | -0.039*** | -0.042*** | -0.032** | 0.002 | 0.002 | 0.002 | 0.002 |
| | (-2.88) | (-2.68) | (-2.89) | (-1.97) | (1.19) | (1.14) | (1.24) | (1.26) |
| *High Rank Indicator* | -0.446** | -0.483*** | -0.524*** | -0.382** | 0.049*** | 0.049*** | 0.052*** | 0.025 |
| | (-2.51) | (-2.76) | (-3.04) | (-2.18) | (2.72) | (2.68) | (2.82) | (1.33) |
| *STAR* | 0.208 | 0.109 | 0.124 | -0.167 | 0.036** | 0.037** | 0.036** | 0.063*** |
| | (1.21) | (0.63) | (0.71) | (-0.86) | (2.29) | (2.32) | (2.28) | (3.69) |
| *Work Experience* | 0.005 | -0.002 | -0.002 | -0.014 | -0.000 | -0.000 | 0.000 | 0.001 |
| | (0.31) | (-0.13) | (-0.14) | (-0.85) | (-0.16) | (-0.00) | (0.00) | (0.53) |
| *# Jobs FINRA* | -0.031 | -0.031 | -0.041 | -0.054 | 0.003 | 0.003 | 0.004 | 0.007 |
| | (-0.70) | (-0.71) | (-0.93) | (-1.11) | (0.68) | (0.72) | (0.83) | (1.48) |
| *Ave Q1 PMAFE t-4_t-1* | 0.026 | 0.049 | 0.070 | -0.090 | 0.021 | 0.020 | 0.019 | 0.019 |
| | (0.05) | (0.10) | (0.15) | (-0.21) | (0.47) | (0.44) | (0.41) | (0.45) |
| *NYC Indicator* | | 0.304* | 0.338* | 0.179 | | -0.002 | -0.004 | -0.015 |
| | | (1.69) | (1.91) | (0.82) | | (-0.09) | (-0.20) | (-0.57) |
| *MBA Indicator* | | 0.225 | 0.256 | 0.508 | | -0.024 | -0.027 | -0.059** |
| | | (0.51) | (0.58) | (1.25) | | (-0.61) | (-0.66) | (-2.15) |
| *Female Indicator* | | 0.073 | 0.082 | -0.041 | | 0.007 | 0.006 | 0.007 |
| | | (0.33) | (0.37) | (-0.17) | | (0.31) | (0.28) | (0.32) |
| *Children Indicator* | | 0.374 | 0.392 | 0.147 | | -0.076 | -0.077 | -0.062 |
| | | (0.72) | (0.75) | (0.27) | | (-1.31) | (-1.33) | (-0.95) |
| *Principal Exam* | | | 0.370 | 0.181 | | | -0.024 | -0.033 |
| | | | (1.64) | (0.73) | | | (-1.06) | (-1.34) |
| 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 |
| $R^2$ | 0.196 | 0.214 | 0.219 | 0.273 | 0.287 | 0.289 | 0.291 | 0.404 |

Table 6: Analyst Stock Level Accuracy Regressions

This table reports results from panel regressions of analyst Q1 forecast accuracy on *AWL*, *PAD*, *PAD* components (*EvPAD* and *OtherPAD*), and other control variables. We decompose *PAD* to information-gathering activities that are related to the analyst's research (*EvPAD*) and other activities (*OtherPAD*). See Section IA.1 of the Internet Appendix for detailed information on the firm-event dataset and *EvPAD* construction. *PMAFE* is the analyst's 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. (Z) stands for a Z-Score adjustment (a mean of zero and a standard deviation of one). We Z-Score adjust both the dependent variable and independent variables of interest. See Table A.1 and Table 1 for details about variable and sample definitions. We require complete quarterly data for the outcome variable and begin our analysis from Q4 of year 2017. We keep analyst-quarter observations that meet the required quarterly login activity filter. To reduce the effect of outliers, *AWL* and *PAD* are winsorized at their 99% level. 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(Z)* | -0.017** | -0.019** | -0.014 | -0.014 | -0.017** | -0.019** | -0.014 | -0.015 |
| | (-2.29) | (-2.50) | (-1.22) | (-1.34) | (-2.28) | (-2.51) | (-1.29) | (-1.42) |
| *PAD(Z)* | 0.001 | 0.003 | 0.000 | 0.003 | | | | |
| | (0.09) | (0.35) | (0.01) | (0.26) | | | | |
| *EvPAD(Z)* | | | | | -0.015** | -0.016** | -0.018** | -0.018** |
| | | | | | (-2.25) | (-2.38) | (-2.43) | (-2.38) |
| *OtherPAD(Z)* | | | | | 0.005 | 0.008 | 0.004 | 0.007 |
| | | | | | (0.76) | (1.05) | (0.43) | (0.72) |
| *Ave Q1 PMAFE t-4_t-1* | 0.465*** | 0.440*** | -0.451*** | -0.451*** | 0.463*** | 0.437*** | -0.461*** | -0.462*** |
| | (5.72) | (5.53) | (-4.53) | (-4.55) | (5.70) | (5.49) | (-4.66) | (-4.68) |
| *Early Forecast* | 0.001** | 0.001** | 0.001* | 0.001* | 0.001** | 0.001** | 0.001* | 0.001* |
| | (2.36) | (2.49) | (1.73) | (1.88) | (2.34) | (2.48) | (1.74) | (1.89) |
| *IBES Years* | | 0.002 | | 0.069 | | 0.002 | | 0.020 |
| | | (1.39) | | (0.10) | | (1.29) | | (0.03) |
| *High Rank Indicator* | | -0.013 | | | | -0.012 | | |
| | | (-0.76) | | | | (-0.72) | | |
| *# Q1 EPS Forecasts* | | 0.003*** | | 0.003*** | | 0.003*** | | 0.003*** |
| | | (4.60) | | (3.48) | | (4.77) | | (3.50) |
| *# of GICS6 Industries* | | 0.007 | | 0.002 | | 0.007 | | 0.004 |
| | | (1.24) | | (0.24) | | (1.31) | | (0.38) |
| *LnSize* | | -0.006 | | -0.010 | | -0.006 | | -0.010 |
| | | (-0.28) | | (-0.42) | | (-0.28) | | (-0.42) |
| *LnBM* | | 0.008 | | 0.004 | | 0.008 | | 0.003 |
| | | (0.55) | | (0.25) | | (0.52) | | (0.22) |
| *StdDev.Ret* | | 0.304 | | 0.111 | | 0.321 | | 0.137 |
| | | (0.44) | | (0.16) | | (0.46) | | (0.19) |
| *InstHold* | | 0.009 | | 0.014 | | 0.009 | | 0.014 |
| | | (0.19) | | (0.28) | | (0.20) | | (0.28) |
| *AMIHUD* | | -0.022 | | -0.023 | | -0.021 | | -0.023 |
| | | (-0.89) | | (-0.92) | | (-0.89) | | (-0.92) |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 34,137 | 34,137 | 34,136 | 34,136 | 34,137 | 34,137 | 34,136 | 34,136 |
| $R^2$ | 0.093 | 0.094 | 0.112 | 0.112 | 0.093 | 0.094 | 0.112 | 0.112 |

Table 7: Analyst Timeliness Regressions

This table reports results from panel regressions of analyst Q1 forecast timeliness on *AWL*, *PAD* components (*EvPAD* and *OtherPAD*), and other control variables. We decompose *PAD* to information-gathering activities that are related to the analyst's research (*EvPAD*) and other activities (*OtherPAD*). See Section IA.1 of the Internet Appendix for detailed information on the firm-event dataset and *EvPAD* construction. *LnTFE* is the natural logarithm of the analyst average timeliness. Analyst timelines in turn, is the 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 an average timeliness of not longer than 30 calendar days. We require complete quarterly data for the outcome variable and begin our analysis from Q4 of year 2017. 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. To reduce the effect of outliers, *AWL* and *PAD* are winsorized at their 99% level. 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(Z)* | -0.053 | -0.084** | -0.023 | -0.020 | -0.050 | -0.081** | -0.023 | -0.020 |
| | (-1.43) | (-2.38) | (-0.69) | (-0.59) | (-1.36) | (-2.33) | (-0.69) | (-0.58) |
| *PAD(Z)* | -0.076** | -0.051 | -0.023 | -0.027 | | | | |
| | (-2.06) | (-1.42) | (-0.66) | (-0.77) | | | | |
| *EvPAD(Z)* | | | | | -0.084*** | -0.077** | 0.005 | 0.004 |
| | | | | | (-2.60) | (-2.56) | (0.24) | (0.17) |
| *OtherPAD(Z)* | | | | | -0.047 | -0.023 | -0.024 | -0.028 |
| | | | | | (-1.34) | (-0.68) | (-0.73) | (-0.83) |
| *IBES Years* | | -0.014* | | -0.996 | | -0.014** | | -0.979 |
| | | (-1.87) | | (-1.05) | | (-1.97) | | (-1.03) |
| *High Rank Indicator* | | -0.082 | | | | -0.076 | | |
| | | (-0.83) | | | | (-0.78) | | |
| *# Q1 EPS Forecasts* | | 0.011*** | | -0.007** | | 0.011*** | | -0.007** |
| | | (3.37) | | (-2.49) | | (3.39) | | (-2.48) |
| *Ave # of Industries t-4_t-1* | | -0.048** | | -0.004 | | -0.047** | | -0.004 |
| | | (-2.15) | | (-0.08) | | (-2.12) | | (-0.09) |
| *Ave Q1 PMAFE t-4_t-1* | | 0.271 | | 0.174 | | 0.275 | | 0.178 |
| | | (1.01) | | (0.80) | | (1.03) | | (0.82) |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,176 | 2,176 | 2,142 | 2,142 | 2,176 | 2,176 | 2,142 | 2,142 |
| $R^2$ | 0.083 | 0.122 | 0.530 | 0.532 | 0.087 | 0.125 | 0.530 | 0.532 |

Table 8: Probability of Being a Star Analyst

This table reports results from panel regressions of a star analyst indicator on *AWL*,*PAD*, and *PAD* components (*EvPAD* and *OtherPAD*), controlling for various fixed effects and analyst characteristics. We decompose *PAD* to information-gathering activities that are related to the analyst's research (*EvPAD*) and other activities (*OtherPAD*). See Section IA.1 of the Internet Appendix for detailed information on the firm-event dataset and *EvPAD* construction. We employ a linear probability model where a dummy variable of being a star analyst in Q4 of year $t$ is regressed on averages of *AWL*, *PAD*, and *PAD*'s components. Since we use the averages of *PAD* and *AWL* during Q1-Q3, we limit our analysis to 2018-2020, where we have full information. The even columns focus on a sub sample where the analyst was not elected as a star analyst in the previous year (NS y-1). Standard errors are clustered by analyst reported in parentheses below the coefficient estimates. See Table A.1 and Table 1 for details about variable and sample definitions. (Z) stands for a Z-Score adjustment (a mean of zero and a standard deviation of one). We Z-Score adjust the indipendent variables of interest. We keep analyst-quarter observations that meet the required quarterly login activity filter. To reduce the effect of outliers, *AWL* and *PAD* are winsorized at their 99% level. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| | ALL | | NS y-1 | | ALL | | NS y-1 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Ave AWL Q1-Q3(Z)* | -0.011 | 0.008 | -0.008 | -0.005 | -0.011 | 0.008 | -0.008 | -0.006 |
| | (-0.50) | (0.38) | (-0.48) | (-0.31) | (-0.50) | (0.38) | (-0.50) | (-0.32) |
| *Ave PAD Q1-Q3(Z)* | $0.099^{***}$ | $0.081^{***}$ | $0.057^{***}$ | $0.055^{***}$ | | | | |
| | (4.38) | (3.62) | (2.69) | (2.72) | | | | |
| *Ave EvPAD Q1-Q3(Z)* | | | | | 0.030 | 0.034 | 0.034 | 0.030 |
| | | | | | (1.30) | (1.55) | (1.64) | (1.49) |
| *Ave OtherPAD Q1-Q3(Z)* | | | | | $0.089^{***}$ | $0.070^{***}$ | $0.045^{**}$ | $0.046^{**}$ |
| | | | | | (4.20) | (3.44) | (2.32) | (2.45) |
| *Ave Q1 PMAFE t-4_t-1* | | -0.057 | | 0.008 | | -0.066 | | -0.006 |
| | | (-0.40) | | (0.08) | | (-0.46) | | (-0.06) |
| *IBES Years* | | $0.020^{***}$ | | $0.010^{**}$ | | $0.020^{***}$ | | $0.009^{**}$ |
| | | (4.92) | | (2.17) | | (4.98) | | (2.12) |
| *High Rank Indicator* | | $0.149^{***}$ | | 0.105 | | $0.148^{***}$ | | 0.105 |
| | | (2.82) | | (1.64) | | (2.80) | | (1.64) |
| *Work Experience* | | -0.007 | | $-0.008^{*}$ | | -0.007 | | $-0.007^{*}$ |
| | | (-1.28) | | (-1.96) | | (-1.30) | | (-1.93) |
| *# Jobs FINRA* | | $-0.038^{***}$ | | -0.006 | | $-0.038^{***}$ | | -0.005 |
| | | (-2.87) | | (-0.65) | | (-2.87) | | (-0.59) |
| *NYC Indicator* | | 0.024 | | 0.007 | | 0.024 | | 0.009 |
| | | (0.36) | | (0.12) | | (0.37) | | (0.16) |
| *MBA Indicator* | | 0.133 | | 0.040 | | 0.129 | | 0.035 |
| | | (1.20) | | (0.45) | | (1.16) | | (0.41) |
| *Female Indicator* | | -0.037 | | -0.049 | | -0.035 | | -0.045 |
| | | (-0.71) | | (-1.06) | | (-0.67) | | (-0.97) |
| *Children Indicator* | | -0.194 | | -0.138 | | -0.194 | | -0.136 |
| | | (-1.53) | | (-1.55) | | (-1.55) | | (-1.56) |
| *Principal Exam* | | -0.005 | | -0.005 | | -0.003 | | -0.005 |
| | | (-0.06) | | (-0.07) | | (-0.04) | | (-0.06) |
| Brokerage Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 510 | 510 | 333 | 333 | 510 | 510 | 333 | 333 |
| $R^2$ | 0.531 | 0.601 | 0.298 | 0.340 | 0.532 | 0.602 | 0.302 | 0.342 |

Table 9: *PAD* and COVID Lockdown Identification Strategy

This table reports results from panel regressions of analyst accuracy on *PAD* and other control variables using a difference-in-difference identification strategy. We focus on the period Q3-2019 to Q2-2020 and use the exogenous drop in *PAD* due to the COVID lockdown as a shock to analysts' 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*. $TREATMENT \times POST$ 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 analyst 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's home address and the covered firm headquarters. FAR (NEAR) refers to stocks whose headquarters are 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.

| | ALL | FAR | NEAR |
|---|---|---|---|
| | (1) | (2) | (3) |
| *TREATMENT* | -0.049 | -0.070 | -0.041 |
| | (-1.34) | (-1.64) | (-0.63) |
| *POST* | -0.038 | -0.046 | 0.067 |
| | (-0.79) | (-0.87) | (0.89) |
| $TREATMENT \times POST$ | 0.117** | 0.128** | -0.017 |
| | (2.47) | (2.29) | (-0.19) |
| *Ave # Stocks t-4_t-1* | 0.006* | 0.008** | -0.001 |
| | (1.79) | (2.08) | (-0.09) |
| *Ave # of Industries t-4_t-1* | -0.008 | -0.004 | 0.003 |
| | (-1.21) | (-0.61) | (0.24) |
| *IBES Years* | -0.002 | -0.004 | 0.001 |
| | (-0.78) | (-1.44) | (0.42) |
| *Ave Q1 PMAFE t-4_t-1* | -0.015 | -0.076 | -0.040 |
| | (-0.14) | (-0.61) | (-0.19) |
| Coverage FE | YES | YES | YES |
| Location FE | YES | YES | YES |
| Analyst Cluster | YES | YES | YES |
| Observations | 407 | 380 | 327 |
| Adj$R^2$ | 0.036 | 0.042 | 0.030 |

Table 10: *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 on 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 analyst 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's home address and the covered firm headquarters. FAR (NEAR) refers to stocks that their headquarters 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.

Panel A: *AWL* and Commute Time Saved

| | 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 |
| Adj$R^2$ | 0.136 | 0.128 | 0.126 | 0.123 | 0.114 | 0.132 | 0.123 | 0.116 |

Panel B: Accuracy - DID

| | ALL | FAR | NEAR |
|---|---|---|---|
| | (1) | (2) | (3) |
| *TREATMENT* | 0.046 | 0.035 | 0.069 |
| | (1.52) | (0.90) | (1.22) |
| *POST* | 0.060 | 0.043 | 0.109 |
| | (1.36) | (0.77) | (1.55) |
| *TREATMENT* $\times$ *POST* | -0.085* | -0.060 | -0.081 |
| | (-1.75) | (-1.04) | (-1.00) |
| *Ave # Stocks t-4_t-1* | 0.006* | 0.009** | -0.000 |
| | (1.89) | (2.23) | (-0.04) |
| *Ave # of Industries t-4_t-1* | -0.009* | -0.007 | -0.003 |
| | (-1.85) | (-1.20) | (-0.25) |
| *IBES Years* | -0.002 | -0.004 | 0.002 |
| | (-0.83) | (-1.63) | (0.50) |
| *Ave Q1 PMAFE t-4_t-1* | -0.012 | -0.086 | -0.005 |
| | (-0.11) | (-0.66) | (-0.02) |
| Firm FE | YES | YES | YES |
| Coverage FE | YES | YES | YES |
| Location FE | YES | YES | YES |
| Analyst Cluster | YES | YES | YES |
| Observations | 395 | 368 | 315 |
| Adj$R^2$ | 0.032 | 0.033 | 0.033 |

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. |
| *LnActive* | 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* | For each analyst 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. |
| *EvPAD* | 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 a day that falls on brokerage firms' or companies' events for the stocks the analyst covers, and zero otherwise. Given that analysts travel for more than one day to attend an event or attend multiple events, we take into account the entire sequence of non-login days that coincide with these events. See Section IA.1 of the Internet Appendix for details about the selection of firm-event series and *EvPAD* construction. The non-*EvPAD* days, which we denote as "Other *PAD*," are calculated as the difference between the quarterly *PAD* and *EvPAD*. |

| 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. |

# IA Internet Appendix

## IA.1 Firm-Event Dataset and EvPad Construction

This section of the Internet Appendix describes the firm events and the construction of our *EvPAD* and *OtherPAD* measures.

1. <u>Firm-Event Dataset</u>:

Our firm-event set includes two sources: Bloomberg's EVTS calendar and analyst and investor days from the Refinitiv StreetEvents Transcripts database. The analyst and investor day file is straightforward, as it includes specific investor day events. In contrast, Bloomberg's EVTS calendar includes many events that are not necessarily related to brokerage firms or companies' hosted events. Consequently, we systematically clean up the event file based on the event descriptions. We then combine both datasets and keep non-overlapping firm-event observations.

We start with the full EVTS calendar records from 2017 to 2021. The file includes 316,024 firm-event observations across various categories. As a starting point, we remove observations that their description includes the keywords: "VIRTUAL," "ANNUAL GENERAL MEETING," "EXTRAORDINARY GENERAL MEETING," "ANALYST BRIEFING", which leaves us with 228,211 firm-event observations. Next, we remove obvious categories that are not related to hosted events. These categories include: CD (credit default), ER (earnings release), TL (timeline), EC (economic calendar), GU (guidance), DV (dividend), and MA (merger and acquisitions). This leaves us with 141,766 firm-event observations concentrated in the CP (conference presentations), CM (company meeting), CS (conference/seminars), and SM (shareholder meeting) categories.

Next, we focus on the following six keywords: day, event, conference, meeting, invest, and analyst. We create six indicators that receive the value of 1 if these words appear in the event description, and zero otherwise. We then go category by category and remove events that do not include any of these keywords. This first pass leaves us with 62,239 firm-event observations across the CP, CM, CS, and SM categories (41,769, 9,472, 6,672, and 4,236 firm-event observations, respectively).

Next, we manually explore each of the six indicators and remove observations that are not related to firm, analyst, and research events. Starting with the CP category, we further remove observations that include the words "CONFERENCE RECAP", "TELECONFERENCE", and "CONFERENCE HIGHLIGHTS." We end up with events such as "Barclays TX Bank Day Investor Conference," "MUFG Securities Oil & Gas Corporate Access Day," "Morgan Stanley Global Health Care Conference," and "Citigroup Global Technology Conference," across 39,371 firm-event observations.

We follow the same procedure for the other categories. Interestingly, the keyword "analyst" in the CM category seems to capture analyst updates or summaries and not related to investor meetings. Such events include descriptions such as "Canaccord: Matthew Ramsay - Analyst Roadshow," and 'Guidepoint: Service Corp (SCI): Deathcare Investing Update," and we remove such observations. We further filter other non-relevant events across other keywords, which leaves us 176 observations. In a similar manner, we end up with 6,624 and 3,813 observations in the CS and SM categories.

We then merge these events with the analyst and investor day dataset, which includes 1,678 firm event observations. We keep all non-overlapping observations, and the final merged file includes 45,286 firm-event observations.

2. <u>Measure construction</u>:

We use the daily login data to construct for each analyst sequences of "in office" or "away" windows. We define an indicator "AWAY" that receives the value of 1 if an analyst is not logged in to the terminal during that day, and zero otherwise. Then, for each analyst, we construct sequences of 0 (in office, AWAY=0) or 1 (away, AWAY=1) based on the analyst's daily time series information. For example, suppose that the analyst's time series history contains the following string of 30 AWAY numbers: 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0. In this case, the sequences constitution is as follows: SEQ1 [0, 0, 0], SEQ2 [1, 1], SEQ3 [0, 0, 0], SEQ4 [1, 1, 1], SEQ5 [0], SEQ6 [1, 1], SEQ7 [0, 0, 0, 0], SEQ8 [1], SEQ9 [0], SEQ10[1, 1, 1, 1, 1, 1] and SEQ11 [0, 0, 0, 0].

After constructing the time-series sequence history for each analyst, we turn to match these sequences with the firm-event file. For this matching, we only keep the away sequences (SEQ2, SEQ4, SEQ6, SEQ8, and SEQ10). To assign a sequence as an *EvPAD* sequence, we need that at least one of the away sequence dates overlaps with the firm-event file, where the matching is done based on the stocks that the analyst covets during the quarter. For each sequence, we flag the days within the sequence that include these events. The number of *EvPAD* days within the sequence can range from 0 (zero match) to N (the maximum number of days in that sequence).

Importantly, traveling for events can overlap with other non-research activities such as meeting institutional clients, which we define as "Other PAD" (*OtherPAD*). To make a cleaner distinction between *EvPAD* and *OtherPAD*, we apply a series of filters to ensure that the *EvPAD* series is related to research activities. First, we drop any away sequence that includes 0 events. Second, we drop any away sequence that includes more than 10 business days. Our assumption is that traveling for more than two weeks is probably contaminated with other non-research activities. Third, we make an additional distinction between short-term travel (up to 5 days) and long-term travel (between 6 to 10 days). For short-term travel, we define the sequence as *EvPAD* if there is at least one event that overlaps with that series. For long-term travel, we require at least 2 events on different days, together with three additional conditions that guarantee a well-dispersed set of events during the sequence window. Specifically, we define three variables: "Days to First Event," which captures the days from the beginning of the sequence and the first event; "Days from Last Event," which captures the days from the last event and the last day in the sequence; and "Max Day Gap between Events," which capture the max gap between consecutive events. We then remove sequences where all three measures are above their $80^{th}$ percentile, across all analysts, conditioning on the number of days in the sequence (i.e., 6, 7, 8, 9, or 10). This prevents situations where, for example, a sequence of 8 away days has two events that are clustered either at the beginning or the end of the sequence, or has one event at the beginning and the other event at the end. In such cases, this sequence is more likely to be related to *OtherPAD*.

Once we flag all*EvPAD* days for each analyst's time-series history, our final *EvPAD* measure is calculated at the analyst-quarter level as the percent of *EvPAD* days from all days in that quarter (similar to the *PAD* calculation). *OtherPAD* is then the difference between *PAD* and *EvPAD*. In our robustness tests, we construct additional *EvPAD* measures that are based only on short-term travel (up to 5 days) and measures that are based using only the CP (the largest) category.

### IA.2 Additional Tests

This section of the Internet Appendix includes additional tests (Tables IA.1 - IA.4).

In our main tests, we use *EvPAD* and *OtherPAD* to proxy for analysts' Percentage Away Days (PAD), which is associated with research and other activities that quantify the extent of private information collection that requires travel. We implicitly assume that analysts, given the nature of their work, do not engage in leisure and travel to meet institutional investors and engage in firm and other information-gathering activities. We repeat the main tests (Section 4) using other alternatives for *EvPAD*. Specifically, we report results based on *EvPAD* sequences only up to 5 days (Table IA.1), and limit our event set to the CP EVTS category, excluding the CS, CM, and SM categories (Table IA.2).

Next, 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, we repeat the main tests (Section 4) using an *intensive* usage measure that captures the analyst's minutes spent on the Bloomberg terminal. The measure, *LnActive*, is calculated as the natural logarithm of the average daily minutes of active Bloomberg usage in a quarter. We report the results in Table IA.3. Overall, the results using *LnActive* are broadly consistent with the results using *AWL*.

Finally, in Table IA.4, we repeat the analysis conducted in Table 6, controlling for Brokerage Firm Peers (team effort). Interestingly, they exhibit negative and somewhat significant coefficients, which suggests that the team effect is associated with higher accuracy. But, importantly, including a control for team effort doesn't alter our findings.

Table IA.1: *EvPAD* - Away Sequences up to 5 Days

This table repeats the analysis conducted in Table 6 (accuracy), Table 7 (timeliness), and Table 8 (star), replacing *EvPAD* that is based on away sequences up to 10 days, with *EvPAD* that is based on away sequences up to 5 days. 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: Accuracy

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *AWL(Z)* | -0.017** | -0.019** | -0.014 | -0.014 | -0.017** | -0.019** | -0.014 | -0.015 |
| | (-2.29) | (-2.50) | (-1.22) | (-1.34) | (-2.24) | (-2.48) | (-1.26) | (-1.39) |
| *PAD(Z)* | 0.001 | 0.003 | 0.000 | 0.003 | | | | |
| | (0.09) | (0.35) | (0.01) | (0.26) | | | | |
| *EvPAD(Z)* | | | | | -0.017** | -0.018*** | -0.018** | -0.018** |
| | | | | | (-2.45) | (-2.67) | (-2.36) | (-2.39) |
| *OtherPAD(Z)* | | | | | 0.005 | 0.008 | 0.004 | 0.007 |
| | | | | | (0.73) | (1.04) | (0.35) | (0.63) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 34,137 | 34,137 | 34,136 | 34,136 | 34,137 | 34,137 | 34,136 | 34,136 |
| $R^2$ | 0.093 | 0.094 | 0.112 | 0.112 | 0.094 | 0.095 | 0.112 | 0.112 |

Panel B: Timeliness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *AWL(Z)* | -0.053 | -0.084** | -0.023 | -0.020 | -0.051 | -0.082** | -0.023 | -0.020 |
| | (-1.43) | (-2.38) | (-0.69) | (-0.59) | (-1.37) | (-2.34) | (-0.69) | (-0.59) |
| *PAD(Z)* | -0.076** | -0.051 | -0.023 | -0.027 | | | | |
| | (-2.06) | (-1.42) | (-0.66) | (-0.77) | | | | |
| *EvPAD(Z)* | | | | | -0.068** | -0.065** | -0.009 | -0.010 |
| | | | | | (-2.26) | (-2.28) | (-0.40) | (-0.44) |
| *OtherPAD(Z)* | | | | | -0.056 | -0.031 | -0.021 | -0.024 |
| | | | | | (-1.56) | (-0.89) | (-0.62) | (-0.72) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,176 | 2,176 | 2,142 | 2,142 | 2,176 | 2,176 | 2,142 | 2,142 |
| $R^2$ | 0.083 | 0.122 | 0.530 | 0.532 | 0.085 | 0.124 | 0.530 | 0.532 |

Panel C: STAR

| | ALL | | NS y-1 | | ALL | | NS y-1 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Ave AWL Q1-Q3(Z)* | -0.011 | 0.008 | -0.008 | -0.005 | -0.011 | 0.008 | -0.008 | -0.005 |
| | (-0.50) | (0.38) | (-0.48) | (-0.31) | (-0.49) | (0.38) | (-0.49) | (-0.31) |
| *Ave PAD Q1-Q3(Z)* | 0.099*** | 0.081*** | 0.057*** | 0.055*** | | | | |
| | (4.38) | (3.62) | (2.69) | (2.72) | | | | |
| *Ave EvPAD Q1-Q3(Z)* | | | | | 0.018 | 0.025 | 0.024 | 0.021 |
| | | | | | (0.78) | (1.14) | (1.32) | (1.22) |
| *Ave OtherPAD Q1-Q3(Z)* | | | | | 0.093*** | 0.074*** | 0.049** | 0.049** |
| | | | | | (4.41) | (3.58) | (2.46) | (2.56) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Brokerage Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 510 | 510 | 333 | 333 | 510 | 510 | 333 | 333 |
| $R^2$ | 0.531 | 0.601 | 0.298 | 0.340 | 0.532 | 0.601 | 0.300 | 0.340 |

Table IA.2: *EvPAD* based on the CP EVTS Category

This table repeats the analysis conducted in Table 6 (accuracy), Table 7 (timeliness), and Table 8 (star), replacing *EvPAD* that is based on all four EVTS categories, with *EvPAD* that is only based on the CP category. 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: Accuracy

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *AWL(Z)* | -0.017** | -0.019** | -0.014 | -0.014 | -0.018** | -0.020*** | -0.015 | -0.016 |
| | (-2.29) | (-2.50) | (-1.22) | (-1.34) | (-2.36) | (-2.60) | (-1.32) | (-1.45) |
| *PAD(Z)* | 0.001 | 0.003 | 0.000 | 0.003 | | | | |
| | (0.09) | (0.35) | (0.01) | (0.26) | | | | |
| *EvPAD(Z)* | | | | | -0.014** | -0.015** | -0.015* | -0.015* |
| | | | | | (-2.00) | (-2.16) | (-1.93) | (-1.93) |
| *OtherPAD(Z)* | | | | | 0.005 | 0.007 | 0.003 | 0.006 |
| | | | | | (0.68) | (1.00) | (0.33) | (0.62) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 34,137 | 34,137 | 34,136 | 34,136 | 34,137 | 34,137 | 34,136 | 34,136 |
| $R^2$ | 0.093 | 0.094 | 0.112 | 0.112 | 0.093 | 0.094 | 0.112 | 0.112 |

Panel B: Timeliness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *AWL(Z)* | -0.053 | -0.084** | -0.023 | -0.020 | -0.052 | -0.083** | -0.022 | -0.019 |
| | (-1.43) | (-2.38) | (-0.69) | (-0.59) | (-1.41) | (-2.38) | (-0.66) | (-0.55) |
| *PAD(Z)* | -0.076** | -0.051 | -0.023 | -0.027 | | | | |
| | (-2.06) | (-1.42) | (-0.66) | (-0.77) | | | | |
| *EvPAD(Z)* | | | | | -0.086*** | -0.076*** | 0.017 | 0.016 |
| | | | | | (-2.79) | (-2.61) | (0.82) | (0.76) |
| *OtherPAD(Z)* | | | | | -0.047 | -0.024 | -0.027 | -0.031 |
| | | | | | (-1.36) | (-0.73) | (-0.82) | (-0.92) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,176 | 2,176 | 2,142 | 2,142 | 2,176 | 2,176 | 2,142 | 2,142 |
| $R^2$ | 0.083 | 0.122 | 0.530 | 0.532 | 0.087 | 0.125 | 0.530 | 0.532 |

Panel C: STAR

| | ALL | | NS y-1 | | ALL | | NS y-1 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Ave AWL Q1-Q3(Z)* | -0.011 | 0.008 | -0.008 | -0.005 | -0.011 | 0.009 | -0.008 | -0.005 |
| | (-0.50) | (0.38) | (-0.48) | (-0.31) | (-0.48) | (0.41) | (-0.45) | (-0.28) |
| *Ave PAD Q1-Q3(Z)* | 0.099*** | 0.081*** | 0.057*** | 0.055*** | | | | |
| | (4.38) | (3.62) | (2.69) | (2.72) | | | | |
| *Ave EvPAD Q1-Q3(Z)* | | | | | 0.032 | 0.032 | 0.035* | 0.030 |
| | | | | | (1.31) | (1.45) | (1.74) | (1.60) |
| *Ave OtherPAD Q1-Q3(Z)* | | | | | 0.088*** | 0.070*** | 0.044** | 0.045** |
| | | | | | (4.06) | (3.32) | (2.19) | (2.30) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Brokerage Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 510 | 510 | 333 | 333 | 510 | 510 | 333 | 333 |
| $R^2$ | 0.531 | 0.601 | 0.298 | 0.340 | 0.532 | 0.602 | 0.303 | 0.342 |

Table IA.3: Replacing *AWL* with *LnCondActive*

This table repeats the analysis conducted in Table 6 (accuracy), Table 7 (timeliness), and Table 8 (star), replacing *AWL* with *LnActive*. 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: Accuracy and *LnActive*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *LnCondActive(Z)* | -0.011 | -0.012 | -0.036** | -0.038** | -0.010 | -0.012 | -0.035** | -0.036** |
| | (-1.35) | (-1.55) | (-2.19) | (-2.24) | (-1.28) | (-1.50) | (-2.10) | (-2.15) |
| *PAD(Z)* | 0.001 | 0.002 | -0.005 | -0.003 | | | | |
| | (0.13) | (0.28) | (-0.47) | (-0.24) | | | | |
| *EvPAD(Z)* | | | | | -0.015** | -0.015** | -0.019** | -0.018** |
| | | | | | (-2.18) | (-2.33) | (-2.58) | (-2.53) |
| *OtherPAD(Z)* | | | | | 0.006 | 0.007 | -0.001 | 0.002 |
| | | | | | (0.77) | (0.96) | (-0.05) | (0.21) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 34,137 | 34,137 | 34,136 | 34,136 | 34,137 | 34,137 | 34,136 | 34,136 |
| $R^2$ | 0.093 | 0.094 | 0.112 | 0.112 | 0.093 | 0.094 | 0.112 | 0.112 |

Panel B: Timeliness and *LnCondActive*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *LnCondActive(Z)* | -0.004 | -0.017 | 0.036 | 0.043 | -0.001 | -0.014 | 0.035 | 0.042 |
| | (-0.11) | (-0.48) | (0.73) | (0.89) | (-0.03) | (-0.39) | (0.71) | (0.87) |
| *PAD(Z)* | -0.067* | -0.043 | -0.017 | -0.020 | | | | |
| | (-1.67) | (-1.10) | (-0.48) | (-0.56) | | | | |
| *EvPAD(Z)* | | | | | -0.083** | -0.077** | 0.007 | 0.005 |
| | | | | | (-2.57) | (-2.55) | (0.30) | (0.24) |
| *OtherPAD(Z)* | | | | | -0.037 | -0.014 | -0.019 | -0.021 |
| | | | | | (-0.99) | (-0.39) | (-0.56) | (-0.63) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Analyst FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,176 | 2,176 | 2,142 | 2,142 | 2,176 | 2,176 | 2,142 | 2,142 |
| $R^2$ | 0.081 | 0.116 | 0.530 | 0.532 | 0.085 | 0.120 | 0.530 | 0.532 |

Panel C: STAR and *LnCondActive*

| | ALL | | NS y-1 | | ALL | | NS y-1 | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *LnAveCondActive Q1-Q3(Z)* | 0.073*** | 0.062** | 0.024 | 0.017 | 0.074*** | 0.064*** | 0.027 | 0.020 |
| | (2.93) | (2.57) | (1.20) | (0.82) | (2.97) | (2.65) | (1.30) | (0.91) |
| *Ave PAD Q1-Q3(Z)* | 0.131*** | 0.103*** | 0.069*** | 0.064*** | | | | |
| | (5.64) | (4.59) | (2.92) | (2.77) | | | | |
| *Ave EvPAD Q1-Q3(Z)* | | | | | 0.043* | 0.044** | 0.040* | 0.034 |
| | | | | | (1.86) | (2.02) | (1.83) | (1.63) |
| *Ave OtherPAD Q1-Q3(Z)* | | | | | 0.117*** | 0.089*** | 0.057*** | 0.054** |
| | | | | | (5.30) | (4.32) | (2.66) | (2.60) |
| Controls | NO | YES | NO | YES | NO | YES | NO | YES |
| Brokerage Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 510 | 510 | 333 | 333 | 510 | 510 | 333 | 333 |
| $R^2$ | 0.542 | 0.608 | 0.301 | 0.341 | 0.542 | 0.609 | 0.305 | 0.343 |

Table IA.4: Analyst Stock Level Accuracy Regressions - Controlling for Brokerage Firm Peers

This table repeats the analysis conducted in Table 6 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) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *AWL(Z)* | -0.018** | -0.017** | -0.019** | -0.018** | -0.014 | -0.013 | -0.015 | -0.014 |
| | (-2.38) | (-2.30) | (-2.52) | (-2.45) | (-1.25) | (-1.21) | (-1.39) | (-1.33) |
| *EvPAD(Z)* | -0.015** | -0.015** | -0.016** | -0.016** | -0.017** | -0.017** | -0.017** | -0.017** |
| | (-2.24) | (-2.25) | (-2.39) | (-2.40) | (-2.37) | (-2.38) | (-2.31) | (-2.33) |
| *OtherPAD(Z)* | 0.004 | 0.004 | 0.006 | 0.006 | 0.005 | 0.005 | 0.008 | 0.008 |
| | (0.57) | (0.59) | (0.86) | (0.87) | (0.47) | (0.47) | (0.77) | (0.76) |
| *Brokerage-Firm PeerAWL* | -0.016* | | -0.014* | | -0.006 | | -0.009 | |
| | (-1.73) | | (-1.67) | | (-0.49) | | (-0.75) | |
| *AUG Brokerage-Firm PeerAWL* | | -0.011 | | -0.010 | | -0.003 | | -0.004 |
| | | (-1.29) | | (-1.19) | | (-0.26) | | (-0.43) |
| Controls | NO | NO | YES | YES | NO | NO | YES | YES |
| Analyst FE | NO | NO | NO | NO | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Coverage x Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Analyst Cluster | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 34,137 | 34,137 | 34,137 | 34,137 | 34,136 | 34,136 | 34,136 | 34,136 |
| $R^2$ | 0.094 | 0.094 | 0.095 | 0.095 | 0.112 | 0.112 | 0.112 | 0.112 |