Mood Swings at Work: Stock Price Movements, Effort and Decision Making[1]

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We show that daily stock price movements affect the mood, effort level, and decision making of employees at Google. Positive current-day stock returns are accompanied by greater reported economic confidence and job satisfaction, shorter working hours, 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 some types of behavior are larger for employees with larger prior stock and option grants. We show that the short-term effects the (plausibly exogenous) shock to moods is exactly the opposite of what one would have expected from cross-sectional correlations. Whereas happier employees perform better and are more lenient evaluators, shocks that increase happiness are accompanied by lower work effort and tougher evaluation.

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If individuals' emotions affect their behavior as consumers, should they also affect their behavior at work? If employees at a firm experience a common emotional shock, should we expect the firm to behave emotionally? Or should we expect these mood swings to be dampened by either professionalism or a detachment that comes from acting as an agent for one's employer?

We show that daily Google stock price movements affect the mood of its employees. Positive returns increase their job satisfaction, their confidence in the company's direction, and their assessment of their own performance. Stock-price induced mood swings are quite transitory, lasting at most one business day. The swings in mood are most pronounced among the quintile of employees with the highest option and restricted stock allocations, while the bottom quintile experiences effects in the opposite direction.

Stock price movements are also accompanied by equally short-term changes in employee effort and decision making. On days with positive stock price movements, employees leave work slightly earlier and engage in less work-related activity across a variety of measures. Employees also become tougher evaluators of innovative ideas and of interview candidates. We also know from prior work that they trade more optimistically in Google's internal prediction market (Cowgill, Wolfers, and Zitzewitz, 2008). While variations in work effort are offset by days with negative stock price movements, effects on evaluations of interview candidates and ideas are more likely to be irreversible in practice. Confirming this, we find that candidates who interview on days with stock appreciation are less likely to be ultimately hired. Ideas that are reviewed on days with stock appreciation likewise receive lower scores and are less likely to be implemented.

While optimal work effort and standards for candidates and ideas can clearly change in response to news that affects the stock price, the transitory nature of the adjustments we document is difficult to rationalize, as is the sign of the effects on hiring and idea adoption. We argue these results are more plausibly interpreted as evidence of stock returns affecting emotions and of emotions affecting behavior. Positive stock returns appear to increase satisfaction with one's own contribution; this is accompanied and perhaps explains a decrease in work effort. Positive returns also increase optimism about Google's prospects and satisfaction with the current direction of the company; this is accompanied by and perhaps explains a higher standard for interviewees and innovative ideas.

The behavioral economics literature has grown vast, but it is almost exclusively focused on the behavior of consumers and individual investors, not managers and employees (see Dellavigna, 2008, for a recent review). The few 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, 2005; Jin and Scherbina, 2006). Beyond this, the productivity effects of friendships (Bandiera, Barankay, and Rasul, 2007) and peer effects (Mas and Moretti, 2006) in firms may have a behavioral component. Apart from these exceptions though, firms in behavioral economics are generally profit-maximizing entities that exploit the biases of their customers, not the subjects of biases themselves.

The literature on mood effects among consumers and investors includes papers that test for mood effects of weather (Schwarz and Core, 1983; Rind, 1996; Hirshleifer and Shumway, 2003) or sports outcomes (Edmans, Garcia, and Norli, 2007). 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.

An offsetting advantage of examining stock-induced rather than weather-induced or sports-induced mood shifts 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 (Benabou and Tirole, 2002 and 2003; Compte and Postlewaite, 2004) or risk-taking (Bernardo and Welch, 2001; Goel and Thakor, 2007). 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 and 1995), 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 subjective 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.

The remainder of the paper is organized around the datasets we draw on.[2] The first section presents our daily-frequency analysis of stock returns and mood, as expressed in surveys of attitudes among Google employees and the general public. The second section presents our analysis of stock price effects on work hours and activity. The third section analyzes effects on interview scores and hiring decisions. The fourth section analyzes effects on idea evaluations and eventual implementation.

A fifth section examines the cross-section correlation between happiness and our outcome measures. As mentioned above, in the cross-section, we find results that are of opposite sign to our results about how employees respond to shocks to their mood.

A final section examines optimal behavior as an alternative explanation for our results, providing a short theoretical analysis of how stock price movements affect optimal economic behavior and discussing the assumptions one would need to maintain to explain our findings away as an optimal response to stock price changes. We argue that any plausible set of assumptions leaves substantial room for interpreting our results as mood effects. A conclusion follows.

I. Stock price changes and moods

Before turning to data from Google, we begin by analyzing the correlation between changes in the U.S. stock market and the economic confidence of the U.S. population. We use data from the political polling firm Rasmussen Reports. Every 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 similar to those in the monthly Michigan Consumer Sentiment and Conference Board Consumer Confidence surveys.[3] Rasmussen publishes 3- and 7-day trailing averages of the responses, which we use to infer nightly averages.[4]

Like the Michigan survey, Rasmussen publishes indices of current economic conditions, future expectations, and an overall index that averages the two. Rasmussen also 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.

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[2] We are grateful to Google for making this data available for research. All of the data we obtained from human resources (e.g., option and stock grants, subjective performance evaluations, job satisfaction survey responses) was anonymized and identified only by an ID# that was used to link datasets.

[3] 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.

[4] To avoid any look-ahead bias, we calculate the nightly average response as 7*TA7(t) – 3*[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*[TA3(t+3) + TA3(t-1)] or 7*TA7(t+6) – 3*[TA3(t+6) + TA3(t+3)]; an averaging of these three alternatives yields a estimate with less noise due to rounding error, but otherwise nearly identical results.

Table 1 presents regressions of changes 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 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 indices. In contrast, there is essentially no evidence of a relationship between economic confidence and stock returns for non-investors. 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 we are aware of at the daily frequency.

The same daily-frequency relationship in present among Google employees. In September 2006, Google conducted a 98-question survey of satisfaction among full-time employees. The survey was administered by email in daily waves over the course of 3 weeks.[5] Questions asked for ratings on a five or seven point scale, with high ratings indicating satisfaction. For each respondent, we calculate a satisfaction score as the simple average of the scaled responses to these questions.[6] Table 2 presents regressions of normalized satisfaction on normalized Google stock returns on the days surrounding the survey completion date. Google stock returns are interacted with normalized log of the shares of restricted stock and option granted to the employee before the survey date.[7] Regressions control for day of the week effects. Standard errors are heteroskedasticity robust and allow for clustering of errors within survey date.

Coefficients for future and twice-lagged Google stock returns are small in magnitude never statistically significant for both main effects and interactions. Prior-day Google stock returns are statistically significant, consistent with either persistent effects of returns or with the fact that Google employees outside the U.S. may have completed their surveys before the U.S. market opened. The specification in the fourth column, which combines Google stock returns on the current and prior day, parsimoniously describes the relationships in the data. In this specification, we find evidence that an employee with average prior stock and option grants is 0.014 standard deviations more satisfied when stock returns are one standard deviations higher, that this effect 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 Google stock return, employees with greater option grants

[5] While we use the timestamps on the survey responses to study variation in mood in response to stock market movements, we should note that Google's purpose in administrating this survey was to get a snapshot of sentiment in the company.
[6] Specifically, we rescale each rating to range from zero to one using the formula (rating – 1)/(maxrating – 1) and then take the simple average of rescaled ratings.
[7] The few survey respondents that had not received stock or option grants were coded as having received the minimum grant in the sample.

report less satisfaction on their surveys. Given that surveys were only returned on 14 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.

Table 3 examines the robustness of these relationships to controlling for additional employee characteristics. Adding controls for employee region, start date, and job grade (the interaction of a job's track and level) does not affect the conclusion that employees with larger stock and option grants are more sensitive to stock price movements.[8] Location in Europe/Africa is correlated with lower satisfaction but more sensitivity to stock price movements. Employees' job level and track is not statistically significantly 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, since employee grants have become smaller as Google has grown from a startup to a larger company.

Table 4 provides separate univariate regressions of aspects of satisfaction on Google stock returns for employees in the top, bottom, and middle three quintiles in terms of prior stock and option grants. Among top quintile employees (who also tend to be more senior), stock returns are positively correlated with nearly every aspect of job satisfaction, except for satisfaction with the culture and colleagues. Employees in the middle three quintiles have positive but generally smaller relationships. Unreported regressions that separate the middle three quintiles revealed coefficients that were fairly similar. Lowest-quintile employees experience opposite signed 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 the least.

II. Stock price changes and work effort

Our data on work hours and activity comes from several sources.[9] Table 5 summarizes the activity data we have for two different groups of employees: software engineers and online advertising sales support staff.Taken together these two groups account for over half of employee time at Google.[10]

[8] Google classifies 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 or VP) job tracks that we omit from the analysis. For Google readers, the letters in parentheses are the internal codes used to refer to each track.

[9] Google generally does not use raw productivity data to evaluate individual employees, as it expects most employees to make significant contributions in ways that cannot be easily quantified. The data we're using mostly comes from Google usage logs for its productivity tools. Google saves these logs in order to maintain and optimize its internal productivity systems. Among other things, the data is used for planning capacity for the tools, assessing the impact of feature changes in the tools and identifying groups affected by changes in the tools.

For software engineers, we have data on Perforce calls, which are calls made to the software that manages Google's codebase, made for example when an engineer checks out a piece of code for editing. We have data on code reviews, which are peer reviews required before a finished piece of code is incorporated into the codebase. We have 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 Google's internal wiki, which documents its code.

The online sales staff provides assistance to Google's advertisers. This assistance includes reviewing and approving ads, working with advertisers to optimize ads to increase response rates, and responding to customer emails. We have data on page views in the Internal Customer Systems (ICS), which is used to approve and optimize ads. We also have data on emails sent to customers who requested help. Table 5 provides counts of the number of times each activity is undertaken in the average workday. 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 are full-time employees who are likely working more than 5.2 hours per day, our activity measures capture only a subset of what employees do at work. Cowgill and Zitzewitz (2008a) discuss this data in more detail.

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 can 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 for Google could require 20 minutes to reach an approval decision. Had we used raw counts, our analysis would count this approval as equal to an easy approval requiring little more than a glance.

We take two steps to limit the influence of these 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 activity itself. Second, for all of our measures, we windsorize daily counts of activity at the 99th percentile of all observations with non-zero activity. In practice, this sets outliers value 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; windsorizing at the 95th percentile). That said, our activity measures are clearly imperfect measures of output, due to both some forms of output being missed by our measures and to heterogeneity in the amount of work represented by a unit of activity.

In Table 6, we present regressions of measures of work hours and activity on surrounding day Google 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. Therefore, the regressions are testing whether, within a given month, a given employee works more or less on the (e.g.) Wednesdays with positive stock returns. Day of the week effect coefficients are obviously large and negative for Saturdays

[10] We apply a narrower definition of software engineer and online sales staff than Google does 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.

and Sundays; employees also have about 0.5 to 1.0 fewer hours with work activity on Friday.[11] The employee*month fixed effects subsume month fixed effects, which are important to control for since average daily returns were higher at the beginning of our sample than the end, and our outcome measures may have trended over time. Standard errors in these regressions allow for clustering of errors by day.

Market efficiency suggests that stock returns on day t should be uncorrelated with information available to the market on day t-1. 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). Therefore any systematic correlation between activity and stock returns should reflect either: 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 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 seems rare enough to not be contributing meaningfully to our results. The first and second possibilities will be impossible for us to distinguish empirically.

The coefficients in Table 6 imply that software engineers work shorter hours on days that Google stock appreciates. A one standard-deviation rise (2.3 percent) is accompanied by 0.038 fewer hours with work activity. It is also accompanied by 0.2 to 0.8 percent of a standard deviation less activity across the measures discussed above. The analogous regressions for online sales staff in Table 7 imply effects of similar sizes (0.044 hours and 0.6 percent of a standard deviation, respectively). For the software engineers, 50-60 percent of the effect on hours occurs 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 occurs outside regular business hours. In unreported regressions, we find that employees with larger prior stock and option grants exhibit greater sensitivity to stock market movements, especially among the software engineers, but that the differences are not statistically significant. 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.

III. Stock price changes and interviews

Google expanded considerably during our sample period and it considers many candidates for every candidate it hires. For candidates under serious consideration, Google requires multiple rounds of interviews. As a result, it has conducted an extraordinary number of interviews in the last 4 years. We restrict our analysis to in-person interviews at Google's offices and due to data limitations exclude

[11] One reason for the finding on Friday is that Google regularly holds company-wide meetings on Friday afternoons.

interviews from international offices. This leaves a sample of over 200,000 interviews of over 50,000 unique candidates. Along with written feedback that is unfortunately not part of our data, each interviewer evaluates 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, and consider an interviewing round successful if it is followed by either another interviewing round or a job offer. Interviewing rounds are successful about 35 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, result in success only about 80 percent of the time.[12] In contrast, interview rounds with mean scores below 2.5 are rarely successful. Cowgill and Zitzewitz (2008b) discuss this data in more detail.

Table 8 analyzes the effect of stock price movements on interview scores and interviewing round 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. Delay is positively correlated with the ultimate interview score, probably 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.[13] The results suggest an interview scores given on a one-standard-deviation positive-return day is 0.005 standard deviations lower, a fairly modestly sized effect. The effect is about three times as large in engineering interviews, which are more analytical. There is no evidence that stock-market effects are stronger or weaker for interviewers with more stock options.

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

[12] One should not expect a perfect correlation given that interview scores are one of many factors that Google considers when evaluating the qualifications of a candidate. For example, the decision to proceed into hiring or a second round of interviews is also based on fit with the job, candidate interest, demonstration of job related knowledge, skills and abilities, and other relevant background information about the candidate. Even with strong interview scores, some candidates can be rejected in the process if other pieces of information collected conflict with what was found in the interviews. Also, candidates sometimes withdraw from the process or decline Google's offers.

[13] 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.

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 a selection bias.

We might expect candidates who interviewed on positive-return days would recieve better performance evaluations after arriving at Google as an employee. We tested this, but found no significant difference. One reason for this result might be the weak power of our test. The selectivity of Google's hiring process means that our sample size was lower than for the regressions in Table 8. In addition, interview scores were imperfect predictor of employee performance for the sample of employees as a whole[14].

IV. Stock returns and innovative ideas

One of the means through which new ideas are communicated and refined at Google is on ideas boards. Ideas are posted to either a general board or to specific boards maintained by specific teams or groups. Readers of the ideas provide numeric ratings (0 to 5) and comments, which often refine and improve the ideas. One example of an idea posted to the ideas board that we can disclose is the internal prediction market we discussed in Cowgill, Wolfers, and Zitzewitz (2008). In this case, as in others, the ideas board functioned as both a place to refine the idea and to recruit volunteers to implement it during their "20 percent time" (time in which Google allows engineers to work on innovative side projects).

Our data include 11,227 ideas that were posted after Google's IPO in August 2004 and that received at least one rating. Of these, about 70 percent were posted to the general ideas board. Ideas' current status is categorized as "done," "project," "future," "workshop," "needs information," "idle," "redundant," or "withdrawn." We treat ideas listed as "done" or "project" as being implemented (or on their way to being implemented). This accounts for 10 percent of ideas. This is probably an undercount given that ideas status is probably not always updated to reflect implementation. That said, the incidence of undercounting should be uncorrelated with our variables of interest.

In Table 9, we examine the relationship between the stock returns surrounding the posting of an idea and measures of idea quality. Ideas posted on or following positive-return days are higher quality: they receive better ratings, more ratings, and are more likely to be implemented. Idea postings are not scheduled in advance the way interviews are, so possible mechanisms for this correlation could include employees having better ideas on positive return days, requiring a higher minimum quality for posting an idea on positive return days, saving good ideas for positive return days, or saving bad ideas for negative return 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.

[14] In some cases, circumstances arise after hiring that causes an employee to be a better or worse performer than anticipated in the interviews. For example: An employee may have skills that were not disclosed in the hiring process that prove to be highly useful in his role at the company. Situations such as these are part of why interview scores do not predict employee performance perfectly. We expect that other companies would experience similar results.

In Table 10, we examine the relationship between the ratings given a particular idea and the stock returns around the date the idea was rated.[15] We find that a given idea receives poorer evaluations on positive return days. Readers with more stock and option grants are more critical of a given idea in general, but 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 9 we find that implementation is negatively correlated with returns following the day is consistent with the former mechanism and suggests that mood effects may be affecting which innovative ideas get implemented.

V. Cross-sectional correlations with job satisfaction

In this section, we examine what the more traditional approach of studying whether job satisfaction is correlated with job performance and decision making would have concluded. In addition to the measures discussed above that can be precisely dated, in this section we can example performance evaluations, which are given once per quarter. Performance evaluations at Google are accompanied by a single numeric score (called a "Perf" score) that ranges from 1.0 to 5.0 but in practice is usually between 2.8 and 4.0. We begin by examining the relationship between these scores and job satisfaction. In Table 11 we report regressions of Perf scores on job satisfaction using Perf scores from 2006Q2, Q3, and Q4, i.e. from one quarter before the job satisfaction survey to one quarter after. Regardless of whether we include controls, we find job satisfaction is correlated with past performance evaluations but not future evaluations.

Regressions examining correlations with activity measures yield mixed results. For online sales staff, satisfied employees had more hours with activity in the past and in the future. For software engineers, however, there is no significant difference. The tables report results for counts of hours with activity, but results using counts of activity as the dependent variable yield similar results. This contrast in results is inconsistent with the correlations with Perf scores, which are positive and roughly equally sized for the two groups.

The last two regressions test whether satisfied employees give higher scores to a given idea or interviewee, and find positive correlations that are statistically significant in the case of the interviews. Of course, since both the satisfaction survey, the idea ratings, and the interview scoring involves rating things on a 1 to X point scale, these correlations could reflect within-person correlation in how they use

[15] 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 9, but are included in the average and counts of ratings in Table 8. Likewise, ideas that received only ratings and no comments are also excluded from Table 9, which accounts for the smaller sample size.

these scales. That said, for interviews in particular there is effort made to train interviewers to score candidates in a consistent manner, such as providing feedback to interviewers who are consistently lenient or harsh outliers, suggesting that the absolute level of scores given by an interviewer affects hiring decisions. Thus higher scores reflects leniency in a meaningful way.

Taken together, the evidence in Table 11 implies a cross-sectional correlation between job satisfaction and both work effort and decision making that is generally the opposite of what we find within-employee. Happier employees work harder and are more lenient, but shocks that make employees happy also make them work less and evaluate more harshly. As mentioned above, two reconciliations of the 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, while the responses to shocks reflect a causal effect.

VI. 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 and options appreciate 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. 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 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. Furthermore, 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.

VII. Conclusion

In this paper we provide evidence of emotions affecting firm behavior. Positive stock returns improve Google employees' mood, which leads them to work slightly less and be choosier in evaluating ideas and candidates. While the mood effects are transitory, the consequences on hiring decision and innovation 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.Since comparable research does not exist for other firms, we cannot say whether the level of sensitivity at Google is especially high or low. Google is unrepresentative of the broader economy in many ways. Its employees have less work experience than in many other companies, 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 have large holdings of company stock or options, and these employees have moods that are more influenced by stock price. Google's stock price is more volatile than many. It also has a flatter organizational structure and provides its employees with more autonomy than many firms, potentially allowing a greater scope for mood effects than at other firms.

On the other hand, Google's leadership has sought to insulate the firm from the impact of short term changes in stock price. It has a dual class share structure that gives early employees a larger share in governance. It offers no guidance to Wall Street analysts. Management actively discourages employees from monitoring changes in short term stock prices and encourages focusing on creating lasting value for shareholders. These factors would suggest that employees at Google might be less sensitive to its stock price to comparable firms. Although Google is unrepresentative of the economy as a whole, it is likely more representative of the entrepreneurial firms that are an important source of innovation. 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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Table 1. 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

Daily economic confidence, as reported each evening to the Rasmussen survey, 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.

Table 2. Recent Google stock returns and employee satisfaction
Dependent variable: Normalized satisfaction score

Main effects					
GOOG return (t+1)	-0.001	0.001			
	(0.026)	(0.019)			
GOOG return (t)	0.016**	0.013	0.012	0.009	
	(0.008)	(0.013)	(0.008)	(0.009)	
GOOG return (t-1)	-0.006	0.002	0.003	0.006	
	(0.017)	(0.004)	(0.004)	(0.005)	
GOOG return (t-2)	0.007	0.003	0.002		
	(0.024)	(0.008)	(0.008)		
GOOG return (t and t-1)					0.014**
					(0.007)
Interactions with Ln(Stock + Options granted)					
GOOG return (t+1)		-0.034			
		(0.024)			
GOOG return (t)		0.048**	0.063***	0.065***	
		(0.021)	(0.013)	(0.012)	
GOOG return (t-1)		0.026*	0.027**	0.024**	
		(0.014)	(0.013)	(0.011)	
GOOG return (t-2)		-0.004	-0.007		
		(0.018)	(0.018)		
GOOG return (t and t-1)					0.060***
					(0.012)
Ln(Stock + Options granted)		-0.181***	-0.180***	-0.181***	-0.183***
		(0.013)	(0.013)	(0.011)	(0.016)
Day of week fixed effects	X	X	X	X	X
Observations	4,927	4,927	4,927	4,927	4,927
Unique business days	14	14	14	14	14
Adjusted R-sq.	0.0357	0.0357	0.0354	0.0354	0.0349

The normalized average response to a 98 question survey about employees' job satisfaction is regressed on normalized Google 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.

Table 3. Recent Google stock returns and employee satisfaction
Dependent variable: Normalized satisfaction score

GOOG return (t and t-1) [normalized]	0.014**	-0.002	0.028
	(0.007)	(0.005)	(0.045)
GOOG return*Ln(Stock + Options granted)	0.060***	0.060***	0.126***
	(0.012)	(0.021)	(0.030)
GOOG return*Start date			0.067**
			(0.034)
GOOG return*Europe/Africa dummy			0.084**
			(0.038)
GOOG return*Asia/Pacific dummy			0.018
			(0.053)
GOOG return*Employee Level			-0.007
			(0.009)
GOOG return*Engineering track			-0.024
			(0.025)
GOOG return*Operations track			-0.058
			(0.050)
Ln(Stock + Options) [normalized]	-0.183***	-0.103**	-0.109**
	(0.016)	(0.055)	(0.055)
Start date [normalized]		0.203***	0.196***
		(0.049)	(0.044)
Europe/Africa dummy		-0.263***	-0.274***
		(0.051)	(0.040)
Asia/Pacific dummy		0.008	0.004
		(0.056)	(0.054)
Employee level*track fixed effects		X	X
Day of week fixed effects	X	X	X
Observations	4,927	4,822	4,822
Unique business days	14	14	14
Adjusted R-sq.	0.0349	0.0944	0.096

The normalized average response to the job satisfaction from Table 2 is regressed on normalized Google stock (GOOG) returns on and prior to the survey date and interactions with employee characteristics. Start date is normalized. Standard errors are heteroskedasticity robust and adjust for clustering within survey response date.

Table 4. Recent GOOG returns and satisfaction, by aspect of job

	Prior stock and option grants		
Job aspect	Lowest quintile	Middle quintiles	Highest quintile
Observations	966	2999	962
Compensation and Benefits	-0.100***	0.021**	0.045***
	(0.025)	(0.011)	(0.014)
Culture	0.001	-0.018***	-0.005
	(0.033)	(0.004)	(0.015)
Direction	-0.062***	0.006	0.052***
	(0.022)	(0.004)	(0.008)
Diversity	-0.024	0.027***	0.052***
	(0.033)	(0.004)	(0.018)
Integrity	-0.072***	0.009***	0.057***
	(0.022)	(0.003)	(0.010)
Opportunity	-0.042*	0.016***	0.073***
	(0.025)	(0.005)	(0.011)
Other People	-0.043	0.015**	-0.001
	(0.047)	(0.007)	(0.006)
Performance Management	-0.063**	0.017*	0.038***
	(0.025)	(0.008)	(0.012)
Personal Satisfaction & Commitment	-0.068**	0.013	0.038***
	(0.027)	(0.009)	(0.013)
Support	-0.051**	0.017***	0.051***
	(0.021)	(0.004)	(0.016)
Work-Life Balance	-0.025	-0.015	0.034***
	(0.035)	(0.010)	(0.007)
Overall (from Table 2, Col 4)	-0.050**	0.010***	0.039***
	(0.023)	(0.003)	(0.007)

Each cell is a coefficient from a regression of the normalized average satisfaction score for specific job aspects on current and prior-day Google stock returns. All regressions include day of the week fixed effects. Standard errors are heteroskedasticity robust and adjust for clustering within survey response date. Standard errors cluster on date of survey completion.

Table 5. 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, 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. 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 6. Employee work activity, hours, and recent stock returns -- software engineering, Jan 2006 to June 2008

	Hours in day with				Activity counts [Normalized]				
Output measures	Hours with any action		Hours with Perforce call		Perforce calls	Wiki edits	Wiki views	Code reviews	Bug actions
Hours included	All	Off hours	All	Offhrs	All	All	All	All	All
GOOG return (t+1)	-0.028	-0.018***	-0.002	-0.005	0.000	-0.004**	-0.007*	-0.011	-0.014*
	(0.018)	(0.006)	(0.013)	(0.006)	(0.002)	(0.002)	(0.004)	(0.007)	(0.008)
GOOG return (t)	-0.038***	-0.019***	-0.020*	-0.012**	-0.002	-0.003**	-0.008***	-0.003	-0.006
	(0.013)	(0.005)	(0.012)	(0.005)	(0.001)	(0.001)	(0.003)	(0.007)	(0.006)
GOOG return (t-1)	-0.032	-0.012	-0.013	-0.009	-0.001	-0.002	-0.005	-0.007	-0.008
	(0.022)	(0.008)	(0.014)	(0.006)	(0.002)	(0.002)	(0.004)	(0.007)	(0.010)
GOOG return (t-2)	-0.018	-0.003	-0.008	-0.002	-0.001	-0.001	-0.003	0.000	-0.002
	(0.023)	(0.008)	(0.016)	(0.007)	(0.002)	(0.002)	(0.005)	(0.008)	(0.011)
Day of week fixed effects	X	X	X	X	X	X	X	X	X
Employee*month fixed effects	X	X	X	X	X	X	X	X	X
Employee days	3,028,700	3,028,700	3,028,700	3,028,700	3,028,700	3,028,700	3,028,700	3,028,700	3,028,700
Unique employee*months	99,571	99,571	99,571	99,571	99,571	99,571	99,571	99,571	99,571
Unique days	882	882	882	882	882	882	882	882	882
Adjusted R-sq.	0.5924	0.5685	0.6862	0.6695	0.6016	0.1332	0.2742	0.4025	0.2821

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). Times are local time in the city in which the employee is located. Standard errors are heteroskedasticity robust and allow for clustering within day.

Table 7. Employee work activity, hours, and recent stock returns -- online sales staff, Jan 2006 to June 2008

Measure	Hours in day with:						Activity counts [normalized]	
Activity	ICS page view		Email		Either		ICS page views	Emails
Hours included	All	Off hours	All	Off hours	All	Off hours	All	All
GOOG return (t+1)	-0.027	-0.005*	-0.019	-0.002	-0.034	-0.005	-0.004	-0.005
	(0.021)	(0.003)	(0.013)	(0.002)	(0.024)	(0.004)	(0.004)	(0.004)
GOOG return (t)	-0.037**	-0.005*	-0.027**	-0.004**	-0.044**	-0.006*	-0.006*	-0.006*
	(0.018)	(0.003)	(0.011)	(0.002)	(0.020)	(0.003)	(0.003)	(0.003)
GOOG return (t-1)	0.003	0.002	0.002	0.000	0.003	0.001	0.003	0.001
	(0.017)	(0.002)	(0.011)	(0.002)	(0.019)	(0.003)	(0.003)	(0.003)
GOOG return (t-2)	-0.014	-0.002	-0.002	-0.001	-0.016	-0.002	-0.001	0.000
	(0.020)	(0.003)	(0.012)	(0.002)	(0.023)	(0.003)	(0.004)	(0.003)
Day of week fixed effects	X	X	X	X	X	X	X	X
Employee*month fixed effects	X	X	X	X	X	X	X	X
Employee days	1,202,088	1,202,088	1,202,088	1,202,088	1,202,088	1,202,088	1,202,088	1,202,088
Unique employee*months	39,898	39,898	39,898	39,898	39,898	39,898	39,898	39,898
Unique days	874	874	874	874	874	874	874	874
Adjusted R-sq.	0.5688	0.362	0.5038	0.3101	0.5616	0.3543	0.4889	0.4853

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). Times are local time in the city in which the employee is located. Standard errors are heteroskedasticity robust and allow for clustering within day.

Table 8. Interview outcomes and surrounding stock returns

Dependent variable	Normalized interview score						Successful interview?	
Specification	Linear						Probit (marginal effects reported)	
Engineering interview?	All	No	Yes	Yes	Yes	Yes	Yes	Yes
GOOG return (t+1)	0.001	0.002	-0.002					
	(0.003)	(0.003)	(0.006)					
GOOG return (t)	-0.005*	-0.002	-0.014**	-0.014**	-0.014**	-0.014**	-0.008*	-0.008*
	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)
GOOG return (t-1)	-0.003	-0.006*	0.005	0.006				
	(0.003)	(0.003)	(0.005)	(0.005)				
GOOG return (t-2)	0.004*	0.004	0.005					
	(0.003)	(0.003)	(0.006)					
Ln(Stock + Options) [normalized]						0.002		0.004
						(0.084)		(0.006)
Ln(Stock + Options)*GOOG return (t)						-0.001		-0.011**
						(0.005)		(0.005)
Day of week fixed effects	X	X	X	X	X	X	X	X
Interviewer fixed effects	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X	X	X	X	X
Days of scoring delay fixed effects	X	X	X	X	X	X	X	X
Dating of stock returns	Day interview score is recorded						Day of interview	
Observations	269,822	205,334	64,488	64,531	64,549	63,556	17,748	17,684
R-squared	0.1852	0.1913	0.1589	0.1588	0.1588	0.1583	0.0384	0.0419
Unique interviewers	8,298	8,298	8,298	8,298	8,298	8,298	NA	NA
Unique interviewees	88,873	71,142	17,731	17,745	17,748	17,684	17,748	17,684
Unique days	1,411	1,411	1,386	1,387	1,390	1,383	1,182	1,177

Table 9. Quality of idea and stock returns surrounding posting

Dependent variable	Mean rating (normalized)			Number of ratings received (normalized)			Implemented?		
Specification	Linear			Linear			Probit (marginal effects reported)		
GOOG return (t+1)	-0.001			0.297			-0.008**		
	(0.015)			(0.242)			(0.003)		
GOOG return (t)	0.000	0.000		0.427*	0.407*		0.002	0.002	
	(0.014)	(0.014)		(0.222)	(0.218)		(0.003)	(0.003)	
GOOG return (t-1)	0.032**	0.032**		0.690**	0.697**		0.006*	0.006*	
	(0.015)	(0.015)		(0.309)	(0.308)		(0.004)	(0.004)	
GOOG return (t-2)	-0.008			0.022			0.000		
	(0.012)			(0.282)			(0.003)		
GOOG return (t and t-1)			0.020			0.746***			0.006*
			(0.013)			(0.264)			(0.004)
Day of week fixed effects	X	X	X	X	X	X	X	X	X
Month fixed effects	X	X	X	X	X	X	X	X	X
Observations	11,224	11,227	11,227	11,224	11,227	11,227	11,715	11,718	11,718
R-squared	0.0204	0.0203	0.0199	0.0553	0.0552	0.0551	0.0217	0.0210	0.0209
Unique days	1,289	1,290	1,290	1,289	1,290	1,290	1,290	1,291	1,291

Table 10. Ratings of ideas and stock returns surrounding rating
Dependent variable: normalized rating

Main effects						
GOOG return (t+1)	-0.008			-0.001		
	(0.015)			(0.015)		
GOOG return (t)	-0.035**	-0.032**		-0.035**	-0.034**	
	(0.015)	(0.015)		(0.015)	(0.015)	
GOOG return (t-1)	-0.023	-0.021		-0.024	-0.021	
	(0.016)	(0.016)		(0.016)	(0.016)	
GOOG return (t-2)	-0.007			-0.008		
	(0.014)			(0.015)		
GOOG return (t and t-1)			-0.036**			-0.038**
			(0.017)			(0.016)
Interactions with Ln(Stock + Options)						
GOOG return (t+1)				0.007		
				(0.015)		
GOOG return (t)				-0.014	-0.015	
				(0.015)	(0.015)	
GOOG return (t-1)				0.005	0.003	
				(0.018)	(0.017)	
GOOG return (t-2)				0.008		
				(0.013)		
GOOG return (t and t-1)						-0.009
						(0.019)
Ln(Stock + Options) [normalized]				-0.298**	-0.298**	-0.298**
				(0.020)	(0.020)	(0.020)
Day of week fixed effects	X	X	X	X	X	X
Idea fixed effects	X	X	X	X	X	X
Observations	28,097	28,102	28,102	28,097	28,102	28,102
R-squared	0.5556	0.5557	0.5557	0.5644	0.5645	0.5644
Unique ideas	8,298	8,301	8,301	8,223	8,226	8,226
Unique days	1,320	1,321	1,321	1,320	1,321	1,321

Table 11. Correlations between job satisfaction, job performance, and decision making

Employees included	All full-time employees			Online sales staff						Software engineers		All full-time employees	
Dependent variable	Subjective performance evaluation (normalized by track*level)			Hours in day with ICS page view			Hours in day with email			Hrs in day with:		Idea ratings	Interview scores
										Any action	Perforce call	[Normalized]	[Normalized]
Time period	2006Q2	2006Q3 (Survey)	2006Q4	2006Q2	Day of survey	2006Q4	2006Q2	Day of survey	2006Q4	2006Q2-Q4	2006Q2-Q4	2005Q4-2007Q3	2005Q4-2007Q3
Univariate regression													
Normalized satisfaction score	0.008***	0.003**	0.0003	-0.006	0.425***	0.268***	0.161***	0.137*	0.105**	-0.065	-0.047	0.016	0.031***
	(0.002)	(0.001)	(0.0015)	(0.080)	(0.122)	(0.063)	(0.051)	(0.086)	(0.042)	(0.043)	(0.037)	(0.029)	(0.007)
Multivariate regression													
Normalized satisfaction score	0.010***	0.005***	0.002	0.045	0.315**	0.174***	0.201***	0.160*	0.096**	-0.061	-0.045	0.009	0.033***
	(0.002)	(0.002)	(0.002)	(0.082)	(0.130)	(0.065)	(0.053)	(0.093)	(0.043)	(0.045)	(0.039)	(0.027)	(0.007)
Ln(Stock + Options) [normalized]	0.004	0.003	-0.001	-0.433**	0.350	0.383***	0.132	0.165	0.282***	0.136	0.090	-0.210**	-0.034*
	(0.003)	(0.002)	(0.002)	(0.193)	(0.284)	(0.138)	(0.120)	(0.212)	(0.099)	(0.093)	(0.086)	(0.082)	(0.018)
Start date [normalized]	-0.010***	-0.007***	-0.008***	-0.753***	-0.333	-0.178	0.305**	0.409	0.393***	0.156	0.109	-0.083	-0.006
	(0.002)	(0.002)	(0.002)	(0.209)	(0.394)	(0.166)	(0.139)	(0.289)	(0.131)	(0.109)	(0.102)	(0.067)	(0.013)
Fixed effects													
Day of week				X	X	X	X	X	X	X	X	X	X
City	X	X	X	X	X	X	X	X	X	X	X	X	X
Employee track*level	X	X	X	X	X	X	X	X	X	X	X	X	X
Other				Day	Day	Day	Day	Day	Day	Day	Day	Idea	Interviewee*date
Standard errors clustered by				Employee	Employee	Employee	Employee	Employee	Employee	Employee	Employee	Employee	Employee
Observations	3,746	4,586	4,827	63,726	855	73,130	63,726	855	73,130	352,143	352,143	8,215	209,092
R-squared	0.0065	0.0010	0.0000	0.2890	0.1633	0.2696	0.2101	0.1585	0.2133	0.1735	0.0194	0.6135	0.8773
Unique employees	3,746	4,586	4,827	777	855	854	777	855	854	1,385	1,385	1,234	4,176