All in a day's work: What do we learn from Analysts' Bloomberg Usage?*

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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 away day (PAD) to proxy for their soft information production. Both AWL and PAD vary much more across analysts than across time. Controlling for coverage, AWL is positively related to the quantity and the timeliness of analyst forecasts, while PAD is negatively related to quantity. Both are positively related to forecast accuracy, even after controlling for analyst fixed effects. COVID lockdown provides further causal evidence. Traveling analysts (with high pre-COVID PAD) experience a significant reduction in forecast accuracy during the lockdown. Using pre-COVID analyst commute time to instrument increased AWL during the lockdown, we find a higher AWL to significantly increase output and improve the accuracy of the forecasts.

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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 provide the first systematic analysis of analysts' work habits by taking advantage of their minute-by-minute Bloomberg terminal usage data.

Bloomberg terminals are widely used by equity analysts. Among other useful functions, Bloomberg allows analysts to explore financial data, utilize existing analytics and examing research by peer analysts.[2] In addition, it constitutes an online social network community. As detailed in Ben-Rephael, Carlin, Da, and Israelsen (2020), 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 terminal users.

Figure 1 provides an example of where we obtain information on user activity. The green dot next to Michael Bloomberg's name on his Bloomberg profile page indicates that he is actively using his personal account. If he were to become inactive for greater than 15 minutes, the dot would turn yellow. If a terminal user is offline, the dot is red, and if a telephone icon appears, it indicates he/she is using the mobile application.

We manually collect minute-by-minute Bloomberg usage data from September 2017 to

[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

March 2021 for 336 sell-side analysts employed by 42 brokerage firms.[3] These analysts use the Bloomberg terminal extensively. For example, they log into the terminal on 72% of the workdays, and on those days, they work actively on the terminal for more than 8 hours on average. Inspection of the platform confirms that it does not provide any entertainment value and is used for work purpose only. Indeed, we find Bloomberg analysts' pre-market (7-9 am) login activity (a natural focal point of the day) to increase in response to market information and firm news concerning the stocks they cover, confirming that Bloomberg usage is work-related.

The detailed Bloomberg usage data allow us to characterize two important dimensions of analysts' work habits. First, it allows us to estimate the average work day length of the analyst when they are not traveling. Bloomberg terminals are typically located at work (and can be accessed via VPN and Bloomberg anywhere app when analysts had to work from home during the COVID lockdown). An inspection of an analyst's intraday Bloomberg activity distribution during a period of time indicates when her work day typically starts and ends. More formally, as in Ben-Rephael, Carlin, Da, and Israelsen (2020), we use an unsupervised machine learning algorithm to construct a measure of Average Workday Length (*AWL*). *AWL* proxies analysts' general effort provision or work ethics. The average *AWL* of analysts in our sample is 9.8 hours. Not surprisingly, *AWL* increased sharply starting during the COVID outbreak in the first quarter of 2020, from less than 10 hours to almost 11 hours. Note that we do not focus on the intensity or total time of Bloomberg usage in our tests as analysts can engage in other productive activities at work, such as meetings, making phone calls, emailing, and reading. Nevertheless, we generally find similar results after replacing *AWL* with a work intensity measure, as reported in the appendix. Moreover,

[3]For emphasis, we did not collect any private information about what the analysts actually did on the terminal: we did not observe any information about messaging, news search, or trading-related activities. As we are only interested in the simple usage of the terminal as a proxy for work habit, we do not collect any sensitive information from corporate firms and keep all identities anonymous in our analysis. Once analysts were matched to IBES and other datasets, their identities were anonymized and the investigators were made blind as to particular identities and results. We do not disclose subject identities in any of the results reported in this paper.

AWL is positively correlated with the pre-market login activity (a correlation of 0.24).

In addition, analysts do not produce information only by working in the office. A large strand of literature suggests that analysts can gather "soft" information away from the office, by attending investor and analyst days, participating in other company events, and meeting the management, etc.[4] We proxy for such soft information production activities using the percentage of workdays when analysts are away from the Bloomberg terminals, or Percentage of Away Days (PAD) in short. Of course, PAD is associated with measurement errors. While the analysts are not on the Bloomberg terminal on that day, they may still be working in the office (though we do filter out analysts from our sample who rarely use the Bloomberg terminal). In addition, even if they are away from the office, there is no guarantee that they are doing work-related travel. Nevertheless, to our best knowledge, PAD amounts to the first systematic attempt to proxy for analyst's soft information production. The average PAD across the sample period is 28.3% which drops from 30% to less than 15% after the COVID lockdown, consistent with the notion that lockdown shuts down the soft information collection channels. To further alleviate measurement error in PAD, we will focus on a simple "travelling" analyst dummy variable in our main empirical analyses. We identify "travelling" analysts in a quarter as those whose PAD is above the sample median.

We estimate AWL and PAD for each analyst-quarter and find both to present persistent analyst characteristics. Neither quarter nor brokerage-firm fixed effect explains more than 10% of their variations. In contrast, the analyst fixed effect explains 49.8% and 57.2% of variations in AWL and PAD, respectively. As expected, AWL and PAD are negatively correlated, though the correlation of -0.23 is not huge, suggesting that "working hard" and "working smart" are not substitutes for each other. Not surprisingly, both work habit measures are positively correlated with the number of stocks analysts cover. In our empirical tests, we control for such mechanical correlations with Coverage $\times$ Time fixed effects, when-

[4]For example, Kirk and Markov (2016) examine the information content of analyst and investor days and its impact on prices. Chang, Chi, and Wu (2017) examine the market reaction to analyst reports following on-site visits to company headquarters for Chinese stocks. Han, Kong, and Liu (2018) find that analysts' company visits improev the accuracy of their earnings forecasts.

ever possible.

Moreover, regressing *AWL* and *PAD* on a battery of time-invariant analyst characteristics obtained from public records on FINRA, LinkedIn and FaceBook reveal that analysts that are longer on I/B/E/S (a proxy for experience) or have a high-ranked title are associated with a higher *PAD* (lower *AWL*). The finding is consistent with the natural link between analyst seniority and the required interactions with management and institutional investors. We use analyst fixed effects in subsequent analyses to control for these time-invariant analyst characteristics.

Equipped with *AWL* and *PAD* measures, we then examine how analysts' work habits are related to both the quantity and quality of their outputs. *AWL* is positively associated with the number of earnings and price target forecasts issued, even after including analyst fixed effects, suggesting a likely causal relation. For example, with analyst fixed effects and other controls, an one-hour increase in *AWL* is associated with 3.4 more EPS forecsts and 0.54 more price target forecasts. In addition, a higher *AWL* is associated with more timely forecasts, though this association becomes insignificant after including analyst fixed effects. Overall, when an analyst works longer in a particular quarter, she produces more forecasts and produces them faster after earnings announcements. In contrast, compared to their peers, "travelling" analysts issue 9.0 fewer EPS forecasts and 1.29 fewer price target forecasts, though the timeliness of their forecasts are not statistically different from that of their peers.

We also examine the accuracy of the EPS forecasts. Since the magnitude of forecast errors varies across stocks and time, and may interact with analysts' coverage choice, we follow Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016) and consider a "Proportional Mean Absolute Forecast Error" (*PMAFE*) which compares the analyst's forecast error against those of her peers covering the same earnings announcement. The most accurate analyst will have a *PMAFE* of -1. A zero *PMAFE* indicates average accuracy. Even with analyst fixed effects and other controls, an one hour increase in *AWL* is associated with a significant reduction in *PMAFE* (or improvement in accuracy) of 0.5%. We also find "travelling" analysts to produce more accurate forecasts than their peers. Specifically, even with analyst fixed effects and other controls, a *HIGH_PAD* dummy is associated with a significant reduction in *PMAFE* (or improvement in accuracy) of 1.8%. Overall, the results suggest that both "working harder" and "working smarter" are associated with more accurate forecasts.

The strong associations between *AWL* or *PAD* and various dimensions of analyst output are obtained with analyst fixed effects, and therefore point towards a causal interpretation. Yet, to further establish causality, we take advantage of the COVID lockdown as an exogenous shock that significantly curtailed travel during the first two quarters of 2020. This shock clearly hurts "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%. Not surprisingly, their output, measured by the quantity of forecasts issued, increased (though not significantly).

As the analysts are locked down at home, their *AWL*s increase by one hour on average. Unlike the reduction in *PAD* which is completely exogenous and beyond analysts' control, the increase in *AWL* during the lockdown could reflect analysts' choices, which may in turn affect their forecast outcomes. We therefore need an instrument for the change in *AWL*. After examining several analyst characteristics (age, gender, and whether they have young children at home), We find that the only significant predictor of the change in *AWL* during lockdown is the pre-COVID commuting time, which we estimated by using the analyst's home and office addresses and Google Maps. Analysts who spent longer time commuting to work during the last two quarters of 2019 naturally save more time by working from home. Indeed, we find one-hour commuting time pre-COVID to predict about a 1.3 hour increase in *AWL* during the lockdown. Using the using long commuting time as an instrument for increased *AWL*, we find *AWL* to significantly increase the total number of forecasts issued and also improve the accuracy of the forecasts (or 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. 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 soft information production. We find both measures are reliably related to the quantity and quality of their forecasts. In addition, we present causal evidence that both dimensions of their work habit leads to improvement in their forecast accuracy.

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 (2021) and Li and Wang (2021) 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 both negative and positive impact on their performance. On one hand, WFH prevents them from collecting soft 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.

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 terminal users are assigned accounts, the company records their “status” by default.[5] 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 the terminal. However, if they stop actively using it for 15 minutes, users' 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, their status is listed as ”mobile”. While using the mobile app, access to an assigned desktop terminal is restricted, so there is no possibility of double-counting. This information, which is publicly available to those with access to a Bloomberg terminal, is limited to the user status and does not include any information about the specifics of what users are doing on the terminal.

Analyst Data:

From the IBES recommendation files, for all recommendations of US stocks since September 2017, we identify analysts first name and last initial as well as the IBES abbreviation for their brokerage firms. We then cross reference these names with a list of all self-identified “analysts” on the Bloomberg terminal during the same period using the “PEOP” function. We verify that the individuals are the same based on the brokerage firm and location.

We want to include to our sample only analysts who are active on the Bloomberg terminal. 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

[5] Only about 10% of terminal users opt-out and set their status to “private”.

minutes that an analyst is actively logged to the terminal 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 login 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. These filters results in a final sample of 336 analysts across 42 brokerage firms. We observed and recorded their status and the time spent on terminal continuously. We also collected all of their recommendations across all US stocks as well as their earnings per share forecasts, across all horizons, long term growth forecasts, and 12-month price target forecasts.

2.2 Analyst Work Habits Measures

Average Workday Length (*AWL*):

To measure *AWL*, use an unsupervised machine learning algorithm - the Gaussian Mixture Model - to identify analysts' typical work habits in a given quarter based on Bloomberg Terminal usage patterns.

Figure 2 illustrated the algorithm for a specific analyst-quarter observation. In the figure, the blue bars represent relative usage patterns throughout the 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 know the probability P^j_{min} that the analysts is actively using the terminal every minute of the day $j \in J \equiv$\{12:00 am, 11:59 pm\}. We construct a pdf by computing $p^i_{min} = P^i_{min}/\sum_J P^j_{min}$. By construction, $\sum_J P^j_{min} = 1$. We then assume that the constructed distribution is a mixture of two normal distributions $k \in \{1, 2\}$, each with mean μ_k and variance σ^2_k, where $\mu_2 > \mu_1$. This captures the notion that analysts' work habits may differ before and after lunch. As mentioned, a reduction in activity on the terminal is the norm in the sample.

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

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

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

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

The EM algorithm consists of two steps: the estimation step (E-Step) and the maximization step (M-Step). In the E-Step, the expectation of the log-likelihood function is calculated for a given set of parameters. In the M-Step, the parameters are re-chosen in order to maximize the expectation. The process continues, iterating between the E-Step and the M-Step until the sequence converges. In our case, the likelihood function involves the likelihood of observing the data given that there are two unobservable Gaussian distributions generating the data. We implement the procedure using the skikit-learn libarary for Python.[6]

Returning to the example in Figure 2, 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 $(\mu_1 - \sigma_1, \mu_2 + \sigma_2)$. For this example, AWL is 9.12 hours.

Percentage Away Day (*PAD*):

To identify "travelling" analysts, we count days when the analyst do not log in to the Bloomberg terminal at all. Specifically, we first define 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. We then average the dummy variable within a quarter to compute the

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

Percentage Away Days (*PAD*).

Clearly, *PAD* measures analysts' work-related travel with errors. Analysts in our sample are frequent users of Bloomberg. It is very likely that they will login to their Bloomberg terminals first thing after they arrive at their offices. Still, it is 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 travelling 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 worked-related travels. To further alleviate measures error in *PAD*, we will focus on a simple "travelling" analyst dummy variable in our main empirical analyses. We identify "travelling" analysts in a quarter as those whose *PAD* is above the median in that quarter. Travelling analysts are more likely to specialize in producing soft information from attending events organized by the firms, meeting management face-to-face, and visiting sites. In contrast, analysts with low *PAD*s are more likely to rely on hard information when making forecasts.

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 can see that the average number of unique stocks covered over the previous four quarters is 17.85. The number of unique industries based on GICS 6-digit codes is 3. The average number of Q1 (Y1) forecasts in a given quarter is 23.1

(24.79). This is based on 16.07 unique stocks, where 77% of the forecasts are for common stocks (Share code 10 or 11). Other forecasts include long-term growth with an average of 5.67 forecasts; stock recommendations with an average of 3.28 recommendations; price targets with an average of 11.8; and all other forecasts with an average of 140.1 forecasts. The number of stock recommendations and price targets is lower than the number of earnings forecasts, with an average of 3.28 and 11.81, respectively.

Panel B reports each group averages together with their differences and associated p-values. Overall, the comparison reveals that Bloomberg analysts are more active than those in the comparison sample, but the differences are not large. For example, Bloomberg analysts cover 2 more stocks and issue 1.75 more quarterly forecasts, on average. Bloomberg analysts also issue 0.4 (1.36) more recommendations (price targets). Finally, both groups display better accuracy than analysts that are not in the same 42 brokerage firms.[7] This is consistent with the fact that larger brokerage firms have more resources and thus are more accurate. 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 the Bloomberg terminal (Panel A), together with the log-in based measures (Panel B), and their correlation matrix (Panel C). Panel A indicates that on average analysts are logged-in to the terminal on 71.7% of the work days. Analysts are active on average 362 minutes (6 hours) per day, which amounts to 30.14 hours per week.

Providing more granular information, Figure 3 depicts the average time spent on the Bloomberg terminal by day-of-the-week and holidays. As in Panel A of Table 2, the daily time spent on the terminal is around 6 hours, but it drops to 5 hours on Fridays. The log-in activity is small during weekends and holidays. In addition, Graph A of Figure 4 plots the

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

average daily minute activity across analysts in a given quarter over time. There is a sharp increase in the minutes spent on the terminal 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. 80% of the time, *AWL*s range from 8 hours to 12 hours. The average *PAD* is 0.283. The distribution of *PAD* is wider, with the 10th percentile of 0.033 and 90th percentile of 0.656.

For emphasis, *AWL* is different from intensity of Bloomberg usage. Using intraday distribution of Bloomberg usage within a quarter, *AWL* tries to measure the typical length of analyst' workday in that quarter, without assuming Bloomberg usage throughout the day. We measure the intensity of Bloomberg usage using *LnCondActive*, defined as the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter. The correlation between *AWL* and *LnCondActive*, while positive, is only 0.25. Not surprisingly, *AWL* and *PAD* are negatively correlated, though the correlation of -0.23 is not huge, suggesting that "working hard" and "working smart" are not substitutes to each other.

Graphs A-C of Figure 4 provide additional information at the quarterly level. Similar to the minutes spend 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* has dropped significantly from Q1 of 2020.

Finally, Figure 5 depicts the log-in measures averages based on stock coverage deciles. In particular, we rank analyst-quarter observations based on the number of stocks that an analyst covered during the recent year. Decile 1 (10) refers to the lowest (highest) number of stocks covered. It is probably not surprising that *PAD* generally increases with the number of stocks covered. For *AWL*, we also observe a positive relation with the stock coverage beyond the first three coverage deciles. In our empirical tests, we control for such mechanical correlations with coverage $\times$ time fixed effects, whenever possible.

2.4 Work Habit Determinants

2.4.1 Login Activity and Market Information

As mentioned, the Bloomberg terminal 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. We show that analysts increase their login activity in response to public information about stocks they cover. To confirm this link, we focus on the 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. Next, various measures of news (RavenPack News Analytics) indicate that analysts increase their login behavior if stocks that 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 $(0.43 \times 0.08 =)$ 0.0344 increase in abnormal login activity. Since the average login activity during 7-9 am is around 0.269, this means an increase of 12.8%. Finally, the pre-market login activity is positively correlated with AWL (a correlation of 0.24), which connects between AWL and analyst effort.

2.4.2 Work Habit Variations 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, and broker fixed effects. We then continue with regressing 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 work histories, the locations of their branch offices, and which FINRA Qualification Exams the analysts have passed. The full name and work history from FINRA helps us locate LinkedIn accounts which provides educational background and Facebook accounts which helps identify whether analysts have children.

Panel A of Table 4 indicates that analyst fixed effects are the most important determinant in explaining the variation in both *AWL* and *PAD*, with an R-squared of 49.8% and 57.2%, respectively. Put differently, *AWL* and PAD are both analyst characteristics. Next, broker fixed-effect explain 9.5% and 12.7% of the variation in *AWL* and *PAD*, which is consistent with work place culture. Both analyst characteristics also change over time, with time fixed-effect explain 5.5% and 9.5% of the variation in *AWL* and *PAD*. The time variation is in part due to the COVID lockdown as evident in Figure 4.

The analysis of analyst characteristics reported in Panel B of Table 4 reveals that analyst time on I/B/E/S (*IBES Years*) and seniority (*High Rank Indicator*) are two important determinants of *AWL* and *PAD*. In particular, an increase in years in the I/B/E/S sample leads to a reduction in *AWL*, but to an increase in *PAD*. In a similar manner, being more senior leads to a lower *AWL* and a higher *PAD*. Other work experience variables such as total work experience (*Work Experience*) and the number of jobs that an analyst had switched (*# Jobs FINRA*) are not statistically nor economically significant. In addition, variables such as NYC location, MBA degree, gender, children and qualifying exam do not load significantly or consistently across the *AWL* and *PAD* specifications. These variables only add around 0.003- 0.027 to the R-squared. Finally, including brokerage firm fixed effects does not alter these findings, but adds between 0.045-0.072 to the R-Squared.

3 Analysts' Work Habits and Performance

3.1 Analysts' Output

In this section, we examine how analysts' work habits are related to their forecast outputs. Table 5 reports results from panel regressions of analyst output on *AWL*. We consider quarterly (Q1) and annually (Y1) earnings forecasts (Panel A), together with other earnings forecasts and price targets (Panel B). We control for lagged dependent variable (*AveDep t-4_t-1*), analyst experience (*IBES Years*), and the average number of industries covered (*Ave # of Industries t-4_t-1*). We include Coverage × Time fixed effects and analyst fixed effects. Standard errors are clustered by analysts.

The *AWL* coefficient estimates are positive and significant regardless of the specification used. Specifications 1 and 5 of Panel A indicate that an one hour increase in *AWL* is associated with an increase of around 0.25 in the number of quarterly forecasts and 0.364 in the number of annual forecasts. In contrast, the coefficients on the "traveling" analyst dummy are negative and significant. Specifications 2 and 4 suggest that relative to their peers, "traveling" analysts with above-median *PAD* produce 1.095 less quarterly forecasts and 1.082 less annual forecasts. The results are similar in Specifications 3 and 7 when *AWL* and *HIGH_PAD* are included simultaneously. Finally, Specifications 4 and 8 further included analyst Fixed-effects and the coefficients become bigger in absolute terms. For example, for the same analyst, an one hour increase in *AWL* is associated with an increase of around 0.306 in the number of quarterly forecasts and 0.539 in the number of annual forecasts. For the same analyst, when she travels more, the number of quarterly (annual) forecasts decreases by 1.554 (1.749).

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

3.2 Analysts' Timeliness

Next, we explore another dimension of analysts output, the timeliness of their forecasts. Timeliness is defined as "how quick an analyst is to issue a forecast after an earnings announcement." Our timeliness measure is calculated as the natural logarithm of the average time in days between the earnings announcement and the subsequent forecast, across all stocks covered by the analyst. Table 6 reports the results. We control for analyst experience (*IBES Years*), the number of Q1 forecasts during the quarter (*# Q1 EPS Forecasts*), the number of industries covered (*Ave # of Industries t-4_t-1*), and analyst forecast accuracy (*Ave Q1 PMAFE t-4_t-1*).

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

3.3 Analysts' Forecast Accuracy

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

We run the 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, how early the analyst forecast is relative to its peers (*Early Forecast*), past analyst accuracy (*Ave Q1 PMAFE t-4_t-1*), number of quarterly forecasts and industries covered (*# Q1 EPS Forecasts*, and *# of GICS6 Industries*), firm size, firm book-to-market, return volatility and institutional holdings.

Table 7 reports the results. Coefficient estimates for both *AWL* and *HIGH_PAD* are negative and significant, regardless of the specification used. In other words, both "working harder" and "working smart" seem to contribute to forecast accuracy. In terms of economic significance, an one hour increase in *AWL* is associated with a reduction in *PMAFE* ranging from 0.5% to 0.7%, or 1.3% to 1.8% of its mean. Similarly, the *PMAFE* of a "traveling" analyst is 1.2% to 1.9% lower than that of her peer, or 3.1% to 4.9% of its mean.

4 Work Habit and Productivity: 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 have been canceled. Our minute-by-minute Bloomberg online status data uniquely allow us to examine in details how sell-side equity analysts changed their work habit during that period. In addition, to the extent that the shocks to their work habit are largely exogenous, we can establish 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 can 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 a 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 a workday. We keep the minimum time based on foot, car, public transport, and bicycle travel. Figure 6 illustrates how we collect this information using a fictitious home address (to preserve anonymity of the analysts in our sample). These filters leave us with 102 identified analysts with full information. Of these 102 analysts, 87 are from the New York area, 7 are from San

Francisco, 6 are from Houston, and 2 are from Chicago.

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

4.1 Pre-COVID *PAD* Identification Strategy

Table 8 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 groups contains the remaining analysts who rarely travelled pre-COVID. The POST dummy equals 1 for 2020Q1-2020Q2 and 0 for 2019Q3-2019Q4. The coefficient on the interaction term ($TREATMENT \times POST$) identifies the impact of *PAD* on forecast outcomes. We examine both the quantity (the number of quarterly, annual EPS forecasts and price target forecasts) and the quality (relative forecast accuracy measured by *PMAFE*) of the output.

Focusing on the treatment effect (*TREATMENT*), consistent with the full sample results in Tables 5 and 7, traveling analysts issue significantly less forecasts and the forecasts are slightly more accurate (though not significant). Focusing on the post effect (*POST*), with all analysts locked down at home, not surprisingly, their outputs increase significantly. The accuracy measure *PMAFE* is not significantly affected since it is a relative accuracy measures (which should not change over time on average). Finally, focusing on the interaction term ($TREATMENT \times POST$), we find the traveling analyst to experience an increase in output (though insignificant) during the COVID lockdown. More importantly, their accuracy (relative to their peers) decreases significantly, as reflected in a significant increase in *PMAFE* of 11.7%. The result provides causal evidence that soft information extracted by traveling analysts increase forecast accuracy.

4.2 Commute Time to Work Identification Strategy

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

To understand such a choice, in Panel A of Table 9, 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 of an analyst with kids under 18-years old, and a few other analyst characteristics reported in Panel B of Table 4 such as yeas in I/B/E/S, MBA degree, work experience, and analyst rank. The average analyst age in the $pre-COVID$ analyzed sample is 44, where the youngest analyst is 30 years old, and the oldest is 62 years old. The pre-COVID sample also includes 10 female analysts and 19 analysts with kids under 18 years old. Both Du (2021) and Li and Wang (2021) document that female analysts, especially those with young children are more negatively affected by the COVID lockdown. By observing their *AWL*s, we can precisely quantify the impact of analysts personal characteristics on their changing workday length.

Table 9 Panel A presents clear evidence that the only significant predictor of analysts' changing *AWL* during COVID lockdown is their commuting time pre-COVID. The result is very intuitive. COVID lockdown makes commuting to office impossible, and analysts spend the time saved from commuting on work. Indeed, Table 9 suggests that one hour saved from not commuting leads to a workday that is 1.3 to 1.4 hours longer. Such a strong and positive relation between pre-COVID commute time and change in *AWL* during the lockdown is evident in the decile bin scatter plot in Figure 7. Importantly, the commute time is measured pre-COVID and therefore cannot be affected by events during the COVID, it can therefore be used as a nice instrument for the change in AWL during the lockdown.

Table 9 Panel B examines the causal impact of AWL on forecast outcomes in a difference-in-difference setting, very similar to that in Table 8. The treatment group ($TREATMENT$) consists of analysts with below-median commute time pre-COVID (2019Q3-2019Q4) who are predicted to have higher increase in AWL during COVID lockdown. The control groups 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 affect forecast outcomes pre-COVID. The post effect again suggests a significant increase in the amount of forecasts issued, as analysts are locked down at home. $PMAFE$, being a relative forecast accuracy measures, does not change for an average analyst. Finally, focusing on the interaction term, we find that analysts with long commute time pre-COVID to experience further increase in output during the COVID lockdown. More importantly, their accuracy (relative to their peers) increases significantly, as reflected in a significant decrease in $PMAFE$ of 8.5%. The result provides causal evidence that a longer workday length increases both the quantity and quality of the forecast.

5 Conclusion

Despite the importance of equity analysts, we still know relatively little about how they spend their working hours. In this paper, we take advantage of their minute-by-minute Bloomberg usage data to quantify two dimensions of their work habits: their average workday length and their soft information production. We find both working harder and working smarter to improve the accuracy of their earnings forecasts.

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

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

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Figure 1: Bloomberg Screenshot

The figure provides a screenshot for Michael Bloomberg that was obtained using the profile search on the Bloomberg terminal. The green dot by Michael Bloomberg's name indicates that he is online. Other possible status indicators are a red dot (offline), a yellow dot (idle), a gray dot (private, opted out), and a mobile phone icon indicates (user is on the mobile Bloomberg app).

Figure 2: 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 $(\mu_1 - \sigma_1, \mu_2 + \sigma_2)$.

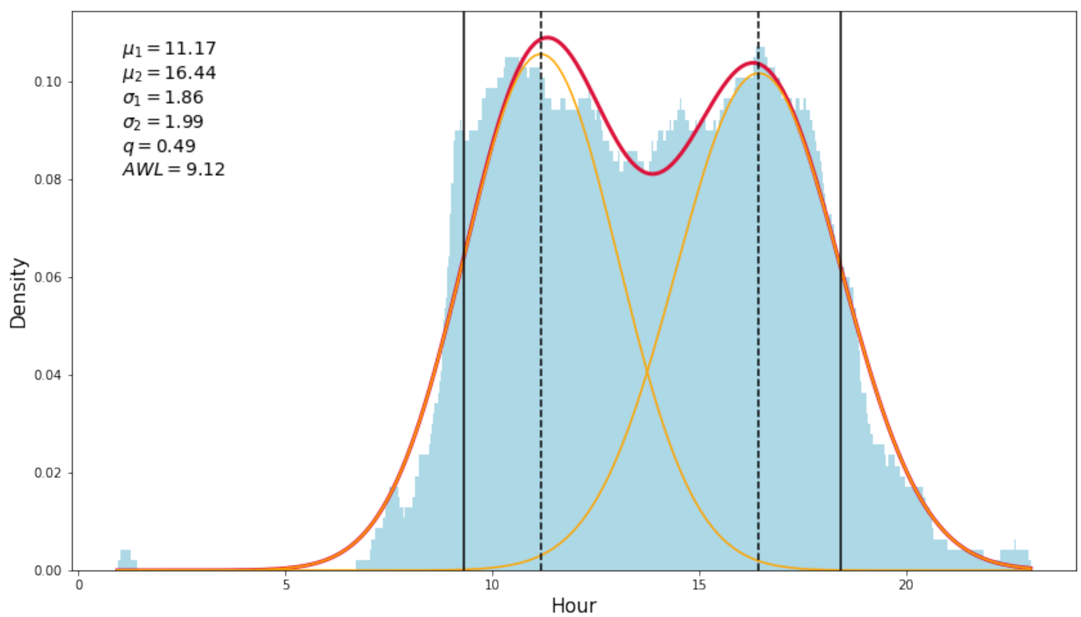


Figure 3: Minutes Active on Terminal based on Day-of-the-Week and Holidays

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

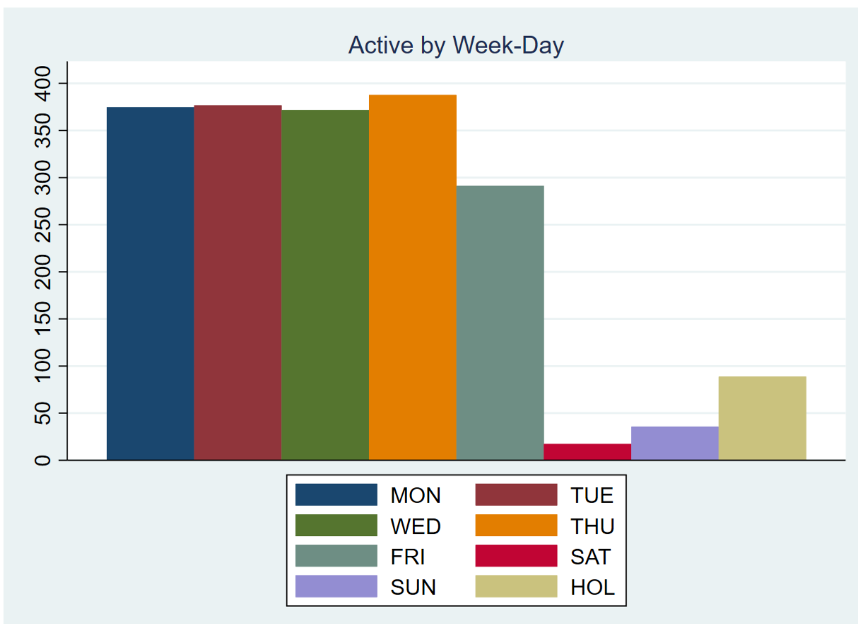
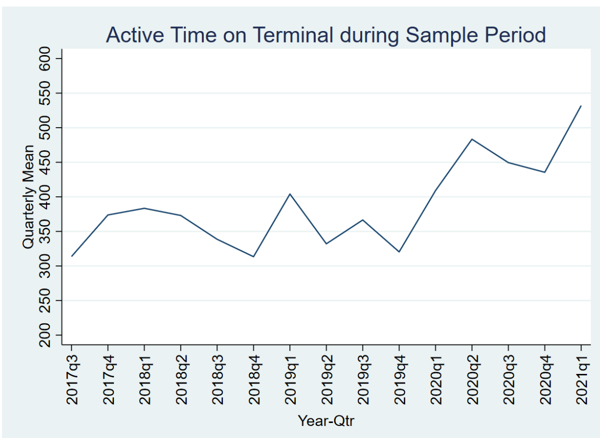


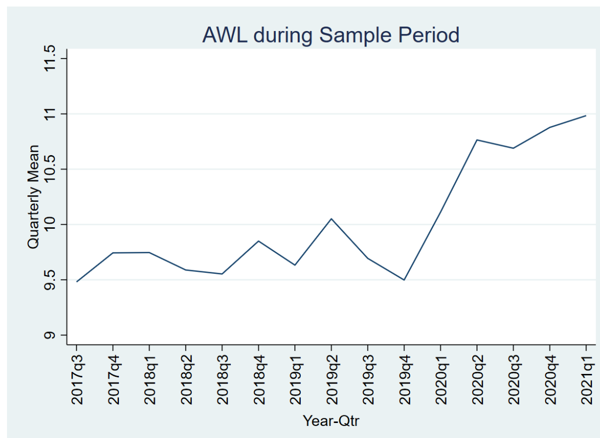
Figure 4: *AWL*, *MPD_ACTIVE* and *PAD* during Sample Period

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



Panel B: *AWL*



Panel C: *PAD*

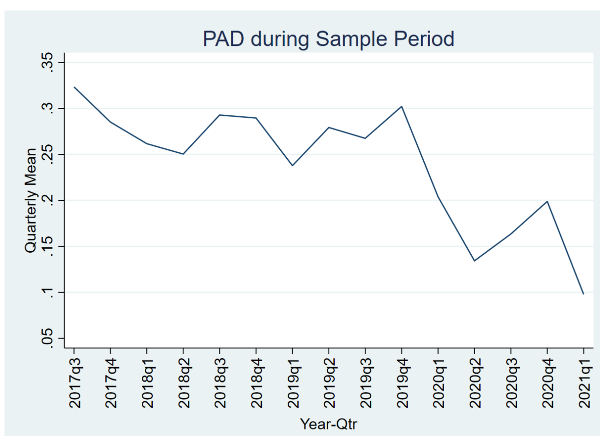
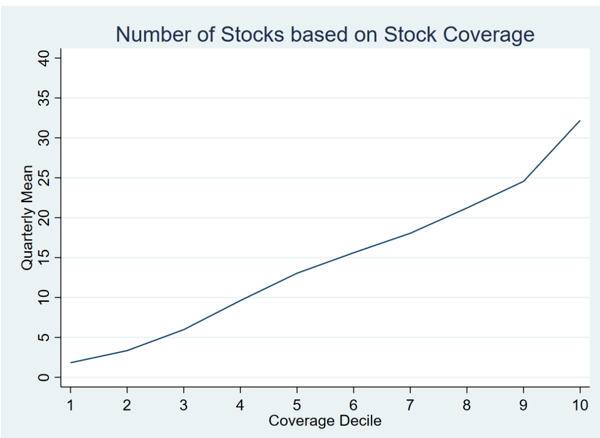


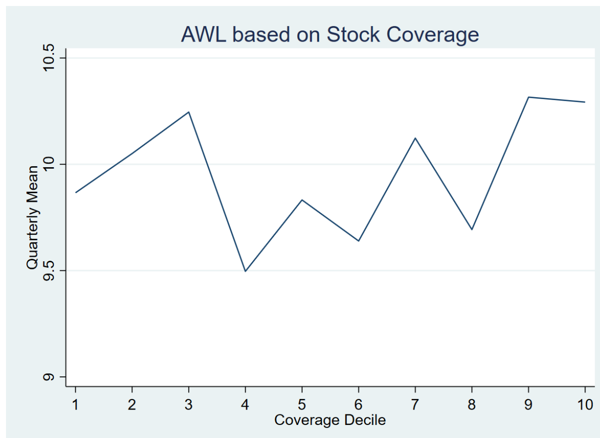
Figure 5: Stocks, *AWL*, Time Active and *PAD* based on Coverage

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

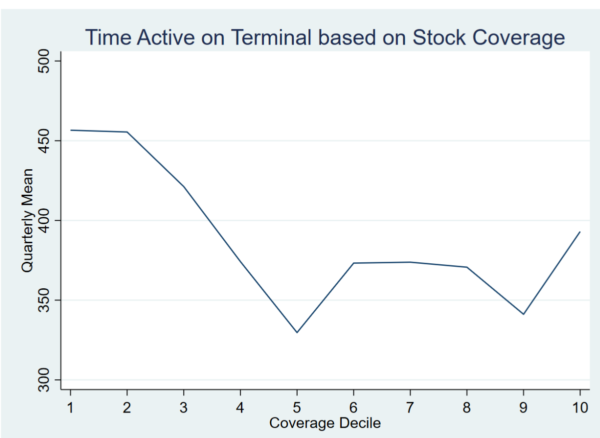
Panel A: Number of Stocks



Panel B: *AWL*



Panel C: Conditional Active Time on Terminal



Panel D: *PAD*

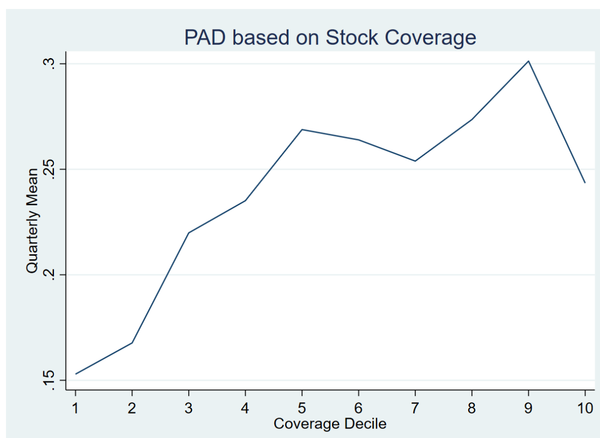


Figure 6: Measuring Commute Time - Example

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

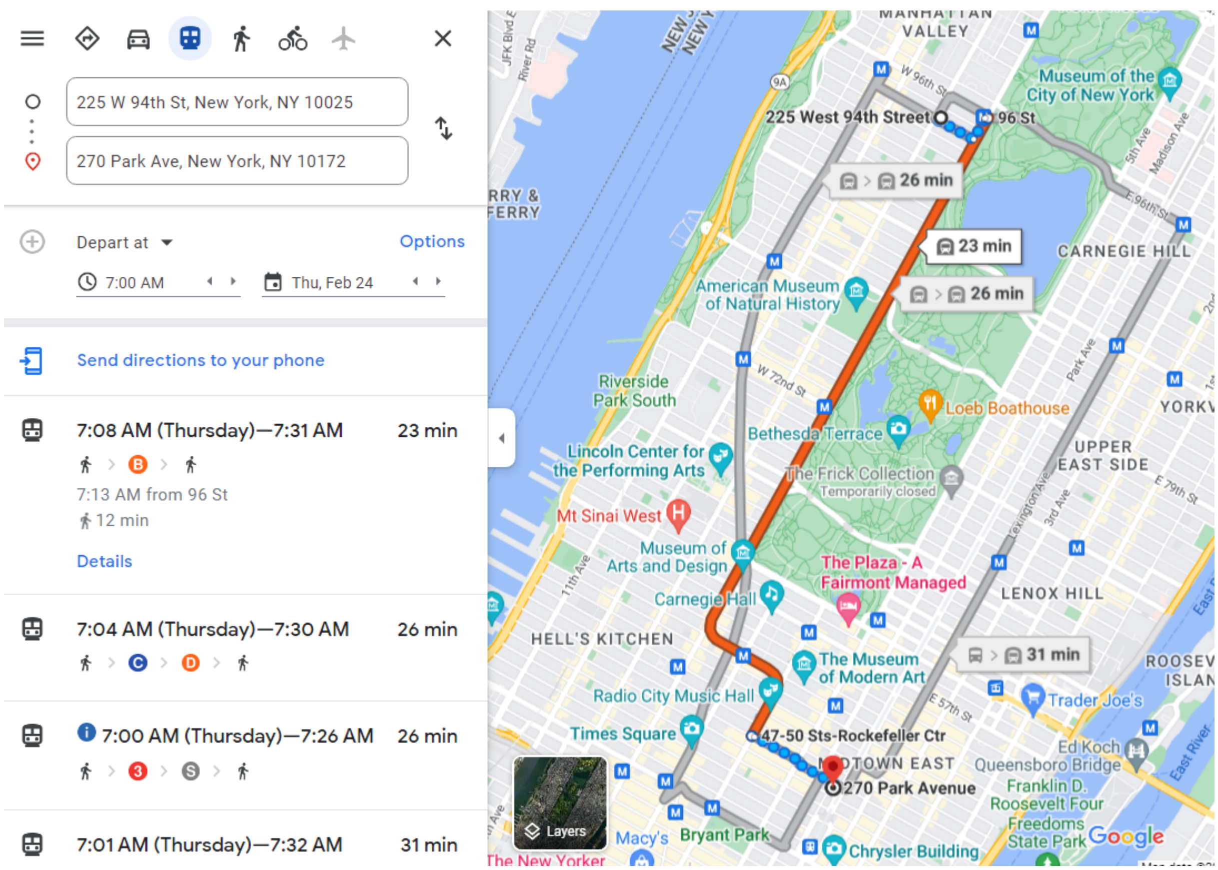


Figure 7: Changes in *AWL* and Commute Time Saved

This figure illustrates the relation between *AWL* and commute-time-saved reported in Table 9, where changes in *AWL* (Q1-Q2 of 2020 minus Q3-Q4 of 2019) are plotted against commute-time-saved deciles. The x-axis reports the average commute time saved for each decile, where the y-axis reports the corresponding average change in *AWL*.

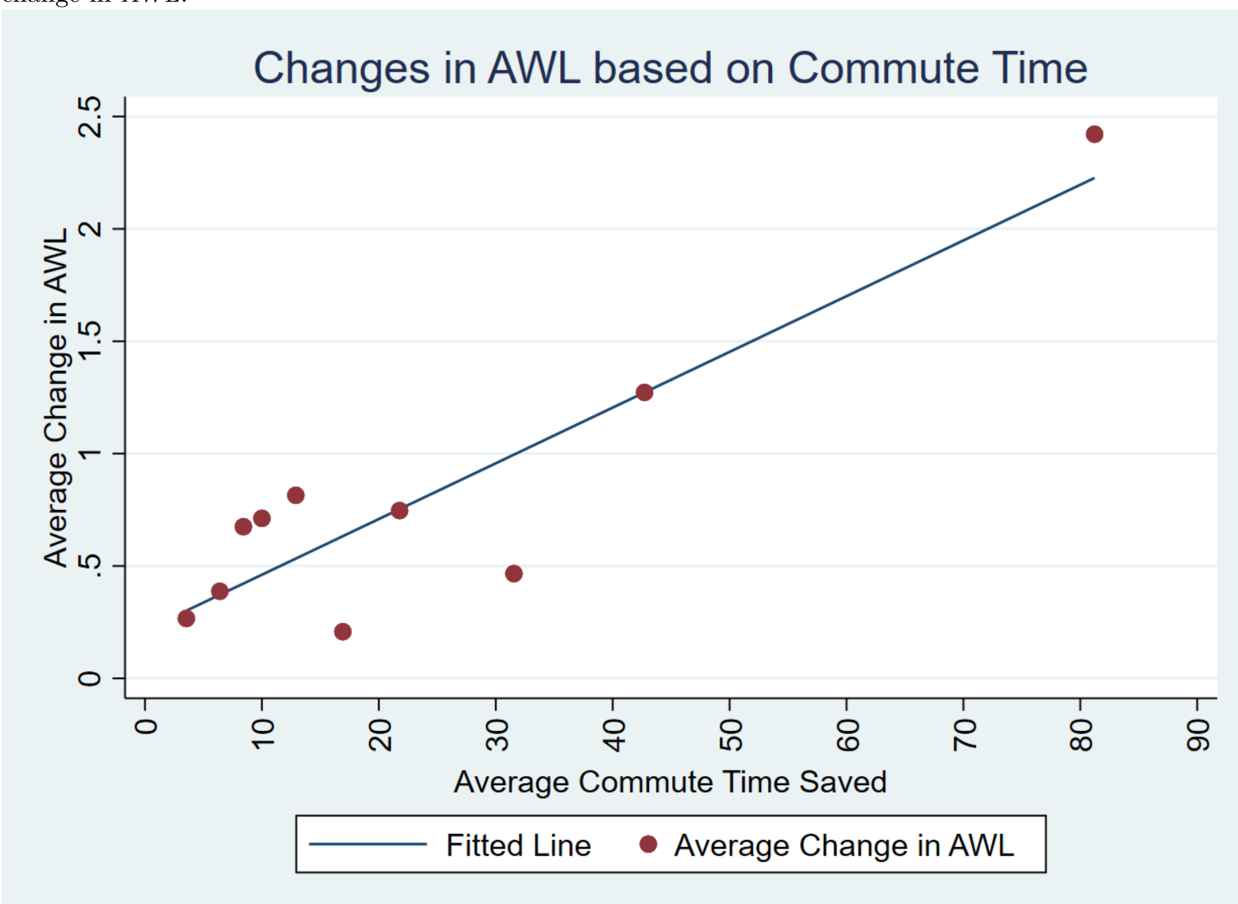


Table 1: Summary stats of analyst output

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

Panel A: The Bloomberg Sample Summary Statistics

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

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

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

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

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

Panel A: Log-in Statistics

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

Panel B: *AWL* and *PAD* statistics

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

Panel C: Correlation matrix

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

Table 3: Analysts Pre-Open Daily Abnormal Login Activity

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

	Analysts Average LogIn Activity During 7-9 AM					
	(1)	(2)	(3)	(4)	(5)	(6)
# Stocks in AbnVOl Decile t-1	0.007***	0.007***	0.006***	0.006***	0.005***	0.005***
	(6.44)	(6.45)	(5.89)	(5.87)	(5.22)	(5.23)
# Stocks in AbsExtRet Decile t-1	0.001	0.001	0.001	0.001	0.001	0.001
	(1.03)	(1.04)	(0.83)	(0.83)	(0.95)	(0.96)
# Stock with AMC News t-1	0.005***			0.004***	0.002	
	(3.35)			(2.65)	(1.33)	
# Stock with AMC Earn News t-1		0.008***				0.001
		(2.87)				(0.25)
# Stock with AMC AR News t-1		-0.013				-0.012
		(-1.53)				(-1.29)
# Stock with BMO News t			0.013***	0.013***		
			(9.06)	(9.06)		
# Stock with BMO Earn News t					0.080***	0.080***
					(12.37)	(12.39)
# Stock with BMO AR News t					0.004***	0.004***
					(3.16)	(3.17)
# Max Industry Earn BMO News Pressure t					0.056***	0.056***
					(3.18)	(3.18)
Analyst FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Coverage FE	YES	YES	YES	YES	YES	YES
Date Cluster	YES	YES	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES	YES	YES
Observations	141,472	141,472	141,472	141,472	141,472	141,472
R^2	0.138	0.138	0.140	0.140	0.149	0.149

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

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

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

	AWL			PAD		
	(1) TIME	(2) ANALYST	(3) BROKER	(4) TIME	(5) ANALYST	(6) BROKER
R^2	0.055	0.498	0.095	0.095	0.572	0.127
Observations	2,874	2,874	2,874	2,874	2,874	2,874

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

	AWL				*HIGH_PAD*			
	(1) *AWL*	(2) *AWL*	(3) *AWL*	(4) *AWL*	(5) *HIGH_PAD*	(6) *HIGH_PAD*	(7) *HIGH_PAD*	(8) *HIGH_PAD*
IBES Years	-0.039***	-0.038***	-0.042***	-0.037**	0.007**	0.007*	0.007*	0.007**
	(-2.68)	(-2.62)	(-2.82)	(-2.31)	(1.97)	(1.91)	(1.95)	(2.20)
High Rank Indicator	-0.446**	-0.487***	-0.529***	-0.418**	0.142***	0.138***	0.143***	0.122**
	(-2.50)	(-2.77)	(-3.08)	(-2.40)	(3.08)	(2.98)	(3.07)	(2.58)
Work Experience	0.007	0.000	0.000	-0.009	-0.000	0.000	0.000	0.001
	(0.45)	(0.02)	(0.01)	(-0.53)	(-0.03)	(0.03)	(0.03)	(0.27)
# Jobs FINRA	-0.033	-0.029	-0.039	-0.044	0.008	0.008	0.009	0.017
	(-0.73)	(-0.65)	(-0.87)	(-0.86)	(0.65)	(0.71)	(0.78)	(1.32)
NYC Indicator		0.319*	0.355**	0.160		0.031	0.027	0.011
		(1.81)	(2.06)	(0.73)		(0.68)	(0.60)	(0.19)
MBA Indicator		0.254	0.288	0.489		-0.110	-0.113	-0.145*
		(0.55)	(0.63)	(1.11)		(-1.45)	(-1.50)	(-1.87)
Female Indicator		0.091	0.099	-0.026		0.001	0.000	0.003
		(0.41)	(0.45)	(-0.11)		(0.02)	(0.00)	(0.05)
Children Indicator		0.263	0.283	0.110		-0.091	-0.093	-0.088
		(0.49)	(0.53)	(0.20)		(-0.74)	(-0.76)	(-0.66)
Principal Exam			0.375	0.208			-0.037	-0.047
			(1.63)	(0.83)			(-0.62)	(-0.82)
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	2,533	2,533	2,533	2,532	2,533	2,533	2,533	2,532
R^2	0.196	0.214	0.218	0.268	0.142	0.145	0.145	0.215

Table 5: Analyst Output Regressions

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

Panel A: Earnings Forecasts

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

Panel B: Other Forecasts

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

Table 6: Analyst Timeliness Regressions

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

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

Table 7: Analyst Stock Level Accuracy Regressions

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

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

Table 8: *PAD* and COVID lockdown Identification Strategy

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

	Output			Accuracy
	(1) Q1	(2) Y1	(3) PTG	(4) PMAFE
TREATMENT	-4.830**	-4.387**	-0.681	-0.049
	(-2.47)	(-2.12)	(-0.30)	(-1.34)
POST	5.546***	6.818***	8.164***	-0.038
	(3.15)	(3.48)	(4.15)	(-0.79)
TREATMENT × *POST*	2.410	1.511	2.631	0.117**
	(1.06)	(0.60)	(0.74)	(2.47)
Ave # Stocks t-4_t-1	1.071***	1.072***	0.829**	0.006*
	(3.08)	(2.93)	(2.07)	(1.79)
Ave # of Industries t-4_t-1	-0.447	-0.754	-1.207*	-0.008
	(-0.63)	(-1.04)	(-1.65)	(-1.21)
IBES Years	-0.370**	-0.298	0.100	-0.002
	(-2.08)	(-1.55)	(0.36)	(-0.78)
Ave Q1 PMAFE t-4_t-1	-1.151	0.052	-6.048	-0.015
	(-0.17)	(0.01)	(-0.70)	(-0.14)
Firm FE	YES	YES	YES	YES
Coverage FE	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Analyst Cluster	YES	YES	YES	YES
Observations	408	408	305	407
AdjR^2	0.561	0.555	0.400	0.036

Table 9: *AWL* and Commute Time Saved Identification Strategy

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

Panel A: *AWL* and Commute Time

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

Panel B: Output and Accuracy

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

A Appendix—Variable Definitions and Additional Tests

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

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

In Table A.3 we explore the relation between *LnCondActive* and analyst forecast accuracy similar to the analysis conducted in Table 7. Across all specifications *LnCondActive* coefficient estimates are negative and statistically significant, suggesting an improvement in the forecast accuracy. Compared with Table 7 the results are somewhat weaker, suggesting that accuracy also depends on other effort provisions during the analyst workday captured by *AWL*.

Finally, in Table A.4 we explore the analysts' timeliness dimension. *LnCondActive* coefficient estimates have the same sign as those reported in Table 6, but they are statistically insignificant, again, suggesting that *AWL* is a more comprehensive measure of the analyst workday activity.

Table A.1: Variable definitions

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

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

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

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

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

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

Panel A: Earnings Forecasts

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

Panel B: Other Forecasts

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

Table A.3: Analyst Stock Level Accuracy Regressions - *LnCondActive*

This table repeats the analysis conducted in Table 7, replacing *AWL* with *LnCondActive*. The sample period is from September 2017 to March 2021. See Table A.1 and Table 1 for details about variable and sample definitions. *LnCondActive* is the natural logarithm of the average daily minutes of active Bloomberg usage conditioning on days with Bloomberg activity in a quarter. Standard errors are clustered by analysts reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

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

Table A.4: Analyst Timeliness Regressions - *LnCondActive*

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

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