Stock Compensation and Employee Attention*

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Abstract

We show that a company's daily stock price movements affect the mood, effort level and decision making of its employees. Positive current-day stock returns are accompanied by greater reported economic confidence and job satisfaction, lower output, shorter working hours, lower per-hour productivity, more optimistically biased beliefs about firm performance, tougher grading of innovative ideas, and tougher evaluation of interviewees. These effects are very short lived, lasting one or two business days. The effects on mood and many types of behavior are larger for employees with larger prior stock and option grants. We show that the short-term effects of (plausibly exogenous) shock to moods is the opposite sign of cross-sectional correlations. Whereas happier employees in the cross section perform better and are more lenient evaluators, shocks that increase happiness longitudinally are accompanied by lower work effort and tougher evaluation.

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"In the early 1990s, it seemed as if every Microsoft employee's computer ran an application that left an image on their screens at all times: a cartoon depiction of a face whose expression changed depending on the direction of the company's stock price. When shares increased in value, the face smiled; when they fell, it frowned."

"Microsoft's Lost Decade" *in* Vanity Fair
by Kurt Eichenwald (2012)

1 Introduction

Paying employees with company stock is increasingly popular; about 28 percent of the US private-sector workforce receives equity compensation.[1] Many of these firms' managers encourage their employees to limit their attention to stock price fluctuations.[2] Despite this, survey evidence by Bryson and Freeman (2014) suggests that about 38% of workers paid in stock check their company's stock price *every day*.[3]

Using corporate administrative data and surveys of the public, we find evidence that daily stock returns affect economic confidence, employee satisfaction, on-the-job behavior, and decision making at work. On a day with positive stock returns, employees report greater satisfaction with the current direction of their employer; they have more optimistically biased beliefs about their employer's future performance; and they give more negative reviews to new ideas on an internal innovation platform. Employees report greater satisfaction with their colleagues, and they give tougher evaluations to new job applicants.

Employees report greater satisfaction with their own job performance, and they work slightly shorter hours and produce less output. All of these effects are very short-lived, lasting one or two business days, and are stronger for employees with larger equity grants.

Variations in work effort could possibly be offset by other days with negative stock price movements.[4] However, effects on evaluations of interview candidates and of new ideas are more likely to be irreversible in practice. Confirming this, we find that candidates who interview on days with stock appreciation are ultimately less likely to be hired. Likewise, ideas that are reviewed on days with stock appreciation receive lower scores and are less likely to ever be implemented.

We find that positive shocks also increase employees' job satisfaction. A large pre-existing literature in psychology and economics suggests that happier workers are more productive. However

[1]These numbers come from the 2014 General Social Survey (GSS), tabulated in Kurtulus and Kruse (2017). For workers in publicly traded companies, the figure is 48%.

[2]Examples include Costco, Google, Twitter, Walmart, and Yahoo. Table 1 contains an incomplete list of high-profile companies whose executives have encouraged employees to ignore short-term fluctuations.

[3]Similar magnitudes of daily stock checkers were estimated by an independent study by Morgan Stanley researchers (Siegal and Mesereau, 2013). A 2016 survey by salary aggregator Open Salary suggested that 45% of workers monitor stock portfolios while at work (*Korea Times*, 2016).

[4]We did test for effects as much as ten lagged business days and found no statistically significant effects in any direction. Our ten-day horizon is longer than the most other longitudinal studies of the productivity/happiness relationship, which typically study contemporaneous correlations. For example, Oswald, Proto and Sgroi (2015) studied effects within a single laboratory session for most of their research. The authors also study correlations between subjects' present-day productivity (measured in laboratory tasks) and recent family tragedies ("a kind of unhappy randomization by nature") to study longer-term effects.

unlike this paper, most evidence from this literature comes from cross-sectional results. In addition, this literature varies widely – and is often silent – about which margins of productivity are affected by happiness and attention shocks. This paper examines overall productivity, but can also separate results on total hours and on per-hour efficiency of work.

Estimating the effects on hours separately from efficiency effects allows us to address the possibility that our shocks shift production into less observable forms. Some forms of productivity (developing a new patent with colleagues at a whiteboard) may be harder to observe and thus may therefore appear "unproductive" to a researcher. Several features of our data allow us to address this question. In addition, we also examined data about the proposal and adoption of productivity-enhancing innovations that allow us to study this phenomena (and other decision-making determinants of productivity) directly.

We study these relationships using both cross-sectional and longitudinal data, and by utilizing longitudinal variation in worker happiness arising exogenously from the stock fluctuations. Like the pre-existing literature, we find positive correlations in cross-sectional regressions. This relationship holds both for total hours and per-hour efficiency, but is stronger for total hours. However, we find the opposite relationship – negative correlations – in our longitudinal analysis of stock fluctuations. These results are also stronger for hours rather than efficiency. As we discuss, the distinction between cross-sectional and panel results likely have practical implications for firms seeking to increase productivity.

Across a variety of outcomes, we find that employees with greater stock compensation are more sensitive to daily fluctuations. A natural interpretation of is that stock grants caused these these stronger fluctuations. However it is also possible that employees selected for higher stock grants are more sensitive to environmental changes generally.

Our study lacks quasi-experimental variation in stock exposure necessary for such a counterfactual claim. However, we report several related pieces of evidence. Across all our outcomes measures, we find that higher stock grantees are *not* more sensitive to the market as a whole – only to their own company's stock. In addition, we examine results from a psychological study of employees using a popular personality assessment from academic psychology (the "Big Five", Digman, 1990; Goldberg, 1993). One personality metric specifically measures fluctuating tendencies like those described in this paper; we show this metric is uncorrelated with the size of employees' stock grants in any economically meaningful way. If anything, the correlation is negative (for reasons well-understood by theory).

This paper contributes to three literatures. First, we provide novel, well-identified field evidence on the relationship between job satisfaction and productivity. This relationship is important for a variety of topics in economics. For example, a well-known theory of wages during recessions (Bewley, 1999; Kawaguchi and Ohtake, 2007) suggests that pay cuts harm productivity through morale. Banerjee and Mullainathan (2008) developed a model of income distribution in which labor intensity depends on outside worries.

Much of the direct evidence on this topic has come from cross-sectional regressions of workers. Where the literature has used panel data to control for unobserved employee characteristics (Wright and Staw, 1999), issues of simultaneity and and reverse causation remain.[5] In addition,

[5]One exception is Oswald et al.'s 2015 laboratory experimental paper that contains some discussion of the happiness

most of the prior happiness and productivity literature is concerned with effects on effort.[6] We extend these papers by showing effects not only on effort, hours and productivity, but also on outcomes related to workers' creativity, innovation and decison-making. We can also test for heterogeneous treatment effects, and we find stronger effects on employee stockholders.

We also contribute to the literature about corporate short-termism (Stein, 1988, 1989; Narayanan, 1985; Holmström and Tirole, 1993; Laverty, 1996). This literature is often focused on how executives manage businesses around short-term quarterly earnings forecasts, perhaps at the expense of longer-term horizons.[7] A commonly proposed solution to this myopia is to compensate employees with equity options with longer vesting horizons.[8]

Our study demonstrates a similar myopia operating at an even higher frequency (daily rather than quarterly) and extending beyond the executive suite. Across a variety of outcomes, we find that giving employees stock options – purportedly the solution to short-termism – is correlated with *stronger* employee reactions to daily fluctuations. Whereas executive short-termism may be an optimal response to their shareholders' myopia, we present evidence in Section 5.1 that the employee myopia in this paper is not optimal and is likely a subconscious emotional reaction (rather than an optimizing response).

Our results also offer a contrast to the Benartzi and Thaler's 1995 "myopic loss aversion." Like the subjects of this paper, the investors in Benartzi and Thaler (1995) monitor portfolio prices in high-frequency. However, their investors responded to negative short-term information by assuming less risk, which drives down profits. By contrast, our investor/employees respond to short-term losses with the opposite behavior: They assume more risk through greater leniency towards new ideas and candidates.[9]

Lastly, we contribute to a growing empirical literature in which agents should in theory behave dispassionately, but in reality are influenced by superfluous factors.[10] The behavioral economics

and productivity effects of workplace perks, motivated in part by Google's use of perks. They find positive causal effects.

[6]One exception in the laboratory is Isen and Reeve (2005) who studied decisions.

[7]Graham et al. (2005) found striking evidence from executive surveys: 78 percent would sacrifice projects with positive net present value if adopting them resulted in the firm missing quarterly earnings expectations.

[8]Flammer and Bansal (2017) examined the effects of compensating executives with long vesting horizons. For identification, they use regression discontinuities in close shareholder votes on long-term executive compensation. They find a positive effect on share prices.

[9]One possible reason for these effects is that the short-term losses in this study are almost certainly "on paper" (Imas, 2016). Imas (2016) shows that subjects experiencing unrealized "paper losses" tends to increase risk-taking, and those facing realized losses tend to decrease risk. Bernstein et al. (2017) also study how on-the-job innovation is affected by financial shocks, using "a unique dataset that links inventors patenting output with their housing transactions." Unlike this paper, they found a negative relationship between losses and risk-taking. "Employees that experienced a negative shock to their housing wealth during the crisis pursued less risky and less innovative projects relative to others in the same firm and metropolitan area."

[10]Such forces include the effects of weather on financial market outcomes (Schwarz and Clore, 1983; Rind, 1996; Hirshleifer and Shumway, 2003) and durable goods purchases (Busse et al., 2015); the effects of hunger on criminal sentencing (Danziger et al., 2011); and the effects of sports on stock returns (Edmans et al., 2007) and domestic violence (Card and Dahl, 2011). The attraction of weather and sports as mood shifters is that in most contexts they should not affect optimal behavior, making mood effects easier to distinguish. Since we instead study the mood effects of stock price movements, we will need to concern ourselves with the possibility that optimal behavior is also changing (Section 5.1).

literature has grown vastly, but it is mostly focused on consumer behavior.[11] With some exceptions,[12] firms in behavioral economics are generally profit-maximizing entities that exploit the biases of their customers – and not subjects of biases themselves (as they are here).

We find effects on effort, hiring and innovation inside firms – three critical variables for firms' success across a wide variety of industries. In particular, the technology industry (our empirical setting) has complained publicly about shortages of qualified workers. The company we study is particularly well-known for its careful and selective screening process during the sample period. These makes our results about hiring particularly costly and surprising.

Although randomness and luck may affect many job searches (Lazear and Shaw, 2018), few papers have demonstrated this empirically.[13] Recent findings by Song et al. (2015) suggest that job placements into successful companies have large effects on workers. If this is true, then recruiters' behavioral biases may have large effects for job seekers' outcomes as well.

Ours is not the first paper to suggest that stock fluctuations are an underlying cause of behavior. Shiller (2002) wrote, "[T]he essence of a speculative bubble is a sort of feedback, from price increases, to increased investor enthusiasm, to increased demand, and hence further price increases." Cutler et al. (1990) modeled "feedback traders," or traders whose behavior, like the subjects in this study, seems to be based on "the history of past returns rather than the expectation of future fundamentals."

Most empirical work emphasizes the first part of Shiller's feedback loop. Ours addresses the second half, by studying how individuals react to price changes. A related paper is Engelberg and Parsons (2016), which studies the effect of stock fluctuations on hospital admissions. They find near-instantaneous, short-lived effects. Engelberg and Parsons's (2016) effects are strongest "particularly for psychological conditions such as anxiety, panic disorder, or major depression." A working paper by Huck (2015) finds similar one-day effects of stock fluctuations on crime.

CEOs throughout the global economy have sought to limit employee attention to stock prices. Table 1 contains a sample of companies where executives have publicly pleaded with employees to ignore short-term stock fluctuations. Among these is Google, the company featured in this paper. Google's pre-IPO shareholder letter famously disparages short-term thinking: "A management team distracted by a series of short term targets is as pointless as a dieter stepping on a scale every half hour." According to public statements, Google employees caught checking the stock price were fined the price of a share (between $160 and $360 during this sample period).

The findings in this paper persist, despite a strong cultural inclination towards long-term thinking at the setting. As the New York Times wrote in 2007,[14] "When it comes to awareness of the

[11]See DellaVigna (2009) for a review.

[12]Exceptions include Malmendier and Tate (2005), who examine the role of CEO overconfidence in investment and merger activity, and work documenting biases such as the disposition effect and sunk cost bias among professional investors (Cici, 2012; Jin and Scherbina, 2011). Beyond this, the productivity effects of friendships (Bandiera, Barankay and Rasul, 2010) and peer effects (Mas and Moretti, 2009) in firms may have a behavioral component.

[13]One exception is the literature on graduating during a recession (Oyer, 2006a,b; Kahn, 2010; Oreopoulos et al., 2012). Theory and empirics by Lazear et al. (2018) suggests that job seekers are affected by luck in who else applies for the same job.

[14]Hafner, Katie. "Google Options Make Masseuse a Multimillionaire." The New York Times (2007). `http://www.nytimes.com/2007/11/12/technology/12google.html?pagewanted=1&ei=5088&en=06966f580d2e02df&ex=1352610000&partner=rssnyt&emc=rss`

stock price, Google is different from other large high-tech companies [...] where the day's stock price is a fixture on many people's computer screens." Similar effects at other companies could be larger.

The remainder of this paper proceeds as usual. Section 2 contains data, including both corporate dataset, as well as some public polling data in support of our claims more generally. Section discusses statistical specifications and identification. Section 4 contains results. We discuss our results in Section 5, particularly the question of whether our findings reflect optimizing decisions or a behavioral response (Section 5.1). We also present novel evidence about whether compensation structure – a notable source of heterogeneous effects in our paper – is an underlying cause of the high-frequency behavioral responses to the stock prices. Finally we conclude in Section 6 by discussing managerial and researcher implications.

2 Data

The outcome data in this paper come from two main sources. We begin by analyzing the correlation between changes in the US stock market and the economic confidence of the broader US population. This provides broader support for our hypothesis about the relationship between stock prices and economic sentiment. Then we turn to employee productivity data from a corporate dataset.

Our survey data of the public comes from the political polling firm Rasmussen Reports from January 2005 to July 2008.[15] Each evening, Rasmussen administers a survey to 500 respondents about the current and future state of the US economy. The questions in Rasmussen's surveys are comparable to those in the monthly Michigan Consumer Sentiment and Conference Board Consumer Confidence surveys.[16] Rasmussen publishes 3- and 7-day trailing averages of the responses, which we use to infer nightly averages.[17]

Like the Michigan survey, Rasmussen publishes indices of current economic conditions, future expectations, and an overall index that averages the two. In our regressions using this data, this average is the outcome variable. Rasmussen publishes separate indices for investors and non-investors. Investors, who account for just over 50 percent of the overall index, are defined as those who report having portfolios greater than $5,000.

Our second source of data comes from Google. Our sample contains daily outcomes from July 2004 to June 2008. We primarily analyze five datasets: i) an employee satisfaction survey, ii) administrative data about work activity, which we use to estimate hours, iii) subjective performance scores, iv) a database of job interviews, and v) a database from an internal idea evaluation plat-

[15]These dates were chosen in order to be contemporaneous with our Google analysis.

[16]Details on this survey are available at http://www.rasmussenreports.com. Rasmussen does not disclose the exact questions asked, but says that they mimic existing surveys. We collected our data from the subscriber-only section of the website.

[17]To avoid look-ahead bias, we calculate the nightly average response as $7 \times TA7(t)$–$3 \times [TA3(t-1) + TA3(t-4)]$, where TAx(s) is the x-day trailing average reported for day s. Alternative calculations include $7 * TA7(t+3)$–$3 \times [TA3(t+3) + TA3(t-1)]$ or $7 \times TA7(t+6)$–$3 * [TA3(t+6) + TA3(t+3)]$; an averaging of these three alternatives yields an estimate with less noise due to rounding error, but otherwise nearly identical results.

form.[18] All data was anonymized.

Job Satisfaction Survey: In September 2006, approximately halfway through our larger sample, the company conducted a 98-question survey of satisfaction among full-time employees. The survey was administered by email in daily waves over the course of three weeks.[19] The purpose of the survey was to sample sentiment in the company among employees for general HR purposes.[20] Questions asked for ratings on a five or seven point scale, with high ratings indicating satisfaction. We used the timestamps on the survey responses in this paper to study the effects of stock market events. For each respondent, we calculate a satisfaction score as the simple average of the scaled responses to these questions.[21] In the results below, we used this as an outcome variable.

Work Activity: Our data on work hours and activity come from several sources. Table 2 summarizes the activity data we have for two different groups of employees: software engineers and online advertising sales support staff. Software engineers accounted for approximately two-fifths of employee-months and online sales staff accounted for one-fifth.[22] Taken together these two groups accounted for a substantial share of activity the company.[23]

Importantly for our research questions, we can use these measures not only to measure total activity, but also to measure total hours. Workers during the sample period enjoyed wide latitude to set their own hours, and were evaluated based on contributions. For the purposes of this paper, we count a clock hour as "working" if at least one work activity takes place within the hour. On an average day, employees in our sample left a time-stamped record of activity in around 5.2 out of 24 hours. Since these were full-time employees who were likely working more than 5.2 hours per day, our activity measures did not capture everything these employees do at work.

For software engineers, we examined data on Perforce calls, which are calls to the software managing the firm's codebase, made for example when an engineer checked out a piece of code for editing. We examined data on code reviews, which are peer reviews required before a finished piece of code was incorporated into the codebase. We also used data on entries to the Buganizer database, which are made when an engineer works on a bug. And finally, we have views and edits of the internal company wiki, which documented its code.

The online sales staff provided assistance to online advertisers. This assistance included reviewing and approving ads, working with advertisers to optimize ads to increase response rates, and responding to customer emails.[24] We used data on page views in an Internal Customer Systems

[18] Some of this data is also studied in Cowgill and Zitzewitz (2017), which contains a similar data description section.

[19] For our survey outcomes only, we examined data only for these three weeks. For all other outcomes, we generally used data for the entire July 2004 to June 2008 period.

[20] The survey was not designed to address the main questions of this paper.

[21] Specifically, we rescaled each rating to range from zero to one using the formula (rating-1)/(maxrating-1) and then took the simple average of the rescaled ratings.

[22] We apply a narrower definition of software engineer and online sales staff than Google did internally, excluding those who do work that is not well captured by our activity measures, such as managers and directors, software engineers working in product management, and more experienced online sales staff who work mainly on special projects.

[23] Google generally did not use raw productivity data to evaluate individual employees. It expected most employees to make significant contributions in ways that cannot be easily quantified. The data we are using mostly came from usage logs for productivity tools. The company saved these logs in order to maintain and optimize internal productivity systems. Among other things, the data were used for planning capacity for the tools, assessing the impact of feature changes in the tools and identifying groups effected by changes in the tools.

[24] The online sales team is described in more detail in a teaching case by Groysberg et al. (2011).

(ICS) tool, which was used to approve and optimize ads. We also used data on emails sent to customers who requested help. Table 2 provides counts of the number of times each activity is undertaken in the average workday.

We adjusted the raw counts of activity to take account of automation and reduce the significant heterogeneity in the amount of work required for a unit of work. For example, automation could allow an online sales representative to approve 100 similar ads at once; this does not represent the same amount of work as approving 100 completely unique ads. Likewise, an ad involving difficult policy issues could require 20 minutes or more to reach an approval decision.

We take two steps to limit the influence of automation issues. First, for Perforce calls and ICS page views, the two activities with the most automation, we count unique five-second periods with any activity rather than the activity itself. Second, for all measures, we winsorize daily counts of activity at the 99th percentile of all observations with non-zero activity. In practice, this sets outlier values to more reasonable levels. The results that follow are robust to variations in the exact procedure followed (e.g., counting activity in unique one or 15-second periods; winsorizing at the 95th percentile rather than the 99th).

Subjective Performance Scores: In addition to the measures discussed above that can be precisely dated, we examined performance evaluations, which are given once per quarter during this period. Performance evaluations were accompanied by a single numeric score (we refer to it as a "subjective performance score") that ranges from 1.0 to 5.0 but in practice is usually between 2.8 and 4.0. Unlike our objective measures, we could not break down the subjective performance scores in to measures of hours, efficiency per-hour or decisionmaking. However we can shows that these subjective performance scores were strongly correlated with the above measures of objective "work activity." Our related working paper (Cowgill and Zitzewitz, 2017) discuss this finding and data in more detail.

Interview Database: The workforce in this paper grew substantially during our sample period. Google's hiring process was selective, and many candidates were screened for each hire. Candidates under serious consideration were interviewed multiple times. As a result, it has conducted an extraordinary number of interviews during the sample period. We restrict our analysis to in-person interviews and exclude interviews for the international offices because of data limitations.

This leaves a sample of about 270,000 interviews of over 88,000 unique candidates.[25] Along with written feedback, each interviewer evaluated the interviewee with a single score between 1.0 and 4.0 (with a minimal increment of 0.1).

We define an "interviewing round" as a group of interviews that are scheduled on the same or consecutive days. We code an interviewing round as successful if it was followed by either another interviewing round or a job offer. In our sample, interviewing rounds were successful about thirty-five percent of the time. Success is well-predicted by a probit regression on the average interview score; the regression equation predicts a success probability of $\Phi[(\text{mean}-3.33)/0.78]$, where Φ is the standard normal CDF. As this equation suggests, even interview rounds with a mean score of 4.0, the maximum score possible, resulted in success only about 80 percent of the time. In contrast, interview rounds with mean scores below 2.5 are rarely successful.

[25] This includes data from many hiring channels, including both unsolicited candidates, referred candidates, campus recruiting candidates, etc.

Idea Database: One of Google's mechanisms for cultivating new ideas was the "ideas board" – an internal system for soliciting, evaluating and implementing new ideas. In this system, ideas were posted to either a general board or to specific boards maintained by specific teams or groups. Volunteer readers of the ideas provided numeric ratings (0 to 5) and comments, which often refined and improved the ideas. Through the discussion on the ideas board, internal entrepreneurs could recruit assistance and demonstrate support and vetting in formal requests for resources.

One successful example of an ideas board submission was the corporate prediction market studied in Cowgill and Zitzewitz (2015). In this case and others, the ideas board functioned as a venue to refine the idea and to recruit volunteers for development during "20 percent time" (time in which Google allowed engineers to develop innovative side projects).[26] Bayus (2013) evaluated a similar system used at Dell.

Our data from Google's ideas board include over 10K ideas. We limited our sample to those received at least one rating. At the time of our sample, each idea's current status was categorized as "done," "project," "future," "workshop," "needs information," "idle," "redundant," or "withdrawn."

We code ideas listed as "done" or "project" as implemented or on their way to being implemented. This accounts for 10 percent of the ideas. This is probably an undercount because statuses are not always updated to reflect implementation. However, the incidence of undercounting should be uncorrelated with the variables of interest in this study.

3 Specifications and Identification

The explanatory variable of interest in this paper are recent daily stock returns. In most of our regressions, we include the current day's Google stock returns, the previous two days' returns and the return from the next business day. We also evaluated even more lagged returns, but none were significant in any specification. Likewise, the results were never sensitive to whether the next-day return was included.[27]

Identification in these regressions comes from the unpredictability of daily stock market returns ahead of time. Market efficiency suggests that stock returns on day t should be uncorrelated with information available to the market on day $t-1$. That is, t will be a surprise given $t-1$, and $t-1$ will be a surprise given $t-2$.

This means that returns should be uncorrelated with many factors that affect how much an employee will plan to work on day t (such as the day of the week, the calendar date, the forecasted weather, scheduled company events that are public knowledge).

Any correlation should therefore reflect 1) a reaction to either the day t stock returns directly, 2) a reaction to events on day t that produced the stock returns, or 3) a correlation between work

[26] A Harvard Business School teaching case, Coles, Lakhani and McAfee (2007), contains additional detail about how this project migrated from the ideas board to implementation.

[27] The US stock markets close at 1PM Pacific Time. Thus, there is the potential that post-1PM news events might influence employee behavior, and yet only be reflected in stock returns the next day. In practice, this channel appears to be unimportant.

activity and news that was released to the market on day t but known to the employee beforehand. An example of the third possibility would be an employee in investor relations planning to work late on the day of a negative earnings announcement. This sort of event is too rare to contribute meaningfully to our results.

The first and second possibilities are impossible for us to distinguish empirically. However, a pre-existing literature sheds light on this question. Shiller (1981) famously claimed that equity returns are too volatile to be explained by news about future cash flows or plausible fluctuations in future discount rates; he instead argued for other reasons for asset price fluctuations. Cutler, Poterba and Summers (1989) collected data from newspapers to estimate what fraction of aggregate stock price variance could be attributed to news. They found that "large market moves often occur on days without any identifiable major news."

Cornell (2013) updated Cutler et al.'s 1989 analysis with more recent data, and reached similar conclusions: "Despite the passage of time and the massive improvement in information technology, it is, if anything, more difficult to tie major stock price movements to fundamental economic news sufficient to rationalize the size of the observed move."

In Engelberg and Parsons's (2016) study of hospital admissions and stock fluctuations, the authors undertake a similar analysis by codifying news developments from the *New York Times* and *Wall Street Journal* for the most extreme quintile of daily returns. Their goal, like ours, was to measure whether news events were responsible for outcomes through non-portfolio channels. Consistent with Cornell (2013) and Cutler et al.'s (1989), they found that more than half of the time (56%), the most extreme daily fluctuations were associated with no detectable news. Removing days with major news from their analysis had no impact on their main findings.[28]

The literature above analyzed the market as a whole, and thus they speak particularly well to our Section 4.1 findings about consumer sentiment in the Rausmussen polls. Other studies have focused on particular assets and sectors (Roll, 1984; Frankel and Meese, 1987; Roll, 1988), showing a similarly small role for news and information. Although none of these authors examine Google stock specifically, these results raise questions about how much of the fluctuation in the price of GOOG can be explained by news that could alter employee behavior through other channels.

4 Results

4.1 Stock price changes and moods in Rasmussen

Table 3 presents regressions of the change in the Rasmussen index on log changes in the S&P 500 index. We analyze changes in the sentiments since the Rasmussen indices (like the Michigan and

[28] Engelberg and Parsons (2016) additionally tested for non-portfolio effects by exploiting geographic differences across firm headquarters. "Intuitively, the idea is that for California residents, stock price fluctuations of California-based firms will contain, on the margin, more non-portfolio information (e.g., about job security) than firms not headquartered in California. [...] a decline in [price of a California-based company's stock] combines portfolio and non-portfolio effects, whereas a non-local firm such as Dallas' ExxonMobil should influence investors primarily through its impact on their portfolios." After separating return fluctuations from local and non-local companies, the authors find that "non-California returns put Californians in the hospital," which they report as circumstantial evidence of portfolio effects.

Conference Board indices) are non-stationary. Although daily changes have an AR(1) coefficient of -0.4, augmented Dickey-Fuller tests with 7 lags do not reject a unit root.

We find a strong relationship between the S&P return on a given day and the confidence of investors that evening. A one standard deviation rise in the S&P (or 0.9 percent) is accompanied by a 0.10 standard deviation change in the investor sentiment indices.

In contrast, there is essentially no evidence of a relationship between economic confidence and stock performance for non-investors. In our organizational results, we find similarly stronger effects for employee stockholders. In our Rasmussen results, there is no statistically significant relationship between economic confidence and future returns, as one might expect in an efficient stock market. There is also no evidence of a relationship with lagged stock returns. While the relationship between the monthly economic confidence surveys and the stock market has been analyzed in the past (e.g. by Otoo, 1999), this is the first analysis at the daily frequency that we are aware of.

4.2 Cross-sectional Correlations with Job Satisfaction

In this section, we use the more traditional approach – studying whether job satisfaction is correlated with job performance and decision-making.

We begin by examining the cross-sectional relationship between subjective performance scores and job satisfaction. In Table 4, we report regressions of the subjective performance scores from 2006Q2 to 2006Q4, i.e. from one quarter before the job satisfaction survey (Column 1) to one quarter after (Column 3). Regardless of including controls, we find job satisfaction is correlated with performance evaluations. Satisfaction is most strongly correlated with recent historical performance scores. The correlation is progressively weaker – but still statistically significant and positive – with concurrent performance evaluations (the quarter of the survey) and for the immediate future (the quarter after the survey).

Cross-sectional regressions examining correlations with objective activity measures yield mixed results. In Table 5, we find that satisfied employees in the online sales organization had more output both the past, contemporaneously, and in the future. Because of the granularity of the timestamps in our data, we can examine productivity on the exact day of the survey and we find the strongest correlations with job satisfaction on the exact day of the survey.

Unlike the subjective performance data, we can break down our output measures into total hours and per-hour efficiency. Although there are correlations with both outcomes separately, the correlation with job satisfaction is stronger for total hours than per-hour efficiency.

However, for software engineers (Table 6), we find either negative correlations or no significant differences, even for activity on the day of the survey. The correlations with job satisfaction are again stronger in magnitude for hours. This contrast in results is inconsistent with the correlations with subjective performance scores, which are positive and roughly equally sized for the two groups.

We next test in Table 7 whether satisfied employees give higher scores to a given idea or interviewee. We find positive correlations for both outcomes, although only the interview effect was statistically significant.

The satisfaction survey, the idea ratings, and the interview scoring involves rating subjects on a 1 to X point Likert scale. As such, these correlations could reflect within-person correlation in how individuals use these scales. However, for interviewing in particular, the company trained interviewers to score candidates in a consistent manner. For example, interviewers were provided feedback who were consistently lenient or harsh outliers. This suggests that higher scores should reflect leniency in a meaningful way.

4.3 Panel Evidence: Job satisfaction survey

Table 8 presents regressions of normalized satisfaction on normalized Google stock returns on the days surrounding the survey completion date. Company stock returns are interacted with a normalized log of the shares of restricted stock and option granted to the employee before the survey date.[29] Our regressions control for day-of-the-week effects. Standard errors are heteroskedasticity robust and allow for clustering of errors within survey dates.

Coefficients for future and twice-lagged company stock returns are small in magnitude and never statistically significant for both main effects and interactions. Prior-day company stock returns are statistically significant, consistent with either persistent effects of returns or with the fact that employees outside the U.S. may have completed their surveys before the U.S. market opened.

The specification in the fifth column, which combines company stock returns on the current and previous day, parsimoniously describes the relationships in the data. In this column, the key explanatory variable is the difference between the average GOOG return (for t and $t-1$) and the average S&P return (again for t and $t-1$). Given that surveys were only returned on fourteen unique business days (the few surveys completed over the weekend are treated as having been completed on Friday), working with the simpler specification with only one stock return variable will be helpful in increasing the statistical power of subsequent analyses.

In this specification, we find evidence that an employee with average prior stock and option grants is 0.01 standard deviations more satisfied when stock returns are one standard deviation higher.

In Table 9 the robustness of these relationships by controlling for additional employee characteristics, and interacting these characteristics with the focal returns variable. The effect of recent stock returns is much larger for employees with greater than average stock and option grants, and that it reverses in sign for employees with smaller than average grants. Furthermore, on a day with an average company stock return, employees with greater option grants reported less satisfaction on their surveys.

Adding controls for employee region, start date, and job level and job ladder interactions does not affect the conclusion that employees with larger stock and option grants are more sensitive to stock price movements. Location in Europe/Africa is correlated with lower satisfaction but more sensitivity to stock price movements. Employee level and track[30] is not statistically significantly

[29] The few survey respondents that had not received stock or option grants were coded as having received the minimum grant in the sample.

[30] Google classified its salaried permanent employees into nine job levels and four main tracks (software engineering (T), technology operations (O), direct sales (SD or SI), and other salaried (E)). There are also non-exempt (N) and

correlated with sensitivity once stock and option grants are controlled for.

Later start dates are correlated with greater satisfaction and more sensitivity to stock price movements. Adding the interaction of start date and stock price movements significantly increases the option grant interaction coefficient, since a later start date is negatively correlated with the amount of stock and option shares granted given that employee grants became smaller as Google grew from a startup to a larger company. Even after controlling both for start date and option grant, we find positive, statistically significant correlations between both variables and job satisfaction.

Table 10 provides separate univariate regressions of aspects of satisfaction on company stock returns for employees. Stock returns are positively correlated with nearly every aspect of job satisfaction, particularly for workers with larger stock and options grants. The results are stronger for satisfaction with opportunity, integrity, support and commitment from the management within the company.

In unreported regressions, we find that the lowest-quintile employees experienced opposite-sign effects that are statistically significant for many dimensions. The results are consistent with stock price appreciation, making most employees more satisfied but having the reverse effect on employees who are benefitted least.

4.4 Stock Returns, Output, Hours and Efficiency

In Tables 11 and 12, we present panel regressions of measures of worker hours, productivity and efficiency on the day surrounding company stock returns. These regressions, like most of those that follow in the paper, include fixed effects for days of the week and for employee×month combinations. These regressions are thus testing whether, within a given month, a given employee works more or less on the days with positive stock returns.

In our control variables, we find that day-of-the-week effect coefficients are obviously large and negative for Saturdays and Sundays. Employees also have about 0.5 to 1.0 fewer hours with work activity on Friday.[31] The employee×month fixed effects subsume month fixed effects, which are important because average daily returns were higher at the beginning of our sample than the end. In addition, our outcome measures may have trended over time. Standard errors in these regressions allow for clustering of errors by day.

The coefficients in Table 11 imply that software engineers accomplish fewer tasks overall, worked shorter hours and are less productive (per hour) on days that company stock appreciated. The effect on output was weaker when examining only core software engineering tasks. The effect on total output appear to be higher on hours than per-hour efficiency.

A one standard-deviation rise (2.3 percent) was accompanied by 0.038 fewer hours with work activity. It is also accompanied by activity 0.6 to 0.8 percent of a standard deviation lower across the measures discussed above.

The analogous regressions for online sales staff in Table 12 imply effects of similar sizes (0.044

executive (X) job tracks.

[31] Our day-of-week findings partly speak to Bryson and Forth (2007), which discusses why productivity may vary across days of the week, and says that "there is scant direct evidence on day-of-week productivity effects."

hours and 0.6 percent of a standard deviation, respectively). For the software engineers, 50-60 percent of the effect on hours occurred outside regular business hours (defined as Monday-Friday, 9 am to 6 pm local time).

For online sales staff, only 15 percent of the effect occurred outside regular business hours. The effects we find of stock market movements on work activity, while consistent across groups of employees and measures, are small, and detectable only because of the size of our data sample. We likely simply lack the statistical power to detect differences in the stock-market sensitivity of different groups of employees.

4.5 Stock Returns and Hiring

Table 13 analyzes the effect of stock price movements on interview scores and pass/fail interview outcomes. The first set of regressions examines the relationship between interview scores and market movements surrounding the day the interview evaluation was written. We analyze this date, since interviewer mood on this date is most likely to affect the interview score. The evaluation date averages 2.5 days after the interview itself. The delay is positively correlated with the ultimate interview score, perhaps because interviewers take more care in assessing interviewees with a better chance of being hired.

Regressions include controls for day-of-the-week effects, year fixed effects, interviewer fixed effects, and fixed effects for the number of days between interview and scoring.[32] The results suggest that an interview score given on a one-standard-deviation positive-return day is 0.005 standard deviations lower, a modestly sized effect. The effect is about three times as large in engineering interviews, which are more analytical and quantitative. This result is surprising, in part because there is no evidence that stock-market effects are stronger (or weaker) for interviewers with more stock options. In addition, screening techniques that are analytical and thus verifiable should be *less* vulnerable to superfluous influences, not moreso.

The second set of regressions examine how the success of an engineering interviewing round relates to market movements on the day of the interview. Based on the reported probit marginal effects, a one-standard-deviation positive market movement reduces the probability of success by approximately 0.8 percentage points, arguably an economically meaningful effect. In addition, interviewing rounds with interviewers with higher average log stock and option grants show more sensitivity to recent market movements. Since interviews are scheduled in advance and stock returns should be difficult to predict in advance, it is unlikely that this result reflect selection bias.

We might expect candidates who interviewed on positive-return days would receive better performance evaluations after arriving at the company as an employee. We tested this, but found no significant difference. One reason for this result might be the low power of our test. Because of Google's hiring selectivity, our sample size was lower than for other analyses in this paper. In addition, interview scores were a noisy, imperfect predictor of worker performance.

[32] Observations with interview scores dated before the interview or more than 30 days after the interview are dropped on the grounds that one of the dates may be misrecorded. These account for 0.9 and 1.5 percent of the potential sample, respectively.

4.6 Stock Returns and New Ideas

In Table 14, we examine the relationship between the stock returns and innovation. We begin by studying outcomes for ideas based on stock returns around when the idea was submitted. We will then examine outcomes for ideas based on the timing of their evaluations (rather than the timing of the ideas' submissions).

Regarding our results on submission timing, we find that ideas submitted on or following positive-return days receive better ratings, a higher number of ratings, and are more likely to be implemented. A natural question is whether the higher quality of ideas comes at the expense of quantity. Unlike job interviews, idea postings are submitted at the employees' individual discretion and are not scheduled. It is possible that on positive-return days, employees' thresholds for submitting an idea is higher, and that bad ideas are strategically suppressed or saved for other days. To attempt to distinguish these mechanisms, we examined the correlation between returns and the number of ideas posted, but found no statistically significant correlation.

In Table 15, we examine the relationship between the ratings given to a particular idea and the stock returns around the timing of the idea's evaluation (rather than it's submission). Evaluators in our setting are volunteers who come from all over the company, are not vetted, and can rate any idea at any time.[33]

We find that ideas received poorer evaluations on positive-return days. This effect is moderated by stock compensation: Evaluators with more stock and option grants were more critical of a given idea in general. However, these highly stock-compensated evaluations are not statistically significantly more sensitive to current day stock returns.

Again, since idea evaluations are not scheduled in advance, the mechanism could be that people are more critical on positive-return days or that they choose to comment on the ideas they are critical of on positive-return days. The fact that in Table 14 we find that implementation is negatively correlated with returns following the day is consistent with the former mechanism. It suggests that mood effects may affect which innovations are implemented.

5 Discussion

Taken together, our data suggests that cross-section correlations between job satisfaction and both work effort and decision making are the opposite of what we find in a within-employee panel data. Happier employees work harder and are more lenient (Tables 4-7), but shocks that make employees happy (Tables 8-10) make them work less and evaluate more harshly (Tables 11-15).

As mentioned above, two possible reconciliations for this difference in results are: 1) the sign of the happiness-productivity and happiness-leniency relationships depends on the length of time period analyzed or 2) the cross-sectional correlations reflect reverse or third-faction causation,

[33]Unfortunately, timestamps of ratings were not preserved in our data, but time-stamps of comments were. We assume that readers who provided both a comment and a rating did so at the same time. Ratings from readers who did not provide a comment cannot be included in Table 15, but are included in the average and counts of ratings in Table 14. Likewise, ideas that received only ratings and no comments are also excluded from Table 15, which accounts for the smaller sample size.

while the responses to shocks reflect a causal effect.

5.1 Mood swings or optimal response to news?

Stock price movements, or the news that produces them, could affect optimal working hours by employees and standards for hiring candidates or implementing innovative ideas. An employee whose company stock appreciates has greater lifetime income, and if leisure is a normal good, he may choose to consume more leisure. Our results imply, however, that employees react to a one-standard-deviation positive return day by leaving work 2.5 minutes earlier that day and then make no detectable changes to their longer-run behavior. This would only make sense as a response to a wealth shock if leisure were infinitely intertemporally substitutable, so that all of the response in lifetime leisure to a wealth shock is taken on the day of the shock. This seems implausible.

Furthermore, the higher standards for ideas and interviewees that we document are unlikely to be a rational response to a higher stock price. A higher stock price likely implies upwardly revised expectations of Google's near and longer-term profitability, size, and ability to invest in new ideas. We find evidence for this interpretation in Google's internal prediction market, where employees were invited to wager on the success of internal company goals such as deadlines and new customer acquisitions.

In Cowgill and Zitzewitz (2015), we study employees' propensity in this market for wagering over-optimistically about their company's goals. Google's prediction market allowed employees to place wagers in an internal financial market tracking success or failure of various internal company goals. In the market's prices, we discover similar short-lived effects of daily fluctuations in company stock. We find that a 2% increase in company stock price – roughly a one standard deviation change – is associated with 3-4 percentage points higher prices in prediction market securities tracking the *successes* of internal goals.

These findings support the interpretation that employees have more optimistic beliefs about future firm performance on positive-return days. In Appendix A of this paper, we reproduce Table 7 from Cowgill and Zitzewitz (2015) (which contains the stock/optimism results) so that readers can assess the evidence for our interpretation. As in this paper, the prediction market effects are quite temporary, as there is no association between the prediction market prices and day $t-2$ returns.

Better economic prospects are likely to complement ideas for improving existing products or launching complementary ones. Better prospects are also likely to complement hiring new employees to work on these projects.

While it is possible to imagine scenarios in which positive news changes expectations of the quality of the future supply of ideas or job candidates, making the application of a higher bar to current candidates appropriate, the effect of good economic prospects on the demand for ideas and job candidates seems likely to predominate.

Even if the effects of good news on future expected supply are important, we would not expect those effects to be so transitory. In short, it is difficult to construct a story that explains our results as an optimal response to news. In our view, this leaves emotion and mood effects as the leading plausible interpretation.

5.2 Stock Compensation and Heterogeneous Effects

The extent to which equity compensation is responsible for or results is hard to measure. The setting of our study is a company that used equity compensation extensively during the sample period. Examining differences between employees with high and low stock grants does not adequately measure the counterfactual. The extensive use of equity compensation at a company may create a climate in which all employees – including those with lower levels of stock compensation – may be more attuned to the stock prices.

In several of our results, we find that employees with greater stock compensation are more sensitive to daily fluctuations. A natural interpretation of is that stock grants caused these these stronger fluctuations. However, the levels of stock compensation are endogenous. In particular, the interactions we document may be the result of selection: Employees selected for higher stock grants could be more sensitive to environmental changes generally.

Our study lacks quasi-experimental variation in stock exposure necessary for such a counterfactual claim. However, we report several related pieces of evidence related to the selection hypothesis. In Table 16, we revisit the daily fluctuations of engineers, online sales workers and the submissions of ideas. We now interact the level of stock compensation with the S&P 500 daily fluctuations. In addition, the regressions prediction job satisfaction in Table 9 contains this interaction in Column 7. Across a variety of outcomes and behaviors, higher stock grantees are not more sensitive to the market as a whole – only to their own company's stock.

We can also examine more direct tests of the selection hypothesis: That employees selected for higher stock grants could be more volatile and reactive generally. A large sub-field of academic psychology develops theory and empirics around fixed personality traits (Barenbaum and Winter, 2008) – including high-frequency reactiveness to environmental stimuli.

Psychologists regard these characteristics as fixed. Almlund, Duckworth, Heckman and Kautz (2011) reviews personality psychology and its implications for economics. They write, "Most psychologists now accept the notion of a stable personality[.]" Most evidence of changing personality takes place over a lifetime – a longer horizon than the approximately two years in this paper. One set of economists (Cobb-Clark and Schurer, 2012) examined the stability of "Big Five" personality traits over a four year period, and found little changes even in the face of adverse life events. They conclude "like other non-cognitive traits, personality can be modeled as a stable input into economic decisions."

Data about the personality traits are a substitute for a counterfactual, but they do address how much stock compensation was correlated with fixed tendency towards volatility and reaction. Within the psychology literature, the quality of "emotional stability" (or its negative pole, "neuroticism") captures the personality trait associated with the high-frequency reactions in this paper.[34] The American Psychological Association Dictionary (2007) defines emotional stability as "predictability and consistency in emotional reactions, with absence of rapid mood changes" and associates neuroticism with "impulsiveness (moody)" and "vulnerability to stress." Toegel and Barsoux (2012) describes neurotic personalities in the Big Five as "reactive, excitable" and "liable to overreact." Some psychological theorists argue that impulsivity is a facet of neuroticism (McCrae

[34] The authors thanks Columbia University psychologists Adam Galinsky, Sandra Matz and Michael Slepian for assistance with this literature.

and John, 1992). John and Srivastava (1999) writes: "Neuroticism contrasts emotional stability and even-temperedness. [...] People who score low on neuroticism can be characterized as [...] calm, even tempered, and relaxed."

Researchers in psychology and economics have documented a positive correlation between neuroticism and risk-aversion (Borghans et al., 2009; Rustichini et al., 2016). This tendency would lead workers who are sensitive to fluctuations to *avoid* more volatile forms of compensation (stock), rather than seeking it out. Selection of volatile workers into stock compensation – at least as it pertains to worker preferences – ought to work the other direction. These preferences may not ultimately affect the size of a worker's stock grant if (for example) the employer had preferences about the form of compensation,[35] and/or if the firm undertakes policies to prevent workers from reducing exposure to company stock. Both these possibilities were realized at Google during the sample period.

Table 17 contains data testing this hypothesis. The psychology literature includes practical assessment methods for measuring personality traits through surveys or other observations. Many private companies use these psychometric assessments to assist with recruiting, training and career development.[36] For example, the official publisher of the Myers–Briggs Type Indicator assessment reports that 88 percent of Fortune 500 companies and 89 of the Fortune 100 companies use their product.

In our setting, industrial psychologists measured the "Big Five" personality characteristics (Digman, 1990; Goldberg, 1993) for a large sample of employees in 2006 (in the middle of our sample). The Big 5 Personality characteristics were measured using a widely used and validated scale: Big Five Inventory (BFI-44, John et al., 1991).

A literature review by John and Srivastava (1999) says that emotional stability is "almost universally accepted personality dimension." As such, it is unsurprising that one of the Big Five personality traits measured in the inventory is the aforementioned "emotional stability" trait.[37]

Our regressions in Table 17, show this metric is uncorrelated with the size of employees' stock grants in any economically meaningful way. These results suggest that higher stock grants were *not* targeted towards workers with fix traits of environmentally sensitivity. If anything, the correlation is the other way – the Big Five "emotional stability" coefficient is positive in all specifications, and is statistically significant until controls are introduced for the worker's job type.

This is consistent with economists prior research suggesting that less emotionally stable workers would seek to *avoid*, rather than seek out, volatile forms of compensation like publicly traded stock.

Given the prior results around risk aversion, one may wonder why stock compensation for could not be even lower for risk-averse employees. Google's inclination to use stock compensation – plus its restrictions on sales and hedging – limits how well employees can escape the volatility of daily fluctuations. According to public statements by executives, Google appears to prefer stock as a

[35] Many employers have claimed that stock compensation helps agency problems and aligns employees and shareholder interests. Oyer (2004) suggest that employers have preferences about forms of compensation for sorting reasons.

[36] "Industrial and organizational psychology" is an APA-recognized sub-speciality of professional psychology, focused on applying psychological insights to workforce management.

[37] The other four personality traits are "agreeableness," "conscientiousness," "extraversion," and "openness."

form of compensation for both sorting and incentive reasons.[38] Nearly all employees are given some form of stock compensation,[39] In addition, Google's stock grants featured vesting schedules and other limits on the timing of sales and an outright ban on employee hedging the stock.[40]

The results in Table 17 are not a substitute for a counterfactual analysis. Borghans, Golsteyn, Heckman and Humphries (2011) discuss identification challenges generally in personality psychology. However, the results suggest that stock compensation is not more targeted towards workers with more volatile personality characteristics. Workers with high stock grants do not appear more environmentally sensitive on a fixed basis. However, it is also possible that the timing of stock grants (mostly around the dates of hiring) are made in a moment in which employees are more subject to volatility. This is not a possibility that our data can address, although the findings of Cobb-Clark and Schurer (2012) and Almlund et al. (2011) suggest these psychological tendencies are stable for the horizon of this paper (and longer), even in the face of adverse life events.

6 Conclusion

In this paper, we provide evidence of emotions affecting firm behavior. In our Rasmussen results, we find a positive effect of daily stock market returns on economic confidence. We then turn to data from Google to examine the effect on workplace outcomes. Positive stock returns improve Google employees' mood, which leads them to work slightly less and be choosier in evaluating ideas and candidates.

Our findings about productivity contrast with some of the incumbent literature about happiness and productivity. Like this literature, we find positive correlations in cross-sectional data. However, we find the opposite relationship – negative relationships – in our longitudinal analysis of stock fluctuations.

The distinction between cross-sectional and panel results have important practical implications for firms. Managers often want to increase productivity through workplace interventions that generate longitudinal variation in worker happiness. Many related papers are explicitly motivated by these interventions.[41]

However, the happiness/productivity relationship may be driven by fixed characteristics that are immune to interventions. If these fixed characteristics drive the correlation, then managers

[38] Google's Founders Letter in its 2014 IPO stated, "The significant employee ownership of Google has made us what we are today." Regarding rationales, Founder Sergey Brin told a journalist that stock is a strong motivation, but moreso for smaller (`https://www.fastcompany.com/75905/three-keys-change`, accessed September 3, 2018). Regarding selection rationales, Google's Chief Human Resources Officer described stock/salary tradeoffs in a book (Bock, 2015) writing, "We even used this as a recruiting screen, reasoning that only risk-seeking, entrepreneurial types would be willing to take a pay cut of $20,000, $50,000, or even $100,000."

[39] Google's Chief Human Resources Officer wrote (Bock, 2015), "Google is one of the few companies of [its] size to grant stock to all employees."

[40] This includes limited trading windows restricting the timing of employee trades. This is to prevent any form of insider trading, as many employees have access to a lot of information. `https://abc.xyz/investor/other/google-code-of-conduct.html`

[41] For example, Oswald, Proto and Sgroi (2015) delivered "short-run happiness shocks" to laboratory in the form of fruit, chocolate and brief comedy clips, and Erez and Isen (2002) gave subjects candy. These interventions generated panel- or longitudinal- variation in worker happiness.

should focus attention away from interventions and towards improving fixed characteristics. The most direct mechanism to change a workforce's fixed characteristics is through hiring, separations and job design.

Although the mood effects are transitory, the consequences on hiring decisions and innovations are longer-term. Although we cannot judge whether Google's decision making is better on positive or negative stock return days, we can safely argue that it could improve outcomes slightly by making its decision making uncorrelated with mood.

An advantage of examining stock-induced (rather than weather-induced) mood shifts that helps offset this cost is that they have additional inherent interest, particularly given the literature on the role of optimism in entrepreneurial firms. This literature points to the intriguing possibility of a positive feedback loop between optimism, effort, and performance. Theorists have argued that optimistic biases may generate motivation (Bénabou and Tirole, 2002; Benabou and Tirole, 2003; Compte and Postlewaite, 2004) or risk-taking (Bernardo and Welch, 2001; Goel and Thakor, 2008). Organizational psychologists have found positive correlations between happiness and both productivity (e.g., Wright and Staw, 1999) and decision making (e.g., Staw and Barsade, 1993). Hermalin and Isen (2008) build on these results and consider happiness as a strategic variable, arguing that firms may alter their competitive strategy to maintain their own morale or demoralize their competitors.

Our results generate some skepticism about this positive feedback story. Like most of the prior work, we also find a positive cross-sectional correlation between happiness and job performance. At the same time, our main result is that a (plausibly exogenous) shock that increases happiness actually reduces work effort. Likewise, while happy workers are easier evaluators of ideas and job applicants, shocks that make them happier make them tougher evaluators.

While our shocks are at a daily frequency and longer-run effects need not be the same, another possible reconciliation is that the cross-sectional correlations reflect reverse causality. People with higher incomes are happier (Easterlin, 1974, 1995; Stevenson and Wolfers, 2008), and workers who are performing better likely either have or expect higher incomes. Likewise, being lenient, particularly when acting as an agent of a firm, may lead directly or indirectly to greater happiness.

Beyond having a more plausible claim to identification, we make two further incremental contributions. First, unlike much of the prior literature, which obtains its outcome measures from performance on survey instruments or performance evaluations, we test the effect of mood on objective measures of employees' performance of core job functions: writing code, assisting advertisers, interviewing candidates, and evaluating ideas. Second, due to Google's size and a management style that favors standardization and quantification, we are able to provide evidence on a much larger scale than any prior study we are aware of.

Google is not representative of the broader economy in many ways. Its employees in this sample are younger, and we find that employees with less experience at Google (and, likely, in the workforce) have moods that are more influenced by stock price. Many of its employees had large holdings of company stock or options, and these employees had moods that are more influenced by stock price. Its stock price is more volatile than many. At the time of our sample, it had a flatter organizational structure and provided its employees with more autonomy than many firms, potentially allowing a greater scope for mood effects. Google also took explicit steps to discourage workers from monitoring prices, including punishments costing hundreds of dollars for employees caught monitoring the company's stock prices.

The issues raised by our paper speak to stock compensation generally. Stock compensation affects about 27% of the US workforce, and is often proposed as a way to align incentives between employees and long-term shareholders.[42] For the median worker paid with stock, stock constitutes about 23% of their salary.[43] Multiple surveys of stock-compensated employees have found that between 33%-40% of stock-compensated workers check their firm's stock price daily.[44] Business leaders from throughout the economy – including at relatively low-tech companies such as Costco and Wal-Mart – have publicly expressed concern about the productivity effects of employees monitoring the stock price.[45]

In addition, Google is likely more representative of the entrepreneurial firms that are an important source of innovation and growth. Understanding the role of emotions and mood in these firms may prove useful to managing them better and improving their performance. Beyond this, our results reinforce the case for viewing firms as entities that may deviate from rationality in ways that behavioral economics can help predict.

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[42] These numbers come from the 2014 General Social Survey (GSS), tabulated in Kurtulus and Kruse (2017).

[43] Source: The 2014 General Social Survey (GSS), tabulated by Blasi, Kruse and Freeman. `https://www.nceo.org/assets/pdf/articles/GSS-2014-data.pdf`.

[44] Bryson and Freeman (2014) found 38% in a survey of mutinational workers, and similar magnitudes of daily stock checkers were estimated by an independent study by Morgan Stanley researchers (Siegal and Mesereau, 2013).

[45] See Table 1 for an incomplete list of companies and executives with such policies.

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Table 1: Public Statements and Policies by Executives against Employees Checking Stock Prices

Company Name	Statement/Policy and Source
Apigee	*"'It's critical not to get distracted by the stock price,' said Chet. 'And this is not only the case when it is low. Even a red-hot stock price can get the team off the focus of what's important."'* – *Forbes*, January 9, 2016.
Costco	*"[Former Costco CEO] Jim Sinegal is famous for saying 'don't worry about the stock price for 10 years."'* – *Washington Post*, October 15, 2014.
Google	*"[Google senior vice president] Marissa Mayer told her team that she didn't want them checking the stock price during the day. When her workers did not respond with full compliance, she instituted another policy: if anyone who worked for her spotted someone else in the group looking at the stock ticker, all he or she had to do was walk over and tap that person on the shoulder. Then that person would have to buy you a share of stock. After a number of involuntary exchanges, people either stopped checking or learned to hide their peeking more effectively."* – Journalist Steve Levy's book *In the Plex*
HomeAway	*"'We've created a bunch of millionaires at our company,' [HomeAway Inc. CEO Brian Sharples] told an audience of investors and startup executives gathered for a Sept. 29 conference in San Francisco. 'The challenge right now is keeping them engaged,' he said."* – *MarketWatch*, October 26, 2011.
Microsoft	*"In the early 1990s, it seemed as if every Microsoft employee's computer ran an application that left an image on their screens at all times: a cartoon depiction of a face whose expression changed depending on the direction of the company's stock price. When shares increased in value, the face smiled; when they fell, it frowned."* *"Microsoft's Lost Decade"* in *Vanity Fair*.
Research in Motion (RIM)	*"There's a rule at Research In Motion Ltd., maker of the habit-forming BlackBerry hand-held e-mail device. Anyone who gets caught checking the stock price at work has to buy doughnuts for every employee in the company." –* Bloomberg News, June 2005.
The Globe.com	*"Mr. Krizelman (CEO) says he does not want employees to be like day traders, checking the stock price 40 to 50 times a day."* – New York Times, July 20, 1999.
Twitter	*"Employees did notice the stock decline, however, but few were comfortable talking about it. Bret Taylor, now CEO of Quip, was Facebook's CTO at the time of the IPO. He says employees refrained from talking about the stock price — saying it was viewed as 'uncool' to worry about it — even though it may have been on their mind. 'For a lot of people, the vast majority of their personal wealth is tied up in the stock of that single company [after an IPO],' says Taylor, who was also at Google during its IPO. 'Not only do you go [from] operating without a lot of public scrutiny, but on top of that, whether or not you have the maturity to try and ignore it, you're sort of seeing your personal wealth fluctuate day to day.' Added a former, mid-level Facebook employee who was also there during the IPO: 'It was almost taboo to talk about it."'* –Mashable, May 14, 2014.
Vascular Solutions	*"If our shareholders lost confidence in our defense strategy, they'd sell off stock and our share price would drop. Our employees would see our falling stock price, see the value of their stock grant decline, and worry that the company would go out of business. Many would leave [...] more employees would get distracted or leave, our performance would suffer, sales would decline [...]"* – CEO Howard Root's memoir, *Cardiac Arrest*.
Wal-Mart	*"I don't necessarily check the stock price every day. I think if I were a shareholder and the CEO spent all of his time focused on the share price, then I would probably be concerned, because the share price follows the results of the company."* – CBS News' *MoneyWatch*, February 5, 2011.
Yahoo	*"CEO Mayer recently ordered Yahoo's stock ticker removed from the home page of the company's internal website, called Backyard, signaling to employees that they should focus on creating better Web services rather than worry about corporate finances. 'I want you thinking about users,' Ms. Mayer has repeatedly said to Yahoo workers, according to people who have interacted with her."* – Wall Street Journal, August 9, 2012. Also: *"None of us should be distracted by the stock price, high or low."* – Yahoo's outside board members in letter to employees on IPO day, 1996.
Zillow	*"[W]e have a prohibition, internally, on employees checking the stock price. I know it happens, but it can't happen in public. If I ever walk into a meeting and people are talking about, 'What's the stock doing today?' that's verboten."* – CEO Spencer Rascoff in an interview with *Motley Fool*, July 29, 2013.

Table 2: Summary of employee activity data

Activity measures by group	Average # per workday	Percent done by group	Data range From	To
Software engineers				
Code reviews (as author or reviewer)	0.5 to 1.0	83%	Jan 2006	Jun 2008
Bugs database actions	2.0 to 5.0	68%	Jan 2006	Jun 2008
Perforce calls (max 1 per 5-second period)	10 to 20	95%	Jan 2006	Jun 2008
Wiki page edits	1.0 to 2.0	74%	Jan 2006	Jun 2008
Wiki page views	5 to 10	64%	Jan 2006	Jun 2008
Hours with above activity	5.2		Jan 2006	Jun 2008
Online sales and operations staff				
Customer service rep (CSR) emails	5 to 10	75%	Jul 2004	Jun 2008
ICS page views	100 to 200	65%	Jul 2004	Jun 2008
Hours with ICS page view or CSR email	5.2		Jul 2004	Jun 2008

Notes: For the purposes of our analysis, the category "software engineers" include those in the software engineering job track (T) in Engineering, Operations, or Sales, excluding managers and directors and those with project, product, or hardware in their title. The category "online sales staff" includes employees in job tracks E or N at level 3 or below in the Sales department in AdWords, AdSense, or Checkout operations.

Table 3: Consumer sentiment and stock index changes, Jan 2005 to July 2008

Dependent variable: Change in daily confidence index

	Investors (Portfolio >= $5k)			Non-investors (Portfolio < $5k)		
	Current	Expectations	Total	Current	Expectations	Total
S&P return (t)	0.089***	0.100***	0.100***	0.005	0.001	0.009
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
S&P return (t-1)	-0.003	-0.026	-0.014	0.041	0.008	0.025
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
S&P return (t-2)	-0.002	0.008	0.002	-0.035	-0.011	-0.028
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Constant	-0.007	-0.006	-0.007	-0.010	-0.008	-0.009
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Day of week FEs	X	X	X	X	X	X
Obs.	892	892	892	892	892	892
Adj R-sq	0.0080	0.0099	0.0106	-0.0002	-0.0032	-0.0017
Rho	-0.474	-0.484	-0.479	-0.493	-0.497	-0.490

Notes: This table presents daily economic confidence, as reported each evening to the Rasmussen survey. It is regressed on log S&P 500 returns. Both confidence changes and S&P returns are divided by their standard deviations. Rasmussen reports 3 and 7-day moving averages, and the nightly numbers are recovered from these averages. Regressions are AR(1) Prais-Winston with heteroskedasticity-robust standard errors.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Correlations between job satisfaction and job performance (subjective evaluation rating)

Dependent Variable: Subjective Performance Evaluation Rating (normalized by track × level)

Panel A: Univariate

	Rating	Rating	Rating
Job Satisfaction Score	0.0097***	0.0048***	0.0028*
	(0.0016)	(0.0015)	(0.0015)
Sample Period	2006, Q2	2006, Q3	2006, Q4
Same Quarter as Job Satisfaction Survey	No	Yes	No
R^2	0.0096	0.0026	0.00084
Observations	3739	4577	4817

Panel B: Multivariate

	Rating	Rating	Rating
Job Satisfaction Score	0.011***	0.0068***	0.0044***
	(0.0017)	(0.0016)	(0.0016)
Ln(Stock + Options)	0.0041	0.0031	-0.0011
	(0.0027)	(0.0024)	(0.0025)
Ln(Start Date)	-0.0096***	-0.0071***	-0.0089***
	(0.0024)	(0.0021)	(0.0021)
City Fixed Effects	Yes	Yes	Yes
Sample Period	2006, Q2	2006, Q3	2006, Q4
Quarter of Survey	No	Yes	No
R^2	0.051	0.035	0.027
Observations	3669	4476	4705

Notes: This table presents cross-sectional regressions between job satisfaction and performance. The outcome variables in these regressions are subjective performance scores (normalized by track × level). The job satisfaction score, stock/option and start date variables are also normalized. All variables described in greater detail in Section 2 (Data). The first column's outcome is the performance score on the quarter before the survey. The second column's outcome is the subjective performance score of the quarter in which the survey is taken. The final column is the subjective performance score after the survey. Standard errors are robust.

The "track" variable refers to a job category. Google classified its salaried permanent employees into nine job levels and four main tracks (software engineering (T), technology operations (O), direct sales (SD or SI), and other salaried (E)). There are also non-exempt (N) and executive (X) job tracks. "Level" refers to promotion level.

Standard errors are robust.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Correlations between job satisfaction and job performance (objective measures, online sales staff)

Panel A: Before the Survey (2006, Q2)

	Output	Output	Hours	Hours	Efficiency	Efficiency
Job Satisfaction Score	0.065**	-0.0087	0.13***	0.022	0.038*	-0.0046
	(0.033)	(0.030)	(0.030)	(0.024)	(0.020)	(0.017)
Ln(Shares+Options)		-0.079		-0.14*		-0.082
		(0.073)		(0.073)		(0.050)
Start date		0.17***		0.30***		0.075*
		(0.058)		(0.062)		(0.040)
Fixed Effects (City, Day, Track×Level)	No	Yes	No	Yes	No	Yes
R^2	0.0030	0.14	0.010	0.39	0.0021	0.089
Observations	54815	54815	54815	54815	38011	38011

Panel B: Day of the Survey (During 2006, Q3)

	Output	Output	Hours	Hours	Efficiency	Efficiency
Job Satisfaction Score	0.21***	0.069*	0.24***	0.13**	0.11***	0.028
	(0.041)	(0.038)	(0.057)	(0.057)	(0.026)	(0.028)
Ln(Shares+Options)		-0.43		-0.37		-0.27
		(0.34)		(0.23)		(0.20)
Start date		-0.021		-0.070		-0.018
		(0.17)		(0.14)		(0.10)
Fixed Effects (City, Track×Level)	No	Yes	No	Yes	No	Yes
R^2	0.027	0.19	0.036	0.21	0.017	0.15
Observations	748	748	748	748	675	675

Panel C: After the Survey (2006, Q4)

	Output	Output	Hours	Hours	Efficiency	Efficiency
Job Satisfaction Score	0.13***	0.044***	0.15***	0.060***	0.12***	0.035*
	(0.020)	(0.016)	(0.018)	(0.015)	(0.021)	(0.018)
Ln(Shares+Options)		-0.39***		-0.24***		-0.50***
		(0.077)		(0.070)		(0.084)
Start date		0.021		0.16***		-0.068
		(0.038)		(0.041)		(0.051)
Fixed Effects (City, Day, Track×Level)	No	Yes	No	Yes	No	Yes
R^2	0.021	0.15	0.021	0.34	0.017	0.14
Observations	63456	63456	63456	63456	38028	38028

Notes: This table presents cross-sectional regressions between job satisfaction and job activities. The outcome variables in these regressions are normalized activity measures. The job satisfaction score, stock/option and start date variables are also normalized. All variables described in greater detail in Section 2 (Data). The first column's outcome is the subjective performance score on the quarter before the survey. The second column's outcome is the subjective performance score of the quarter in which the survey is taken. The third column is the performance score after the survey. Standard errors are clustered by employee.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Correlations between job satisfaction and job performance (objective measures, engineering)

Panel A: Before the Survey (2006, Q2)

	Output	Output	Hours	Hours	Efficiency	Efficiency
Normalized Satisfaction Score	-0.0035**	-0.0034***	-0.020*	-0.021**	-0.0068**	-0.0063**
	(0.0014)	(0.0013)	(0.011)	(0.010)	(0.0033)	(0.0030)
Ln(Shares+Options)		-0.0084**		0.029		-0.019***
		(0.0035)		(0.030)		(0.0064)
Start date		0.0024		0.062***		0.000051
		(0.0026)		(0.018)		(0.0042)
Fixed Effects (City, Day, Track×Level)	No	Yes	No	Yes	No	Yes
R^2	0.00065	0.043	0.00043	0.22	0.00071	0.0062
Observations	124745	124745	124745	124745	73281	73281

Panel B: Day of the Survey (During 2006, Q3)

	Output	Output	Hours	Hours	Efficiency	Efficiency
Normalized Satisfaction Score	-0.0013	-0.0017	0.0044	0.0045	-0.0037	-0.0041
	(0.0023)	(0.0024)	(0.024)	(0.024)	(0.0048)	(0.0049)
Ln(Shares+Options)		0.011*		0.042		0.021
		(0.0065)		(0.087)		(0.015)
Start date		0.015***		0.078		0.016**
		(0.0046)		(0.051)		(0.0074)
Fixed Effects (City, Day, Track×Level)	No	Yes	No	Yes	No	Yes
R^2	0.000098	0.013	0.000019	0.022	0.00058	0.015
Observations	1682	1681	1682	1681	1448	1445

Panel C: After the Survey (2006, Q4)

	Output	Output	Hours	Hours	Efficiency	Efficiency
Normalized Satisfaction Score	-0.0015	-0.0015	-0.013	-0.015	-0.0040**	-0.0034*
	(0.00095)	(0.00096)	(0.011)	(0.011)	(0.0017)	(0.0018)
Ln(Shares+Options)		0.00043		0.074**		-0.011*
		(0.0024)		(0.030)		(0.0061)
Start date		0.0046**		0.076***		-0.0013
		(0.0019)		(0.018)		(0.0034)
Fixed Effects (City, Day, Track×Level)	No	Yes	No	Yes	No	Yes
R^2	0.00016	0.050	0.00017	0.24	0.00041	0.0060
Observations	155035	155035	155035	155035	84984	84984

Notes: This table presents cross-sectional regressions between job satisfaction and job activities. The outcome variables in these regressions are normalized activity measures. The job satisfaction score, stock/option and start date variables are also normalized. All variables described in greater detail in Section 2 (Data). Note that the survey was administered in Q3 2006. Standard errors are clustered by employee.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Correlations between job satisfaction and job performance (decision outcomes)

	Idea Ratings	Idea Ratings	Interview Scores	Interview Scores
Job Satisfaction Score	-0.0067	0.025	0.040***	0.033***
	(0.039)	(0.028)	(0.011)	(0.0073)
Ln(Shares+Options)		-0.21**		-0.033*
		(0.082)		(0.018)
Start date		-0.085		-0.0047
		(0.067)		(0.013)
Fixed Effects (City, Day, Track×Level)	No	Yes	No	Yes
Other Fixed Effects	None	Idea	None	Applicant
R^2	0.000033	0.64	0.0014	0.88
Observations	8209	8113	208817	204146

Notes: This table presents cross-sectional regressions between job satisfaction and decison-making activities. The outcome variables in these regressions are decision-making measures. "Idea Ratings" refers to the the normalized score given to each idea by volunteer evaluators. The job satisfaction score, stock/option and start date variables are also normalized. All variables described in greater detail in Section 2 (Data). Note that the survey was administered in Q3 2006. Standard errors clustered by employee.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Recent Company stock returns and employee satisfaction

	Satisfaction	Satisfaction	Satisfaction	Satisfaction	Satisfaction
GOOG Return (t+1)	-0.011				
	(0.017)				
GOOG Return (t)	0.030**	0.033***		0.033***	
	(0.011)	(0.0083)		(0.0083)	
GOOG Return (t-1)	0.0091	0.0083		0.0083	
	(0.0085)	(0.0083)		(0.0083)	
S&P Return (t)	-0.061**	-0.068***		-0.068***	
	(0.025)	(0.018)		(0.018)	
S&P Return (t-1)	-0.056***	-0.054***		-0.054***	
	(0.018)	(0.017)		(0.017)	
GOOG Return (t and t-1)			0.018**		
			(0.0079)		
S&P Return (t and t-1)			-0.047**		
			(0.017)		
GOOG - S&P return (t and t-1)					0.010**
					(0.0047)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.0025	0.0025	0.0023	0.0025	0.0022
Observations	4927	4927	4927	4927	4927

Notes: The normalized average response to a survey about employee job satisfaction is regressed on normalized company stock (GOOG) returns around the survey date and interactions with the normalized log of shares of options and restricted stock granted to an employee prior to the date of the survey. Standard errors are heteroskedasticity robust and adjust for clustering within survey response date.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Recent Company stock returns and employee satisfaction, by employee characteristics

	Satisfaction	Satisfaction	Satisfaction	Satisfaction	Satisfaction	Satisfaction	Satisfaction
GOOG - S&P return (t and t-1)	0.010**	0.019***	0.026***	0.014**	0.069	0.062	0.037***
	(0.0047)	(0.0042)	(0.0065)	(0.0053)	(0.043)	(0.043)	(0.0080)
Ln(Stock + Options granted)		-0.11	-0.16***	-0.100	-0.068	-0.058	-0.085
		(0.072)	(0.019)	(0.065)	(0.046)	(0.042)	(0.059)
Start Date		0.19***		0.19***	0.22***	0.23***	0.21***
		(0.049)		(0.050)	(0.034)	(0.036)	(0.049)
Europe/Africa		-0.25***		-0.25***	-0.24***	-0.25***	
		(0.048)		(0.046)	(0.033)	(0.035)	
Asia/Pacific		0.046		0.037	0.034	-0.0075	
		(0.056)		(0.058)	(0.051)	(0.049)	
Engineering track		0.14***		0.14***	0.13***		
		(0.037)		(0.037)	(0.033)		
Operations track		-0.088		-0.088	-0.11*		
		(0.057)		(0.057)	(0.061)		
Employee level		0.012		0.012	0.0050		
		(0.015)		(0.015)	(0.012)		
GOOG - S&P return (t and t-1)×Ln(Stock + Options granted)			0.041**	0.035*	0.11***	0.11***	
			(0.014)	(0.018)	(0.035)	(0.031)	
GOOG - S&P return (t and t-1)×Start date					0.070***	0.067***	
					(0.020)	(0.016)	
GOOG - S&P return (t and t-1)×Europe/Africa					0.065**	0.077***	
					(0.028)	(0.026)	
GOOG - S&P return (t and t-1)×Asia/Pacific					0.0072	0.012	
					(0.050)	(0.048)	
GOOG - S&P return (t and t-1)×Engineering track					-0.021	-0.023	
					(0.020)	(0.017)	
GOOG - S&P return (t and t-1)×Operations track					-0.045	-0.040	
					(0.036)	(0.035)	
GOOG - S&P return (t and t-1)×Employee Level					-0.015	-0.014	
					(0.010)	(0.010)	
S&P return (t and t-1)×Ln(Stock + Options granted)							0.029
							(0.041)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Fixed Effects	None	None	None	None	None	Track x Level	Track x Level
R^2	0.0022	0.079	0.035	0.080	0.083	0.096	0.085
Observations	4927	4822	4927	4822	4822	4822	4822

Notes: The normalized average response to the job satisfaction from Table 8 is regressed on normalized company stock (GOOG) returns on and prior to the survey date and interactions with employee characteristics. Start date and log of shares are normalized. Standard errors are heteroskedasticity robust and adjust for clustering within survey response date.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: Recent GOOG returns and satisfaction, by aspect of job

Panel A

	Comp/Benefits	Culture	Direction	Diversity	Integrity	Opportunity
GOOG - S&P return (t and t-1)	0.0064	-0.016	0.0096	0.036***	0.0097	0.021***
	(0.0069)	(0.0094)	(0.0080)	(0.010)	(0.0087)	(0.0056)
GOOG - S&P return (t and t-1)×Ln(Stock + Options granted)	0.024	0.051**	0.062***	0.033**	0.080***	0.073***
	(0.014)	(0.023)	(0.0099)	(0.012)	(0.022)	(0.012)
GOOG - S&P return (t and t-1)×Start date	0.022**	0.030**	0.039**	0.027	0.060*	0.055***
	(0.0085)	(0.013)	(0.014)	(0.018)	(0.029)	(0.018)
Ln(Stock + Options granted)	0.26***	-0.14***	-0.094***	0.050***	0.021	0.033
	(0.023)	(0.028)	(0.015)	(0.016)	(0.027)	(0.020)
Start Date	0.24***	-0.0094	0.14***	0.22***	0.26***	0.19***
	(0.014)	(0.018)	(0.023)	(0.023)	(0.041)	(0.031)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.041	0.026	0.052	0.036	0.065	0.035
Observations	4813	4802	4804	4785	4801	4821

Panel B

	Other People	Perf. Management	Commitment	Support	Work-Life Balance
GOOG - S&P return (t and t-1)	0.0048	0.018	0.010	0.018*	-0.0045
	(0.0085)	(0.013)	(0.0069)	(0.0087)	(0.019)
GOOG - S&P return (t and t-1)×Ln(Stock + Options granted)	0.044**	0.057***	0.072***	0.074***	0.041**
	(0.019)	(0.017)	(0.017)	(0.013)	(0.016)
GOOG - S&P return (t and t-1)×Start date	0.047*	0.041**	0.051**	0.047**	0.014
	(0.023)	(0.019)	(0.018)	(0.020)	(0.016)
Ln(Stock + Options granted)	0.024	-0.12***	0.0053	-0.022	-0.055**
	(0.020)	(0.023)	(0.021)	(0.021)	(0.020)
Start Date	0.24***	0.17***	0.22***	0.26***	0.15***
	(0.022)	(0.022)	(0.024)	(0.031)	(0.024)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.049	0.076	0.049	0.082	0.042
Observations	4804	4804	4821	4823	4821

Notes: Each column is a regression of the normalized average satisfaction score for a specific job aspect on current and prior-day Google stock returns interacted with the log of stock and option shares granted and start date. Start date and log of shares are normalized. All regressions include day of the week fixed effects. Standard errors are heteroskedasticity robust and adjust for clustering within survey response date. “Commitment” is stands for “Personal Satisfaction and Commitment.” “Perf. Management” stands for “Performance Management.”

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Employee work activity, hours, and recent stock returns – software engineering, Jan 2006 to June 2008

Panel A

	Output	SweHours	Hours	Off Hours	Efficiency
GOOG Return (t+1)	-0.0033	-0.0038	-0.0047	-0.0012	-0.0042
	(0.0063)	(0.0043)	(0.0058)	(0.0020)	(0.0055)
GOOG Return (t)	-0.011*	-0.0073	-0.0097	-0.0058**	-0.0081
	(0.0064)	(0.0045)	(0.0060)	(0.0024)	(0.0055)
GOOG Return (t-1)	-0.0033	-0.0019	-0.0032	-0.0021	-0.0020
	(0.0064)	(0.0043)	(0.0056)	(0.0026)	(0.0056)
GOOG Return (t-2)	0.000031	-0.0017	-0.0021	0.0026	-0.0015
	(0.0057)	(0.0038)	(0.0050)	(0.0018)	(0.0049)
S&P Return (t)	0.0073	0.0031	0.0046	0.0055***	0.0053
	(0.0058)	(0.0041)	(0.0054)	(0.0019)	(0.0052)
S&P Return (t-1)	0.0047	0.0022	0.0028	0.0039*	0.0033
	(0.0060)	(0.0042)	(0.0056)	(0.0020)	(0.0053)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.45	0.37	0.44	0.43	0.28
Observations	4685133	4685133	4685133	2462266	4685133

Panel B

	Output	SweHours	Hours	Off Hours	Efficiency
GOOG - S&P return (t and t-1)	-0.0075**	-0.0054**	-0.0075**	-0.0036**	-0.0060**
	(0.0035)	(0.0022)	(0.0029)	(0.0017)	(0.0030)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	0.45	0.37	0.44	0.43	0.28
N	4702253	4702253	4702253	2464854	4702253

Panel C

	Output	SweHours	Hours	Off Hours	Efficiency
GOOG - S&P return (t and t-1)	0.25	0.11	0.15	0.051	0.20
	(0.16)	(0.080)	(0.091)	(0.032)	(0.14)
GOOG - S&P return (t and t-1)×Ln(Stock + Options granted)	-0.011	-0.0071	-0.0086	-0.00099	-0.0096
	(0.0078)	(0.0048)	(0.0052)	(0.0011)	(0.0069)
GOOG - S&P return (t and t-1)×Start date	-0.000015	-0.0000070	-0.0000091*	-0.0000032*	-0.000012
	(0.0000095)	(0.0000047)	(0.0000053)	(0.0000019)	(0.0000083)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.45	0.37	0.44	0.43	0.28
Observations	4702253	4702253	4702253	2464854	4702253

Notes: All outcome variables, stock return variables, start date and log of shares variables been normalized. "Off hours" refers to all activity on weekends and activity outside normal working hours (9 am to 6 pm). "SweHours" is equal to hours of software engineering tasks. Times are local time in the city in which the employee is located. Standard errors are heteroskedasticity robust and allow for clustering within day.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12: Employee work activity, hours, and recent stock returns – online sales staff, Jan 2006 to June 2008

Possibly say something here about normalization

Panel A

	Email (All)	ICS Output	Output	Hours	Productive Off Hours	Efficiency
GOOG Return (t+1)	-0.010	-0.0049	-0.0068	-0.0092	-0.00055	-0.0054
	(0.014)	(0.053)	(0.0045)	(0.0060)	(0.0023)	(0.0041)
GOOG Return (t)	-0.024	-0.089*	0.0014	-0.0089	-0.0046*	0.0068
	(0.016)	(0.053)	(0.0053)	(0.0068)	(0.0025)	(0.0058)
GOOG Return (t-1)	0.0047	-0.028	0.0014	0.00039	-0.00079	0.0042
	(0.015)	(0.051)	(0.0051)	(0.0067)	(0.0024)	(0.0044)
GOOG Return (t-2)	-0.0022	0.013	-0.0052	-0.0062	-0.00045	0.0015
	(0.013)	(0.046)	(0.0046)	(0.0056)	(0.0021)	(0.0033)
S&P Return (t)	0.011	-0.0025	0.0013	0.0043	0.0017	-0.00044
	(0.011)	(0.038)	(0.0033)	(0.0047)	(0.0017)	(0.0027)
S&P Return (t-1)	-0.0050	0.053	-0.00060	-0.000017	0.00045	-0.0036
	(0.012)	(0.041)	(0.0034)	(0.0049)	(0.0019)	(0.0024)
Fixed Effects (Day-of-Week, User ×Month)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.52	0.57	0.57	0.35	0.36
Observations	1476338	1476338	1476338	1476338	1476338	902576

Panel B

	Email (All)	ICS Output	Output	Hours	Productive Off Hours	Efficiency
GOOG-S&P return (t and t-1)	-0.011*	-0.053**	-0.00100	-0.0069*	-0.0027**	0.0048
	(0.0058)	(0.025)	(0.0035)	(0.0036)	(0.0011)	(0.0045)
Fixed Effects (Day-of-Week, User ×Month)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.52	0.57	0.57	0.35	0.36
Observations	1477797	1477797	1477797	1477797	1477797	903246

Panel C

	Email (All)	ICS Output	Output	Hours	Productive Off Hours	Efficiency
GOOG-S&P return (t and t-1)	-0.0066	-0.074**	-0.0012	-0.0057	-0.0025**	0.0037
	(0.0055)	(0.037)	(0.0045)	(0.0044)	(0.0011)	(0.0039)
GOOG-S&P return (t and t-1)×Ln(Stock + Options granted)	-0.0083*	0.18	0.0039	-0.00080	-0.00033	-0.0015
	(0.0049)	(0.11)	(0.0061)	(0.0043)	(0.0012)	(0.0055)
GOOG-S&P return (t and t-1)×Start date	-0.0099	0.046	0.00041	-0.0027	-0.00050	0.0021
	(0.0066)	(0.040)	(0.0039)	(0.0036)	(0.0012)	(0.0046)
Fixed Effects (Day-of-Week, User ×Month)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.52	0.57	0.57	0.35	0.36
Observations	1477797	1477797	1477797	1477797	1477797	903246

Notes: An observation is a day (Monday-Sunday). All outcome variables, stock return variables, start date and log of shares variables been normalized. "Off hours" refers to all activity on weekends and activity outside normal working hours (9 am to 6 pm). Times are local time in the city in which the employee is located. Standard errors are heteroskedasticity robust and allow for clustering within day.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 13: Recent stock returns and interview outcomes

Panel A: Interviews

	Score	Score	Score	Score	Score	Score
GOOG - S&P return (t and t-1)	-0.0023**	-0.0018*	-0.0039*	-0.0023**	-0.0016	-0.0029
	(0.00096)	(0.0011)	(0.0023)	(0.00097)	(0.0011)	(0.0023)
GOOG - S&P return (t and t-1)×Ln(Stock + Options granted)				0.0018	0.0044***	-0.0082***
				(0.0013)	(0.0015)	(0.0032)
Fixed Effects (Day-of-Week, Year, Interviewer)	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	Non-Eng	Eng	All	Non-Eng	Eng
R^2	0.17	0.18	0.14	0.17	0.18	0.13
Observations	440940	342320	98620	425856	328456	97400

Panel B: Job Applicants

	Mean Score	Passed	Mean Score	Passed
GOOG Return (t+1)	0.011	0.0013		
	(0.0086)	(0.0034)		
GOOG Return (t)	-0.012	-0.0068**	-0.0098	-0.0069**
	(0.0085)	(0.0033)	(0.0087)	(0.0033)
GOOG Return (t-1)	0.013	0.0077**		
	(0.0098)	(0.0036)		
GOOG Return (t-2)	0.00054	-0.0018		
	(0.0098)	(0.0037)		
Fixed Effects (Day-of-Week, Year)	Yes	Yes	Yes	Yes
Other Fixed Effects	Requisition	Requisition	Requisition	Requisition
Sample	Eng	Eng	Eng	Eng
R^2	0.0050	0.11	0.0048	0.11
Observations	13056	13056	13069	13069

Notes: In the first set of regressions, each observation is an interview. In the second set of regressions, each observation is an interviewee (stock return data is based on the date of the interview panel). All stock return variables, start date and log of shares variables been normalized. Standard errors are heteroskedasticity robust and allow for clustering within day.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 14: Quality of idea and stock returns surrounding posting

Panel A

	Avg Rating	Num Ratings	Implemented
GOOG Return (t+1)	-0.0010	0.32	-0.0077**
	(0.016)	(0.24)	(0.0031)
GOOG Return (t)	0.0059	0.37	0.0022
	(0.015)	(0.22)	(0.0032)
GOOG Return (t-1)	0.040**	0.57*	0.0066*
	(0.017)	(0.31)	(0.0035)
GOOG Return (t-2)	-0.00011	-0.25	-0.0022
	(0.012)	(0.32)	(0.0031)
Fixed Effects (Day-of-Week, Year)	Yes	Yes	Yes
R^2	0.019	0.063	0.014
Observations	11387	11387	11914

Panel B

	Avg Rating	Num Ratings	Implemented
GOOG - S&P return (t and t-1)	0.022**	0.37**	0.0018
	(0.0096)	(0.16)	(0.0020)
Fixed Effects (Day-of-Week, Year)	Yes	Yes	Yes
R^2	0.019	0.063	0.014
Observations	11390	11390	11917

Panel C

	Avg Rating	Num Ratings	Implemented
GOOG - S&P return (t and t-1)	0.018**	0.35**	0.0030
	(0.0080)	(0.16)	(0.0022)
GOOG - S&P return (t and t-1)$\times$Ln(Stock + Options granted)	0.011	-0.11	0.0058**
	(0.011)	(0.23)	(0.0029)
GOOG - S&P return (t and t-1)$\times$Start Date	-0.0038	-0.033	0.0024
	(0.011)	(0.21)	(0.0030)
Fixed Effects (Day-of-Week, Year)	Yes	Yes	Yes
R^2	0.026	0.065	0.014
Observations	10605	10605	11068

Notes: The unit of observation is an idea submission. Standard errors are heteroskedasticity robust and allow for clustering within day. All stock return variables, start date and log of shares variables been normalized.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 15: Ratings of ideas and stock returns surrounding rating

	Rating	Rating	Rating	Rating	Rating
GOOG Return (t+1)	-0.0038				
	(0.0072)				
GOOG Return (t)	-0.017**	-0.016**			
	(0.0075)	(0.0073)			
GOOG Return (t-1)	-0.011	-0.010			
	(0.0080)	(0.0077)			
GOOG Return (t-2)	-0.0035				
	(0.0070)				
GOOG - S&P return (t and t-1)			-0.036**	-0.038**	-0.035**
			(0.016)	(0.016)	(0.016)
Ln(Stock + Options granted)				-0.30***	-0.32***
				(0.020)	(0.031)
GOOG - S&P return (t and t-1)×Ln(Stock + Options granted)				-0.013	-0.023
				(0.012)	(0.018)
GOOG - S&P return (t and t-1)×Start Date					-0.0100
					(0.015)
Fixed Effects (Day-of-Week, Idea)	Yes	Yes	Yes	Yes	Yes
R^2	0.56	0.56	0.56	0.57	0.57
Observations	28213	28218	28105	28105	28075

Notes: The unit of observation is the rating of an idea. Standard errors are heteroskedasticity robust and allow for clustering within day. All outcomes, stock return variables, start date and log of shares variables been normalized.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 16: Employee work activity, stock grants and recent S&P returns – Jan 2006 to June 2008

Panel A: Software Engineers

	Output	SweHours	Hours	Off Hours	Efficiency
S&P Return (t and t-1)	0.0024	0.00012	0.00032	0.0031***	0.0014
	(0.0030)	(0.0022)	(0.0030)	(0.0012)	(0.0027)
S&P return (t and t-1)×Ln(Stock + Options granted)	0.0056	0.0036	0.0045	0.00039	0.0049
	(0.0039)	(0.0027)	(0.0031)	(0.00054)	(0.0036)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.45	0.37	0.44	0.43	0.28
Observations	4702253	4702253	4702253	2464854	4702253

Panel B: Online Sales Staff

	Email (All)	ICS Output	Output	Hours	Productive Off Hours	Efficiency
S&P Return (t and t-1)	-0.00060	0.0023	0.00015	0.000068	0.00018	-0.00057
	(0.0068)	(0.025)	(0.0023)	(0.0031)	(0.0011)	(0.0017)
S&P return (t and t-1)×Ln(Stock + Options granted)	0.0024	-0.11	-0.0077*	-0.0037	-0.00092	-0.0034
	(0.0044)	(0.091)	(0.0040)	(0.0028)	(0.0010)	(0.0035)
Fixed Effects (Day-of-Week, User ×Month)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.52	0.57	0.57	0.35	0.36
Observations	1477797	1477797	1477797	1477797	1477797	903246

Panel C: Ideas

	Avg Rating	Num Ratings	Implemented
S&P Return (t and t-1)	0.0098	0.42**	0.0018
	(0.0095)	(0.19)	(0.0030)
S&P return (t and t-1)×Ln(Stock + Options granted)	0.0075	0.0054	0.0049*
	(0.0094)	(0.19)	(0.0027)
Fixed Effects (Day-of-Week, Year, Emp.)	Yes	Yes	Yes
R^2	0.45	0.51	0.36
Observations	10605	10605	11068

Notes: An observation is a day (Monday-Sunday). “Off hours” refers to all activity on weekends and activity outside normal working hours (9 am to 6 pm). “SweHours” is equal to hours of software engineering tasks. Times are local time in the city in which the employee is located. All stock return variables, start date and log of shares variables been normalized. Standard errors are heteroskedasticity robust and allow for clustering within day.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 17: Big Five Measures and and Stock Grants

	Stock+Options	Stock+Options	Stock+Options	Stock+Options	Stock+Options
Big Five: Emotional Stability	0.071***	0.072***	0.016	0.016	0.011
	(0.025)	(0.026)	(0.021)	(0.016)	(0.016)
Other Big 5 Measures	No	Yes	Yes	Yes	Yes
Start Date	No	No	Yes	Yes	Yes
Job Type FEs	No	No	Yes	Yes	Yes
Job Grade FEs	No	No	No	Yes	Yes
Department FEs	No	No	No	No	Yes
R^2	0.033	0.044	0.49	0.71	0.71
Observations	3285	3285	3285	3285	3280

Notes: This table presents cross-sectional regressions predicting the normalized size of a stock grants. The measure of “Emotional Stability” comes from the Big Five Inventory and has been normalized. Standard errors are heteroskedasticity robust.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Appendices

A Table 7 from Cowgill and Zitzewitz (2015)

Recent Google returns and optimistic trading in internal prediction market

Dependent variable: Profitability of each bet

	(1)	(2)	(3)	(4)	(5)	(6)
Optimism*Google log stock return (t+1)	-0.869	-0.228	-0.303	-1.006	-0.646	-0.830
	(0.720)	(0.659)	(0.671)	(0.675)	(0.603)	(0.565)
Optimism*Google log stock return (t)	-1.158	-0.185	-0.243	-0.015	0.196	0.255
	(0.796)	(0.455)	(0.434)	(0.610)	(0.613)	(0.488)
Optimism*Google log stock return (t-1)	-2.022***	-1.318**	-1.296**	-2.618***	-2.112***	-1.414**
	(0.744)	(0.569)	(0.561)	(0.767)	(0.658)	(0.628)
Optimism*Google log stock return (t-2)	-0.695	0.037	0.063	-0.103	-0.043	-0.042
	(0.436)	(0.302)	(0.287)	(0.316)	(0.354)	(0.316)
Topics included	All	All	All	Completion	Completion	Completion
Google stock returns (t+1, t, t-1, t-2)	Y	Y	Y	Y	Y	Y
Interactions of Google stock returns (t+1 to t-2) with calendar quarter fixed effects		Y	Y	Y	Y	Y
Interactions of Google stock returns (t+1, t, t-1, t-2) with extremeness and price-1/N			Y	Y	Y	Y
S&P and Nasdaq returns (t+1, t, t-1, t-2) and interactions with optimism					Y	Y
Day of week fixed effects and interactions with optimism						Y
Observations	37,910	37,910	37,910	11,590	11,590	11,590
R-squared	0.095	0.155	0.159	0.489	0.505	0.522

Notes: Each observation in these regressions is a wager placed in Google's internal company prediction market. This market allowed employees to place wagers confidentially on the probability of success of various internal goals. Bets were binary (expired at either zero or one) and were traded in a continuous double auction with separate securities for each outcome (Berg et al., 2008). Additional details can be found in Cowgill and Zitzewitz (2015).

The dependent variable is these regressions is the percentage point return to expiry (i.e., expiry value - price). Each trade can also be coded as "optimistic" or not, depending on whether the bet was on the success (vs failure) of Google's internal company goals. Our previous paper found that optimism in this market was overpriced, so that optimistic bets were thus unprofitable (on average).

In the table above, we show the interaction between optimism (expressed via the prediction market) and recent fluctuations in GOOG stock. We find that a 2% increase in Google's stock price (approximately a one standard deviation change) is associated with prediction market prices for securities tracking optimism outcomes being priced 3-4 percentage points higher, compared to their pricing on an average day.

Columns 1-3 include all trades from all markets for which optimism can be signed), while columns 4-6 include only markets on the timing of project completion. Standard errors are heteroskedasticity-robust and allow for clustering within markets and calendar months.

* significant at 10%; ** significant at 5%; *** significant at 1%.