# Uncovering the Hidden Effort Problem[*]

Azi Ben-Rephael[†]
Bruce I. Carlin[‡]
Zhi Da[§]
Ryan D. Israelsen[‖]

December 14, 2023

**Abstract**

We analyze minute-by-minute Bloomberg online status and study how the effort provision of executives in public corporations affects firm value. While executives spend most of their time doing other activities, patterns of Bloomberg usage allow us to characterize their work habits as measures of effort provision. We document a positive effect of effort on unexpected earnings and cumulative abnormal returns following earnings announcements, and a reduction in credit default swap spreads. This is robust to using exogenous weather patterns as an instrument. Long-short, calendar-time, effort portfolios earn significant average daily returns. Finally, we revisit agency issues that have received attention in the prior academic literature.

JEL Codes: D23, D24, J24, L21
Keywords: Moral hazard, effort provision, firm value

[*] We are grateful for feedback from Tom Bates, Alex Butler, Alan Crane, Jeff Coles, David De Angelis, Gene Fama, Simon Gervais, Jessica Jeffers, Steve Kaplan, Mike Lemmon, Yang Liu, William Mann, Kevin Murphy, Stefan Nagel, Lubos Pastor, David Robinson, James Weston, David Yermack, and Luigi Zingales. Also, we acknowledge helpful feedback from seminar participants at the University of Chicago, Washington University in St. Louis, University of Texas, Notre Dame, University of Maryland, Drexel University, Rice University, University of Alberta, Nanyang Tehcnological University, George Washington University, Central University of Finance and Economics, and Dongbei University of Finance and Economics, and conference attendees at the ASU Sonoran Winter Finance Conference the 2020 Northern Finance Meetings, and the 2021 American Finance Meetings. We also appreciate the advice and counsel from Richard Zansitis (Vice President and General Counsel for Rice University). This study was approved by the IRB at Rice University and use of the data was approved by Bloomberg Finance L.P.

[†] Azi Ben-Rephael is at Rutgers Business School. abenrephael@business.rutgers.edu , +1 (973) 353-1728.
[‡] Bruce Carlin is at the Jones School of Business at Rice University (carlin@rice.edu) and the NBER.
[§] Zhi Da is at the Mendoza College of Business at University of Notre Dame. zda@nd.edu, +1 (574) 631-0354.
[‖] Ryan Israelsen is at the Broad College of Business at Michigan State University. israels4@msu.edu, +1 (517) 353-6982.

## 1. Introduction

The moral hazard problem due to hidden effort is ubiquitous, but is hard to study empirically. If the principal in any organization cannot observe the effort provision made by their executives, it is a bigger challenge when an outside empiricist or a market investor wants to study basic questions such as whether executive effort affects firm value or what motivates them to work harder. Outsiders can perform statistical inference, much like the principal, based on compensation contracts and firm outcomes (e.g., stock prices or earnings). But these calculations are limited because they face the hidden action problem too.

How could one study an executive's work habits (e.g., their workday length) without inducing an observer effect or covertly spying on them?[1] A good prospect would be to find something that is highly correlated with the time they spend working, like the amount of time their office lights are on (at home or work), their computer is active, or their office phone (or cell phone) is in use. Certainly, none of these is perfect, but they do convey some information about an executive's daily work habits.

In this paper, we hand-collect usage microdata from personal Bloomberg accounts for CEO's, CFO's, and other top executives from publicly traded firms, many of which are in the S&P500 and are not financial firms. Clearly, we expect most executives to be doing other tasks than using Bloomberg all day, so we do not use the intensity or total time on the platform in our tests. Instead, we use an algorithm based on quarterly or annual login activity to estimate the length of their workday, as a proxy of effort provision. We perform cross-sectional and time series tests to examine how this effort affects firm value, and we revisit several agency issues that have received attention in the past, such as the effect of compensation discontinuities and peer competition on executive behavior.

Bloomberg is commonly used in Corporate America as a source of financial information and a way for corporate executives to communicate with analysts and market investors via instant messaging. When users are logged into their personal account, they are identified as "online" to others, and this is publicly observable. A green dot on an executive's profile page indicates that he/she is actively using the terminal. If the user were to become inactive for greater than 15

[1] Direct monitoring has been used to assess *how* executives spend their time (e.g., Mintzberg, 1973; Bandiera, Hansen, Pratt, and Sadun, 2020). But explicit monitoring and self-reported data present obstacles when examining moral hazard problems like effort provision because explicit monitoring may change their behavior (produce an observer effect).

minutes, the dot would turn yellow. If an executive is offline, the dot is red, and if a telephone icon appears, it indicates he/she is using the mobile application.[2]

We collected this on-line status, minute-by-minute, during 2017-2020 and provide evidence that monitoring Bloomberg usage is a plausible way to measure work effort. We simultaneously collected cell phone location data and provide anecdotal evidence that our measures of Bloomberg usage capture when executives are in their corporate office. We show that Bloomberg activity spikes around earnings announcements for both CEO's and CFO's, and that its intensity of use was higher during the COVID pandemic when executives' business travel was restricted. We also show that Bloomberg usage drops for executives when their local weather is more favorable during the spring and summertime, consistent with more leisure and less work effort.

Importantly, we show that the account activity that we measure directly depends on the owner of each account, not someone else at the firm. We amass a dataset of events where an executive is participating or speaking, and document almost no simultaneous activity on the Bloomberg platform. For example, we show that during analyst and investor days, the Bloomberg account for every single executive in our sample is inactive.

We use data across an entire year or quarter to estimate the typical start time and end of a workday for each executive, and the average workday length is computed as the difference. The algorithm takes into account that executives may not use Bloomberg every day and often login intermittently and sporadically. Figure 1 shows a histogram of the annual daily usage for one of the CFO's in our sample. For each minute of a 24-hour period, the y-axis measures the probability that the executive is active on their Bloomberg account during the course of a year. As is common in our data, there is a peak mid-morning and in the afternoon, with a dip during lunchtime.

Our estimation-maximization (EM) algorithm uses the observation that this function appears to be similar to a mixed distribution of two normal distributions, one for the morning and one in the afternoon. The algorithm provides estimates of the underlying moments of the two distributions and we construct a distance measure called the Average Workday Length (*AWL*) to

[2] We did not collect any private information about what the executives actually did on the platform: 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 platform as a proxy for work effort, we did not collect any sensitive information from corporate firms and kept all identities anonymous in our analysis. Once subjects were matched to compensation and firm information, 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.

proxy for the length of each executive's workday.[3] It is important to note that an executive can access Bloomberg sporadically and have a high *AWL*. So, *AWL* is different from measures of the intensity of overall Bloomberg usage.

We investigate the effect of *AWL* on firm performance in several ways. In our regressions, we include individual executive fixed effects to control for all time-invariant, unobserved characteristics. We also include measures of insider trading to account for the influence that private information potentially has on earnings surprises and abnormal returns.

Using a measure of standardized unexpected earnings (*SUE*; Foster, Olsen, and Shevlin, 1984), we find that higher effort is associated with subsequent earnings surprises. Then, we show that effort provision has a positive and persistent effect on cumulative abnormal returns (CAR's) following earnings announcements. A one-hour increase in the average workday length is associated with a CAR of 25-50 basis points that persists for 10 weeks following the announcement. Motivated by this result, we form calendar-time portfolios using a trading strategy based on extreme changes in quarterly executive effort relative to past effort. We document that a risk-adjusted, long-short effort portfolio yields 7.33 basis points per day (37 bps over 5 days), a quantity that is plausible, robust, and statistically significant.

Not surprisingly, fifty percent of the firms in our sample are from the finance industry. One concern is that this is driving our results. To address this, we separately analyze the subset of non-financial firms and find that our SUE and CAR results are at least as strong, if not stronger. For non-financial firms, a one-hour increase in the average *AWL* is associated with a CAR of 80-100 basis points at 7-10 weeks following an earnings announcement.

Another valid concern is that measures of firm value and our measure of executive effort are co-determined. To address this, we use exogenous local variation in weather patterns as an instrument. Daily historical data from Weather Underground allows us to divide days in each quarter into good and bad days. This is an exogenous variable that we include in first stage regressions.[4] Then, in second stage regressions, using fitted values we show that predicted *AWL* is associated with both earnings surprises and cumulative abnormal returns. Also, we show that the earnings improvements associated with predicted *AWL* accumulate over time (subsequent

[3] We collected cell phone location data and show that it appears to corroborate that *AWL* provides a meaningful estimate of work activity. Besides *AWL*, as we discuss in the paper, we have also constructed other Bloomberg-based measures of daily workday effort and find our main results to be robust. We include those in the Appendix.

[4] We validate this instrument using cellular geolocation data.

quarters), do so more quickly for higher Q firms, and appear to arise through lower costs, not higher revenues.

Another consideration is that executives are frequently compensated based on their firm's earnings or stock price. These measures might be subject to some degree of manipulation. To address this, we collect data on credit default swaps that are traded on the firms in our sample. To our knowledge, no executive is explicitly given incentives to improve the default risk of their firm as measured by the credit default swap spread. Consistent with the earnings findings, we find that an increase in average *AWL* in one quarter is associated with an improvement (a reduction) in the firm's CDS spreads in the next quarter.[5]

Our ability to estimate executive effort allows us to investigate some agency issues that have received attention in the academic literature. The first is how executives behave when there are discontinuities in their compensation (Healy, 1985; Degeorge, Patel, and Zeckhauser, 1999; Murphy, 2000).[6] The mere presence of goals and targets induces kinks, whereby earning compensation may be outside an executive's locus of control.

To investigate this, we study changes in executive *AWL* in response to firm performance *within* the fiscal year. Specifically, we consider whether firm performance in the 1st half of the year affects whether earning a cash bonus is within an executive's locus of control for the second half.[7] We document a large, positive, and statistically significant change in *AWL* when midyear performance is on pace with set targets. But, when midyear earnings are either exceeding or lagging behind compensation targets, executives employ less effort. Since the targets do not change, but beliefs about achieving them do, this within-executive result is a causal effect.

Finally, we consider how competition with other firms affects executive effort. We analyze how the growth in sales of competing firms in an industry affects *AWL* over the next quarter when the quarterly results are revealed. The idea is that executive performance is also measured by changes in market share. Thus, a reduction in market share relative to peers should result in more effort (i.e., a higher *AWL*). We find that, while a firm's *own* growth in sales has no significant effect

---

[5] The magnitudes are small, but statistically significant. A one hour increase in average AWL is associated with a reduction of -1.50 basis points. Firms in our sample have an average of $34.7 billion in long-term debt. This amounts to an annual savings of $5.2 million. While small, this does appear to be an economically plausible effect.

[6] For example, Healy (1985) shows that floors and caps in compensation plans give executives the incentive to manage earnings.

[7] For the executives in our sample, their compensation contracts did not change within the year. We confirm this by reviewing 8-K filings for the firms in our sample and screening for disclosures under item 5.02.

on executive *AWL* over the next quarter, growth in peer sales has a positive and significant effect. The effect is economically significant, where a 10% increase in peer sales results in an increase of 0.25-0.45 hours per day over the next quarter. This evidence suggests that peer pressure motivates executives to work harder.

The contribution of this paper is to characterize how executive effort affects firm value. Until now, this has been an unresolved question. Indeed, Murphy (1999) argues that we continue to know very little about how executive effort affects firm value, largely because financial markets are efficient and executive effort is unobservable.[8] Likewise, Yermack (2014) argues that effort provision is difficult to analyze directly "as we cannot observe a [sic] CEO's hour-to-hour activities". Some existing studies by Yermack (2014) and Biggerstaff, Cicero, and Puckett (2017) try to study how effort affects firm value by studying vacation travel and golf habits, but both acknowledge that it is impossible to know what business activities potentially take place during those times.

So, why does our measure of workday length improve firm value so robustly? The likely explanation is due to confirming an agency cost hypothesis. That is, a longer work day demonstrates more commitment to the firm. This is consistent with Yermack (2014) and Biggerstaff, Cicero, and Puckett (2017) who study the flip side of the problem: how leisure activities affect firm value. So, we view our paper as a companion to those studies in that we analyze the executive's substitution away from leisure to work harder for their firm.

The remainder of the paper is organized as follows. In Section 2, we describe the data collection and provide sample statistics. There we construct our variables of interest and provide support for using our measure of effort. Section 3 provides an analysis of executive effort and firm outcomes. In Section 4, we study agency and other incentives to employ effort. Section 5 concludes.

[8] Cowgill and Zitzewitz (2015) do show that employees with more exposure to Google stock have better performance. Ostensibly, this is because of higher hidden effort provision, but this remains uncertain since only an outcome measure is observable (performance).

## 2. Data and Sample Statistics

### *2.1 Sample Construction and Summary Statistics*

***Bloomberg User Data:*** When Bloomberg users are assigned accounts, the company records their "status" by default.[9] Status is either designated as "online", "idle", "offline", or "mobile". When users first log on to the platform, their status changes from offline to online, and it remains that way while they use Bloomberg. However, if they stop using it for 15 minutes, the user's status automatically changes to "idle". Eventually, and depending on the users' settings, a user is logged off after a long period of inactivity. Also, when users are logged in via the "Bloomberg Anywhere" application on their mobile device, the status is listed as "mobile". While using the mobile app, access to an assigned desktop is restricted, so there is no possibility of double counting.

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

During 2017-2020, we used the profile search and followed 2,734 users with executive in their title (e.g., "Chief Financial Officer", "Chief Executive Officer", etc.). We recorded their name, title, location, firm name, and followed their user status continuously over the entire time series. At no time did we collect the content of their use: we did not observe their text messaging, news search, or trading activity. The only data we collected is the time that each person actually uses the platform.

The majority of the 2,734 executives in our user dataset work in private firms. Of that number, 474 are "named executives" at 308 unique public firms. Executives list their geographic location in their profile. While there are concentrations in the Northeast, Texas, Chicago, and California, there is a large geographic dispersion. Forty-three states plus the District of Columbia are represented. When we analyze the effect of effort on abnormal returns, we analyze 1,128 executive-quarter observations. To study the effect of contracting on effort, we use the ISS Incentive Lab database, which collects compensation information from proxy statements and

[9] Users may set their profile status to "private", but only 9.5% of Executives do so.

provides it in tabular format. After merging the set of named executives with the Incentive Lab database, we are left with 252 top executives from 174 publicly-traded companies, and 520 executive-year observations. In our sample, 27% of executive-year observations are for CEOs while 45% are for CFOs. The remainder are named executives with other roles.

Table 1 provides summary statistics at the executive-fiscal year level for the executives in our sample. Panel 1.A presents statistics on firm characteristics. *Size* is the market capitalization (in millions of dollars) of the firm's stock (CRSP item *prc* times *shrout*) at the end of the previous fiscal year; *Q* is Tobin's Q; *leverage* is long term debt (Compustat item *dltt*) plus debt in current liabilities (Compustat item *dlc*) all divided by total assets (Compustat item *at*); *productivity* is revenues (Compustat item *sale*) divided by total assets. The mean market capitalization for the executives' firms is $43 Billion, with a median of $12.9 Billion. We use the natural logarithm of size in our regressions (*ln_size)*. Tobin's Q is about 1.58, on average. The average ratios of debt to assets is 0.31, and average ratio of revenues to assets is 0.35.

Panel 1.B breaks executive-year observations into industries based on the 4-digit SIC code of their firms according to the Fama-French 12 industry classifications. The panel shows that roughly half of the observations are from executives at financial firms, which is not surprising given the nature of the Bloomberg platform. The next most common industry (12.5% of the observations) is "Other", which consists of firms in industries with fewer firms that do not fit into the remaining 11 industries. "Energy" is the third most common industry (9.2% of observations), followed by Utilities (6.3%), and Healthcare (6.2%). Business Equipment, Chemicals, Manufacturing, Telecommunications, Consumer NonDurables, Consumer Durables, and Wholesale and Retail collectively make up the remaining 11.2% of observations.

### *2.2 Patterns of Bloomberg Usage*

***Summary Statistics:*** First, we examine patterns in the raw activity data and then provide evidence that the user data captures a plausible measure of effort provision. While we collect data through 2020, much of our analysis uses data from 2017-2019. This is due to the need to collect other variables and the highly unusual events that arose during the COVID pandemic.

Table 2 provides some summary statistics of user activity. For the 520 executive-year periods that we collect between September 2017 and December 2019, we have an average of 178 days of data per executive-year. On average, 129 of those are workdays, which we define as Monday through Friday. There is an average of 31 weeks per executive-year.

The "Bloomberg Usage" section of Table 2 provides statistics for active platform and mobile usage for various timeframes. On average, executives in our sample are actively using Bloomberg for 6.92 hours per week and they spend much less time on the mobile app than on the platform – about 30 minutes per week, on average. They spend very little time on Bloomberg on the weekend or at night, which we define as 6pm on a given day to 3am the following morning.[10] Also, executives tend to spend little time on Bloomberg on holidays, about thirty minutes per day on average.

These patterns tend to suggest that Bloomberg use is a work activity, rather than one of leisure. To see this visually, Figure 2 presents the average percentage of executives that actively use the platform during each minute of workdays. Active use is very limited, on average, before about 7am, and after about 6pm. There is also a drop in activity during the lunch hour. Thus, the general activity level is concentrated during the traditional 9 to 5 workday. In Figure 3, we examine average activity throughout the week. The histogram shows that activity is generally higher at the beginning of the workweek and declines throughout the week. During a workweek, effort is typically lowest on Friday.[11]

***Activity around salient events:*** To further explore the plausibility of Bloomberg usage as a proxy for time spent at work, we next examine whether activity is higher on days with important firm-level events. Figure 4 Panel A shows the average number of active hours in event time for all executives, relative to their firm's quarterly earnings announcement. A trend line is fitted (using OLS) separately for the periods before and after the announcement date. The day with the highest amount of activity is the earnings announcement date. Following the announcement, activity drops and steadily increases until the next announcement. Panel B shows the same figure for the subset of Chief Financial Officers, where the pattern is more pronounced. Panel C presents the figure for the subset of CEOs. Again, activity is the highest on the announcement date, but is also high the following day.

---

[10] These times are based on each executive's local time. We extend the nighttime window to include 3 am in case they work late and because activity on the platform is at a daily minimum at 3am.
[11] In the figure, we use *AWL* as our measure of activity. We describe this variable in detail in Section 2.3.

It is also instructive how usage changed during the COVID-19 pandemic of 2020, once executives experienced restricted travel, less access to leisure activities, and more time at home. Figure 5 provides a comparison of daily activity in 2020 with previous years (2018 and 2019) for the months of March, April, May, and June. By inspection, it is apparent that Bloomberg activity increased during the pandemic and use of the platform extended later into the evening hours. These findings are consistent with more remote work habits and substituting time on a computer for travel or leisure when they are made less available. Also, this appears to provide support for the idea that Bloomberg usage is in fact helpful in describing the work habits of its users.

Additionally, as one would expect, any measure of an executive's work habits should decrease when they are given incentives to engage in leisure activities. We investigate this in Section 3.2 using historical weather data from Weather Underground. Consistent with an agency cost hypothesis, it is evident that work activity as measured with Bloomberg online status does decrease when the weather improves in an executive's locale during the spring and summertime.

***Validation of personal use:*** We rule out the possibility that an executive's personal account is being accessed by other people such as their assistants or underlings. To investigate this, we look at usage habits by executives during key firm level events where they are not only likely to be in attendance, but speaking as an active participant. These include shareholder meetings, analyst days, earnings releases, and conference calls.

We collect this information using the Bloomberg corporate events calendar (function "EVTS") which includes the name, type, and timing of each event as well as a description. Categories include earnings calls, earnings releases, annual meetings, investment banking conferences/presentations, analyst days, and investor days, among others. For each event for which we can identify the date and start time, we examine executive activity on the platform during the first 30 minutes of the event. We use a short window since the lengths of the events vary and the end-time is not always documented. We count the number of executives who are not active on the platform at any point during that 30-minute window and aggregate by executive role and event.

We use Bloomberg's categories and descriptions to categorize events. For the investment banking conferences/presentations and analyst and investor days, we examine the event transcripts on Factiva in order to determine who was present. Executives who were not present are excluded from those two categories. The vast majority of annual meetings do not have transcripts on Factiva. Table 3 provides platform usage statistics for each of these categories.

The results are striking. For the analyst and investor days, the Bloomberg account for every single executive is inactive. During investment banking conferences, more than 99% of executives are not active on the platform. In the full sample of almost 1,500 observations, there are only 6 cases (4 unique executives) where there is activity on an executives' Bloomberg account during an event. For annual meetings, more than 90% of the time, there is no activity on the platform for CEOs, CFOs, and other executives. These results are overwhelmingly consistent with the notion that account activity is typically carried out by the executive him- or herself.

For reference, Table 3 also presents results for two other events where the executive may or may not have access to the Bloomberg platform, depending on the situation – earnings releases and earnings calls. The data suggest that there is relatively less inactivity during an earnings release: 74.6% of CEOs are inactive, 72.4% for CFOs, and 81.3% for other executives. Finally, during earnings calls, about 87% of CEOs, 89% of CFOs and 87% of other executives are not actively using their Bloomberg account.

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

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

These limitations prevented us from carrying out cross-sectional tests to correlate Bloomberg usage with geolocation data.[12] Notwithstanding, there were seven devices and three executives that we could reliably use to observe whether Bloomberg activity appears to reflect time spent in the office. For these devices and 40,609 pings on workdays, we find that when an executive's Bloomberg status is "active", any cell phone activity within 15-minutes is located in their corporate building 97.9% of the time. In contrast, when executives are outside of the building footprint, we find that 99.6% of the time, there is no platform activity in the previous 15 minutes.[13] While these statistics by no means provide comprehensive evidence for our entire sample of executives, it is reassuring that these correlations are so high for the devices and executives that we could clearly identify.

### *2.3 Effort Measures*

At first glance, it might be attractive to create simple measures based on examining individual days to evaluate when an executive is on the platform, such as the average number of days per week or the average daily time between the first and last login. However, while these measures are intuitive, they underestimate the executives' work habits if executives log into Bloomberg intermittently and at different times of the day.[14]

As such, we aggregate each executive's activity across a fixed time period (one year or one quarter) and construct a distributional measure based on the aggregate data that better controls for the intermittent, and perhaps erratic, usage of the platform. Examples of overall usage patterns are given in Figures 2 and 3. By inspection, the distribution appears similar to the mixture of two normal distributions, one for the morning and one after lunch. Clearly, the pattern in the data is not derived from a distribution per se, but we use this observation to construct our primary workday length measure, *Average Workday Length (AWL)*.

---

[12] This exercise highlights the benefits of Bloomberg data over cell-phone data in studying executive effort. While geolocation data have potential advantages, the lack of cross-sectional coverage and the inability to cleanly identify the user of a device is a drawback relative to the use of Bloomberg data.
[13] We use this individual data in Section 2.3 to help validate our *AWL* measure.
[14] In previous versions of this paper, we showed that higher measures of these variables were associated with increased firm value (e.g., earnings surprises). But, because of the sporadic use of Bloomberg by some exectuives, workday length was estimated at approximately 3.5 hours, which we feel is implausible for the exectives in our sample.

For each executive and year, we know the probability $P_{min}^{j}$ that the executive is logged on every minute of the day $j \in J \equiv \{12:00\ am, 11:59\ pm\}$. We construct a pdf by computing

$$p_{min}^{i} = \frac{P_{min}^{i}}{\sum_J P_{min}^{j}}$$

By construction, $\sum_J p_{min}^{j} = 1$. We then assume that the constructed distribution is a mixture of two normal distributions $k \in \{1, 2\}$, each with mean $\mu_k$ and variance $\sigma_k^2$. Both $\mu_1$ and $\mu_2$ are times of the day, where $\mu_2 > \mu_1$ since $\mu_2$ is in the afternoon and $\mu_1$ is in the morning. Indeed, many executives have different work habits. Also, as described above, a dip in activity around lunchtime is very frequent in our sample.

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

$$\mu_{1,2} = q\mu_1 + (1-q)\mu_2$$
$$\sigma_{1,2}^2 = q\sigma_1^2 + (1-q)\sigma_2^2 + q(1-q)(\mu_2 - \mu_1)^2$$

Using these two equations, we perform an expectation-maximization (EM) algorithm to estimate all five parameters for each executive $(q, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$.

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 candidate parameters. In the M-Step, the parameters are re-chosen in order to maximize the expectation. The process continues, iterating between the E-Step and the M-Step until the sequence converges. In our case, the likelihood function involves the likelihood of observing the data given that there are two unobservable Gaussian distributions generating the data. We implement the procedure using the scikit-learn library for Python.[15]

For each executive, we create the workday length measure *AWL* with the estimated vector $(\hat{\mu}_1, \hat{\mu}_2, \hat{\sigma}_1^2, \hat{\sigma}_2^2)$, which is computed as follows:

$$AWL = (\hat{\mu}_2 - \hat{\mu}_1) + \hat{\sigma}_1 + \hat{\sigma}_2$$

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

The distance *AWL* measures the difference between the means of the two distributions and adds a standard deviation on each side. As such, it allows for the more diverse work habits that are present in our executive sample.

Figure 6 provides three visual examples of how *AWL* is constructed. The shaded blue area is each executive's underlying Bloomberg activity, which has been converted into a pdf. The two yellow curves are the normal distributions derived from the EM algorithm and the red curve is the resultant mixed distribution. As can be appreciated, the estimated mixture closely approximates the underlying activity, and captures differences in morning versus afternoon work activity. The variable *AWL* is the distance between the two solid lines in the plot.[16]

The last panel in Table 2 also provides summary statistics for *AWL*. The mean level of *AWL* during the sample is about 9.5 hours with a standard deviation of about 2 hours. This is likely to be a superior measure of executive work habits as its magnitude is more consistent with what we would intuitively expect. Figure 7 provides a histogram that provides a distribution of *AWL* for executives in our sample. *AWL* varies more across executives than within each of them. We find that mean (median) standard deviation of *AWL* within executive is 1.4 (1.0) hours, while the corresponding standard deviations across executives are 1.7 (2.0) hours.

To help validate that *AWL* captures activity at work, we return to the cell phone data. Though we were only able to identify a handful of devices used by executives, one particular executive is especially active in the data. We were able to identify three devices belonging to that executive that show up a total of 92,893 times during the sample period. Using his cell phone data to identify when he is at work, we estimate a *AWL* statistic and compare it to the *AWL* estimated using Bloomberg activity. Figure 8 shows that the two measures are remarkably similar. The Average Workday Length based on Bloomberg usage is 8.0 hours, while it is 7.88 hours based on geolocation data. Admittedly, this is only one executive, but it does provide some reassurance that the *AWL* measure estimated with Bloomberg platform usage plausibly captures work habits.

[16] We have constructed other distributional measures that estimated ranges of times within the day in which 85% of the usage occurred for each executive. The analysis was repeated with 80% and 90% as well. Each of these workday length measures predict earning surprises and abnormal returns. We provide this evidence in the Appendix.

## 3. Effort Provision and Firm Outcomes

Now, we address a long-standing question whether and how much incentives and effort provision improve firm value. From a theoretical perspective, greater effort should increase the probability of good outcomes (Holmstrom and Milgrom, 1987; Edmans, Gabaix, and Jenter, 2017). Alternatively, effort may be inefficient in many cases or misguided. Either way, as Murphy (1999) points out, studying this has been challenging in the past: because changes in executive compensation or ownership grants are public information, equity prices adjust quickly (i.e., markets are efficient). Therefore, previous studies have been constrained because investigators had to connect incentives to firm value directly, without measuring the intermediate step of effort provision (Morck, Shleifer, and Vishny, 1988; Jensen and Murphy, 1990; Hall and Liebman, 1998). That is, investigators had no better information than equity market participants did. However, since we are able to measure executive effort directly here and this is not observable to (or followed by) equity market participants, we can now revisit these issues.

### *3.1 Earnings Surprises and Abnormal Returns*

We start by examining whether executives' effort provision during the fiscal quarter affects firm earnings surprises. We use Standardized Unexpected Earnings (*SUE*), which is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior, divided by the standard deviation of these differences measured over the previous eight quarters (Foster, Olsen, and Shevlin, 1984).

The independent variable is *AWL* measured during the fiscal quarter. In our regression, we focus on CEOs and CFOs and include measures of insider trading to control for private information that may be related to both effort provision and earnings. The variables *log_purchase* and *log_sell* are defined as the log value of open market insider purchases and sells that the executive made that quarter. Two analogous variables *log_purchase_all* and *log_sell_all* capture buying and selling by all insiders at the firm. We include executive fixed-effects which allows us to study a time-invariant, unobservable characteristics at the executive level.[17]

According to Table 4, effort has a positive effect on *SUE* in all specifications. Roughly, a one standard deviation increase in *AWL* leads to a 0.11 standard deviation increase in *SUE*. In the final specification of Table 4, we examine whether this result is present in non-financial firms,

[17] We have also run regressions using changes in *AWL* relative to 4-quarters prior and find qualitatively similar results.

which make up about half of the sample. The results are significant and the point estimates are in fact larger when focusing on this subset of executives.[18]

Next, we study the effect of effort provision on cumulative abnormal returns (CARs) around firm earnings announcements. To measure abnormal returns, we use a Fama-French 3-Factor model to estimate factor loadings using a year of past returns (after skipping the most recent week) and create daily alphas. Then, we regress cumulative abnormal returns on *AWL* from day 1 post-earnings announcement through 50 trading days (10 weeks), just prior to the next earnings announcement season. We include standardized unexpected earnings, *SUE*, to capture the impact of the earnings surprise on returns. Additionally, to capture information that may be known to insiders at the firm, but not yet public, we include our four measures of insider trading by the executive and other insiders (*log_purchase, log_sell, log_purchase_all,* and *log_sell_all*). We include executive individual fixed effects to control for time-invariant executive characteristics.

Table 5 shows that effort has a positive and persistent effect on returns. Panel 5.A examines all executives. The coefficients indicate that an increase in the length of the executive's workday by an hour is associated with a one-day abnormal return of 27.35 basis points. This increases over time and plateaus in a persistent 30-50 basis point CAR at 4-10 weeks. In Panel 5.B, we focus on executives at non-financial firms and find larger coefficients, though statistical significance is slightly lower over some horizons. These findings imply that unobserved effort that is not fully anticipated by an efficient market becomes incorporated into asset prices over time. Before now, where hidden effort was undetectable, this effect could not be appreciated. But, as we document, it is significant and independent of other executive attributes.

Motivated by the results in Table 5, we study the effect of effort on stock returns by forming calendar-time portfolios around earnings announcements. We form portfolios using an implementable trading strategy based on extreme changes in quarterly executive effort relative to past effort. We create two portfolios, *High_Effort*, and *Low_Effort*. To be included in the high effort portfolio on a given day, we require (1) the change in *AWL* for a stock's executive relative to *AWL* four quarters prior to be in the top 10% for all executives for the same fiscal quarter end; and (2) the earnings announcement must have occurred within the past five trading days. The low

[18] In untabulated resuts, we verify that our results also hold for non-financial firms using the first 5 specifications from Table 4. Table A.5 in the Internet appendix repeats the analysis of Table 4 after winsorizing *AWL* at the 10th and 90th percentiles of the distribution. In what follows, we also include Table A.6 in the Internet appendix that also repeats the analysis of Table 5 after winsorizing *AWL* at the 10th and 90th percentiles of the distribution.

effort portfolio is defined analogously, with the change in *AWL* in the bottom 10% of all executives with the same fiscal quarter end. To reduce noise, when there are fewer than 2 stocks satisfying the two criteria on a given day, we substitute the risk free rate of return. Portfolio returns are value-weighted using each stock's market capitalization. We also form a portfolio that is long *High_Effort* and short *Low_Effort*. Both raw returns and risk-adjusted returns are reported. We use the Fama-French 3-factor model to adjust for risk. Factor loadings are estimated using a year of past daily stock returns (skipping the most recent week).

Table 6 presents the mean returns and standard errors in basis points per day. According to the results, the risk-adjusted long-short portfolio yields 7.33 basis points per day, or 37 bps over 5 days. This quantity is plausible and statistically significant.

One concern that might arise is that measuring the effect of effort on firm value using earnings or stock prices might be confounded by the fact that executives are typically given bonuses based on these metrics. In some circumstances, these quantities may be subject to manipulation. To address this, we study the relationship between *AWL* and a firm's credit default swap spread. To our knowledge, no executive in our sample is compensated based on this, so it is not subject to management or manipulation.

We obtain CDS spread data from DataStream for the firms in our sample. We use the 5-year CDS contracts, which have the broadest coverage. For each firm and quarter, we keep the spread quote from the last available day in the quarter. Since not all firms have active contracts during our sample period, our final sample includes 574 observations over 89 executives and 57 firms.

We report the results in Table 7, where we run regressions of firm CDS spreads in quarter *t*+1 on executive effort (*AWL*) in quarter *t*, the firm's CDS spread (*Spread*) in quarter *t*, measures of insider trading in quarter *t*, and other firm characteristics. In Specifications1-2, we only include *Spread* during quarter t and the *AWL* during quarter t. A one hour increase in *AWL* is associated with a reduction of -0.879 to -0.929 basis points in CDS spreads. Once we control for firm characteristics and include executive fixed effects (Specification 4), the magnitudes increase to negative 1.50 basis points. Including executive fixed effects ensures that we measure the impact of the individual executive effort on CDS spreads.

Next, controlling for insider trading activity during quarter *t* (Specifications 5 and 6) does not alter our findings. This alleviates the concerns that *AWL* is high (or low) due to the firm performance during the quarter, which is associated with subsequent CDS spreads. In the last two specifications we exclude financial firms. Note that the coefficient estimates are not materially different from what is reported in the other specifications. However, the low number of observations makes the estimation noisier, which reduces the statistical significance levels. Finally, although we use an AR1 model throughout our specifications (i.e., controlling for *Spread* t), a first differences model (i.e., *Spread t*+1 – *Spread t*) virtually provides the same set of results.

### *3.2 Weather as an Exogenous Instrument*

Measuring a causal impact of effort on firm outcomes is difficult. For example, an important deal arising during a quarter may cause both higher earnings *and* more time in the office for the firm's executives.[19] More generally, if things are going well at the firm, an executive may simply enjoy being in the office more. Of course, if things are particularly bad, they may also be forced to increase their work hours. Regardless, to alleviate concerns that effort provision and outcomes are co-determined, we use variation in local weather as an exogenous shock to effort provision. Specifically, we use the weather near the end of the workday as a shock to the propensity to leave work early. This may occur because of incentives to enjoy good weather during some months of the year, or because of the need to deal with inclement conditions during others.

We measure whether the weather is better than normal using the "feels like" metric from Weather Underground, which captures how the air temperature is perceived on exposed skin.[20] We gather historical weather data for each location, each day from 2017 Q3 through 2019 Q4. Next, we measure how close "feels like" is to 72 degrees – which is the midpoint of the "thermal comfort zone" – between 3pm and 6pm local time on workdays.[21] For example, a "feels like" temperature of 65 would have a value of 7 and a "feels like" of 100 would be 28. So, how close "feels like" is to 72 degrees is computed as |F-72|, where F is the "feels like" temperature.

Next, we divide days into two categories: "good weather" and "bad weather" based on whether the "feels like" distance to 72 is below, or above the quarter median value, respectively. This is done across the entire sample period for each quarter and location. In other words, a "good weather" day in January, February and March means something different than a "good weather"

[19] We thank the editor for pointing out this example.
[20] See https://www.wunderground.com/maps/temperature/feels-like.
[21] See The Commission for Thermal Physiology of the International Union of Physiological Sciences (2003) and Bröde et al., 2012.

day in July, August, and December. For each executive, we estimate *AWL* each quarter across all years for "good weather" and "bad weather" days, separately. Note that executives are required to be in the sample for at least two years for a given quarter which allows us to exploit exogenous variation within a specific year-quarter in the next step.

In Table 8 we regress these two *AWL* measures on a "good weather day" indicator as well as executive-quarter fixed effects to get an idea of how effort differs across these days. While the first column indicates that there is no overall difference in *AWL* across good- and bad-weather days for a given executive, columns 2 and 3 indicate that behavior does differ depending on the season. During warmer months – when weather is more likely to be close to the thermal comfort zone, executives spend about 12 minutes less at work per day when afternoons are more pleasant. During colder months, when weather is almost always unpleasant, we find the opposite. The typical executive spends about 19 less minutes per day in the office on *bad* weather days.

One explanation is that during warmer months, better weather makes leisure activities more attractive. This seems intuitive and supports an agency cost hypothesis. The fact that better weather during colder months leads to more work may arise from several etiologies. Better weather has been shown to have a positive effect on mood and productivity (e.g., Kamstra, Kramer, and Levi, 2003). Alternatively, bad weather in the wintertime may force executives to leave work early to avoid poor traffic conditions.

To examine this further, we return to the geolocation data. Each workday from January 1, 2018 through March 10, 2020, for each firm headquarters in our sample, we examine how long nearby commuting employees stay at work. To identify these employees, we first identify the most likely home and work locations associated with the roughly 100 million devices in the geolocation sample in a given month. These are places where the devices are most often found during typical sleep or work hours, respectively. Having identified work and home for each device, we define "nearby" as employees working within a two-mile radius of the headquarters of the executive's firm. To capture the potential impact of weather on travel, we further restrict the sample to "commuting employees" as those who live at least two miles from their place of employment as well as at least two miles from the executive's office.

Figure 9 provides a fictional example of this two-mile area which defines "nearby" employees. The red marker/white circle indicate the executive's office location and the red circle traces out a two-mile radius around the office which defines "nearby". In this this example, the blue star identifies the workplace of a nearby employee and the black triangle indicates that employee's home. This nearby employee works within two miles of the executive. Moreover, this employee is also a "commuting" employee because he/she lives more than two miles from work (as indicated by the blue dotted circle) and at least two miles from the executive's workplace.

Across 212 headquarters locations we arrive at 127,565 headquarters-day observations with a mean number of devices of 5,047. For each nearby commuting employee, we measure the length of their time at work on a given day using the arrival and departure time based on the location of their mobile phone throughout the day. Finally, at the headquarters-day level, we collect the median values across employees of the arrival time, departure time, and time at work. Finally, we merge this with the "good weather day" indicator based on location of the headquarters.

Table 9 presents the results of regressing these median times on the good weather indicator along with various combinations of fixed effects. Panel 9.A includes days in calendar quarters 1 and 4 while Panel 9.B includes days in quarters 2 and 3. The first three columns are analogous to the results on executives in Table 8 and indicate that the weather impacts the median time at work for commuting employees around the executive's headquarters in a similar way to the executive. Namely, employees spend more time at work on good weather days during fall and winter months and less time on good weather days in spring and summer. Interestingly, the sensitivity of executives work habits to weather is larger than for the median commuter, suggesting that they have more flexibility.

The next two sets of columns for Panels A and B present results based on median arrival and departure times. The results are consistent with the notion that employees are more likely to arrive late and leave a little early on bad weather days in fall and winter. As hypothesized, this pattern flips during quarters 2 and 3. Employees tend to leave work a little early when the weather is more ideal during those months. There are mixed results on arrival times, though magnitudes are smaller than those associated with departure. This is not surprising as the weather variable is measured between 3pm and 6pm.

Having shown that variation in weather affects work habits, we employ a 2SLS regression, in which we estimate the following in the first stage:

$$AWL_{j,y,q} = \alpha + \beta weather\ AWL_{j,y,q} + \vartheta_{j,y,q}$$

where

$$weather\ AWL = [W_{Good,j,y,q}AWL(good)_{j,q} + W_{Bad,j,y,q}AWL(bad)_{j,q}]$$

is constructed with a weighted-average of good weather and bad weather days within a quarter. Then, in the second stage, we estimate

$$Y_{j,y,q} = \delta + \varphi\widehat{AWL}_{j,y,q} + \varepsilon_{j,y,q}$$

where

$$\widehat{AWL}_{j,y,q} = \hat{\alpha} + \hat{\beta} weather\ AWL_{\ j,y,q}$$

and $Y_{j,y,q}$ is an outcome variable (e.g., *SUE*, *CAR*, etc.). Regressions include executive and year-quarter fixed effects where indicated.

We again examine whether effort is related to earnings surprises. Specifically, we regress predicted *AWL* on SUE while controlling for executive fixed effects among other variables. Table 10 presents the results of these regressions using all days. As seen across all 6 specifications, we find a positive relation between predicted effort and earnings surprises. [22] So, for a given executive, when effort is predicted to be higher in a specific quarter based on exogenous variation in weather, we find that earnings are unexpectedly higher in that same quarter. The inclusion of year-quarter and executive fixed effects does not change the qualitative result. The final three specifications control for insider buying and selling – both by the executive as well as other executives at the firm. There is virtually no impact on the coefficient of interest. In terms of economic significance, a 1-standard deviation increase in predicted *AWL* leads to an increase in SUE of between 0.06 and 0.14 standard deviations – depending on the specification. The coefficients and economic magnitudes are consistent with those from the OLS analysis in Table 4.

Using our instrument, we examine how predicted *AWL* impacts future earnings. We form earnings surprise windows of 1, 2, 3, and 4 quarters long, beginning with the contemporaneous quarter. The dependent variable is the cumulative sum of the individual quarters' SUE. According to Panel A of Table 11, while some value becomes incorporated contemporaneously, much of it accumulates in successive quarters.

Our identifying assumption here implies that the covariance between variation in the weather and a firm's return process is zero, except for its effect through executive effort. Obviously, this cannot be tested directly. But, we do a few things that make it plausible. First, if

[22] Table A.7 in the Internet appendix repeats the analysis of Table 10 after winsorizing *AWL* at the 10th and 90th percentiles of the distribution. In what follows, we also include Table A.8 in the Internet appendix that repeats the analysis of Table 13 after winsorizing *AWL* at the 10th and 90th percentiles of the distribution.

inclement weather were to affect supply chains for some firms, the exclusion restriction would be violated. Clearly, this is unlikely to be true for financial firms. In the internet appendix, we repeat the analysis on the subset of firms that are financials, which is about half our sample. We obtain similar results, which is reassuring (Tables A.9 and A.10).

Second, the variation in weather that we exploit are temperature differences and bad weather, but not extreme events like blizzards or hurricanes. But, to alleviate concerns about severe weather disturbances driving our results in winter months, we drop the worst 10% of days in Q1 and Q4. Our results remain robust (Tables A.11 and A.12).

Admittedly, it is interesting to consider the channel through which executives might affect firm value and future earnings. That is, in our sample, how does executive effort increase firm value and is this impact immediate or long-lasting? Value may arise because of increasing revenues, decreasing costs, establishing a hard-working firm culture by example, or identifying new projects. We examine this next. With revenue data from I/B/E/S, we construct a standardized unexpected revenue (SUR) measure using the same methodology as with SUE. Likewise, taking the difference in revenue and earnings measures, we construct a similar measure of surprises in Total Cost. Panel B of Table 11 indicates that our executives' impact on earnings does not appear to come through higher revenues on average. However, according to Panel C, executive effort does appear to be associated with reductions in costs over the subsequent year.

Interestingly, we show that the relationship between executive effort and outcomes depends on the Tobin's Q for a firm. We divide firms into two groups – high and low Q based on the industry-year median Q in the sample. As in Table 11, we examine contemporaneous and future earnings. Table 12 presents the results. Panel A indicates that (predicted) executive effort impacts growth firms' earnings quickly, with the effect increasing over the following year. By contrast, Panel B shows that the impact of executive effort at value firms takes much longer to impact earnings, though the magnitude is just as large over a one-year horizon.

Finally, we turn to earnings announcement returns. We repeat the analysis from Table 5, using our predicted *AWL* measure. We regress cumulative abnormal returns over various horizons starting on the earnings announcement day all the way through 10 weeks on predicted *AWL*, SUE, and various controls including an executive fixed effect. Table 13 presents the results which indicate that there is a positive relation between abnormal announcement returns that grows in magnitude with time and becomes statistically significant after 1 to 2 weeks. As in Table 5, because we control for SUE, this represents information that is not included in the earnings surprise itself. Moreover, we control for insider trading which is meant to capture private information at the executive-level.

## 4. Effort Provision and Agency

### *4.1 Incentives and the Locus of Control*

Healy (1985) was the first to consider how executives behave when there are discontinuities in their compensation. When targets and goals are included in employment contracts, this introduces kinks into the compensation that executives may earn based on performance. Healy (1985) and others focused on how these discontinuities affected earnings management and investment within the firm (Degeorge, Patel, and Zeckhauser, 1999; Murphy, 2000).

A natural question to consider is how executives employ effort in similar circumstances. What is at issue is whether earning more money is within their locus of control. If firm performance is such that an executive is far from attaining a goal or is well past a target, then employing extra effort is unlikely to yield a marginal benefit. In such cases, earning compensation is outside of their locus of control. In contrast, if an executive is on pace to earn extra compensation (i.e., at a compensation kink), there is a higher marginal benefit of effort and securing extra compensation is within their locus of control.[23]

In the Definitive Proxy Statement (SEC form DEF 14A), public firms disclose their compensation contracts from the previous fiscal year for "named executives". Proxy statements are filed in advance of each firm's annual shareholder meeting, which typically are released during Q1. Item 402(a)(3) in SEC Regulation S-K defines the named executives as the CEO, the CFO, and at least three other executives with the highest compensation, and up to two former executives that served during the year and would have been in the previous category.

Proxy statements provide information on the type of compensation that each executive would receive – fixed wage, cash bonus, equity, option grant – as well as the target metric that would be used to compute end-of-year compensation (e.g., EBITDA, EPS, or Sales). While each

[23] As noted earlier, Healy (1985) describes this as the presence of floors and caps in compensation plans. An executive is outside their locus of control when they earn the floor or the cap and are well away from the incentive zone of their compensation scheme.

proxy statement is backward looking, this allows us to study how ex ante contracting affects subsequent effort. For example, the 2019 proxy statement for a particular firm describes the compensation package and goals that its top executives received at the beginning of 2018.

For our purposes here, we use the ISS Incentive Lab database, which collects compensation information from proxy statements and provides it in tabular format. After merging the set of named executives with the Incentive Lab database with our Bloomberg data, we are left with 252 top executives from 174 publicly-traded companies, and 520 executive-year observations.

Table 14 provides statistics on these executives' compensation contracts. We define the following variables: *value_stock_owned* is the dollar value of the executive's stockholdings in the firm measured using price at the beginning of the fiscal year; *salary* is the executives' fixed salary during the fiscal year; *cash_perf* is the target dollar amount of the cash-based performance incentive bonus from the executive's compensation contract for the fiscal year; *stock_perf* is the target dollar amount of the stock-based performance incentive bonus from the contract; *stock_time* and *option_time* are the values of the time-based stock and option grants, respectively, from the contract; predicted compensation, *pred_comp*, is the sum of *salary*, *cash_perf*, *stock_perf*, *stock_time*, and *option_time*.

The top section of Table 14 indicates that 27% of executive-year observations are for CEOs while 45% are for CFOs. The remainder are named executives with other roles. The middle section of the panel provides summary statistics on compensation contracts. The mean value of the firm's own stock held by the executive is about $69 Million, with a median of $10.7 Million. Executives in the sample own about 0.77% of the firm, on average, but this is highly skewed with a median of only 0.07%. The average annual predicted compensation is roughly $7.2 million, and is broken into incentive compensation of roughly $3.7 million that depends on attaining particular targets (*cash_perf* and *stock_perf*) and fixed compensation of roughly $3.5 million that is guaranteed while the executive is employed by the firm (*salary*, *stock_time*, and *option_time*).

The final section of Table 14 provides a breakdown of the average weights of the metric types that determine the performance-based cash bonuses. While Incentive Lab provides many metrics (e.g., EBIT, customer satisfaction, etc.) as well as the metric types (e.g., Accounting), it does not provide the value-weight of each metric in the compensation formula. That is, for a particular executive, Incentive Lab determines the frequency with which a target or metric is used, not the proportion of the bonus that is linked to that particular measure. Consequently, we gather this information manually from the proxy statements. We find that accounting metrics make up about 62.8% of the metric types in the performance formulas in our sample. Metrics in the "Other" category make up about 27.6% of the formulas, on average. These are non-accounting based metrics that are typically industry- or firm-specific. Individual (stock price) performance makes up about 7.1% (2.5%) of the weight on average in our sample.

The way we investigate the effect of locus of control on effort is to examine changes in *AWL* in response to firm performance *within* a fiscal year. Specifically, we study whether executive effort varies based on how close or far away from the targets firm performance is as the year goes on. When achieving bonuses is within the locus of control for an executive, we would expect them to exert more effort to secure higher compensation.

While compensation contracts are known to executives in advance and are typically not subsequently changed, firms do occasionally modify contracts during the year for various reasons. Such material changes necessitate the filing of Form 8-K with the SEC. If these changes are present in our sample, it may affect the interpretation of our results. To address this issue, we examine all 8-K filings issued by firms from the sample used in Table 14. We focus on Item 5.02 in the 8-K which includes changes in compensation. Within that subset of filings, we identify those that include the words "compensation", "change" or "modify". Next, we carefully read the resulting filings to identify the exact nature of the event that triggered the 8-K as well as the specific executive associated with the event, if any. We find no evidence of any changes in contracts during the year in this sample.

We proceed to examine whether and when executives increase effort in the 2$^{nd}$ half of the fiscal year, in response to firm performance in the 1$^{st}$ half. We posit that when earnings per share in the first half of the year are on pace to finish close to the annual EPS target specified in the executive's cash bonus contract, executives would employ more effort to ensure that they attain their set EPS goals. For each executive whose cash bonus contract includes an earnings-per-share target, and for whom we have Bloomberg profile activity data for at least one fiscal quarter in the first half of the year and one quarter in the second half of the year, we measure the quantity $\left|2 * (EPS_{Q1} + EPS_{Q2}) - EPS\,Target\right| / EPS\,Target$, where $EPS_{Q1}$ and $EPS_{Q2}$ are the firm's earnings per share in the 1$^{st}$ and 2$^{nd}$ fiscal quarter, and *EPS Target* is the executive's annual EPS target. This measures the absolute percentage projected deviation from the earnings target based on the first half of the year. The variable *target_1_pct* is equal to 1 when this quantity is less than 1% and 0 otherwise.

In Table 15, we regress the change in *AWL* from the first half of the fiscal year to the second half on the interaction between *target_1_pct* and *pct_cash_perf* and other control variables. The coefficient on the interaction term is positive, large in magnitude, and statistically significant. This implies that when a firm's midyear performance is far from compensation targets (high or low), and achievement of a bonus is outside their locus of control, they employ less effort in the second half of the year. It is when success or failure is within their potential control that they exert more effort. Also, because we study changes in *AWL* – a within-executive effect – this supports a causal relationship.

### *4.2 Effort and Competition*

The last consideration that we explore is how executives respond to competition in the product market place. To measure competition, we focus on the firm's growth in quarterly sales relative to its peers. The idea is that an increase in peer firm sales relative to the firm should induce more effort since executive performance is also assessed by market share. To construct a representative set of peers, for each firm, we include up to 10 closest peers (when the data allows), using the GICS6 industry classification. Closest peers are defined based on the smallest absolute difference in firm market cap.

Our measure of growth in quarterly sales (*%Chng_Sales*) is defined as the percentage change in the firm's sales during fiscal quarter *t* relative to the firm's quarterly sales 4 quarters prior [(Sales t - Sales t-4)/Sales t-4)] in %. In a similar manner, *%Chng_PeerSales* is defined as the percentage change in the firm's peers' sales during fiscal quarter *t* relative to the firm's peers' quarterly sales 4 quarters prior. We then calculate the market-cap value-weighted average across all peers.

We report the results in Table 16. Following the same methodology in Table 4, we run quarterly regressions executive effort (*AWL*) on lagged changes in quarterly firm sales and lagged changes in quarterly peer firms' sales. All specifications include executive fixed effects, thus the analysis is conducted at the executive level. In Specifications 1-3, we explore the effect of both firm growth in sales and peer growth in sales on changes during quarter *t*-1 on *AWL* over the next quarter. Strikingly, while the firm's own growth in sales does not predict subsequent changes in

*AWL*, growth in peer firms' sales has a positive and significant effect on *AWL*. The effect is economically significant. A 10% increase in peer firm's sales is associated with 0.26 more hours of effort per day during the next quarter (0.026 x 10 =0.26). Note that the quarterly financial results are reported toward the end of the first month of the subsequent quarter. Thus, our estimates likely underestimate the true effect, since *AWL* is estimated over the entire quarter period.

Controlling for firm characteristics slightly attenuates the effect of peer firms (0.024, Specification 6). Including changes in sales in quarter *t*-2 confirms that executives do respond to the changes in sales of the most recent quarter (i.e., *t*-1). In the last two specifications, we exclude financial firms. The coefficient estimates almost double, where a 10% increase in peer firm's sales is associated with 0.45 more hours of effort per day during the next quarter (0.045 x 10=0.45).

## 5. Conclusion

While hidden action problems are ubiquitous in firms and markets, technology is making it easier to assess hidden action problems. Indeed, the use of cookies and web traffic surveillance makes it easier to follow peoples' actions, even when they do not suspect it. We predict that such monitoring may eventually shed light on many unresolved issues in economics.

In this paper, we do not employ such tactics, but rely on a publicly available measure to characterize how effort affects firm-value. While we are careful not to collect information about the nature of how actually executives use Bloomberg (for privacy reasons), we are able to conclude that higher attention to their firm and higher workday length appear to be associated with positive earnings surprises and abnormal stock returns. This was not obvious ex ante, since it could have been the case that effort was inefficient or possibly misguided.

Finally, we consider several agency issues that have been highlighted in the academic literature. We find that executives do decrease effort when the benefit of receiving higher compensation is outside of their locus of control and when weather conditions make it attractive to engage in outside activities during the spring and summertime. In contrast, effort provision does appear to respond positively to competition within an executive's industry, measured by sales growth by competing firms.

## References


Aboody, D., Johnson, N. B., and Kasnik, R. “Employee stock options and future firm performance: Evidence from option repricings”. *Journal of Accounting and Economics* 50: 74–92, 2010.

Bandiera, O., Hansen, S., Pratt, A., and Sadun, R. “CEO Behavior and Firm Perfomance”. Forth coming in *Journal of Political Economy*.

Bebchuk, L. A., and Fried, J. M. “Executive Compensation as an Agency Problem”. *Journal of Economic Perspectives* 17: 71–92, 2003.

Bennett, B., Bettis, J. C., Gopalan, R. and Milborn, T. “Compensation goals and firm performance”. *Journal of Financial Economics* 124: 307–330, 2017.

Berle, A., A. and Means, G. C. *The Modern Corporation and Private Property*, New York, 1932.

Bertrand, M. and Mullainathan, S. “Are CEO’s rewarded for luck? The ones without principals are”. *Quarterly Journal of Economics* 116(3): 901-932, 2001.

Biggerstaff, L., Ciceero, D.C., and Puckett, A. “FORE! An Analysis of CEO Shirking”. *Management Science* 63(7): 2302-2322, 2017.

Bröde, P., Fiala, D., Błażejczyk, K., Holmér, I., Jendritzky, G., Kampmann, B., Tinz, B., and Havenith, G. "Deriving the operational procedure for the Universal Thermal Climate Index (UTCI)." *International Journal of Biometeorology* 56, no. 3 (2012): 481-494.

Cogwill, B. and Zitzewitz, E. “Incentive Effects of Equity Compensation: Employee-level evidence from Google”. Working paper, Dartmouth College.

Coughlan, A. T. and Schmidt, R.M. “Executive compensation, management turnover, and firm performance”. *Journal of Accounting and Economics* 7: 43–66, 1985.

Core, J. and Guay, W. “The Use of Equity Grants to Manage Optimal Equity Incentive Levels”. *Journal of Accounting and Economics* 28: 151–84, 1999.

Core, J. and Guay, W. “Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price Volatility”. *Journal of Accounting Research* 40: 613–30, 2002.

Degeorge, F., Patel, J. and Zeckhauser, R. "Earnings management to exceed thresholds." *Journal of Buriness* 72(1): 1-33, 1999.

Edmans, A. and Gabaix, X. “Executive Compensation: A Modern Primer”. *Journal of Economic Literature* 54(4), 1232-1287, 2016.

Edmans, A., Gabaix, X., and Jenter, D. “Executive Compensation: A Survey of Theory and Evidence”. Chapter 9 in Benjamin E. Hermalin and Michael S. Weisbach (eds.), *Handbook of the Economics of Corporate Governance*, Elsevier: Amsterdam, 383-539, 2017.

Foster, G., Olsen, C. and Shevlin, T. "Earnings releases, anomalies, and the behavior of security returns." *Accounting Review* 59(4): 574-603, 1984.

Frydman, C. and Saks, R.E. “Executive Compensation: A New View from a Long-Term Perspective, 1936–2005”. Review of Financial Studies 23(5): 2099- 2138, 2010.

Gormley, T. A., Matsa, D. A., and Milborn, T. “CEO compensation and corporate risk: Evidence from a natural experiment”. *Journal of Accounting and Economics* 56: 79-101, 2013.

Hall, B. J., and Liebman, J. B. “Are CEOs Really Paid Like Bureaucrats?” *Quarterly Journal of Economics* 113: 653–91, 1998.

Hall, B.J. and Murphy, K.J. “Stock Options for Undiversified Executives”. *Journal of Accounting and Economics* 33(1): 3-42, 2002.

Hayes, R.M., Lemmon, M., and Qui, M. “Stock options and managerial incentives for risk-taking: Evidence from FAS 123R”. *Journal of Financial Economics* 105: 174-190, 2012.

Healy, P.M. “The Effect of Bonus Schemes on Accounting Decisions”. *Journal of Accounting and Economics* 7: 85-107, 1985.

Holmstrom, B. and Milgrom, P. “Aggregation and Linearity in the Provision of Intertemporal Beliefs”. *Econometrica* 55(2): 303-328, 1987.

Jensen, M. C. and Murphy, K.J. “Performance Pay and Top-Management Incentives”. *Journal of Political Economy* 98(2): 225-264, 1990.

Kamstra, Mark, J., Lisa A. Kramer and Maurice D. Levi. “Winter Blues: A SAD Stock Market Cycle .” *American Economic Review*, 93(1):324-343.

Mehran, H. “Executive compensation structure, ownership, and firm performance”. *Journal of Financial Economics* 38: 163–184, 1995.

Mintzberg, H. *The Nature of Managerial* Work Harper and Row., New York, 1973.

Morck, R., Shleifer,A., and Vishny, R.W. “Management owenership and market valuation: An empirical analysis”. *Journal of Financial Economics* 20: 293-315, 1988.

Murphy, K. J. “Corporate Performance and Managerial Remuneration: An Empirical Analysis”. *Journal of Accounting and Economics* 7:11–42, 1985.

Murphy, K.J. “Executive Compensation” in Orley Ashenfelter and David Card (eds.) *Handbook of Labor Economics*, Vol. 3b, Elsevier Science North Holland, Chapter 38: 2485-2563, 1999.

Murphy, K. J. “Performance Standards in Incentive Contracts,” *Journal of Accounting and Economics* 30 (3): 245-78, 2000.

Tartarini, F., Schiavon, S., 2020. pythermalcomfort: A Python package for thermal comfort research. SoftwareX 12, 100578. https://doi.org/10.1016/j.softx.2020.100578

The Commission for Thermal Physiology of the International Union of Physiological Sciences (2003) Glossary of terms for thermal physiology. *Journal of Thermal Biology* 28:75–106. doi:10.1016/S0306-4565 (02)00055-4

Yermack, D. “Do corporations award CEO stock options effectively?”. *Journal of Financial Economics* 39: 237-269, 1995.

Yermack, D. Tailspotting: “Identifying and profiting from CEO vacation trips”. *Journal of Financial Economics* 113: 252-269, 2014.

Zare, S., Hasheminejad, N., Shirvan, H. E., Hemmatjo, R., Sarebanzadeh, K., and Ahmadi, S. "Comparing Universal Thermal Climate Index (UTCI) with selected thermal indices/environmental parameters during 12 months of the year." *Weather and Climate Extremes* 19 (2018): 49-57.

## Tables and Figures:

### Table 1. Summary Statistics:

The table reports the summary statistics of firm characteristics (Panel A) of executives' firms, executives' and their industries (Panel B). Our full sample includes data 520 executive-year observations for 252 named executives online on Bloomberg with accounting data on Compustat. *Size* is the market capitalization of the firm's stock (measured in millions of dollars), *Q* is Tobin's Q, Leverage is long term debt (Compustat item *dltt*) plus debt in current liabilities (Compustat item *dlc*) all divided by total assets (Compustat item *at*). *productivity* is revenues (Compustat item *sale*) divided by total assets. Industries in Panel B are defined using the Fama French 12 industry definitions which are available on Kenneth French's website.

### Panel 1.A – Firm Characteristics

| Variable | N | Mean | Std Dev | 25th Pctl | Median | 75th Pctl |
|---|---|---|---|---|---|---|
| size | 520 | 43,194 | 68,842 | 5,389 | 12,894 | 51,390 |
| Q | 520 | 1.588 | 1.102 | 1.018 | 1.179 | 1.755 |
| Leverage | 520 | 0.314 | 0.239 | 0.118 | 0.269 | 0.455 |
| productivity | 520 | 0.353 | 0.393 | 0.060 | 0.237 | 0.494 |

**Panel 1.B – Industries**

| Industry | N OBS | Pct of Sample |
|---|---|---|
| Finance | 284 | 54.6% |
| Other | 65 | 12.5% |
| Energy | 48 | 9.2% |
| Utilities | 33 | 6.3% |
| Healthcare | 32 | 6.2% |
| Business Equipment | 17 | 3.3% |
| Chemicals | 10 | 1.9% |
| Consumer NonDurables | 10 | 1.9% |
| Telecommunications | 9 | 1.7% |
| Manufacturing | 8 | 1.5% |
| Wholesale and Retail | 3 | 0.6% |
| Consumer Durables | 1 | 0.2% |

## Table 2. Effort Measures

The table reports the summary statistics of platform usage by executives as well as the derived effort measure. Our sample includes data for 252 named executives that are online on Bloomberg during sample period at firms with data in the Compustat database. Summary statistics for Bloomberg usage are presented for both "Active" and "Mobile", where Active indicates that the executive is actively using the Bloomberg platform and Mobile indicates that the executive is actively using the Bloomberg Professional mobile application. The effort measure *AWL* (Average Workday Length) is our measure of workday length (in hours) during the fiscal year. See Section 2.3 for details on the construction of *AWL*. Data used in the table cover the period from September 2017 to December 2019 and effort and usage variables are measured over the fiscal year of a given executive's firm.

| | | | | | | |
|---|---|---|---|---|---|---|
| Sample Coverage: | | | | | | |
| named executives: | 252 | | | | | |
| executive-year obs: | 520 | | | | | |
| mean days: | 178 | | | | | |
| mean workdays (Mon-Fri): | 129 | | | | | |
| mean weeks: | 31 | | | | | |
| | Active Hours | | | Mobile Hours | | |
| Bloomberg Usage: | Mean | Median | St Dev | Mean | Median | St Dev |
| weekly | 9.92 | 5.31 | 5.81 | 0.45 | 0.15 | 0.96 |
| evenings (Mon-Fri) | 0.13 | 0.06 | 0.29 | 0.05 | 0.01 | 0.11 |
| weekend (per day) | 0.06 | 0.00 | 0.19 | 0.02 | 0.00 | 0.08 |
| holidays | 0.54 | 0.14 | 0.86 | 0.04 | 0.00 | 0.27 |
| Effort Measure: | Mean | St Dev | 25th pctl | Median | 75th Pctl | |
| *AWL* (Average Workday Length) | 9.47 | 2.10 | 8.13 | 9.19 | 10.46 | |

## Table 3. Executive Activity During Events

The table provides statistics on executive activity on the Bloomberg platform during investment banking conferences/presentations, analyst days, investor days, annual meetings, earnings releases, and earnings calls. Executives are considered "inactive" if they are not actively using the Bloomberg platform at any point during the 30 minutes following the beginning of the event. For the Conference/Presentation and Analyst/Investor Day events, we examine transcripts of the events on Factiva to determine whether the executive was present. For those two events, we exclude any active executives who are not listed as participants in the event. Data on event descriptions, dates, start times, and other details are collected from the Bloomberg platform using the "EVTS" function. Data cover the fiscal years 2017 – 2019.

| | CEOs | | | CFOs | | | Other | | |
|---|---|---|---|---|---|---|---|---|---|
| | events | inactive | pct | events | inactive | pct | events | inactive | pct |
| Conference/Presentation | 410 | 408 | 99.5% | 784 | 783 | 99.9% | 287 | 284 | 99.0% |
| Analyst/Investor Day | 35 | 35 | 100.0% | 55 | 55 | 100.0% | 27 | 27 | 100.0% |
| Annual Meeting | 70 | 66 | 94.3% | 122 | 111 | 91.0% | 67 | 61 | 91.0% |
| Earnings Release | 327 | 244 | 74.6% | 543 | 393 | 72.4% | 316 | 257 | 81.3% |
| Earnings Call | 312 | 271 | 86.9% | 544 | 486 | 89.3% | 303 | 263 | 86.8% |

### Table 4. Effort and Earnings Surprise

The table provides results of regressions of earnings surprises on CEO and CFO effort, measures of insider trading, and firm characteristics. The measure of earnings surprise is Standardized Unexpected Earnings (SUE), which is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior divided by the standard deviation of these differences measured over the previous eight quarters. Effort is defined as *AWL* during the fiscal quarter associated with the earnings. The first 6 specifications include executives in all industries while specification 7 is limited to those in non-financial firms. Four measures of insider trading are included in the regressions based on insider trading during the fiscal quarter. The variables *log_purchase*, and *log_sell*, are the log dollar amount of open market insider purchases and sales, respectively, by the executive during the fiscal quarter associated with the earnings announcement. The variables *log_purchase_all* and *log_sell_all* are the log dollar amount of open market insider purchases and sales by all insiders at the firm during the fiscal quarter. Insider trading data are from the SEC Edgar database. User activity is from Bloomberg, earnings per share data are from I/B/E/S, and Fama-French 12 industry definitions are from Ken French's website. Firm characteristics, size, leverage, productivity, and Tobin's Q are from CRSP and Compustat and are included where indicated. An intercept is estimated in each regression, but not reported. Standard errors are clustered by executive and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *AWL* | 0.079** | 0.084** | 0.075** | 0.080*** | 0.081*** | 0.086*** | 0.069** |
| | (0.033) | (0.033) | (0.031) | (0.031) | (0.030) | (0.030) | (0.034) |
| *log_purchase* | -0.042 | 0.001 | -0.043 | -0.008 | -0.041 | -0.006 | -0.077 |
| | (0.043) | (0.044) | (0.039) | (0.040) | (0.039) | (0.040) | (0.064) |
| *log_sell* | -0.007 | 0.005 | -0.008 | 0.002 | -0.008 | 0.002 | 0.001 |
| | (0.016) | (0.016) | (0.017) | (0.017) | (0.017) | (0.017) | (0.027) |
| *log_purchase_all* | | -0.046*** | | -0.038*** | | -0.037** | -0.058*** |
| | | (0.014) | | (0.015) | | (0.015) | (0.021) |
| *log_sell_all* | | -0.015 | | -0.012 | | -0.011 | -0.017 |
| | | (0.010) | | (0.010) | | (0.010) | (0.016) |
| Excluding Financial Firms? | N | N | N | N | N | N | Y |
| Firm Controls? | N | N | Y | Y | Y | Y | Y |
| Industry FE? | N | N | N | N | Y | Y | Y |
| Executive FE? | Y | Y | Y | Y | Y | Y | Y |
| N OBS | 980 | 980 | 980 | 980 | 980 | 980 | 459 |
| R-Squared | 0.408 | 0.420 | 0.432 | 0.440 | 0.465 | 0.472 | 0.529 |

## Table 5. Effort and Earnings Announcement Returns

The table provides results of regressing cumulative abnormal stock returns (in basis points) around earnings announcements on executive effort measured during the fiscal quarter associated with the earnings as well as standardized unexpected earnings (SUE), and measures of insider trading during the fiscal quarter. Panel A provides results for all executives. Panel B provides results for executives at non-financial firms. Each reported coefficient represents a single regression using *AWL*. Cumulative returns are measured using the Fama-French 3 Factor model where factor loadings are estimated using a year of past daily stock returns (skipping the most recent week). Cumulative abnormal returns are presented for ranges of 1 through 50 trading days where the first day is the trading day that includes the announcement. Platform activity is from Bloomberg and stock price data are from CRSP. Fama French factor portfolios are from Ken French's website. SUE is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior divided by the standard deviation of these differences measured over the previous eight quarters. Four measures of insider trading are included in the regressions. The variables *log_purchase*, and *log_sell*, are the log dollar amount of open market insider purchases and sales, respectively, by the executive during the fiscal quarter associated with the earnings announcement. The variables *log_purchase_all* and *log_sell_all* are the log dollar amount of open market insider purchases and sales by all insiders at the firm during the fiscal quarter. Insider trading data are from the SEC Edgar database. To be included in the sample, an executive must have been active on Bloomberg for at least four fiscal quarters. 1,128 observations are included in the regressions in Panel 5.A. 457 observations are included in the regressions in Panel B. All regressions include individual executive fixed effects. Standard errors, clustered by executive, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

**Panel 5.A – All Executives**

| Variable | 1-day | 2-day | 3-day | 4-day | 5-day | 6-day | 7-day | 8-day | 9-day |
|---|---|---|---|---|---|---|---|---|---|
| *AWL* | 27.35 * | 29.46 ** | 25.99 ** | 23.27 * | 25.07 ** | 27.79 ** | 27.21 ** | 28.56 ** | 31.90 ** |
| | (14.01) | (13.37) | (12.12) | (12.24) | (12.42) | (12.12) | (12.68) | (14.00) | (14.86) |
| *SUE* | 19.43 ** | 21.52 ** | 20.27 * | 20.49 * | 19.73 * | 19.11 | 17.79 | 17.16 | 17.72 |
| | (8.68) | (10.29) | (10.60) | (10.84) | (11.51) | (12.77) | (12.79) | (13.14) | (13.64) |
| *log_purchase* | 20.45 * | 21.05 | 15.56 | 5.33 | 9.04 | 3.92 | 8.15 | 10.89 | 7.50 |
| | (10.74) | (13.84) | (11.25) | (13.75) | (14.19) | (12.69) | (14.31) | (15.92) | (17.23) |
| *log_sell* | 1.74 | 2.50 | 2.48 | 1.55 | 1.63 | 1.20 | -0.06 | 0.64 | 2.42 |
| | (3.96) | (4.25) | (4.10) | (4.21) | (4.36) | (4.52) | (4.67) | (4.73) | (4.98) |
| *log_purchase_all* | 2.91 | 3.60 | 3.40 | 4.15 | 1.59 | 4.42 | 5.84 | 3.75 | 1.98 |
| | (4.41) | (4.84) | (5.09) | (4.92) | (4.91) | (4.87) | (5.40) | (5.36) | (5.52) |
| *log_sell_all* | 0.23 | -0.53 | -1.70 | -1.14 | -0.89 | -1.95 | -2.03 | -0.57 | -0.29 |
| | (2.49) | (2.70) | (2.85) | (2.94) | (3.06) | (3.16) | (3.42) | (3.38) | (3.46) |
| Executive FE? | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| N OBS | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 |
| R-Squared | 0.16 | 0.16 | 0.15 | 0.13 | 0.13 | 0.13 | 0.12 | 0.13 | 0.13 |

| Variable | 2-week | 3-week | 4-week | 5-week | 6-week | 7-week | 8-week | 9-week | 10-week |
|---|---|---|---|---|---|---|---|---|---|
| *AWL* | 26.72 * | 26.73 * | 32.85 ** | 39.51 ** | 44.36 ** | 47.05 ** | 47.34 ** | 47.26 * | 49.16 * |
| | (14.96) | (14.34) | (16.63) | (18.20) | (20.23) | (22.68) | (23.06) | (24.57) | (26.09) |
| *SUE* | 15.91 | 20.90 | 30.39 * | 26.07 * | 14.47 | 19.43 | 14.41 | 17.35 | 17.46 |
| | (13.24) | (14.48) | (15.39) | (14.29) | (16.72) | (17.37) | (18.12) | (18.40) | (19.54) |
| *log_purchase* | 5.31 | -4.79 | -6.92 | -6.08 | -21.11 | -21.79 | -14.80 | -24.49 | -22.02 |
| | (19.15) | (20.63) | (23.07) | (25.84) | (25.85) | (29.91) | (30.02) | (31.07) | (32.68) |
| *log_sell* | 2.35 | 3.58 | 4.55 | 4.19 | 3.34 | 2.03 | 3.15 | 1.35 | -2.35 |
| | (5.39) | (5.47) | (6.36) | (7.14) | (7.49) | (7.24) | (7.15) | (7.58) | (8.10) |
| *log_purchase_all* | 1.93 | 4.45 | 5.24 | 5.26 | 11.17 | 12.73 | 16.64 * | 21.07 ** | 19.47 * |
| | (5.63) | (5.81) | (6.30) | (7.60) | (8.64) | (8.74) | (9.43) | (10.22) | (10.85) |
| *log_sell_all* | -0.95 | -2.57 | -4.92 | -7.45 | -7.57 | -7.55 | -7.92 | -9.13 | -10.52 * |
| | (3.61) | (4.02) | (4.50) | (4.86) | (5.09) | (5.28) | (5.27) | (5.61) | (5.79) |
| Executive FE? | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| N OBS | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 | 1,128 |
| R-Squared | 0.13 | 0.13 | 0.14 | 0.15 | 0.14 | 0.15 | 0.15 | 0.14 | 0.12 |

## Panel 5.B – Executives at Non-Financial Firms

| Variable | 1-day | 2-day | 3-day | 4-day | 5-day | 6-day | 7-day | 8-day | 9-day |
|---|---|---|---|---|---|---|---|---|---|
| *AWL* | 43.91 * | 43.19 * | 33.64 * | 33.91 * | 33.61 * | 35.18 * | 35.33 * | 42.05 * | 49.16 |
| | (19.33) | (21.67) | (18.07) | (15.26) | (15.57) | (15.77) | (16.61) | (20.88) | (24.13) |
| *SUE* | 34.64 * | 41.87 | 44.85 | 45.59 | 47.96 | 49.14 | 44.28 | 42.16 | 39.93 |
| | (17.02) | (25.21) | (28.07) | (27.63) | (27.56) | (28.71) | (28.60) | (25.68) | (27.94) |
| *log_purchase* | 25.34 *** | 11.49 | 15.82 | -1.15 | 4.13 | -2.29 | 1.77 | 6.05 | -3.70 |
| | (6.12) | (11.34) | (8.93) | (14.48) | (10.95) | (18.59) | (16.59) | (18.80) | (24.51) |
| *log_sell* | 1.18 | 2.96 | 1.74 | 0.56 | 2.29 | 3.51 | 3.25 | 2.85 | 6.36 |
| | (6.26) | (6.35) | (6.29) | (7.63) | (7.29) | (6.42) | (6.63) | (6.51) | (6.10) |
| *log_purchase_all* | 3.32 | 5.25 | 5.27 | 7.78 | 2.63 | 6.71 | 7.17 | 5.54 | 3.52 |
| | (10.28) | (9.98) | (11.06) | (10.73) | (10.23) | (9.56) | (11.32) | (10.42) | (10.37) |
| *log_sell_all* | -2.42 | -3.71 | -5.98 | -6.16 | -6.03 | -8.08 | -8.83 | -6.30 | -5.98 |
| | (5.13) | (4.68) | (6.10) | (6.19) | (5.53) | (4.99) | (6.47) | (5.07) | (4.82) |
| Executive FE? | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| N OBS | 457 | 457 | 457 | 457 | 457 | 457 | 457 | 457 | 457 |
| R-Squared | 0.196 | 0.19 | 0.175 | 0.15 | 0.15 | 0.15 | 0.14 | 0.14 | 0.14 |

| Variable | 2-week | 3-week | 4-week | 5-week | 6-week | 7-week | 8-week | 9-week | 10-week |
|---|---|---|---|---|---|---|---|---|---|
| *AWL* | 39.16 | 42.05 * | 58.50 * | 69.11 ** | 88.63 ** | 95.07 *** | 91.33 ** | 96.37 *** | 104.38 *** |
| | (22.00) | (20.94) | (29.94) | (29.49) | (28.90) | (26.85) | (27.33) | (26.83) | (26.61) |
| *SUE* | 39.69 | 42.64 | 50.16 | 49.77 | 24.43 | 35.23 | 9.51 | 14.76 | 11.47 |
| | (29.89) | (37.26) | (30.21) | (29.56) | (28.83) | (27.83) | (33.68) | (67.41) | (75.52) |
| *log_purchase* | -12.69 | -29.57 | -44.45 | -57.07 | -66.04 | -80.73 | -72.36 | -81.99 | -90.72 |
| | (32.33) | (35.57) | (37.47) | (43.39) | (50.01) | (61.47) | (50.40) | (56.71) | (61.07) |
| *log_sell* | 6.34 | 2.10 | 3.63 | 0.85 | 0.58 | -1.97 | 0.42 | -0.94 | -7.32 |
| | (5.81) | (4.96) | (6.20) | (5.18) | (5.08) | (4.64) | (6.15) | (4.66) | (8.17) |
| *log_purchase_all* | 4.53 | 1.58 | 1.39 | 1.66 | 5.62 | 8.08 | 13.07 | 26.26 | 19.93 |
| | (9.09) | (9.62) | (7.82) | (8.29) | (10.10) | (7.69) | (10.24) | (16.78) | (14.85) |
| *log_sell_all* | -6.73 | -8.84 * | -14.09 ** | -16.00 ** | -18.07 *** | -20.43 *** | -21.77 ** | -22.44 *** | -22.74 *** |
| | (3.85) | (4.44) | (5.35) | (3.59) | (4.11) | (5.65) | (6.56) | (6.43) | (6.67) |
| Executive FE? | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| N OBS | 457 | 457 | 457 | 457 | 457 | 457 | 457 | 457 | 457 |
| R-Squared | 0.14 | 0.13 | 0.15 | 0.18 | 0.16 | 0.18 | 0.17 | 0.17 | 0.14 |

## Table 6. Calendar Time Portfolio Returns

The table reports mean returns of calendar time portfolios around earnings announcements based on changes in executive effort during the fiscal quarter relative to the fiscal quarter one-year prior, where effort is defined using *AWL*. We report results for two portfolios, *High_Effort* and *Low_Effort*, as well as a portfolio that is long High Effort and short Low Effort. To be included in the High Effort portfolio on a given day, we require the change in *AWL* for the stock's executive to be in the top 10% for all executives in the sample with the same fiscal quarter end, and the earnings announcement corresponding to the fiscal quarter must have occurred within the past five trading days. The Low Effort portfolio is defined analogously, with change in *AWL* in the bottom 10%. The High minus Low portfolio is the return of the High Effort portfolio minus the return of the Low Effort Portfolio. Portfolio returns are value-weighted using market capitalization weights. To reduce noise, if the number of stocks on any given day in a portfolio drops below 2, we replace the portfolio return with the risk free rate. Both raw returns and risk adjusted returns are presented in basis points. The Fama-French 3-factor model is used to adjust for risk. Factor loadings are estimated using a year of past daily stock returns (skipping the most recent week). Platform activity is from Bloomberg and stock price data are from CRSP. Fama French factor portfolios are from Ken French's website. Newey-West standard errors using 5 lags are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| Portfolio | Mean (bps) |
|---|---|
| Raw Return | |
| High Effort | 4.678* |
| | (2.498) |
| Low Effort | -2.520 |
| | (2.822) |
| High minus Low | 7.198* |
| | (3.686) |
| Risk-Adjusted Return | |
| High Effort | 4.579*** |
| | (1.569) |
| Low Effort | -2.751 |
| | (2.355) |
| High minus Low | 7.330*** |
| | (3.129) |

## Table 7. Effort and Credit Default Swap Spreads

The table provides results of regressions of firm CDS spreads in quarter *t*+1 on executive effort (*AWL*) in quarter *t*, the firm's CDS spread (*Spread*) in quarter *t*, measures of insider trading in quarter *t*, and other firm characteristics. Daily data of 5-year CDS spreads are obtained from DataStream. For each firm and quarter, we keep the last trading day in that quarter. We keep firms with active CDS contracts during our sample period and end up with 574 observations over 89 executives and 57 firms. Due to the persistence in CDS spreads, we control for lagged *Spread* (i.e., an AR1 model). However, using first difference (Spread *t*+1 – Spread *t*) virtually provides the same results. To reduce the effect of outliers, we trim observations where the quarterly changes in spread are at the top and bottom 1% of their distribution. We include four measures of insider trading include *log_purchase* (*sell*), which is the log dollar amount of open market insider purchases (sales) by the executive during quarter *q*, and *log_purchase_all* (*sell_all*), which is the log dollar amount of open market insider purchases (sales) by all insiders during quarter *q*. Insider trading data are from the SEC Edgar database. Platform activity is from Bloomberg, earnings per share data are from I/B/E/S, and Fama-French 12 industry definitions are from Ken French's website. Firm characteristics, size, sales, leverage, productivity, and Tobin's Q are from CRSP and Compustat and are included where indicated. An intercept is estimated in each regression, but not reported. All specifications include year fixed effects. Standard errors are clustered by executive and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *AWL* | -0.879 *** | -0.929 ** | -0.976 ** | -1.504 ** | -1.486 ** | -1.410 ** | -0.964 | -1.113 |
| | (0.330) | (0.380) | (0.390) | (0.600) | (0.600) | (0.590) | (0.720) | (0.690) |
| *Spread* | 0.995 *** | 0.998 *** | 0.994 *** | 0.700 *** | 0.700 *** | 0.704 *** | 0.672 *** | 0.591 *** |
| | (0.040) | (0.040) | (0.040) | (0.150) | (0.150) | (0.150) | (0.194) | (0.185) |
| *log_purchase* | | | | | -0.277 | | | |
| | | | | | (0.730) | | | |
| *log_sell* | | | | | -0.104 | | | |
| | | | | | (0.100) | | | |
| *log_purchase_all* | | | | | | -0.269 | | |
| | | | | | | (0.240) | | |
| *log_sell_all* | | | | | | -0.097 | | |
| | | | | | | (0.130) | | |
| *Firm Controls?* | NO | NO | YES | YES | YES | YES | NO | YES |
| *Industry FE?* | NO | YES | YES | YES | YES | YES | YES | YES |
| *Executive FE?* | NO | NO | NO | YES | YES | YES | YES | YES |
| *Excluding Financials?* | NO | NO | NO | NO | NO | NO | YES | YES |
| *N OBS* | 574 | 574 | 574 | 574 | 574 | 574 | 260 | 260 |
| *R-Squared* | 0.924 | 0.923 | 0.925 | 0.928 | 0.928 | 0.928 | 0.940 | 0.943 |

## Table 8. Executive Effort on Good and Bad Weather Days

The table provides results of regressing quarterly *AWL* for good-weather and bad-weather days on a good-weather indicator for all quarters, quarters 2 and 3 and quarters 1 and 4. Good- and bad-weather *AWL* are estimated for each executive for each quarter using data for all years in the sample. Days are considered to be good- (bad-) weather if they are better (wors) than median for the quarter-location where "better" is defined how close (in absolute value) the "feels like" metric is to 72 degrees between 3pm and 6pm on workdays. The dummy variable *good weather days* indicates the *AWL* is measured on days with better than median weather. To be included in the sample, an executive must have been active on Bloomberg for the same quarter across multiple years. Historical weather data are from Weather Underground. 1,350 observations are included in the full set of quarters. All regressions include executive-quarter fixed effects. Standard errors, clustered by executive, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| Variable | All Quarters | Q2 & Q3 | Q1 & Q4 |
|---|---|---|---|
| *good weather days* | 0.078 | -0.201* | 0.323*** |
| | (0.228) | (0.106) | (0.110) |
| Exec-Quarter FE? | Y | Y | Y |
| N OBS | 1,350 | 632 | 718 |
| R-Squared | 0.943 | 0.792 | 0.954 |

## Table 9. Commuting Employee Work Habits on Good and Bad Weather Days

The table provides results of regressing commuting employee median time at work, median arrival time, and median departure time by location on a good-weather indicator and various fixed effects for quarters 1 and 2 (Panel A) and quarters 2 and 3 (Panel B). Days are considered to be good- (bad-) weather if they are better (worse) than median for the quarter-location where "better" is defined how close (in absolute value) the "feels like" metric is to 72 degrees between 3pm and 6pm on workdays. The dummy variable *good weather days* indicates the day is a better-than-median-weather day. Time at work, arrival time, and departure times are based on mobile device data for commuting employees working in a two-mile radius around executives' office locations. Commuting employees are those who live at least two miles from their place of employment – and live at least two miles from the executive's office. Home and work are inferred based on the most common location of a given device during typical sleep and work hours in a given month. Arrival and departure times are the first and last time a device is observed at work on a given day. Mobile phone geolocation data are from Reveal Mobile. Historical weather data are from Weather Underground. 127,565 headquarter-day observations are included in the full set of quarters. Regressions include month, day-of-week, and Headquarters fixed effects as indicated. Standard errors, clustered by firm, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

### Panel 9.A – Quarters 1 and 4

| Variable | median time at work | | | median arrival time | | | median departure time | | |
|---|---|---|---|---|---|---|---|---|---|
| *good weather day* | 0.089*** | 0.088*** | 0.075*** | -0.067*** | -0.068*** | -0.049*** | 0.022*** | 0.021*** | 0.026*** |
| | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) | (0.005) | (0.008) | (0.008) | (0.006) |
| month FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| day of week FE | N | Y | Y | N | Y | Y | N | Y | Y |
| HQ FE | N | N | Y | N | N | Y | N | N | Y |
| N | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 |
| R-squared | 0.226 | 0.238 | 0.342 | 0.053 | 0.055 | 0.403 | 0.161 | 0.181 | 0.358 |

### Panel 9.B – Quarters 2 and 3

| Variable | median time at work | | | median arrival time | | | median departure time | | |
|---|---|---|---|---|---|---|---|---|---|
| *good weather day* | -0.084*** | -0.080*** | -0.033*** | 0.017* | 0.022** | -0.017*** | -0.067*** | -0.058*** | -0.050*** |
| | (0.010) | (0.010) | (0.006) | (0.009) | (0.009) | (0.006) | (0.008) | (0.009) | (0.005) |
| month FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| day of week FE | N | Y | Y | N | Y | Y | N | Y | Y |
| HQ FE | N | N | Y | N | N | Y | N | N | Y |
| N | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 |
| R-squared | 0.024 | 0.041 | 0.285 | 0.028 | 0.042 | 0.309 | 0.016 | 0.096 | 0.412 |

## Table 10. Predicted Effort and Earnings Surprises – 2SLS

The table reports 2SLS estimates from regressions of earnings surprises CEO and CFO effort. In the first stage (Panel A), we estimate the following equation:

$$AWL_{j,y,q} = \alpha + \beta weather\ AWL_{\ j,y,q} + \vartheta_{j,y,q}$$

where *weather AWL* is a weighted average of good-weather and bad-weather *AWL* and the weights are the percentage of good- or bad-weather days, respectively during the specific fiscal quarter:

$$weather\ AWL = [W_{Good,j,y,q} AWL(good)_{j,q} + W_{Bad,j,y,q} AWL(bad)_{j,q}]$$

Good- and bad-weather *AWL* are estimated for each executive using weather that is better than median or worse than median, respectively, for the same fiscal quarter across all years in the sample. Days are considered to be good- (bad-) weather if they are better (worse) than median for the quarter-location where "better" is defined how close (in absolute value) the "feels like" metric is to 72 degrees between 3pm and 6pm on workdays. In the second stage (Panel B), we estimate the following equation:

$$SUE_{j,y,q} = \delta + \varphi \widehat{AWL}_{j,y,q} + \varepsilon_{j,y,q}$$
$$\widehat{AWL}_{j,y,q} = \hat{\alpha} + \hat{\beta} weather\ AWL_{\ j,y,q}$$

where Standardized Unexpected Earnings (SUE) is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior divided by the standard deviation of these differences measured over the previous eight quarters and $\widehat{AWL}$ is the fitted value from the first-stage estimation. Regressions include executive and year-quarter fixed effects where indicated. The final 4 columns include log dollar amount of open market insider purchases and sales, respectively, by the executive and separately, all executives at the firm during the fiscal quarter associated with the earnings announcement. Insider trading data are from the SEC Edgar database. Platform activity is from Bloomberg, earnings per share data are from I/B/E/S. Historical weather data used in estimating good- and bad-weather AWL are from Weather Underground. To be included in the sample, an executive must be active for the same fiscal quarter across multiple years. There are 1,260 observations in the full sample. Standard errors are clustered by executive and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

### Panel 10.A – First Stage

| | AWL | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *weather* AWL | 0.508*** | 0.526*** | 0.332*** | 0.343*** | 0.507*** | 0.526*** | 0.331*** | 0.343*** |
| | (0.041) | (0.042) | (0.037) | (0.043) | (0.042) | (0.042) | (0.037) | (0.043) |
| Insider trading controls? | N | N | N | N | Y | Y | Y | Y |
| year-quarter FE? | N | Y | N | Y | N | Y | N | Y |
| executive FE? | N | N | Y | Y | N | N | Y | Y |
| N OBS | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 |
| R-squared | 0.37 | 0.67 | 0.43 | 0.67 | 0.38 | 0.43 | 0.62 | 0.67 |

**Panel 10.B – Second Stage**

| | SUE | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\widehat{AWL}$ | 0.093*** | 0.097*** | 0.058*** | 0.063*** | 0.087*** | 0.094*** | 0.067*** | 0.067*** |
| | (0.028) | (0.031) | (0.022) | (0.025) | (0.027) | (0.029) | (0.022) | (0.025) |
| Insider trading controls? | N | N | N | N | Y | Y | Y | Y |
| year-quarter FE? | N | Y | N | Y | N | Y | N | Y |
| executive FE? | N | N | Y | Y | N | N | Y | Y |
| N | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 |
| Centered R-squared | -0.01 | 0.08 | 0.46 | 0.55 | 0.01 | 0.12 | 0.47 | 0.55 |

## Table 11. Predicted Effort and Future Outcomes – 2SLS

The table provides second stage results of 2SLS regressions of future cumulative earnings, revenue, and total cost surprises on predicted CEO and CFO effort, measures of insider trading, and executive fixed effects. In the first stage, we estimate the following equation:

$$AWL_{j,y,q} = \alpha + \beta weather\ AWL_{\ j,y,q} + \vartheta_{j,y,q}$$

where *weather AWL* is a weighted average of good-weather and bad-weather *AWL* and the weights are the percentage of good- or bad-weather days, respectively during the specific fiscal quarter:

$$weather\ AWL = [W_{Good,j,y,q} AWL(good)_{j,q} + W_{Bad,j,y,q} AWL(bad)_{j,q}]$$

Good- and bad-weather *AWL* are estimated for each executive using weather that is better than median or worse than median, respectively, for the same fiscal quarter across all years in the sample. Days are considered to be good- (bad-) weather if they are better (worse) than median for the quarter-location where "better" is defined how close (in absolute value) the "feels like" metric is to 72 degrees between 3pm and 6pm on workdays. In the second stage we estimate the following equation:

$$MEASURE_{j,y,q} = \delta + \varphi \widehat{AWL}_{j,y,q} + \varepsilon_{j,y,q}$$

$$\widehat{AWL}_{j,y,q} = \hat{\alpha} + \hat{\beta} weather\ AWL_{\ j,y,q}$$

where MEASURE is a measure of the surprise in either earnings, revenues, or costs. $\widehat{AWL}$ is the fitted value from the first-stage estimation. The measure of earnings surprise is Standardized Unexpected Earnings (SUE), which is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior divided by the standard deviation of these differences measured over the previous eight quarters. Revenue surprises – Standardized Unexpected Revenue (SUR), is defined similarly, using revenue. We define total cost surprise as the difference in these two measures. For all three measures, we examine cumulative surprises over 1-quarter, 2-quarters, 3-quarters, and 4-quarters where the beginning of each of the windows includes the quarter in which effort is measured. Insider trading data are from the SEC Edgar database. Platform activity is from Bloomberg, revenue and earnings per share data are from I/B/E/S. Historical weather data used in estimating good- and bad-weather AWL are from Weather Underground. An intercept is estimated in each regression, but not reported. Standard errors are clustered by executive and are reported in parentheses. To be included in the sample, an executive must be active for the same fiscal quarter across multiple years. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

**Panel 11.A – Earnings Surprises – 2SLS, Second Stage**

| Variable | Q1 | Q1-Q2 | Q1-Q3 | Q1-Q4 |
|---|---|---|---|---|
| $\widehat{AWL}$ | 0.067*** | 0.047 | 0.118* | 0.315* |
| | (0.022) | (0.054) | (0.065) | (0.093) |
| Insider Trading controls? | N | Y | Y | Y |
| executive FE? | Y | Y | Y | Y |
| N OBS | 1,260 | 1,258 | 1,257 | 1,254 |
| Centered R-Squared | 0.466 | 0.410 | 0.409 | 0.427 |

**Panel 11.B – Revenue Surprises – 2SLS, Second Stage**

| Variable | Q1 | Q1-Q2 | Q1-Q3 | Q1-Q4 |
|---|---|---|---|---|
| $\widehat{AWL}$ | -0.098* | -0.167 | -0.021 | 0.024 |
| | (0.058) | (0.118) | (0.083) | (0.071) |
| Insider trading controls? | Y | Y | Y | Y |
| executive FE? | Y | Y | Y | Y |
| N OBS | 1,248 | 1,244 | 1,242 | 1,240 |
| Centered R-Squared | 0.411 | 0.538 | 0.602 | 0.649 |

**Panel 11.C – Total Cost Surprises – 2SLS, Second Stage**

| Variable | Q1 | Q1-Q2 | Q1-Q3 | Q1-Q4 |
|---|---|---|---|---|
| $\widehat{AWL}$ | -0.190* | -0.216* | -0.133 | -0.297*** |
| | (0.060) | (0.121) | (0.087) | (0.091) |
| Insider Trading controls? | Y | Y | Y | Y |
| executive FE? | Y | Y | Y | Y |
| N OBS | 1,247 | 1,243 | 1,240 | 1,236 |
| Centered R-Squared | 0.358 | 0.443 | 0.498 | 0.540 |

## Table 12. Predicted Effort and Future Earnings – High vs. Low Q – 2SLS

The table provides second stage results of 2SLS regressions of future cumulative earnings surprises on predicted CEO and CFO effort for high (Panel A) and low (Panel B) firms. In the first stage, we estimate the following equation for the full sample:

$$AWL_{j,y,q} = \alpha + \beta weather\ AWL_{\ j,y,q} + \vartheta_{j,y,q}$$

where *weather AWL* is a weighted average of good-weather and bad-weather *AWL* and the weights are the percentage of good- or bad-weather days, respectively during the specific fiscal quarter:

$$weather\ AWL = [W_{Good,j,y,q} AWL(good)_{j,q} + W_{Bad,j,y,q} AWL(bad)_{j,q}]$$

Good- and bad-weather *AWL* are estimated for each executive using weather that is better than median or worse than median, respectively, for the same fiscal quarter across all years in the sample. Days are considered to be good- (bad-) weather if they are better (worse) than median for the quarter-location where "better" is defined how close (in absolute value) the "feels like" metric is to 72 degrees between 3pm and 6pm on workdays. In the second stage we estimate the following equation separately for high- and low-Q firms:

$$SUE_{j,y,q} = \delta + \varphi \widehat{AWL}_{j,y,q} + \varepsilon_{j,y,q}$$

$$\widehat{AWL}_{j,y,q} = \hat{\alpha} + \hat{\beta} weather\ AWL_{\ j,y,q}$$

where SUE is Standardized Unexpected Earnings (SUE), which is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior divided by the standard deviation of these differences measured over the previous eight quarters. We examine cumulative surprises over 1-quarter, 2-quarters, 3-quarters, and 4-quarters where the beginning of each of the windows includes the quarter in which effort is measured. $\widehat{AWL}$ is the fitted value from the first-stage estimation. Firms are classified as high or low Q based on whether their Q is higher or lower than the median Q of all sample firms in the same (Fama-French 12) industry in the same year. Control variables include firm characteristics, measures of insider trading, and executive fixed effects. Firms at the median are dropped from the analysis. Insider trading data are from the SEC Edgar database. Platform activity is from Bloomberg, earnings per share data are from I/B/E/S. Historical weather data used in estimating good- and bad-weather AWL are from Weather Underground. An intercept is estimated in each regression, but not reported. Standard errors are clustered by executive and are reported in parentheses. To be included in the sample, an executive must be active for the same fiscal quarter across multiple years. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

**Panel 12.A – Above Median Q – 2SLS, Second Stage**

| | Q1 | | Q1-Q2 | | Q1-Q3 | | Q1-Q4 | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\widehat{AWL}$ | 0.518** | 0.479** | 0.760** | 0.686** | 0.983** | 0.872* | 1.241** | 1.087* |
| | (0.208) | (0.194) | (0.355) | (0.340) | (0.487) | (0.473) | (0.602) | (0.577) |
| Firm Controls? | N | Y | N | Y | N | Y | N | Y |
| Insider Trading? | Y | Y | Y | Y | Y | Y | Y | Y |
| Executive FE? | Y | Y | Y | Y | Y | Y | Y | Y |
| N OBS | 445 | 445 | 445 | 445 | 445 | 445 | 445 | 445 |
| Centered R-squared | 0.213 | 0.308 | 0.391 | 0.454 | 0.442 | 0.495 | 0.471 | 0.529 |

**Panel 12.B – Below Median Q – 2SLS, Second Stage**

| | Q1 | | Q1-Q2 | | Q1-Q3 | | Q1-Q4 | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\widehat{AWL}$ | -0.009 | -0.016 | 0.015 | 0.005 | 0.474 | 0.431 | 1.364** | 1.283** |
| | (0.107) | (0.096) | (0.212) | (0.191) | (0.397) | (0.345) | (0.655) | (0.561) |
| Firm Controls? | N | Y | N | Y | N | Y | N | Y |
| Insider Trading? | Y | Y | Y | Y | Y | Y | Y | Y |
| Executive FE? | Y | Y | Y | Y | Y | Y | Y | Y |
| N OBS | 447 | 447 | 447 | 447 | 447 | 447 | 447 | 447 |
| Centered R-squared | 0.484 | 0.499 | 0.503 | 0.525 | 0.427 | 0.474 | 0.217 | 0.282 |

**Table 13. Predicted Effort and Earnings Announcement Returns – 2SLS**

The table provides second stage results of 2SLS regressions of cumulative abnormal stock returns (in basis points) around earnings announcements on predicted executive effort measured during the fiscal quarter associated with the earnings as well as standardized unexpected earnings (SUE), and measures of insider trading during the fiscal quarter and an executive and year-quarter fixed effect. In the first stage, we estimate the following equation:

$$AWL_{j,y,q} = \alpha + \beta weather\ AWL_{\ j,y,q} + \vartheta_{j,y,q}$$

where *weather AWL* is a weighted average of good-weather and bad-weather *AWL* and the weights are the percentage of good- or bad-weather days, respectively during the specific fiscal quarter:

$$weather\ AWL = [W_{Good,j,y,q} AWL(good)_{j,q} + W_{Bad,j,y,q} AWL(bad)_{j,q}]$$

Good- and bad-weather *AWL* are estimated for each executive using weather that is better than median or worse than median, respectively, for the same fiscal quarter across all years in the sample. Days are considered to be good- (bad-) weather if they are better (worse) than median for the quarter-location where "better" is defined how close (in absolute value) the "feels like" metric is to 72 degrees between 3pm and 6pm on workdays. In the second stage we estimate the following equation:

$$CAR_{j,y,q} = \delta + \varphi \widehat{AWL}_{j,y,q} + \varepsilon_{j,y,q}$$

$$\widehat{AWL}_{j,y,q} = \hat{\alpha} + \hat{\beta} weather\ AWL_{\ j,y,q}$$

where CAR is Cumulative Abnormal Returns measured using the Fama-French 3 Factor model where factor loadings are estimated using a year of past daily stock returns (skipping the most recent week). Cumulative abnormal returns are presented for ranges of 1 through 50 trading days where the first day is the trading day that includes the announcement. Platform activity is from Bloomberg and stock price data are from CRSP. Fama French factor portfolios are from Ken French's website. $\widehat{AWL}$ is the fitted value from the first-stage estimation. Each reported coefficient represents a single regression using $\widehat{AWL}$. Cumulative returns are measured using the Fama-French 3 Factor model where factor loadings are estimated using a year of past daily stock returns (skipping the most recent week). Cumulative abnormal returns are presented for ranges of 1 through 50 trading days where the first day is the trading day that includes the announcement. Platform activity is from Bloomberg and stock price data are from CRSP. Fama French factor portfolios are from Ken French's website. SUE is defined as the difference in the current quarterly earnings per share and the earnings per share 4 quarters prior divided by the standard deviation of these differences measured over the previous eight quarters. Four measures of insider trading are included in the regressions. The variables *log_purchase*, and *log_sell*, are the log dollar amount of open market insider purchases and sales, respectively, by the executive during the fiscal quarter associated with the earnings announcement. The variables *log_purchase_all* and *log_sell_all* are the log dollar amount of open market insider purchases and sales by all insiders at the firm during the fiscal quarter. Insider trading data are from the SEC Edgar database. To be included in the sample, an executive must be active in the same fiscal quarter for multiple years. 1,244 observations are included in the regressions. All regressions include individual executive fixed effects. Standard errors, clustered by executive, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| Variable | 1-day | 2-day | 3-day | 4-day | 5-day | 6-day | 7-day | 8-day | 9-day | 10-day | 11-day |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\widehat{AWL}$ | 3.98 | 4.75 | 12.75* | 12.56 | 17.13* | 20.93* | 18.20* | 26.51** | 24.73** | 27.90* | 34.98*** |
| | (3.53) | (4.56) | (7.90) | (8.63) | (9.90) | (11.40) | (11.26) | (13.54) | (11.97) | (15.28) | (13.52) |
| SUE? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Insider Trading? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-Quarter FE? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Executive FE? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| N OBS | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 |
| Centered R-squared | 0.195 | 0.175 | 0.208 | 0.217 | 0.247 | 0.263 | 0.292 | 0.284 | 0.309 | 0.314 | 0.337 |

| Variable | 12-day | 13-day | 14-day | 15-day | 4-week | 5-week | 6-week | 7-week | 8-week | 9-week | 10-week |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\widehat{AWL}$ | 47.90*** | 54.63*** | 45.07*** | 61.67*** | 81.78*** | 42.18* | 24.22 | 2.51 | -22.83 | -2.52 | -16.10 |
| | (14.70) | (16.86) | (16.54) | (18.52) | (23.90) | (22.83) | (23.29) | (23.95) | (29.17) | (28.91) | (30.15) |
| SUE? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Insider Trading? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-Quarter FE? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Executive FE? | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| N OBS | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 | 1,244 |
| Centered R-squared | 0.353 | 0.375 | 0.398 | 0.391 | 0.413 | 0.483 | 0.579 | 0.656 | 0.665 | 0.636 | 0.593 |

### Table 14. Ex-Ante Incentive Contracts

The table reports the summary statistics of the excutives' compensation and targets. This sample consists of 252 executives with compensation data in ISS Incentive Lab, resulting in 520 executive-year observations. *value_stock_owned* is the dollar value of the executive's stockholdings in the firm. *salary* is the executives' fixed salary during the fiscal year. *cash_perf* is the target dollar amount of the cash-based performance incentive bonus from the executive's compensation contract for the fiscal year. *stock_perf* is the target dollar amount of the stock-based performance incentive bonus from the contract. *stock_time* and *option_time* are the values of the time-based stock and option grants, respectively, from the contract. Predicted compensation, *pred_comp*, is the sum of *salary*, *cash_perf*, *stock_perf*, *stock_time*, and *option_time*. The cash performance metric types *Accounting*, *Individual*, *Stock Price*, and *Other* are the weights of the categories for the metrics that determine the executive's cash based incentive program. Metrics are categorized by incentive lab and the weights of each metric are collected from the proxy statements.

| Variable | N | Mean | Std Dev | 25th Pctl | Median | 75th Pctl |
|---|---|---|---|---|---|---|
| Executive Role | | | | | | |
| *CEO* | 520 | 27% | | | | |
| *CFO* | 520 | 45% | | | | |
| Compensation Contracts | | | | | | |
| *value_stock_owned* | 520 | 68,952 | 239,370 | 3,081 | 10,693 | 38,826 |
| *pct_firm_owned* | 520 | 0.77% | 3.81% | 0.02% | 0.07% | 0.21% |
| *pred_comp* | 520 | 7,227 | 14,706 | 2,203 | 4,178 | 7,696 |
| *salary* | 520 | 783 | 452 | 500 | 675 | 1,000 |
| *cash_perf* | 520 | 1,180 | 1,944 | 138 | 643 | 1,350 |
| *stock_perf* | 520 | 2,530 | 3,963 | 360 | 1,239 | 3,016 |
| *stock_time* | 520 | 2,154 | 12,269 | 0 | 345 | 1,295 |
| *option_time* | 520 | 566 | 1,304 | 0 | 0 | 497 |
| Cash Performance Metric Types | | | | | | |
| *Accounting* | 520 | 62.79% | | | | |
| *Other* | 520 | 27.60% | | | | |
| *Individual* | 520 | 7.08% | | | | |
| *Stock Price* | 520 | 2.53% | | | | |

## Table 15. Incentive Contracts and Effort – Earnings Targets

The table provides results of regressions of changes in *AWL* between the 1st half of the fiscal year and the 2nd half of the fiscal year on a *target_1_pct*, which indicates that earnings per share in the 1st half of the fiscal year are on an annualized pace to finish within 1% of the annual target in the executive's cash bonus compensation contract, on the variable *pct_cash_perf*, and on an interaction between the two variables. *target_1_pct* is equal to 1 if the quantity $\left|2 * \left(EPS_{Q1} + EPS_{Q2}\right) - EPS\ Target\right| / EPS\ Target$ is less than 1%, where *Q1* and *Q2* indicate the first two fiscal quarters of the year and *EPS Target* is the EPS target in the executive's bonus contract. Additional control variables include the logarithm of predicted compensation, *log_pred_comp*, the logarithm of the value of shares of the firm's stock owned by the executive, and the firm characteristics leverage, size, productivity, and Tobin's Q, as well as executive role fixed effects, industry fixed effects, and fiscal year fixed effects, where indicated. The final specification includes *AWL* (measured over the entire fiscal year) as a dependent variable. The prefixes *log* on the compensation variable indicates a natural logarithm of the variable while the prefix *pct* indicates that the variable has been scaled by predicted compensation, *pred_comp*. *CEO* and *CFO* fixed effects indicate whether the executive's role is that of the Chief Executive Officer or Chief Financial Officer, respectively. Platform activity data are from Bloomberg. Target bonus award amounts and other compensation data are from ISS Incentive Lab and variables are defined in Table 14. Twelve Fama French Industry Fixed Effects and Fiscal Year fixed effects are included. Data from 55 executives with profile activity data on Bloomberg for at least one quarter in the first half of a fiscal year and one quarter in the second half are included in the regressions. Standard errors are clustered by executive and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| | CHANGE IN AWL | | | AWL |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| *pct_cash_perf*target_1_pct* | 21.068 ** | 22.724 ** | 19.669 ** | |
| | (7.251) | (7.715) | (7.769) | |
| *target_1_pct* | -5.193 ** | -5.495 ** | -4.575 ** | |
| | (1.949) | (2.141) | (2.257) | |
| *log_pred_comp* | 0.471 | 0.822 * | 0.739 | -0.129 |
| | (0.417) | (0.449) | (0.581) | (0.483) |
| *pct_cash_perf* | -1.617 | -1.911 | -1.378 | 2.720 * |
| | (2.253) | (2.262) | (2.153) | (1.470) |
| *log_shares_owned* | -0.033 | -0.061 | -0.076 | -0.057 |
| | (0.236) | (0.271) | (0.281) | (0.192) |
| Firm Characteristics | YES | YES | YES | YES |
| Executive Role FE? | NO | YES | YES | YES |
| Industry FE? | NO | NO | YES | YES |
| Fiscal Year FE? | NO | NO | YES | YES |
| N OBS | 91 | 91 | 91 | 91 |
| R-Square | 0.13 | 0.17 | 0.25 | 0.39 |

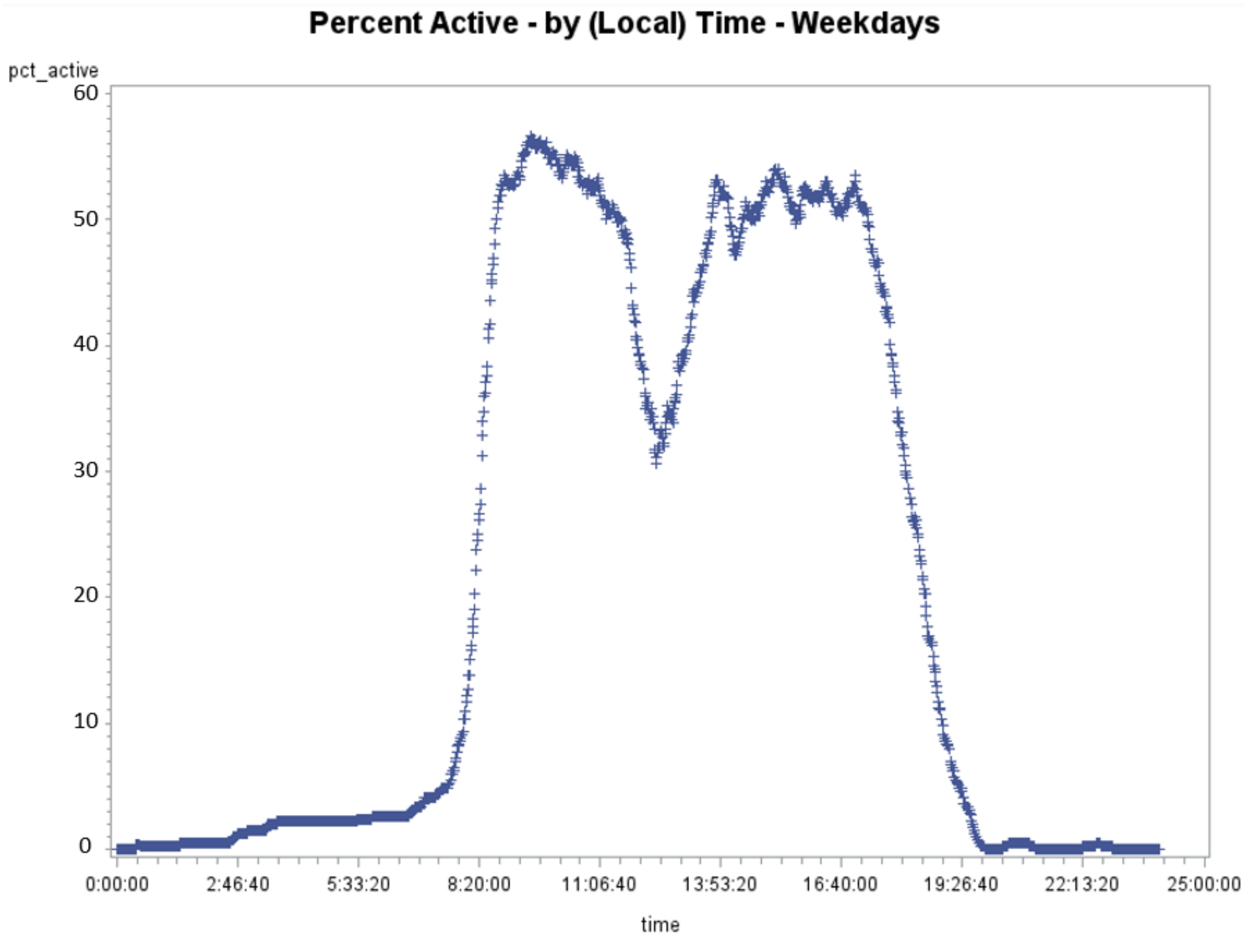
### Table 16. Effort and Industry Competition

The table provides results of quarterly regressions executive effort (*AWL*) on lagged changes in quarterly firm sales and lagged changes in quarterly peer firms' sales and an executive fixed effect. *%Chng_Sales* is defined as the percentage change in the firm's sales during fiscal quarter *t* relative to the firm's quarterly sales 4 quarters prior [(Sales t - Sales t-4)/Sales t-4)] in %. In the table, *Lag1* (*Lag2*) means the *%Chng_Sales* in quarter *t*-1 (*t*-2). In a similar manner, *%Chng_PeerSales* is defined as the percentage change in the firm's peers' sales during fiscal quarter *t* relative to the firm's peers' quarterly sales 4 quarters prior. For each firm, include up to 10 closest peers based on the GICS6 industry classification, where closest peers are defined based on the smallest absolute difference in firm market cap. To aggregate the peer information, we calculate the market-cap value-weighted average across all peers. To reduce the effect of outliers, we trim *%Chng_Sales* and *%Chng_PeerSales* at the top and bottom 1% of their distribution. Platform activity is from Bloomberg, earnings per share data are from I/B/E/S, and Fama-French 12 industry definitions are from Ken French's website. Firm characteristics, size, leverage, productivity, and Tobin's Q are from CRSP and Compustat and are included where indicated. An intercept is estimated in each regression, but not reported. All specifications include year fixed effects. Standard errors are clustered by executive and are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Lag1_%Chng_Sales* | -0.001 | | -0.003 | -0.003 | | -0.004 | -0.005 | -0.010 | -0.012 |
| | (0.006) | | (0.006) | (0.007) | | (0.007) | (0.008) | (0.010) | (0.011) |
| *Lag1_%Chng_PeerSales* | | 0.025 ** | 0.026 ** | | 0.023 ** | 0.024 ** | 0.029 ** | 0.045 *** | 0.043 *** |
| | | (0.011) | (0.011) | | (0.011) | (0.011) | (0.011) | (0.015) | (0.013) |
| *Lag2_%Chng_Sales* | | | | | | | -0.011 ** | | |
| | | | | | | | (0.005) | | |
| *Lag2_%Chng_PeerSales* | | | | | | | 0.001 | | |
| | | | | | | | (0.009) | | |
| *Firm Controls?* | NO | NO | NO | YES | YES | YES | YES | NO | YES |
| *Year FE?* | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| *Industry FE?* | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| *Executive FE?* | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| *Excluding Financials?* | NO | NO | NO | NO | NO | NO | NO | YES | YES |
| *N OBS* | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,205 | 527 | 527 |
| *R-Squared* | 0.406 | 0.409 | 0.408 | 0.406 | 0.409 | 0.408 | 0.403 | 0.327 | 0.328 |

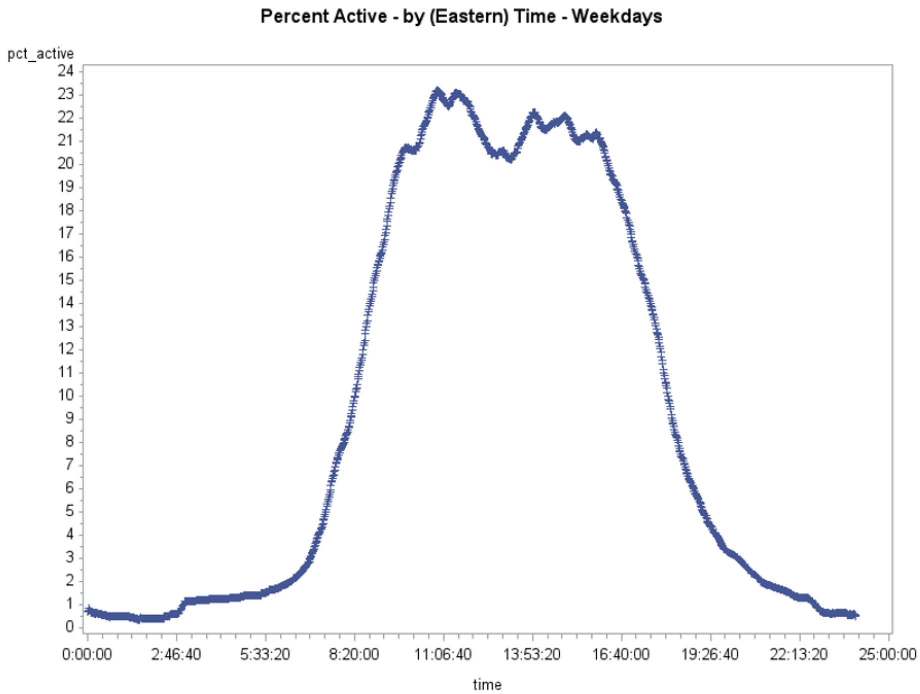
## Figure 1. Example of an Executive's Annual Platform Activity

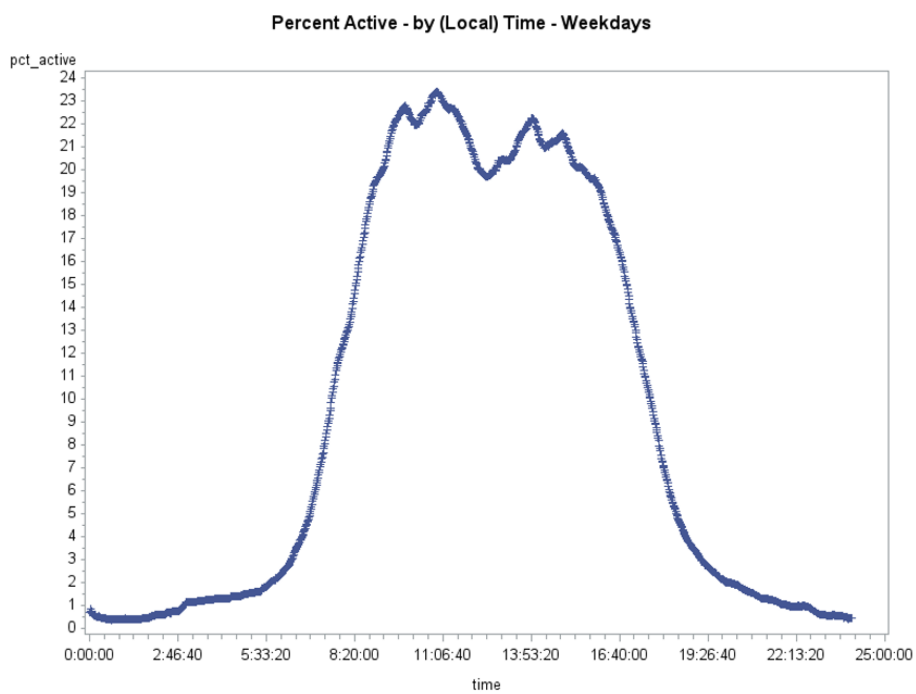
This figure describes the Bloomberg platform activity for a CFO in our sample. The x-axis is each time (minute) during 24-hours. The y-axis measures the probability during the year that the CFO is active on the platform at each time, given that the day is not a holiday and it is a weekday.



## Figure 2. Executive Intraday Platform Activity

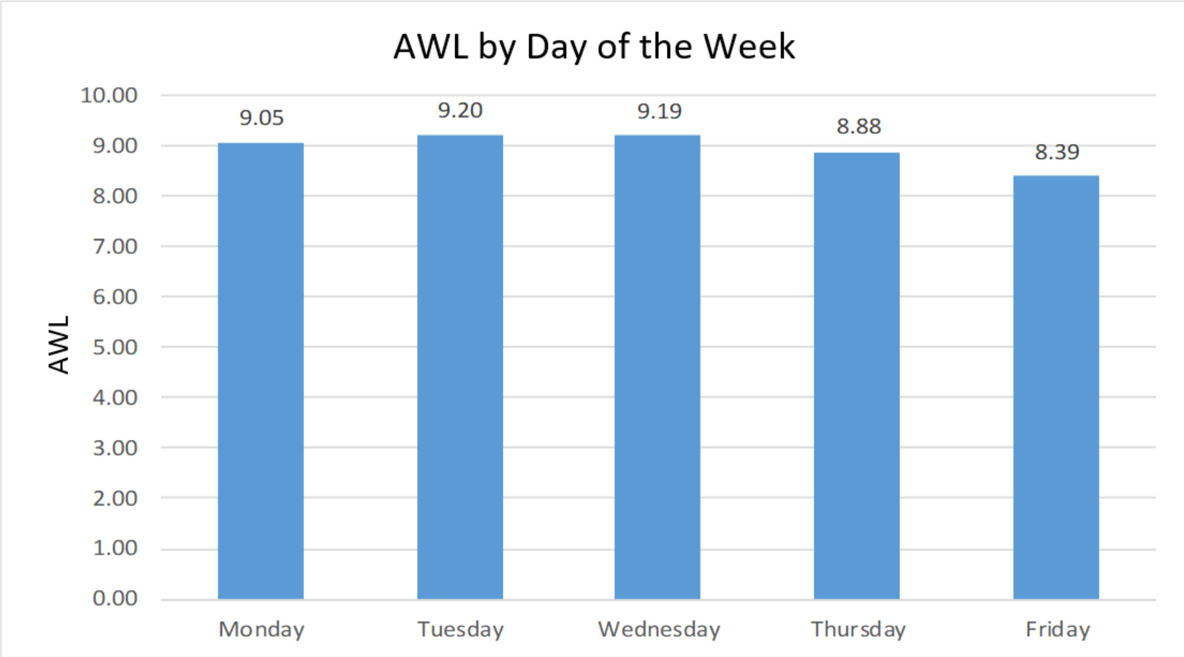
The figure provides the average percentage of executives that are active on the Bloomberg platform at a given time on weekdays (Monday through Friday) across the sample period. Panel A averages based on the Eastern time zone, while Panel B includes averages based on the local time zone of the Executive. Data are from Bloomberg.



## Figure 3. Effort by Day of the Week

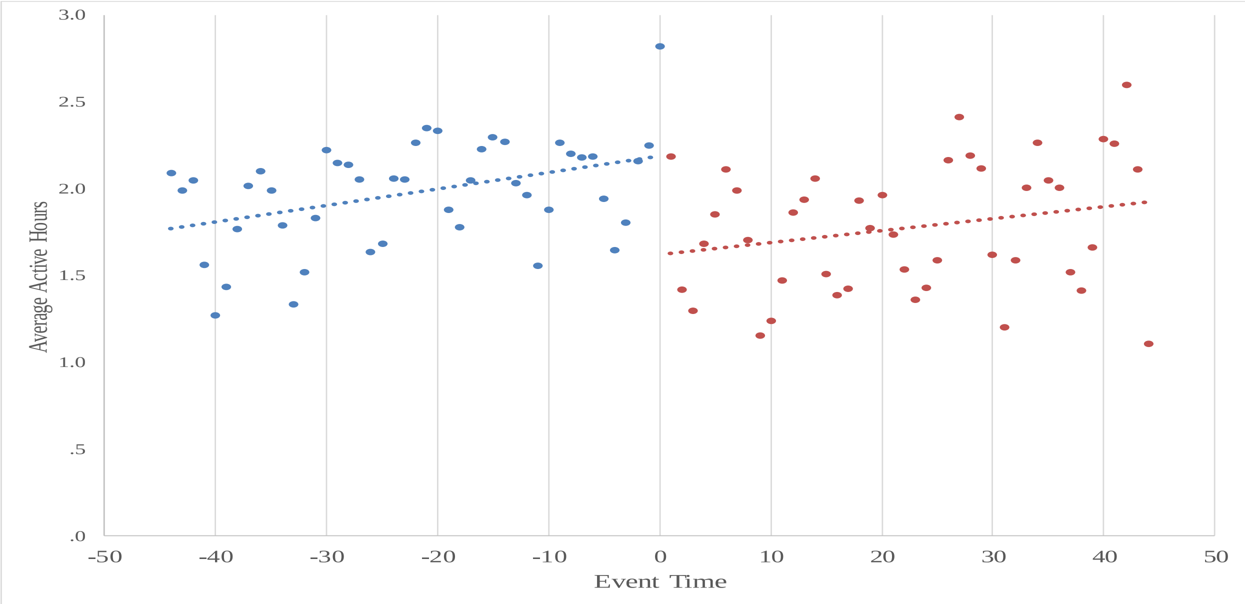
The figure provides the average AWL measure for each day of the week for the full sample.



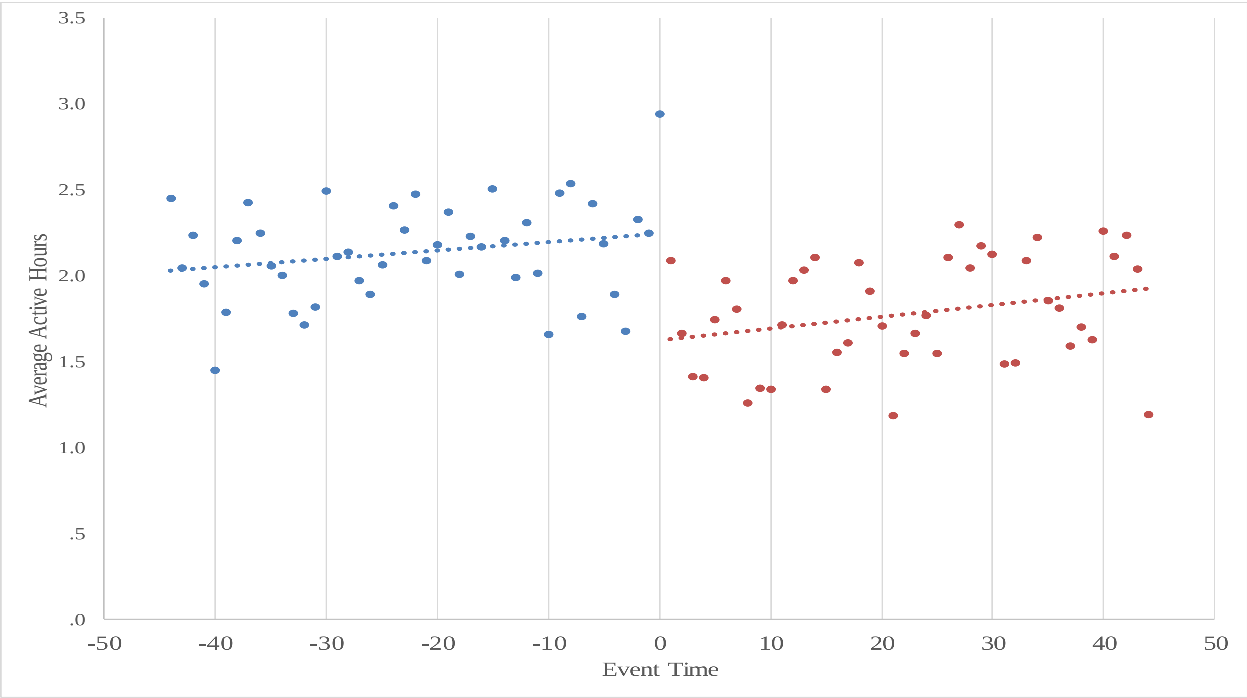

## Figure 4. Executive Activity and the Earnings Announcement Cycle

The figure includes executive platform activity through the quarter relative to the firm's earnings announcement. Effort is defined as hours online on the platform. Panel A presents results for all executives in the sample while Panel B presents results for CFOs and Panel C presents results for CEOs.

### Panel 4A: Executive Activity



**Panel 4B: CFO Activity**




**Panel 4C: CEO Activity**

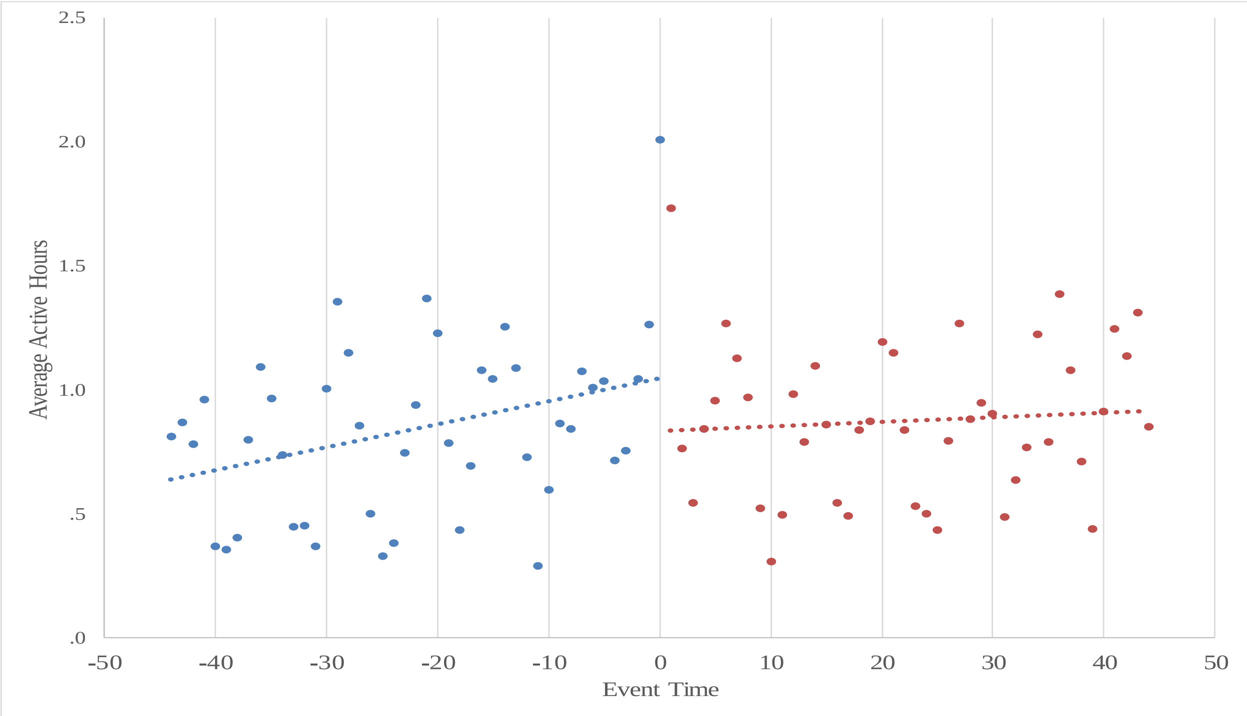
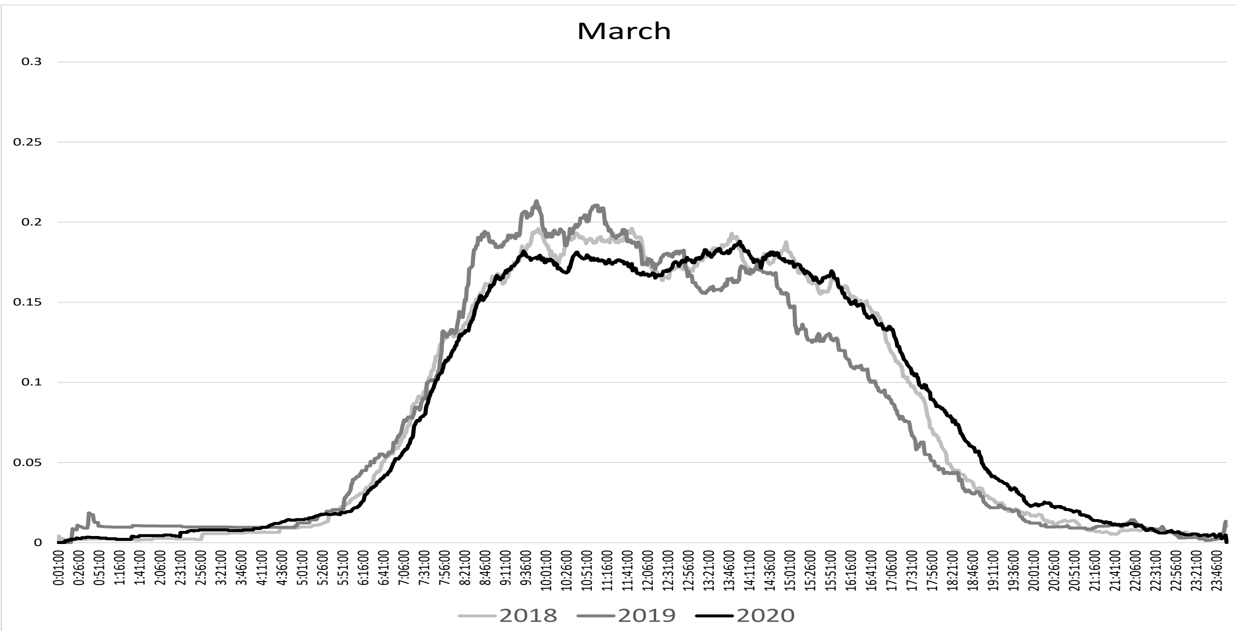


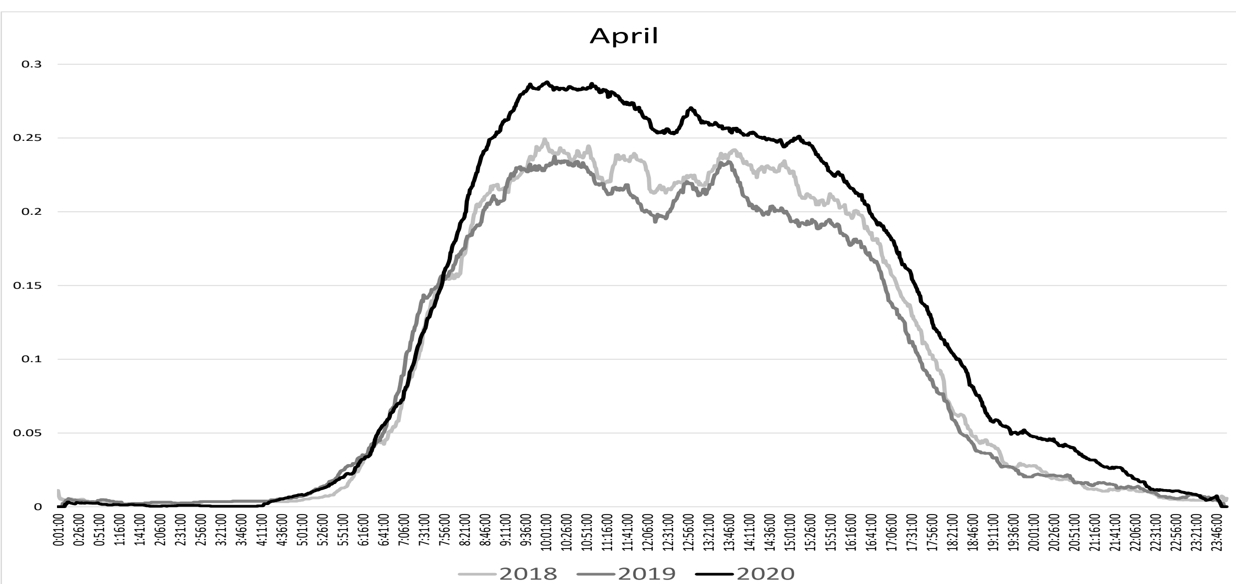
**Figure 5. Executive Intraday Platform Activity during the COVID-19 Pandemic**

The figure provides the average percentage of executives that are active on the Bloomberg platform at a given time on weekdays (Monday through Friday) for the months of March (Panel A), April (Panel B), May (Panel C), and June (Panel D) for the years 2018, 2019, and 2020. Averages are based on the local time zone. Data are from Bloomberg.

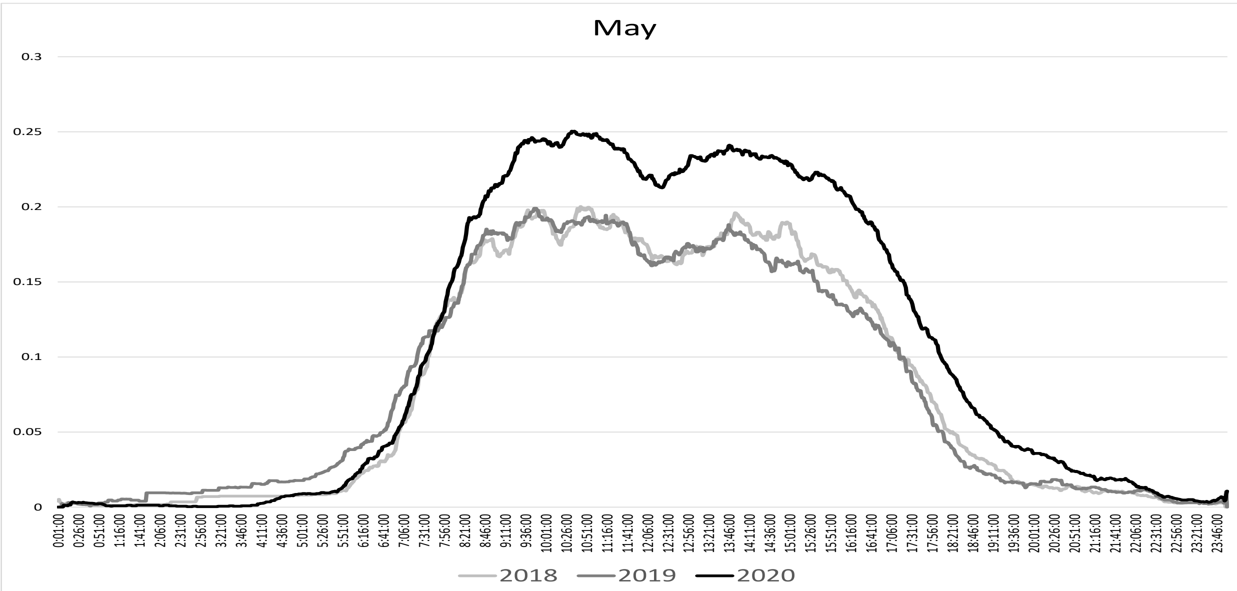
## Panel 5A – Activity during March



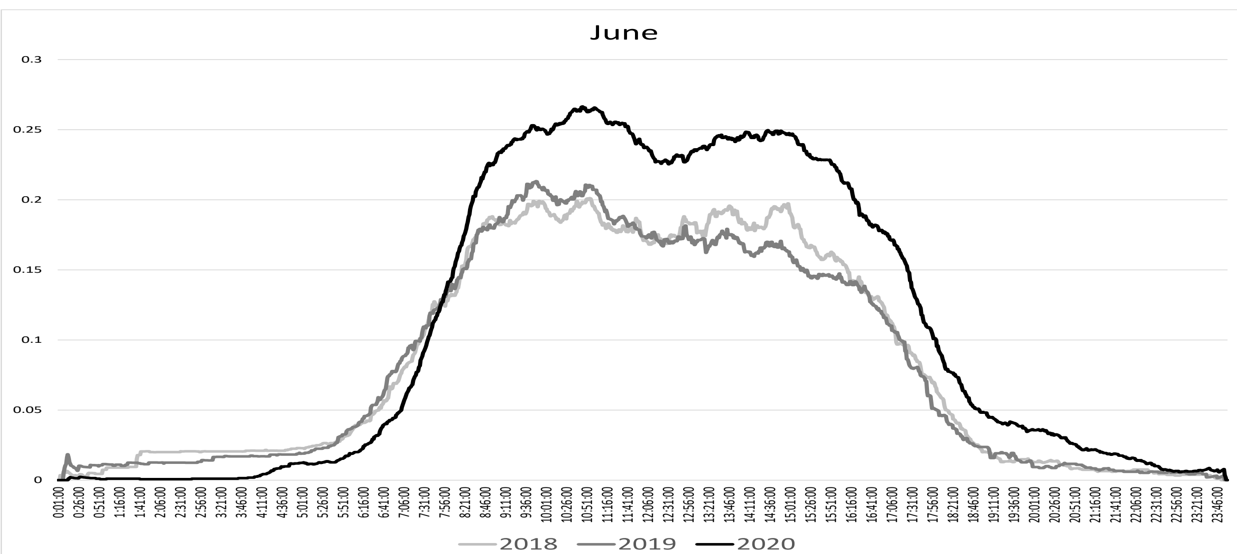

## Panel 5B – Activity during April



**Panel 5C – Activity during May**



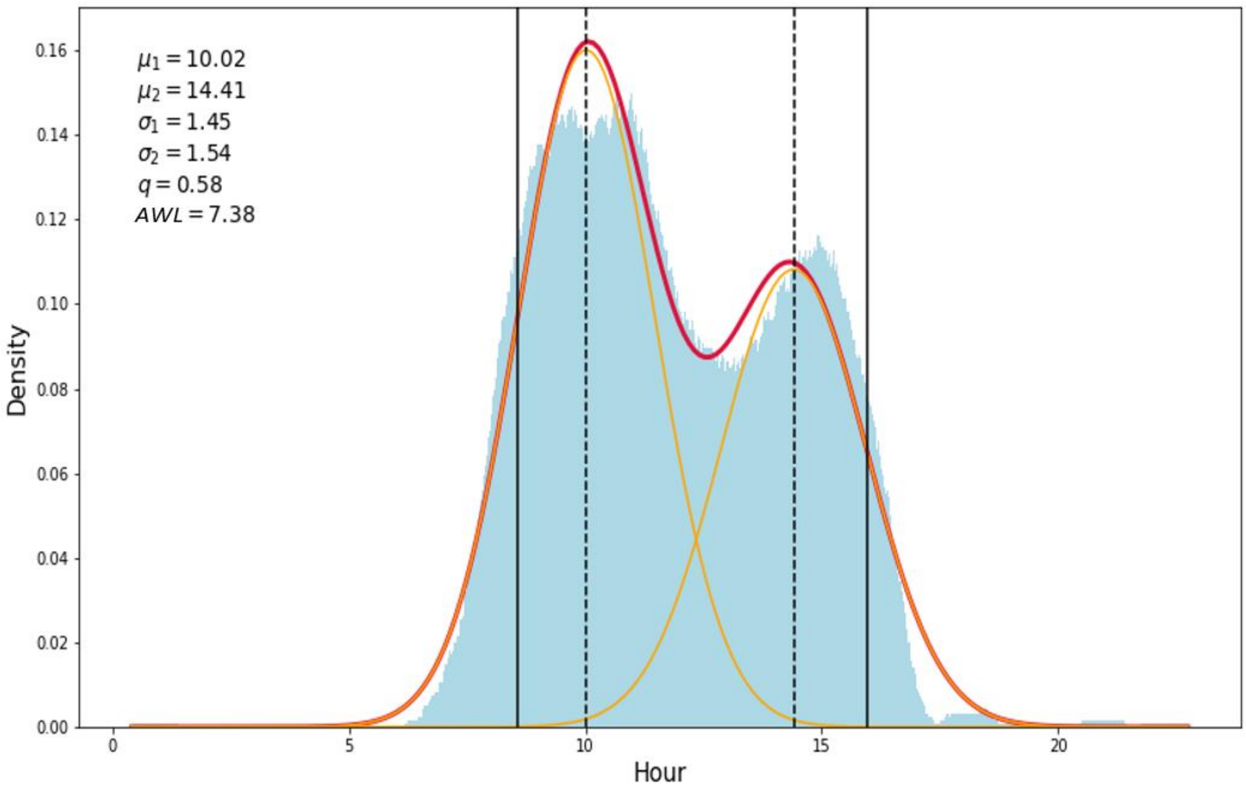

**Panel 5D – Activity during June**



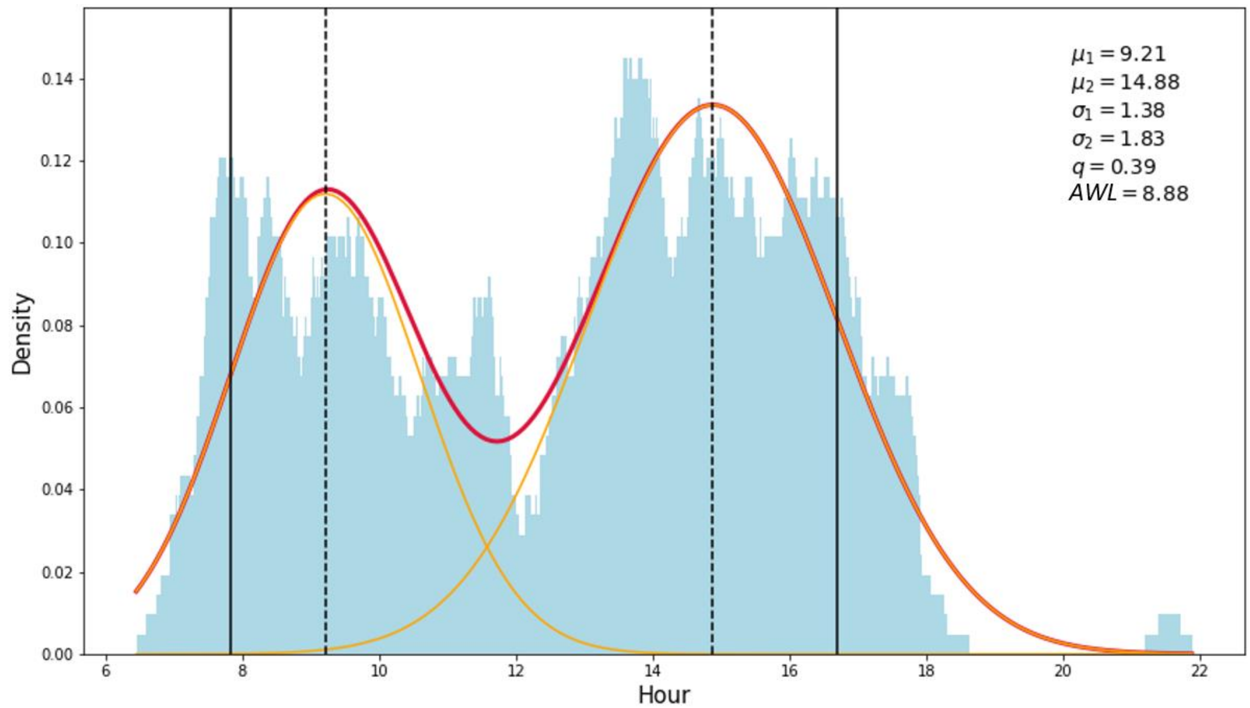
## Figure 6. Average Workday Length Examples

The figure provides an example of the AWL measure for three executive-year observations. 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 $(\mu_1 - \sigma_1, \mu_2 + \sigma_2)$.

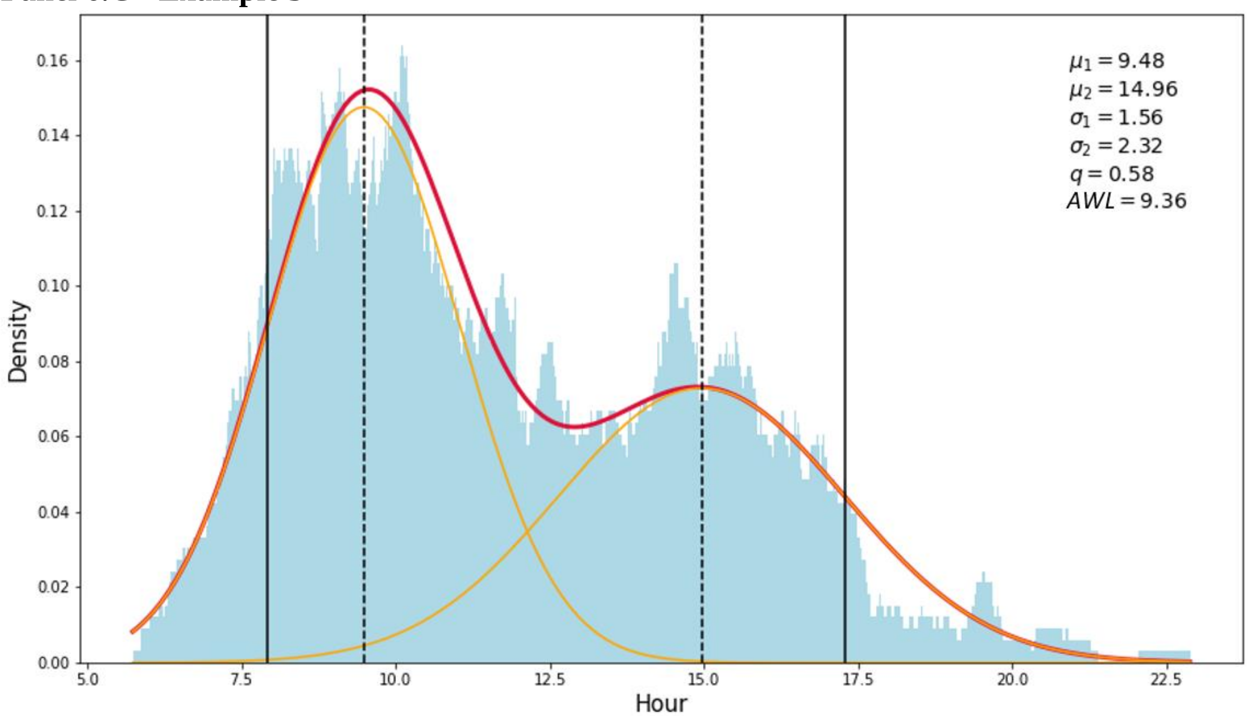
### Panel 6.A - Example 1



**Panel 6.B - Example 2**

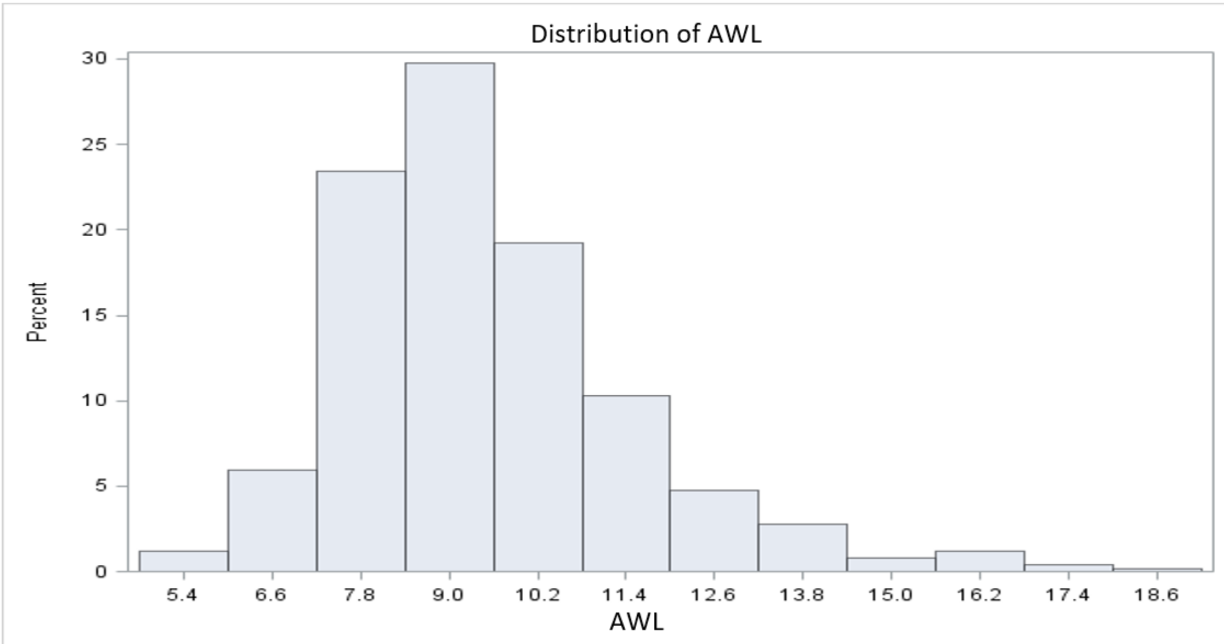



**Panel 6.C - Example 3**



## Figure 7. Effort Measure Histogram

The figure provides a histogram of the effort measure *AWL* (Average Workday Length).



## Figure 8. Comparing AWL using Bloomberg and Cell Phone Activity – Example

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

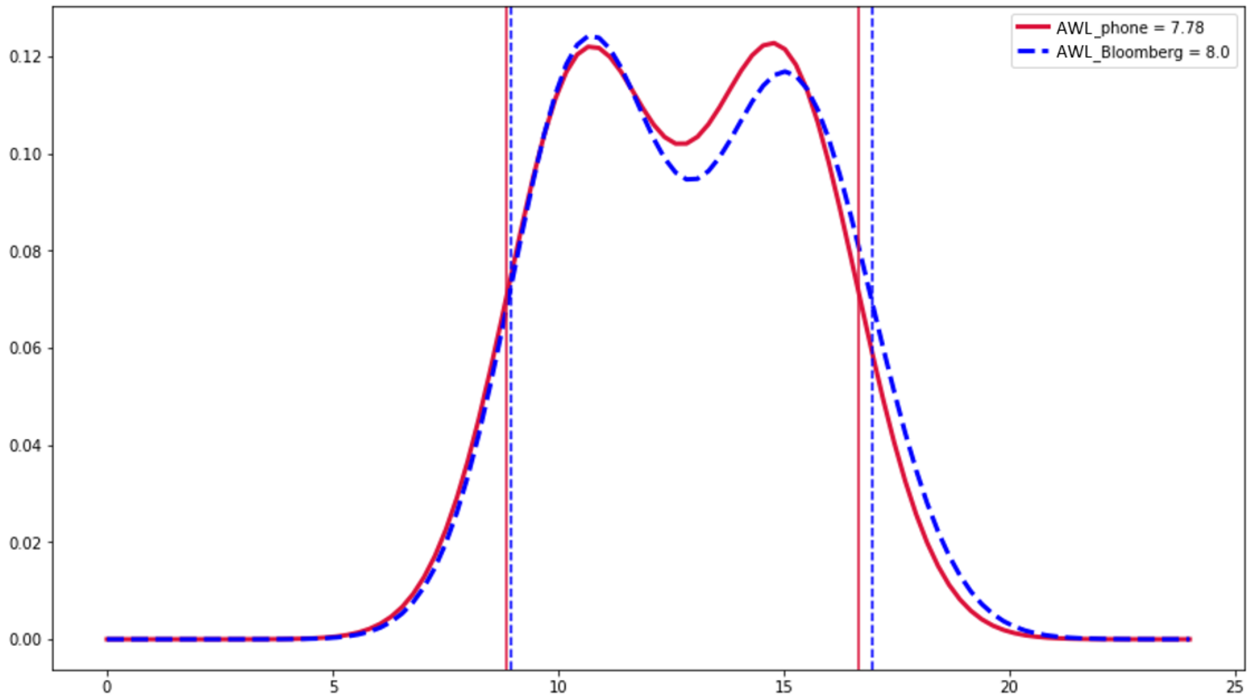


**Figure 9. Example of a Nearby Commuting Employee**

This figure provides an example of a "nearby commuting employee" identified using mobile phone geolocation data. The red marker and white circle indicate the executive's office location and the red circle defines a two mile radius around the office. In this fictional example, the blue star identifies the workplace of a nearby employee and the black triangle indicates his/her home. This "nearby" employee works within two miles of the executive. Moreover, this employee is also a "commuting" employee because he/she lives more than two miles from work (as indicated by the blue dotted circle) and more than two miles from the executive's workplace.