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# Uncovering the Hidden Effort Problem

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## 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 important agency issues from the literature.

THE MORAL HAZARD PROBLEM DUE to hidden effort is ubiquitous but is hard to study empirically. If the principal of an organization cannot observe the effort provided by their executives, it is a bigger challenge for outside empiricists or market investors who want to study basic questions such as whether executive effort affects firm value or what motivates them to work harder. Much like the principal, firm outsiders can perform statistical inference based on

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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 then can one study an executive's work habits (e.g., their workday length) without inducing observer effects or covertly spying on them?[1] A good candidate measure would be one 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 or cell phone is in use. While no such measure would be perfect, it would convey some information about an executive's daily work habits.

In this paper, we hand-collect usage microdata from personal Bloomberg accounts for CEOs, CFOs, and other top executives from publicly traded firms, many of which are in the S&P500 and are not financial firms. Because we expect most executives to be performing tasks other than using Bloomberg most of the day, 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 for effort provision. We then perform cross-sectional and time-series tests to examine how such 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 as a platform for 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 is idle for greater than 15 minutes, the dot turns yellow. If an executive is offline, the dot is red. A telephone icon indicates the executive is using the mobile application.[2]

We collect this online status, minute-by-minute, for the period 2017 to 2020 and provide evidence that monitoring Bloomberg usage is a plausible way to measure work effort. We simultaneously examine cell phone location data and provide anecdotal evidence that our measures of Bloomberg usage capture when executives are in their corporate office. In particular, we show that Bloomberg activity spikes around earnings announcements for both CEOs and CFOs, and that its intensity of use was higher during the COVID pandemic

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

[2] We did not collect any private information about what the executives actually did on the platform. For example, 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 made blind as to particular identities and results. We do not disclose subject identities in any of the results reported in this paper.

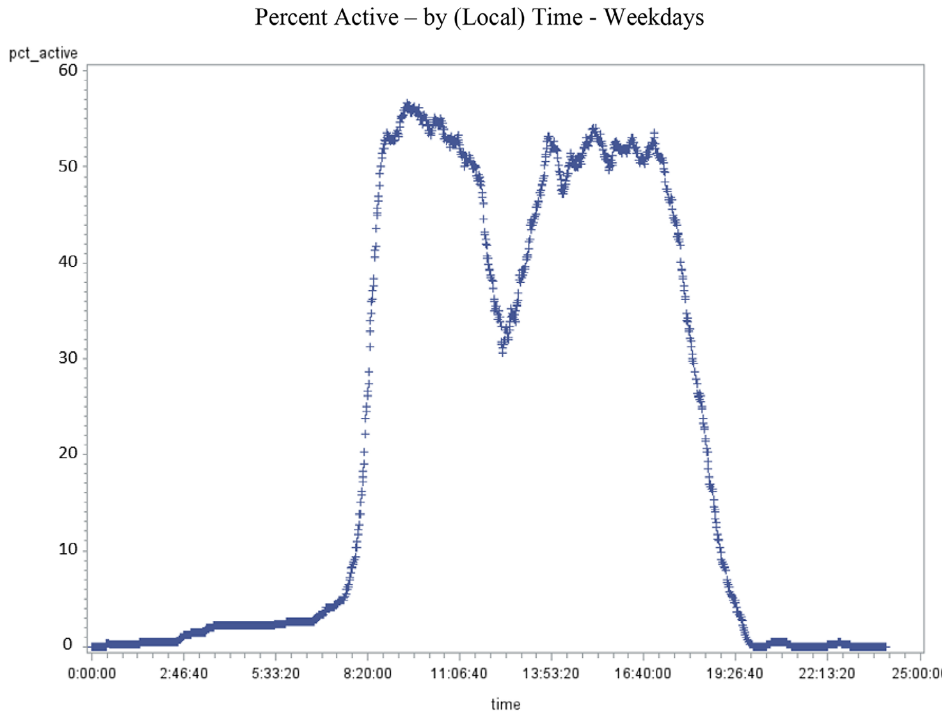



**Figure 1. Example of an executive's daily platform activity**. The figure describes the daily Bloomberg platform activity of a CFO in our sample over the course of a year. The $x$-axis is time in hours, minutes, and seconds over the 24 hours in a day. The $y$-axis is the probability that the CFO is active on the platform each minute of a day, given that the day is not a holiday or a weekend. The data come from Bloomberg. (Color figure can be viewed at wileyonlinelibrary.com)

when executives' business travel was restricted. We also show that executives' Bloomberg usage drops when their local weather is more favorable during the spring and summer, 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. When we amass a data set of events in which an executive is participating or speaking, we document almost no simultaneous activity on the Bloomberg platform. For example, we show that during analyst and investor days, the Bloomberg account of every single executive in our sample is inactive.

We use data across an entire year or quarter to estimate the typical start and end times of each executive's workday, and compute the average workday length (*AWL*) as the difference. The algorithm accounts for the fact that executives may not use Bloomberg every day and often login intermittently and sporadically. Figure 1 provides a histogram of the annual daily usage for one of the CFOs 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 both midmorning 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 for the afternoon, with the algorithm providing estimates of the underlying moments of the two distributions. Using this algorithm, we construct a distance measure called the *AWL* to proxy for the length of each executive's workday.[3] It is important to note that an executive can access Bloomberg sporadically and at the same time have a high *AWL*. Thus, *AWL* is distinct 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 unobserved time-invariant 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. We further show that effort provision has a positive and persistent effect on cumulative abnormal returns (CARs) following earnings announcements: a one-hour increase in *AWL* is associated with a CAR of 25 to 50 basis points (bps) 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 bps per day (37 bps over five days), a quantity that is plausible, robust, and statistically significant.

Not surprisingly, 50% of the firms in our sample are from the finance industry. One may be concerned that this pattern is driving our results. To address this concern, we separately analyze the subset of nonfinancial firms and find that our *SUE* and CAR results are at least as strong if not stronger. For nonfinancial firms, a one-hour increase in average *AWL* is associated with a CAR of 80 to 100 bps 7 to 10 weeks following an earnings announcement.

Another valid concern is that measures of firm value and our measure of executive effort are codetermined. To address this concern, we use exogenous local variation in weather patterns as an instrument. Daily historical data from Weather Underground allow us to divide days in each quarter into good days and bad days. This is an exogenous variable that we include in first-stage regressions.[4] Next, in second-stage regressions, using fitted values we show that predicted *AWL* is associated with both earnings surprises and CARs.

[3] We collected cell phone location data and show that these data support the view that *AWL* provides a meaningful estimate of work activity. In addition to *AWL*, as we discuss in the paper, we construct other Bloomberg-based measures of daily workday effort and find that our main results continue to hold. We present these additional results in the Internet Appendix. The Internet Appendix may be found in the online version of this article.

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

We also show that the earnings improvements associated with predicted *AWL* accumulate over time (in subsequent quarters), do so more quickly for firms with higher Q, and appear to arise through lower costs rather than 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 concern, we collect data on credit default swaps (CDSs) 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 CDS spread. Consistent with the earnings findings, we find that an increase in average *AWL* in one quarter is associated with an improvement (i.e., a reduction) in the firm's CDS spread in the next quarter.[5]

Our ability to estimate executive effort allows us to investigate some agency questions that have received attention in the academic literature. The first is how do executives respond to discontinuities in their compensation (Healy (1985), Degeorge, Patel, and Zeckhauser (1999), Murphy (2000)).[6] The mere presence of goals and targets induces kinks, which may result in earnings compensation being outside an executive's locus of control.

To investigate this question, we study changes in executive *AWL* in response to firm performance *within* the fiscal year. Specifically, we consider whether firm performance in the first half of the year affects whether earning a cash bonus is within an executive's locus of control in the second half of the year.[7] We document a large, positive, and statistically significant change in *AWL* when midyear performance is on pace with set targets. However, when midyear earnings are 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 sales growth of competing firms in an industry affects *AWL* over the next quarter when quarterly results are revealed. The idea is that executive performance is also captured by changes in market share. Thus, a reduction in market share relative to peers should result in greater effort (i.e., higher *AWL*). We find that while a firm's *own* sales growth has no significant effect on executive *AWL* over the next quarter, growth in peer sales has a positive and significant effect. This effect is economically significant, with a 10% increase in peer sales resulting in an increase of 0.25

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

[6] For example, Healy (1985) shows that floors and caps in compensation plans give executives incentives 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.

to 0.45 hours per workday 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 open 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 CEO's hour-to-hour activities." Yermack (2014) and Biggerstaff, Cicero, and Puckett (2017) try to study how effort affects firm value by examining vacation travel and golf habits, but both acknowledge that it is impossible to know what business activities potentially take place during those times.

In this context, why does our measure of workday length improve firm value so robustly? The likely explanation is due to a longer workday confirming an agency cost hypothesis. that is, demonstrating more commitment to the firm. This view 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. Accordingly, we view our paper as a complement 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 I, we describe the data collection and provide sample statistics, discuss the construction of our variables of interest, and provide support for our measure of effort. Section II provides our analysis of executive effort and firm outcomes. In Section III, we study agency and other incentives to employ effort. Section IV concludes.

## I. Data, Sample Statistics, and Effort Measure

### A. Sample Construction and Summary Statistics

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

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

[9] While may set their profile status to private, only 9.5% of executives do so.

Other users of the platform can view the status of any other Bloomberg user by employing the "PEOP" or 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 to 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, and firm name, and we 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 are the time that each individual actually used the platform.

The majority of the 2,734 executives in our user data set 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 also a large geographic dispersion, with 43 states plus the District of Columbia 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 Institutional Shareholder Services 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, 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 correspond to CEOs while 45% correspond to CFOs. The remainder is named executives with other roles.

Table I provides summary statistics at the executive × fiscal-year level for the executives in our sample. Panel 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*); and *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 ratio of debt to assets is 0.31, and the average ratio of revenues to assets is 0.35.

Panel B groups executive-year observations into industries based on the four-digit SIC code of their firm 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

**Table I**
**Summary Statistics**

The table reports summary statistics for firm characteristics of executives' firms (Panel A) and the distribution of executives' industries (Panel B). Our full sample includes 520 executive-year observations for 252 named executives on the Bloomberg platform 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*), and *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 A: Firm Characteristics

| Variable | $N$ | Mean | Std Dev | 25$^{th}$ Pctl | Median | 75$^{th}$ Pctl |
|---|---|---|---|---|---|---|
| *Size* | 520 | 43,194 | 46,842 | 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 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% |

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.

### B. Patterns of Bloomberg Usage

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

Table II provides summary statistics on 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, of which on average,

**Table II**

**Effort Measures**

The table reports summary statistics for platform usage by executives as well as the derived effort measure. Our sample includes data for 252 named executives on the Bloomberg platform during the sample period at firms with data on Compustat. Summary statistics for Bloomberg usage are presented separately for both "Active Hours" and "Mobile Hours," 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 II.C 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 an executive's firm.

| Sample Coverage | |
|---|---|
| Named executives: | 252 |
| Executive-year obs.: | 520 |
| Mean days: | 178 |
| Mean workdays (Mon–Fri): | 129 |
| Mean weeks | 31 |

Bloomberg Usage

| | Active Hours | | | Mobile Hours | | |
|---|---|---|---|---|---|---|
| | 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 |
| Weekends (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 |

129 are workdays, which we define as Monday through Friday. We observe an average of 31 weeks per executive-year.

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

These patterns suggest that Bloomberg use is a work activity, rather than one of leisure. To see this visually, Figure 2 plots for workdays the average

[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 3 am.

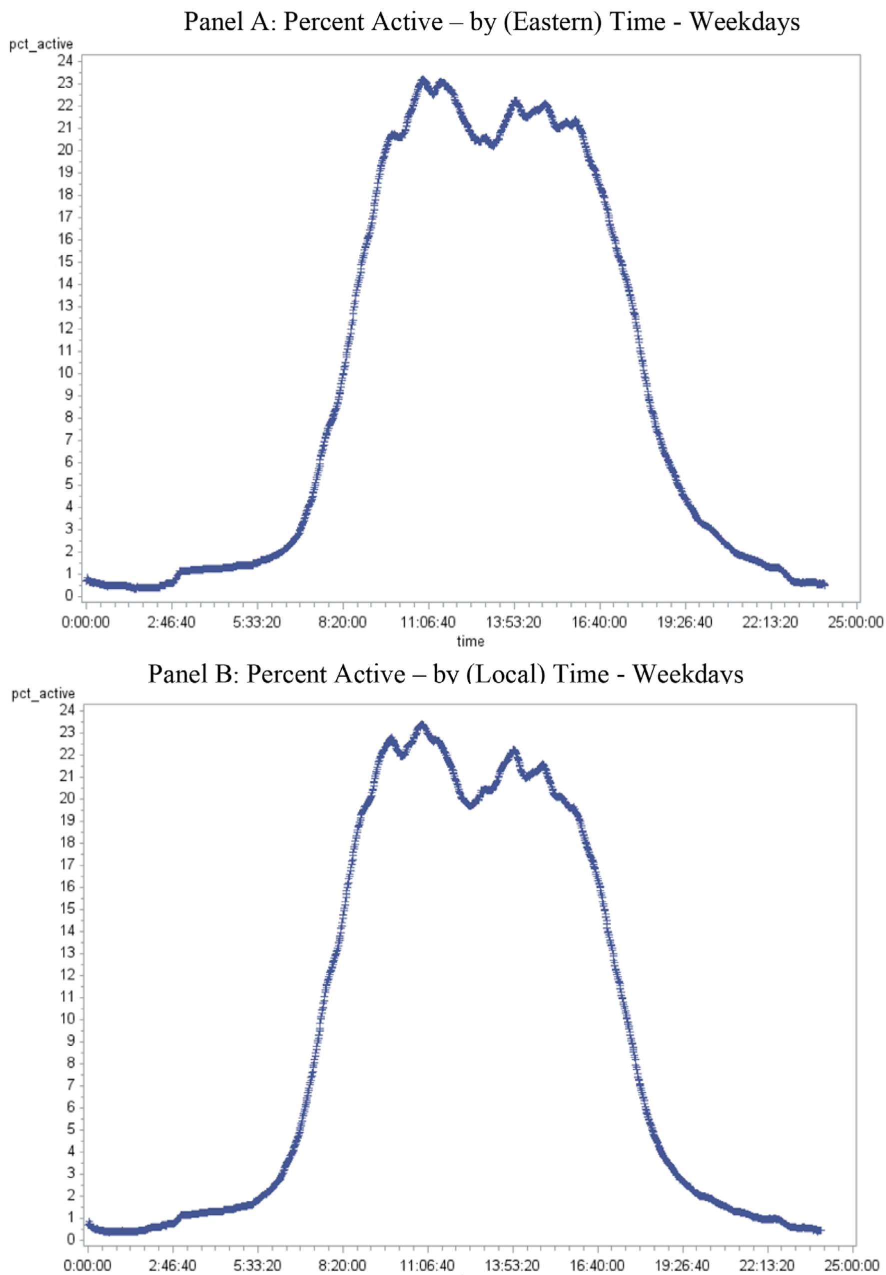



**Figure 2. Executive intraday platform activity**. The figure provides the average percentage of executives that are active on the Bloomberg platform at a given time of the day on weekdays (Monday through Friday) across the sample period. Panel A is based on the Eastern time zone, while Panel B is based on the local time zone of the executive. The data come from Bloomberg. (Color figure can be viewed at wileyonlinelibrary.com)

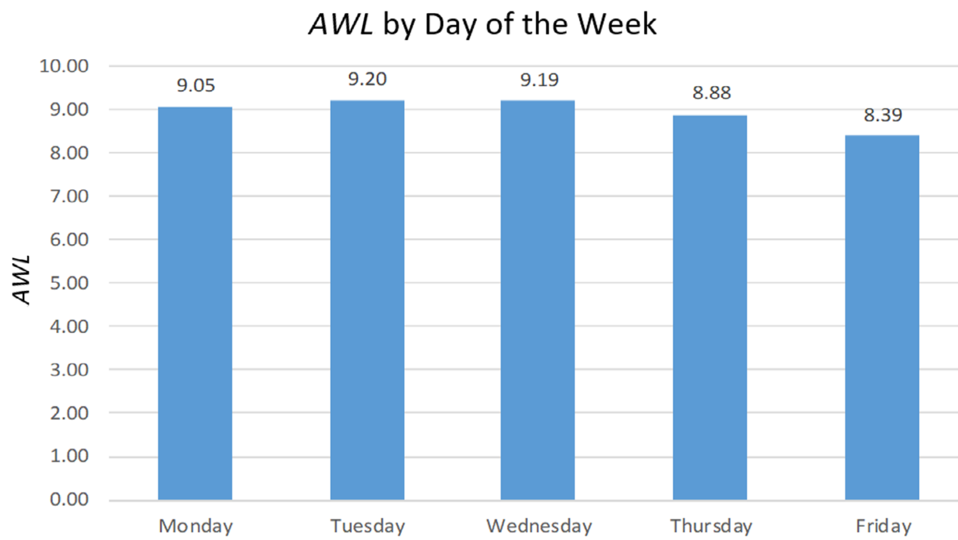



**Figure 3. Effort by day of the week**. The figure shows the average *AWL* measure for each day of the week for the full sample. The data come from Bloomberg. (Color figure can be viewed at wileyonlinelibrary.com)

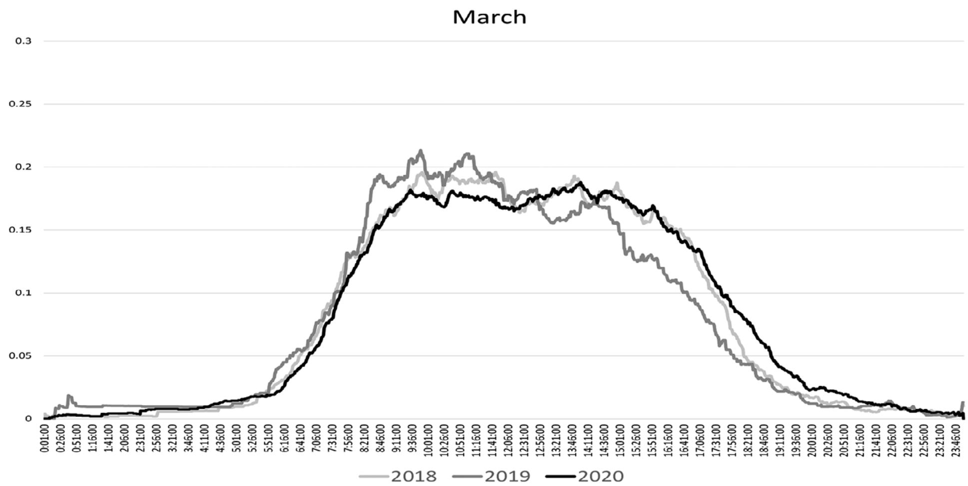
percentage of executives that actively use the platform during each minute of the day. As can be seen, active use is very limited, on average, before approximately 7 am, and after approximately 6 pm; there is also a drop in activity during the lunch hour. Thus, executives' Bloomberg activity is generally concentrated during the traditional 9 am-to-5 pm workday. In Figure 3, we examine average activity across days throughout the workweek. The histogram shows that activity is generally higher at the beginning and middle of the workweek and then declines toward the end of the week, typically being 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. We fit a trend line (using ordinary least squares) 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 then steadily increases until the next announcement. Panel B repeats the analysis of Panel A for the subset of CFOs only and shows that the pattern is more pronounced. Panel C repeats the analysis for the subset of CEOs only and shows that activity is highest on the announcement date and is also high the following day.

[11] In the figure, we use *AWL* as our measure of activity. We describe this variable in detail in Section II.C.


**Figure 4. Executive activity and the earnings announcement cycle**. The figure shows 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 only, and Panel C presents results for CEOs only. The data come from Bloomberg. (Color figure can be viewed at wileyonlinelibrary.com)

Panel A: Activity during March




Panel B: Activity during April

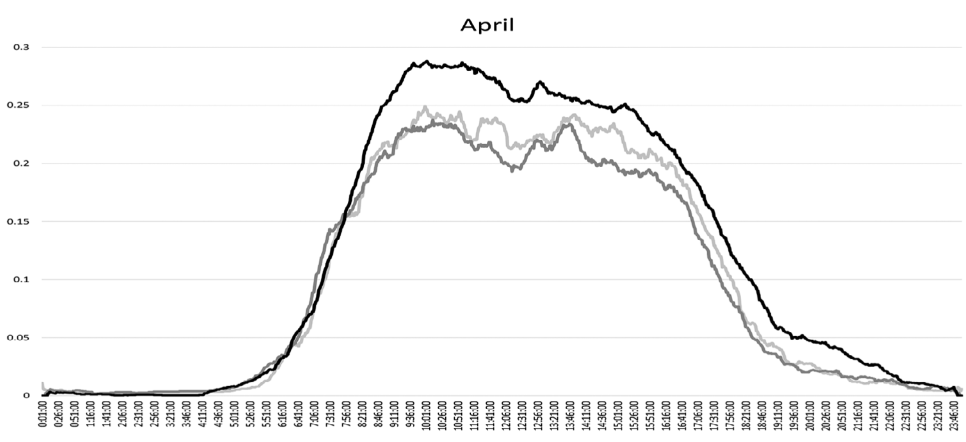
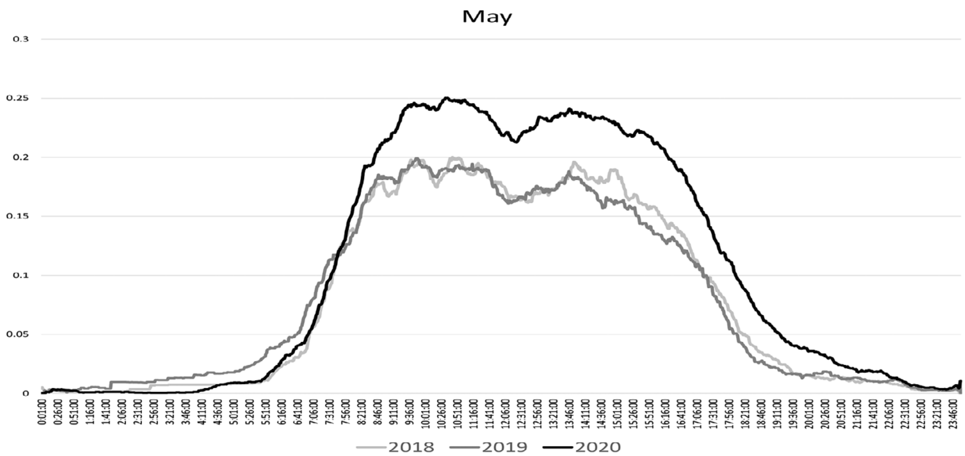



**Figure 5. Executive intraday platform activity during the COVID-19 pandemic**. The figure shows the average percentage of executives that are active on the Bloomberg platform at a given time on weekdays (Monday through Friday) for the months of March (Panel A), April (Panel B), May (Panel C), and June (Panel D) for the years 2018, 2019, and 2020. Averages are based on the local time zone. The data come from Bloomberg.

Panel C: Activity during May




Panel D: Activity during June

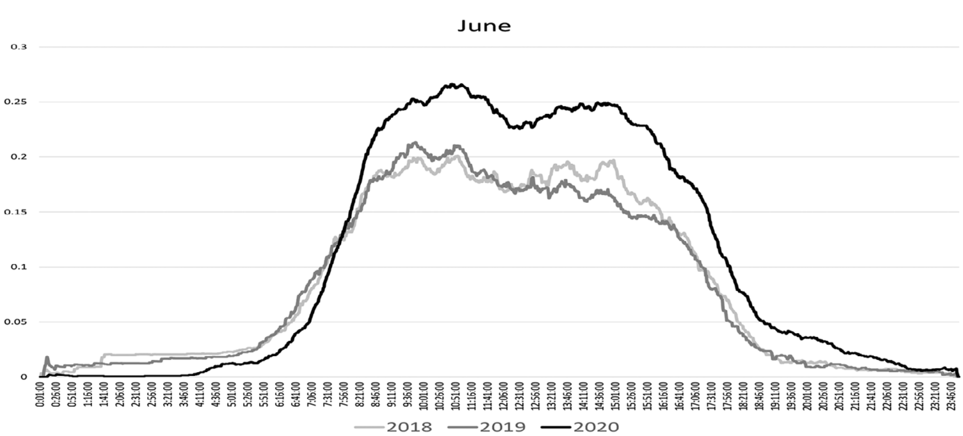



**Figure 5.** *Continued*

It is also instructive to examine how executives' usage of Bloomberg was affected by the COVID-19 pandemic of 2020, during which time once executives experienced less 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. As can be seen, 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 with substituting time on a computer for travel or leisure when these activities are less available. These findings also provide support for the idea that Bloomberg usage is a useful measure of the work habits of its users.

One would additionally expect any measure of an executive's work habits to decrease when they are given incentives to engage in leisure activities. We investigate this conjecture in Section III.B using historical weather data from Weather Underground. Consistent with an agency cost hypothesis, we find that work activity as measured by Bloomberg online status does indeed decrease when the weather improves in an executive's locale during the spring and summer.

*Validation of Personal Use*: To rule out the possibility that an executive's personal account is being accessed by other people such as their assistants, we look at usage by executives during key firm-level events where they are not only likely to be in attendance, but also speaking as an active participant. Such events 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 event lengths 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 the 30-minute window and aggregate by executive role and event.

We use Bloomberg's categories and descriptions to categorize events. For investment banking conferences/presentations and analyst and investor days, we examine the event transcripts on Factiva 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 III provides platform usage statistics for each of these categories.

The results are striking. For 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 six cases (four unique executives) for which there is activity on an executive's Bloomberg account during an event. For annual meetings, there is no activity on the platform for CEOs, CFOs, and other executives more than 90% of the time. These results are overwhelmingly consistent with the view that account activity is typically carried out by the executive him- or herself.

For reference, Table III also presents results for two other events during which an executive may or may not have access to the Bloomberg platform depending on the situation—earnings releases and earnings calls. The data suggest that during earnings releases, 74.6% of CEOs, 72.4% of CFOs, and 81.3% of other executives are inactive. During earnings calls, about 87% of

**Table III**

**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 types of 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 to 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% |

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 the period 2018 to 2020. While the identification number of each device is anonymized, Reveal Mobile provides the "home" latitude and longitude associated with each device. We combine these data with residential address history for each executive in our sample from Mergent Intellect to create a list of potential executive cell phones 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 information with the Bloomberg data. Several disadvantages of the cell phone data precluded this exercise for many of our executives, rendering 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 the executive. Second, many of the executives opted out of location tracking, which meant that they appeared in the geolocation data only sporadically or not at all. Third, while we used Google Places API to identify each corporate building footprint, many executives live and work in tall buildings and hence 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, we were able to identify 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 corporate building footprint, we find no platform activity in the previous 15 minutes 99.6% of the time.[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.

### C. Effort Measures

At first glance, it might be attractive to evaluate when an executive is on the platform by creating simple measures based on examining individual days, 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 will underestimate 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 aggregate data that better controls for 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 measure of workday length, *AWL*.

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

$$p^i_{min} = \frac{P^i_{min}}{\sum_J P^j_{min}}.$$

By construction, $\sum_J p^j_{min} = 1$. We then assume that the constructed distribution is a mixture of two normal distributions $k \in \{1,\ 2\}$, each with mean $\mu_k$

[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 these individual-specific data in Section II.C 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). However, because of the sporadic use of Bloomberg by some executives, workday length was estimated at approximately 3.5 hours, which we feel is implausible for the executives in our sample.

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. We find that executives do indeed display 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 a probability $(1-q)$ that it is 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 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 rechosen 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 $(\hat{\mu}_1,\ \hat{\mu}_2,\ \hat{\sigma}_1^2,\ \hat{\sigma}_2^2)$,

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

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 examples of how *AWL* is constructed. The shaded blue area corresponds to 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 resulting mixed distribution. As can be seen, 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]

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

[16] We 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 earnings surprises and abnormal returns. We provide this evidence in the Internet Appendix.

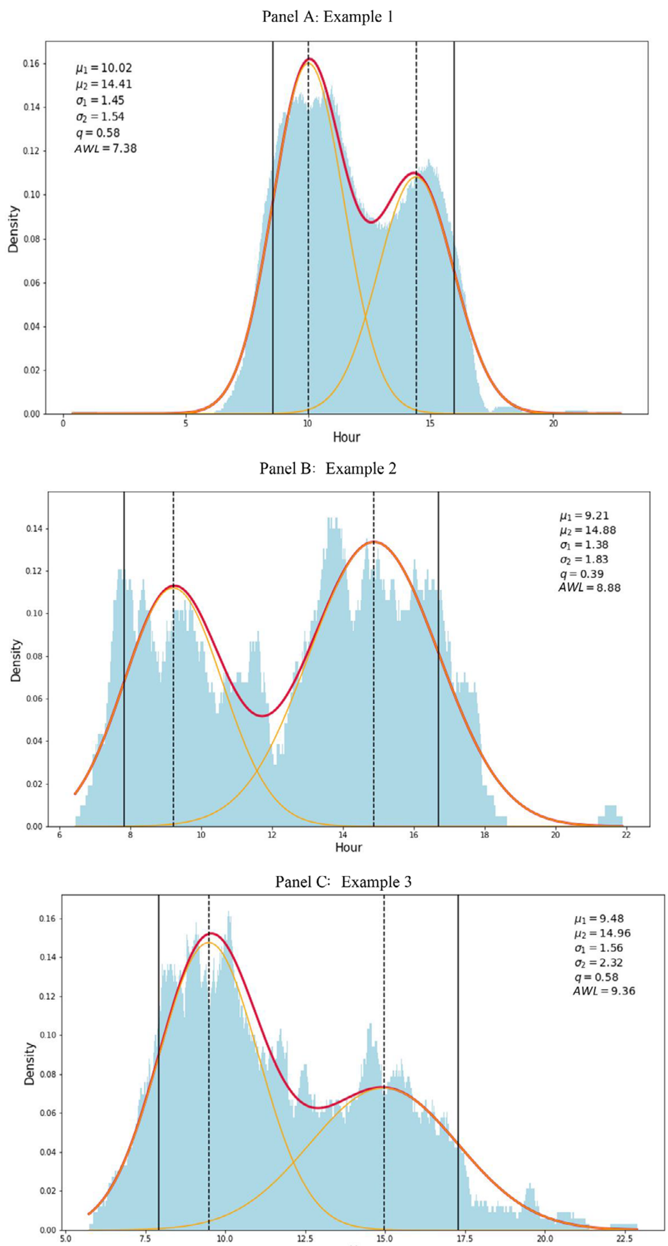



**Figure 6. Average workday length examples**. The figure provides an example of the *AWL* measure for three executive-year observations. Blue bars represent the empirical probability density function (pdf) based on activity on Bloomberg. The red curve is the estimated Gaussian mixture model pdf using 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 $(\mu_1 - \sigma_1,\ \mu_2 + \sigma_2)$. The data come from Bloomberg. (Color figure can be viewed at wileyonlinelibrary.com)

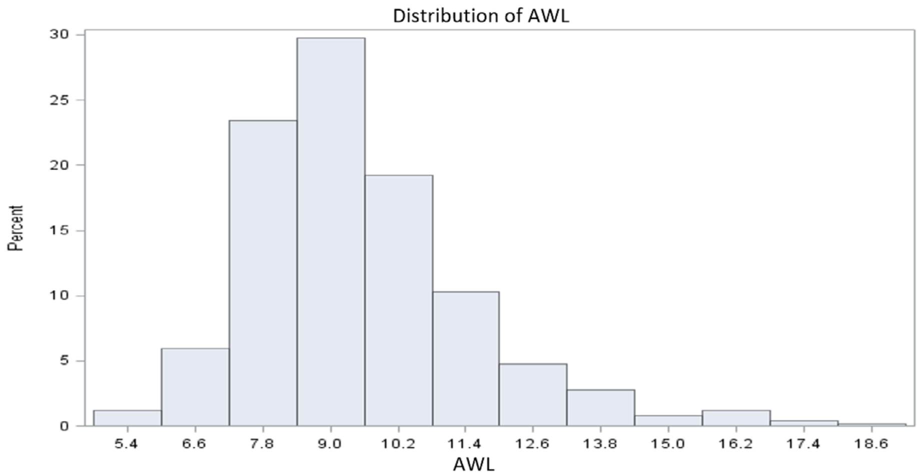



**Figure 7. Effort measure histogram**. The figure provides a histogram of the effort measure *AWL* (Average Workday Length). The data come from Bloomberg. (Color figure can be viewed at wileyonlinelibrary.com)

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

To help verify 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 an *AWL* statistic and compare it to the *AWL* estimated using Bloomberg activity. Figure 8 shows that the two measures are remarkably similar. The *AWL* based on Bloomberg usage is 8.0 hours, while it is 7.88 hours based on geolocation data. Admittedly, this result pertains to only one executive, but it does provide some reassurance that the *AWL* measure estimated with Bloomberg platform usage plausibly captures work habits.

## II. Effort Provision and Firm Outcomes

In this section, we address the long-standing question of to what degree does effort provision, and hence incentives, increase firm value. From a

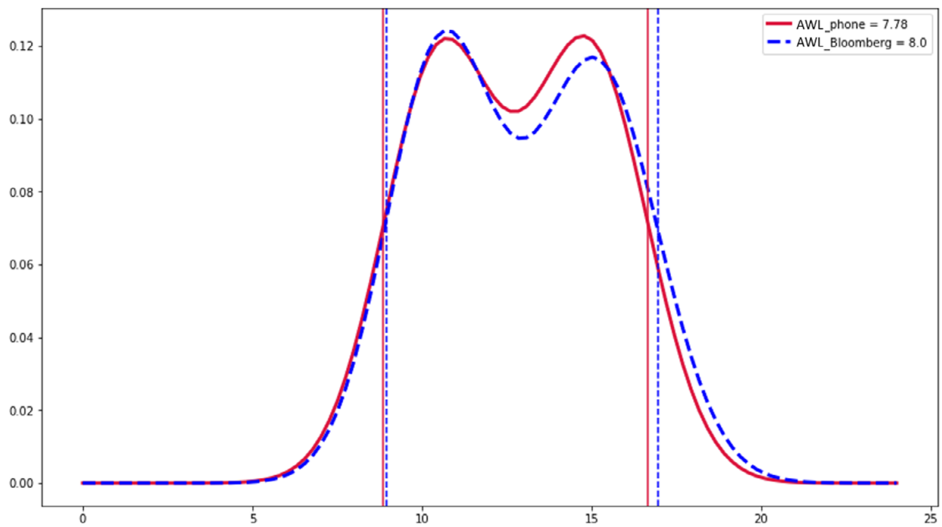



**Figure 8. Comparing *AWL* using Bloomberg and cell phone activity—example**. The figure provides an example of *AWL* measured using cell phone usage data and Bloomberg platform activity for an executive for 2018 to 2019. The blue (dashed) and red (solid) curves are the estimated Gaussian mixture model pdf using the iterative Expectation-Maximization (EM) algorithm for the cell phone data and the Bloomberg platform usage data, respectively. The sets of vertical lines represent the beginning and end of the *AWL* measures. The platform data come from Bloomberg and the cell phone data from Reveal Mobile. (Color figure can be viewed at wileyonlinelibrary.com)

theoretical perspective, greater effort may increase the probability of good outcomes (Holmstrom and Milgrom (1987), Edmans, Gabaix, and Jenter (2017)), or effort may be inefficient or misguided. As Murphy (1999) points out, studying this question has been difficult, however, because changes in executive compensation and equity ownership grants are public information, and equity prices adjust quickly (i.e., markets are efficient) which has constrained investigators to connect incentives to firm value directly, without capturing the intermediate step of effort provision (Morck, Shleifer, and Vishny (1988), Jensen and Murphy (1990), Hall and Liebman (1998)). That is, investigators have had no better information than equity market participants did. In this paper, we construct a direct measure of executive effort that is not observable to (or followed by) equity market participants, which allows us to shed light on this question.

### *A. Earnings Surprises and Abnormal Returns*

We start by examining whether executives' effort provision during the fiscal quarter affects firms' earnings surprises. We use *SUE*, the difference in the current quarterly earnings per share (EPS) and the EPS four quarters prior, divided by the standard deviation of this difference 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. The 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 allow us to study unobservable, time-invariant characteristics at the executive level.[17]

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

We next study the effect of effort provision on CARs around firm earnings announcements. To measure abnormal returns, we use the Fama-French three-factor model to estimate factor loadings using a year of past returns (after skipping the most recent week) and create daily alphas. We then regress CARs on *AWL* from day 1 postearnings announcement over 50 trading days (10 weeks), just prior to the next earnings announcement season. We include *SUE* to capture the impact of the earnings surprise on returns. In addition, 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 individual executive fixed effects to control for time-invariant executive characteristics.

Table V shows that effort has a positive and persistent effect on returns. Panel A examines all executives. The coefficients indicate that a one-hour increase in the length of the executive's workday is associated with a one-day abnormal return of 27.35 bps. This effect increases over time and plateaus in a persistent 30 to 50 bp CAR at 4 to 10 weeks. In Panel B, we focus on executives at nonfinancial 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 is incorporated into asset prices over time. In prior analyses in which hidden effort was undetectable, this effect could not be appreciated. As we document, however, it is significant and independent of other executive attributes.

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

[18] We verify that our results also hold for nonfinancial firms using the first five specifications from Table IV. Table IAV in the Internet Appendix repeats the analysis of Table IV after winsorizing *AWL* at the $10^{th}$ and $90^{th}$ percentiles of the distribution. We also include Table IAIV that also repeats the analysis of Table V after winsorizing *AWL* at the $10^{th}$ and $90^{th}$ percentiles of the distribution.

**Table IV**

## 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*), defined as the difference between the current quarterly EPS and the EPS four quarters prior divided by the standard deviation of this difference measured over the previous eight quarters. Effort is defined as *AWL* during the fiscal quarter associated with the earnings. The first six specifications include executives in all industries while specification (7) is limited to those in nonfinancial 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 come from the SEC Edgar database. User activity comes from Bloomberg, EPS data come 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, clustered by executive, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| | (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 |
| $R^2$ | 0.408 | 0.420 | 0.432 | 0.440 | 0.465 | 0.472 | 0.529 |

Motivated by the results in Table V, 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 (i) the change in *AWL* for a stock's executive relative to *AWL* four quarters prior to be in the top 10% across all executives for the same fiscal quarter-end, and (ii) the earnings announcement must have occurred within the past five trading days. The low-effort portfolio is defined analogously, with the change in *AWL* in the bottom 10% across all executives for the same fiscal quarter-end. To reduce noise, when fewer than two stocks

**Table V**

**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 on standardized unexpected earnings (*SUE*) and measures of insider trading during the fiscal quarter. Panel A reports results for all executives. Panel B reports results for executives of nonfinancial firms only. Each reported coefficient represents a single regression using *AWL*. Cumulative returns are measured using the Fama-French three-factor model, where factor loadings are estimated using a year of past daily stock returns (skipping the most recent week). Cumulative abnormal returns (CARs) are presented for 1 through 50 trading days where the first day is the trading day that includes the announcement. Platform activity comes from Bloomberg and stock price data from CRSP. Fama-French factor portfolios are from Ken French's website. *SUE* is defined as the difference between the current quarterly EPS and the EPS four quarters prior divided by the standard deviation of this difference 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 come 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. A total of 1,128 observations are included in the regressions in Panel A; and 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 A: All Executives

| | 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** | 31.9** |
| | (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) |

(*Continued*)

**Table V**—*Continued*

| Panel A: All Executives | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1-Day | 2-Day | 3-Day | 4-Day | 5-Day | 6-Day | 7-Day | 8-Day | 9-Day |
| 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 |
| $R^2$ | 0.16 | 0.16 | 0.15 | 0.13 | 0.13 | 0.13 | 0.12 | 0.13 | 0.13 |
| | 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 |
| $R^2$ | 0.13 | 0.13 | 0.14 | 0.15 | 0.14 | 0.15 | 0.15 | 0.14 | 0.12 |

| Panel B: Executives at Nonfinancial Firms | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 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 |

(*Continued*)

**Table V**—*Continued*

| Panel B: Executives at Nonfinancial Firms | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1-Day | 2-Day | 3-Day | 4-Day | 5-Day | 6-Day | 7-Day | 8-Day | 9-Day |
| | (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 |
| $R^2$ | 0.196 | 0.19 | 0.175 | 0.15 | 0.15 | 0.15 | 0.14 | 0.14 | 0.14 |
| | 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 |
| $R^2$ | 0.14 | 0.13 | 0.15 | 0.18 | 0.16 | 0.18 | 0.17 | 0.17 | 0.14 |

**Table VI**

**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 the 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 two, 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 three-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 comes from Bloomberg and stock price data 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 | –2.52 |
| | (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) |

satisfy 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 three-factor model to adjust for risk. Factor loadings are estimated using a year of past daily stock returns (skipping the most recent week).

Table VI presents the mean returns and standard errors in bps per day. According to the results, the risk-adjusted long-short portfolio yields 7.33 bps per day, or 37 bps over five days. This quantity is both 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 concern, we study the relationship between *AWL* and a firm's CDS spread. To our knowledge, no executive in our sample is compensated based on the CDS spread, 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 five-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 VII, 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 specifications (1) and (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 in CDS spreads of –0.879 to –0.929 bps. When we control for firm characteristics and include executive fixed effects (specification (4)), the magnitude increases to –1.50 bps. Including executive fixed effects ensures that we measure the impact of the individual executive's effort on CDS spreads.

Next, we find that controlling for insider trading activity during quarter $t$ (specifications (5) and (6)) does not alter our findings. This result alleviates the concern that *AWL* is high (or low) due to firm performance during the quarter, which is associated with subsequent CDS spreads. In the last two specifications, we exclude financial firms. The coefficient estimates are not materially different from the results reported in the other specifications. However, the low number of observations makes the estimation noisier, which reduces statistical significance. 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*) provides virtually the same results.

### *B. Weather as an Exogenous Instrument*

Measuring a causal impact of effort on firm outcomes is difficult. For example, an important deal arising during one quarter may lead to 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, while if things are going particularly poorly, they may be forced to increase their work hours. To alleviate concerns that effort provision and outcomes are codetermined, 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. Such shock may occur, for example, because of incentives to enjoy good weather during

[19] We thank the Editor for pointing out this example.

**Table VII**

**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 for five-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 for 89 executives and 57 firms. Due to the persistence in CDS spreads, we control for lagged *Spread* (i.e., an AR1 model). However, using the first-difference (Spread $t + 1$ – Spread $t$) provides virtually the same results. To reduce the effect of outliers, we trim observations for which the quarterly change in spread is in the top or bottom 1% of their distribution. We include four measures of insider trading in the regressions: *log_purchase* (*sell*), the log dollar amount of open-market insider purchases (sales) by the executive during quarter $q$, and *log_purchase_all* (*sell_all*), and the log dollar amount of open-market insider purchases (sales) by all insiders during quarter $q$. Insider trading data come from the SEC Edgar database, platform activity from Bloomberg, EPS data from I/B/E/S, and Fama-French 12-industry definitions 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. All specifications include year 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.

| | (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 |
| $R^2$ | 0.924 | 0.923 | 0.925 | 0.928 | 0.928 | 0.928 | 0.940 | 0.943 |

some months of the year, or because of a need to respond to with inclement conditions during others.

We capture 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] Specifically, we first collect historical weather data for each location each day from 2017 Q3 through 2019 Q4. Next, we measure how close the "feels like" temperature is to 72°, which is the midpoint of the "thermal comfort zone, " between 3 pm and 6 pm local time on workdays.[21] How close the "feels like" temperature is to 72° is computed as $|$F-72$|$, where F is the "feels like" temperature. For example, a "feels like" temperature of 65° would have a value of 7 while a "feels like" temperature of 100° would have a value of 28.

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. We do this across the entire sample period for each quarter and location and thus a good weather day in January, February, and March means something different than a good weather day in July, August, and September. For each executive, we estimate *AWL* each quarter across all years separately 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 VIII, we regress the two *AWL* measures on a good-weather day indicator and executive-quarter fixed effects to get an idea of how effort differs across these two types of 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 for these results 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 finding 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

[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).

**Table VIII**

**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, Q2 and Q3, and Q1 and Q4. Good- and bad-weather *AWL* are estimated for each executive-quarter using data for all years in the sample. Days classified as having good (bad) weather if they are better (worse) than the median for the quarter-location, where "better" is defined how close (in absolute value) the "feels like" metric is to 72° between 3 pm and 6 pm on workdays. The dummy variable *Good Weather Day* indicates that the day is a better-than-median weather day. To be included in the sample, an executive must have been active on Bloomberg for the same quarter across multiple years. Historical weather data come from Weather Underground. A total of 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.

| | All Quarters | Q2 & Q3 | Q1 & Q4 |
|---|---|---|---|
| *Good Weather Day* | 0.078 | –0.201* | 0.323*** |
| | (0.228) | –0.106 | (0.110) |
| Exec-quarter FE | N | Y | Y |
| N obs. | 1,350 | 632 | 718 |
| $R^2$ | 0.943 | 0.792 | 0.954 |

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. Having identified work and home for each device, we define "nearby" employees 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, " defines as those employees 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 the two-mile area that defines "nearby" employees. The red marker/white circle indicates the executive's office location, and the red circle traces out a two-mile radius around the office that defines "nearby." In 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 in our sample, we arrive at 127,565 headquarters-day observations with a mean number of devices of 5,047. For each nearby commuting employee, we measure their length of time at work on a given day using arrival and departure times 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 arrival time, departure time,

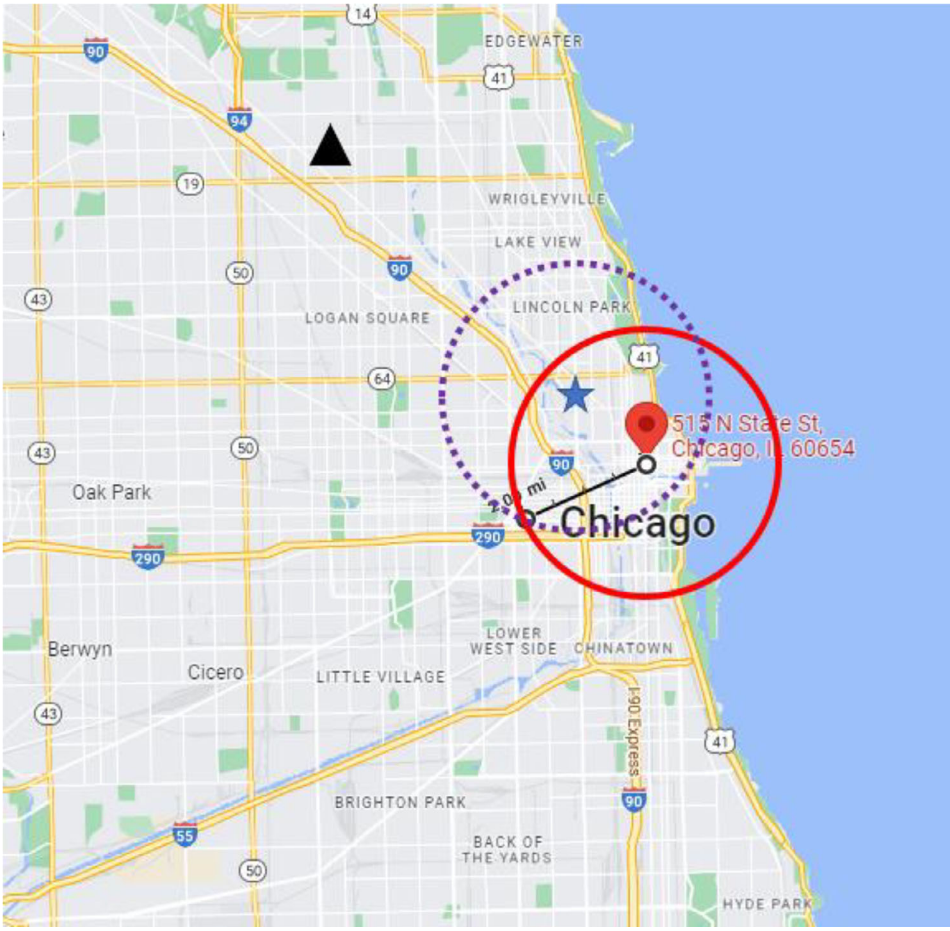



**Figure 9. Example of a nearby commuting employee**. The figure provides an example of a nearby-commuting employee identified using mobile phone geolocation data. The red circle marker and white circle indicate the executive's office location and the solid red circle defines a two-mile radius around 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. (Color figure can be viewed at wileyonlinelibrary.com)

and time at work. Finally, we merge these data with the good-weather day indicator based on location of the headquarters.

Table IX presents the results of regressing these median times on the good-weather indicator along with various combinations of fixed effects. Panel A includes days in calendar quarters Q1 and Q4 while Panel B includes days in quarters Q2 and Q3. The first three columns are analogous to the results on executives in Table VIII and indicate that the weather impacts the median time at work for commuting employees around the executive's headquarters in

**Table IX**

**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 Q1 and Q4 (Panel A) and Q2 and Q3 (Panel B). Days are classified as having good (bad) weather if they are better (worse) than the median for the quarter-location, where "better" is defined as how close (in absolute value) the "feels like" metric is to 72° between 3 pm and 6 pm on workdays. The dummy variable *Good Weather Day* indicates that 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 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 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 come from Reveal Mobile, and historical weather data from Weather Underground. A total of 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 A: Q1 and Q4

| | 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 obs. | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 | 68,239 |
| $R^2$ | 0.226 | 0.238 | 0.342 | 0.053 | 0.055 | 0.403 | 0.161 | 0.181 | 0.358 |

Panel B: Q2 and Q3

| 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 obs. | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 | 59,326 |
| $R^2$ | 0.024 | 0.041 | 0.285 | 0.028 | 0.042 | 0.309 | 0.016 | 0.096 | 0.412 |

a similar way to the executive. More specifically, employees spend more time at work on good weather days during the fall and winter months and less time at work on good weather days in the 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 in Panels A and B present results based on median arrival and departure times. The results are consistent with the view that employees are more likely to arrive late and leave a little early on bad-weather days in the fall and winter. As expected, these patterns flip during Q2 and Q3. During these quarters, employees tend to leave work a little early when the weather is more pleasant. Results on arrival times are mixed but magnitudes are smaller than those associated with departure. This is not surprising as the weather variable is measured between 3 pm and 6 pm.

Having shown that variation in weather affects work habits, we employ a two-stage least squares (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

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

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 X presents the results of these regressions using all days. As seen across all six 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 the 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 by other executives at the firm. There is virtually no impact on the coefficient of interest. In terms

[22] Table IAVII repeats the analysis of Table X after winsorizing *AWL* at the 10th and 90th percentiles of the distribution. We also include Table IAVIII, which repeats the analysis of Table XIII after winsorizing *AWL* at the 10th and 90th percentiles of the distribution.

**Table X**

## 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 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 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 classified as having good (bad) weather if they are better (worse) than the median for the quarter-location, where "better" is defined as how close (in absolute value) the "feels like" metric is to 72° between 3 pm and 6 pm on workdays. In the second stage (Panel B), we estimate the 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 EPS and the EPS four quarters prior divided by the standard deviation of this difference 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 four 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 come from the SEC Edgar database, platform activity from Bloomberg, EPS data from I/B/E/S, and historical weather data used in estimating good- and bad-weather *AWL* 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, clustered by executive, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: First Stage

| | *AWL* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (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 |
| Centered $R^2$ | 0.37 | 0.67 | 0.43 | 0.67 | 0.38 | 0.43 | 0.62 | 0.67 |

(*Continued*)

**Table X**—*Continued*

Panel B: Second Stage

| | *SUE* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (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 obs. | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 | 1,260 |
| Centered $R^2$ | –0.01 | 0.08 | 0.46 | 0.55 | 0.01 | 0.12 | 0.47 | 0.55 |

of economic significance, a one-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 IV.

Using our instrument, we examine how predicted *AWL* impacts future earnings. We form earnings surprise windows of one, two, three, and four 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 XI, while some value is 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 take a few steps to make it plausible. First, if inclement weather were to affect supply chains for some firms, the exclusion restriction would be violated. As this is unlikely to be relevant for financial firms, in the Internet Appendix we repeat the analysis on the subset of firms that are financials, which comprises about half of our sample. We obtain similar results, which are reassuring (Tables IA.IX and IA.X).

Second, the variation in weather that we exploit is based on temperature differences and good-versus-bad weather days, but not extreme events like blizzards or hurricanes. 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 continue to hold (Tables IA.XI and IA.XII).

It is also interesting to consider the channel through which executives might affect firm value and future earnings, that is, how executive effort increases firm value whether that impact is immediate or persistent. Value may rise because of increasing revenues, decreasing costs, establishing a hard-working firm culture by example, or identifying new projects. We examine this question 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, we construct a measure of the total cost surprise. Panel B of Table XI 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 a firm's Tobin's Q. We divide firms into two groups—high and low Q based on the industry-year median Q in the sample. As in Table XI, we examine contemporaneous and future earnings. Table XII 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.

**Table XI**

## 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 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 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 classified as having good (bad) weather if they are better (worse) than the median for the quarter-location, where "better" is defined as how close (in absolute value) the "feels like" metric is to 72° between 3 pm and 6 pm on workdays. In the second stage. we estimate the 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 earnings, revenues, or costs, and $\widehat{AWL}$ 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 EPS and the EPS four quarters prior divided by the standard deviation of this difference measured over the previous eight quarters. Revenue surprises – standardized unexpected revenue (SUR) is defined similarly using revenue. We define the total cost surprise as the difference between these two measures. For all three measures, we examine cumulative surprises over one quarter, two quarters, three quarters, and four quarters where the beginning of each of the windows includes the quarter in which effort is measured. Insider trading data come from the SEC Edgar database, platform activity from Bloomberg, revenue and earnings per share data from I/B/E/S, and historical weather data used in estimating good- and bad-weather *AWL* are from Weather Underground. An intercept is estimated in each regression. Standard errors, clustered by executive, 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 A: Earnings Surprises—2SLS, Second Stage

| | 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 $R^2$ | 0.466 | 0.410 | 0.409 | 0.427 |

Panel B: Revenue Surprises—2SLS, Second Stage

| | 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 $R^2$ | 0.411 | 0.538 | 0.602 | 0.649 |

(*Continued*)

**Table XI**—*Continued*

Panel C: Total Cost Surprises—2SLS, Second Stage

| | 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 $R^2$ | 0.358 | 0.443 | 0.498 | 0.540 |

Finally, we turn to earnings announcement returns. We repeat the analysis from Table V using our predicted *AWL* measure. We regress CARs over various horizons starting on the earnings announcement day all the way through 10 weeks on predicted *AWL*, *SUE*, and various controls including executive fixed effects. Table XIII presents the results. We find a positive relation between abnormal announcement returns that grows in magnitude with time and becomes statistically significant after one to two weeks. As in Table V, because we control for *SUE*, this represents information that is not included in the earnings surprise itself. We also control for insider trading, which is intended to capture private information at the executive level.

## III. Effort Provision and Agency

### A. 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 executives' performance-based compensation. Healy (1985) and others focus on how these discontinuities affected earnings management and investment within the firm (Degeorge, Patel, and Zeckhauser (1999), Murphy (2000)).

A natural question that arises is how executives' effort responds under 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 either far from attaining a goal or well past a target, then expending extra effort is unlikely to yield a marginal benefit. In such cases, an executive's 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), then there is a higher marginal benefit of effort and securing extra compensation is within their locus of control.[23]

[23] As noted earlier, Healy (1985) describes this as the presence of floors and caps in compensation plans. An executive's compensation 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.

**Table XII**

**Predicted Effort and Future Earnings—High versus 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 Q (Panel A) and low Q (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 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 classified as having good (bad) weather if they are better (worse) than the median for the quarter-location, where "better" is defined as how close (in absolute value) the "feels like" metric is to 72° between 3 pm and 6 pm 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, which is defined as the difference in the current quarterly EPS and the EPS four quarters prior divided by the standard deviation of this difference measured over the previous eight quarters. We examine cumulative surprises over one quarter, two quarters, three quarters, and four 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 above or below 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 come from the SEC Edgar database, platform activity from Bloomberg, earnings per share data from I/B/E/S, and historical weather data used in estimating good- and bad-weather *AWL* from Weather Underground. An intercept is estimated in each regression. Standard errors, clustered by executive, 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 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 $R^2$ | 0.213 | 0.308 | 0.391 | 0.454 | 0.442 | 0.495 | 0.471 | 0.529 |

(*Continued*)

**Table XII**—*Continued*

Panel 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 $R^2$ | 0.484 | 0.499 | 0.503 | 0.525 | 0.427 | 0.474 | 0.217 | 0.282 |

**Table XIII**

## 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 on standardized unexpected earnings (*SUE*), measures of insider trading during the fiscal quarter, and executive and year-quarter fixed effects. In the first stage, we estimate the 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 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 classified as having good (bad) weather if they are better (worse) than the median for the quarter-location, where "better" is defined as how close (in absolute value) the "feels like" metric is to 72° between 3 pm and 6 pm on workdays. In the second stage, we estimate the 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 three-factor model, where factor loadings are estimated using a year of past daily stock returns (skipping the most recent week). CARs are presented for 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 $\widehat{AWL}$. *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 come from the SEC Edgar database, platform activity from Bloomberg, stock price data from CRSP, Fama-French factor portfolios from Ken French's website, earnings per share data from I/B/E/S, and historical weather data used in estimating good- and bad-weather *AWL* from Weather Underground. To be included in the sample, an executive must be active in the same fiscal quarter for multiple years. A total of 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.

| | 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 $R^2$ | 0.195 | 0.175 | 0.208 | 0.217 | 0.247 | 0.263 | 0.292 | 0.284 | 0.309 | 0.314 | 0.337 |

(*Continued*)

**Table XIII**—*Continued*

| | 1-Day | 2-Day | 3-Day | 4-Day | 5-Day | 6-Day | 7-Day | 8-Day | 9-Day | 10-Day | 11-Day |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 $R^2$ | 0.353 | 0.375 | 0.398 | 0.391 | 0.413 | 0.483 | 0.579 | 0.656 | 0.665 | 0.636 | 0.593 |

In the Definitive Proxy Statement (SEC [Securities and Exchange Commission] 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, as well as 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 receives—fixed wage, cash bonus, equity, option grant—as well as the target metric used to compute end-of-year compensation (e.g., EPS, or sales). While each 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, we obtain compensation information from 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 in 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 XIV provides statistics on these executives' compensation contracts. In particular, we provide evidence on the following variables: *Value_stock_owned*, the dollar value of the executive's stockholdings in the firm measured using price at the beginning of the fiscal year; *Salary*, the executives' fixed salary during the fiscal year; *Cash_perf*, the target dollar amount of the cash-based performance incentive bonus from the executive's compensation contract for the fiscal year; *Stock_perf*, the target dollar amount of the stock-based performance incentive bonus from the contract; *Stock_time* and *Option_time*, the values of the time-based stock and option grants, respectively, from the contract; and predicted compensation, *Pred_comp*, the sum of *Salary*, *Cash_perf*, *Stock_perf*, *Stock_time*, and *Option_time*.

The top section of Table XIV indicates that 27% of executive-year observations are for CEOs while 45% are for CFOs. The remainder is 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 split 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 XIV provides a breakdown of the average weights of the metric types that determine the performance-based cash bonuses. While

**Table XIV**

## Ex Ante Incentive Contracts

The table reports summary statistics for executives' 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 executive's 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.

| | *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 | 7,277 | 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% | | | | |

Incentive Lab provides many measures (e.g., earnings before interest and taxes (EBIT), customer satisfaction, etc.) as well as their corresponding metric type (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. We construct these data 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. Measures in the "Other" category make up about 27.6% of the performance formulas, on average. These are nonaccounting-based targets 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.

To investigate the effect of locus of control on effort, we 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 firm performance is from the targets as the year goes on. When achieving a bonus is within an executive's locus of control, we would expect them to exert more effort to secure higher compensation.

While compensation contracts are known to executives in advance and typically are not changed subsequently, firms do occasionally modify contracts during the year for various reasons. Such material changes necessitate the filing of Form 8-K with the SEC. To the extent such changes are present in our sample, this 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 XIV. 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 the extent to which executives increase effort in the second half of the fiscal year, in response to firm performance in the first half of the year. We posit that when EPS in the first half of the year is on pace to finish close to the annual EPS target specified in the executive's cash bonus contract, executives employ more effort to ensure that they attain their defined EPS goal. For each executive whose cash bonus contract includes an EPS 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 $|2 * (EPS_{Q1} + EPS_{Q2}) - EPS\ Target|/EPS\ Target$, where $EPS_{Q1}$ and $EPS_{Q2}$ are the firm's EPS in the first and second fiscal quarters, 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 one when this quantity is less than 1% and zero otherwise.

In Table XV, 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 an executive's performance targets (high or low), and achievement of a bonus is outside the executive's locus of control, they employ less effort in the second half of the year. Thus, when success or failure is within their potential control, they exert more effort. Also, because we study changes in *AWL*, which is a within-executive effect, this result supports a causal relationship.

### B. 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 focal firm should induce more effort

**Table XV**

**Incentive Contracts and Effort—Earnings Targets**

The table provides results of regressions of changes in *AWL* between the first half of the fiscal year and the second half of the fiscal year on *Target_1_pct*, which indicates that EPS in the first 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, *Pct_cash_perf*, and on the interaction between the two variables. *target_1_pct* is equal to one if the quantity $|2 * (EPS_{Q1} + EPS_{Q2}) - EPS\ Target|/EPS\ Target$ 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 *log* prefix on the compensation variable indicates the natural logarithm of the variable, while the *pct* prefix 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 come from Bloomberg and target bonus award amounts and other compensation data from ISS Incentive Lab. Variables are defined in Table XIV. Fama-French 12-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, clustered by executive, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

| | *CHANGE IN AWL* | | | *AWL* |
|---|---|---|---|---|
| | (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 |
| $R^2$ | 0.13 | 0.17 | 0.25 | 0.39 |

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 Global Industry Classification Standard 6-digit code (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

**Table XVI**

## 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 executive fixed effects. *%Chng_Sales* is defined as the percentage change in the firm's sales during fiscal quarter $t$ relative to the firm's quarterly sales four quarters prior [(Sales $t$ – Sales $t$ – 4)/Sales $t$ – 4)] in percent. In the table, *Lag1* (*Lag2*) means the *%Chng_Sales* in quarter $t$ – 1 ($t$ – 2). Similarly, *%Chng_PeerSales* is defined as the percentage change in peers firms' sales during fiscal quarter $t$ relative to peers firms' quarterly sales four quarters prior. For each firm, we include up to the 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 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 comes from Bloomberg, earnings per share data from I/B/E/S, and Fama-French 12-industry definitions are 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. All specifications include year 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.

| | (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 |
| $R^2$ | 0.406 | 0.409 | 0.408 | 0.406 | 0.409 | 0.408 | 0.403 | 0.327 | 0.328 |

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

We report the results in Table XVI. Following the same methodology in Table IV, we run quarterly regressions of executive effort (*AWL*) on lagged changes in quarterly firm sales and lagged changes in quarterly peer firms' sales. All specifications include executive fixed effects, and thus the analysis is conducted at the executive level. In specifications (1) to (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 statistically significant effect on *AWL*. The effect is also economically significant: a 10% increase in peer firms' sales is associated with 0.26 more hours of effort per day during the next quarter ($0.026 \times 10 = 0.26$). Note that the quarterly financial results are reported toward the end of the first month of the subsequent quarter. Our estimates therefore likely underestimate the true effect, since *AWL* is estimated over the entire quarter.

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 changes in sales in the most recent quarter (i.e., $t-1$). In the last two specifications, we exclude financial firms. The coefficient estimates almost double, with a 10% increase in peer firm sales associated with 0.45 more hours of effort per day during the next quarter ($0.045 \times 10 = 0.45$).

## IV. Conclusion

While hidden action problems are ubiquitous in firms and markets, technology is making it easier to assess these 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 instead rely on a publicly available measure to characterize how effort affects firm value. While for privacy reasons we are careful not to collect information about the nature of how executives use Bloomberg, we are able to conclude that higher attention to their firm and longer workday length appear to be associated with positive earnings surprises and abnormal stock returns. This is not obvious ex ante, since it theoretically may have been the case that effort was inefficient or possibly misguided.

Finally, we consider several agency issues that have been raised in the academic literature. We find that executives 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 summer. In contrast, effort provision appears to respond positively to competition within an executive's industry, as measured by sales growth of competing firms.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

**Appendix S1:** Internet Appendix.
**Replication Code.**