# Effect of Mood and Worker Incentives on Workplace Productivity*

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**Abstract**

We leverage data on call-center workers to explore the causal effect of mood on their productivity in the field. Mood is measured through an online "mood questionnaire" which the workers are encouraged to fill out daily. We find that better mood actually *decreases* worker productivity for workers whose compensation is largely fixed. The effect of mood becomes more positive the more a worker's compensation is based on performance (high-powered incentives). This finding holds both at a correlational level and in two IV settings, where mood is instrumented for by weather or, alternatively, by whether the local professional sports team played/won the day before. We interpret these findings, and others in the literature, through the lens of a model where, consistent with experimental evidence, mood affects risk attitudes. We rule out a number of threats to the exclusion restrictions. *JEL Codes: J24, M52*

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# 1 Introduction

Does positive mood necessarily increase worker productivity? A lot of managerial literature claims that "good mood" improves workplace productivity. However, the managerial literature is not based on causal evidence. Recently, economists have begun addressing mood as a causal determinant of productivity. In a laboratory setting, Oswald et al. (2015) manipulate a subject's mood and then measure the subject's performance in an experimental task (e.g., performing long additions). In an observational setting (call centers operators), Bellet et al. (2019) use weekly variation in weather as an instrument for worker mood. Both papers find that exogenously improving mood improves productivity. In both papers, albeit to different extents, workers are "paid for performance." How might the incentive scheme affect the results? This is the subject of our paper.

We observe workers who are subject to different incentive schemes. Among those workers whose pay is*less determined by performance*, we find the opposite result: *better weather-induced mood results in lower productivity*. We replicate this finding in the case where the mood shock is given by the performance of a local sports team, rather than by weather. However, within the subgroup workers whose pay is more dependent on performance we replicate, at least directionally, the finding that is already present in the literature: the impact of positive mood on productivity is zero, or even positive.

Mood is measured through an online "mood questionnaire" which the workers are encouraged to fill out daily: see Figure 1.[1] Productivity is measured by the number of calls per worker/hour, and by other measures including downtime. The panel structure of the data (i.e., workers observed in different locations for multiple periods) allows us to use worker fixed effects and geographical variation of weather. Identification therefore leverages within-worker daily variation in mood and within-location variation of weather. Our call-center setting is especially suitable for our purposes because variation in call-center demand (a likely confounder of productivity) is national, and thus independent of local shocks to mood.

More than 80% of the observations in our study have no performance component to com-

[1]The mood questionnaire arises from the company's desire to measure worker engagement.

**Figure 1:** Screenshot of Mood Questionnaire


pensation. Looking at the average effect in the entire sample, and controlling for worker time-invariant characteristics (like worker ability), we find that better mood is *negatively* correlated with productivity in this sample. We instrument for mood with local weather on the same day and, separately, with whether a local professional sports team won or lost the day before. The first-stage estimates are as expected: rain worsens mood, and the local sports team losing worsens mood too. Using these two instruments we estimate that positive mood has a very sizable, and similarly-sized for both instruments, negative causal effect on our call-center workers' productivity. Both IV estimates are much larger than the OLS estimates (correlation between mood and productivity). We provide direct evidence of a reverse-causation bias in the OLS estimates that may partly account for this difference.

Looking at the heterogeneous effect across workers, positive mood has a zero, or even positive effect on performance, depending on how large a fraction of realized compensation is the productivity-based component. This finding needs to be taken with a grain of salt because realized compensation is endogenous to performance. However, the finding holds even across work descriptions: positive mood has a more favorable effect on the productivity of sales representatives (whose compensation is more sensitive to performance) than customer service workers (largely on fixed wage).

The causal interpretation of our estimates rests on the assumption that the effect of weather or sporting events on productivity is mediated by mood alone. A first concern is that demand might be related to weather (and maybe also to sports events). However, our call centers face a national demand: calls from all over the U.S. are first centrally directed then routed to individual call centers; in fact, demand happens to be uncorrelated with our instruments. A second concern is that our instruments might affect the number of hours a worker shows up at work (e.g., bad weather may increase traffic; sports events may increase the likelihood that a worker shows up late); and this may affect productivity, even *per hour*. However, we show that the results hold if we control for the "number of hours at work," or if we replicate the analysis on the subsample of workers who live close to the office. A third concern, which is specific to our weather instrument, is that forecasted weather might require workers to waste productive time rearranging their schedules (if rain is forecasted, cancel the BBQ, and vice versa). The idea is that if rain is forecasted tomorrow, a worker might have to spend some time today in order to rearrange her personal schedule. To assess the importance of this concern, we regress productivity at time $t-1$ on rain at time $t$; but we find no effect.

Through what channel might short-term mood shifts affect performance? We consider two. First, worse mood might decreases sociability and increase performance. Second, worse mood might make the worker more ambiguity averse. (A decision maker is said to be ambiguity-averse if she evaluates any bet pessimistically, i.e., as if expecting an unfavorable state of nature to occur systematically; see Gilboa and Schmeidler 2009). Both effects have been documented in the literature.[2] Only the second channel, however, theoretically predicts the observed empirical pattern: with fixed wage, positive mood decreases productivity; but with pay-for-performance, it increases it.

To understand this theoretical prediction, consider a pay-for-performance setting where the variance of performance is larger if effort is higher (this would be the case if, for example, effort scales the output distribution multiplicatively). Then, a worker who exerts high effort is subjected to additional compensation risk. When more uncertainty-averse, the worker will focus on the downside of that additional risk, and thus be *less inclined* to exert effort. In a fixed-wage setting, instead, incentives come from the risk of being fired. When the worker focuses on the downside of that risk, she will be *more inclined* to exert effort. This theoretical argument can explain why a negative mood *increases effort* when the wage is fixed, and decreases it under pay-for-performance. It is because, with pay-for-performance, risk is associated with the carrot, whereas with a fixed wage, risk is associated with the stick.

[2]See Section 2 for a description of the literature.

The paper proceeds as follows: Section 2 discusses the related literature; Section 3 presents statistics and explains our institutional context. Sections 4 and 5 identify the correlation and the causal effect of mood on productivity: OLS and IV results, respectively, and discusses potential threat to the IV identification strategy. Section 6 explores the heterogeneous effect by compensation scheme. Section 7 presents the theoretical framework. Section 8 concludes by discussing the external validity of our results.

# 2 Related Literature

This section discusses the literature that relates arguably-exogenous variation in mood to risk-taking, and to productivity.

**Mood and risk-taking** It is uncontroversial that decreasing peoples' mood makes them more risk averse. In lab experiments, Johnson and Tversky (1983) show that experimentally inducing negative affect increases subjects' estimates of the frequency of unrelated risks (what we call ambiguity aversion). Their finding is replicated by, among others, Wright and Bower (1992) and Yuen and Lee (2003). Cyders et al. (2008) summarizes this literature as follows:

> "In general, induced positive mood produces increased risk taking."

Some studies have measured risk appetite in the lab using mood variation generated outside the lab. Smoski et al. (2008) document that clinically depressed individuals are more risk-averse. Fehr-Duda et al. (2011) replicate Johnson and Tversky (1983) surveying the subjects' mood before the experiment, and using monetary incentives to elicit risk-taking attitudes. In both cases the variation in mood is not controlled experimentally.

Finally, Otto and Eichstaedt (2018) comes closest to our work because their study is fully in-the-wild and they use very similar instruments for mood (sunny days and wins by the local sport team). They demonstrate that at the city level, positive mood is associated with risk taking (lottery participation).

**Mood and productivity** "Mood" in our paper measures a form of self-reported positive affect at work. Positive affect is a form of "subjective well-being" (SWB). There is a large literature on the relationship between SWB and work performance. Tenney et al. (2015) provide an excellent survey. Almost all observational studies in this literature report a positive correlation between SWB and a host of outcomes including: subjective and objective work performance metrics, unemployment, health, relationship outside of work, etc. However, most of the observational studies are cross-sectional and correlational in nature and thus not conclusive about causality (Tenney et al. 2015, p.40).[3] Closest to our setting, Rothbard and Wilk (2011) do not find a statistically significant relationship between call center workers' mood and productivity as measured by the number of calls per hour. However, the source of variation in mood is unmodeled, so again, no causal inference may be drawn.

In the lab, Oswald et al. (2015) manipulate a subject's mood and then measure the subject's performance in an experimental task (e.g., performing long additions). This paper comes as close as possible to demonstrating that mood *causally* affects "work-like" behavior. If one accepts this premise, then one must also keep an open mind toward observational studies where mood is plausibly instrumented for, such as Bellet et al. (2019) and our paper. As mentioned before, Bellet et al. (2019) is closest to our paper in identification strategy, but the results are the opposite: good mood causes higher performance. We take their finding at face value, and propose a theory that explains the difference based on the fact that pay-for-performance is more prevalent in their setting.[4] Therefore, we view their paper as highly complementary to ours.

Finally, Cowgill and Zitzewitz (2013) relate variation in Google's stock price to its workers' job satisfaction (interpreted as mood) and hours spent working. They find that stock-price improvements caused higher job satisfaction and, encouragingly for our argument, *fewer* hours spent working. It must be acknowledged, however, that stock price may not be the perfect instrument. If a drop in the stock price was interpreted as a signal that Google was doing less well than expected, the worker might rationally fear about her own career trajectory within the

[3]Gallup Inc. has measured workplace well-being for decades, and has long supported the notion of a link between wellbeing and productivity. Jim Harter, Chief Scientist of Gallup's Workplace Wellbeing Practices, writes that "Investigation of the happy productive worker clearly links emotional well-being with job performance."

[4]70% of their workers receive a "large performance bonus" (Bellet et al. 2019, p. 23).

firm, and rationally respond by working harder quite independently of shifts in mood.

**Mood, Sociability, and Productivity** Inducing a better mood experimentally has been shown to increase subjects' vulnerability to distractions (Pacheco-Unguetti & Parmentier 2016), and to increase sociability (see Cunningham 1988 and the literature cited therein). Both effects may hinder productivity. In fact, in the context of a seafood-processing plant in Vietnam, Park (2016) shows that productivity declines by up to 9% when workers have their friends nearby and socialize. In the context of call-center workers in China, Bloom et al. (2014) show that workers who work from home are 13% more productive. The effect is attributed, partly, to the relative quiet at home and, possibly, to the absence of socializing. Overall, this literature suggests a possible channel: in a number of work settings, better mood may increase sociability and decrease performance.

# 3 Data and institutional setting

Our call-center data cover 2,720 workers located in 9 call centers across 9 different US states from January 2015 to February 2016. 72% of call centers workers are females. They are 34 years of age on average and mean tenure is 38 months.

Each call center representative works in a cubicle with a computer and a headset. Whenever a representative is ready to accept calls, she is asked to clock in to the IT system and calls are automatically routed into her headset. A call from any location in the US is randomly allocated to whichever worker in any of the locations happens to be available. To take a break, a worker temporarily pauses the system. In this case she stops receiving calls and is logged as not available to receive calls. At the end of the working day, the employee is asked to clock out of the system.

**Productivity and Earnings Data** The IT records provide us with detailed information on worker's daily productivity (see Table 1, Panel A). For each worker, we know the number of hours she shows up at work (mean is 6.3) and the proportion of these hours that are "unproductive" (i.e., downtime: off the phone and unavailable to receive a call; mean is 10%). We also have information on the number of calls per hour handled by each worker (mean is 7) and the average call duration (7 minutes per call on average). Finally, the company provided us with information on average daily customer satisfaction (Likert scale 1-10, average 8). Customer-reported productivity measures are available for only 63% of the calls; this may be because few customers are selected to answer these questions, or because few customers choose to answer them. In the latter case an issue of selection arises, but we have no visibility of customers non-response, so we take these numbers at face value.

Workers are divided into two positions: customer service representatives, and sales representatives. Customer service representatives provide information about products and services, take orders, respond to customer complaints, and process returns. Sales representatives evaluate consumer needs, recommend and sell products.[5] Neither position is segregated in specific call center locations. Workers in the two positions are similar in terms of tenure, age, gender but differ in the compensation scheme. Customer service representatives are paid a fixed hourly rate (mean is 11.8 dollars per hour) and earn almost no commission on top of that (see Table 1, Panel B). Sales representatives earn a lower fixed hourly salary (mean is 9.6 dollars per hour) with commissions on top (4.2 dollars per hour on average). Commissions are paid on a bi-weekly basis based on the "number of calls per hour" and "sales per hour." Relative to customer service representatives, sales representatives have thus a larger share of realized monthly compensation that is productivity-based and recorded by the firm as "variable" (see Figure A.1).

Our preferred measure of productivity is the "number of calls per hour," because it is available for both positions. (Productivity is recorded hourly, rather than "per day" or "per shift," and workers are compensated hourly in this firm.) As a measure of downtime, we report "the proportion of time a worker is unproductive" (off the phone and unavailable to receive a call).[6] We do not focus on the "number of hours an employee shows up at work" as a key outcome variable because: (1) workers are compensated hourly and (2) schedules are set by the firm a week in advance and are thus unaffected by daily mood. We will provide empirical evidence of this later. We also do not focus on "sales per hour" as a measure of productivity because the

[5]The call-center workers we study in this paper are different from those in Coviello et al. (2020).

[6]In Table A.1, we show that the our proxy of downtime ("proportion of time a worker is unproductive") is negatively correlated with the "number of calls per hour" and with the "average customer satisfaction."

**Table 1:** Summary Statistics

| VARIABLES | Obs. | Mean | S.D. |
|---|---|---|---|
| **Panel A. Productivity (N=Workers*Days)** | | | |
| # hours at work | 232,292 | 6.30 | 1.94 |
| # calls per hour | 232,292 | 7.08 | 2.85 |
| % "unproductive" time | 232,292 | 0.10 | 0.07 |
| Average call duration (in minutes) | 232,292 | 6.95 | 3.25 |
| Average daily customer satisfaction (1 to 10) | 84,965 | 7.94 | 2.68 |
| **Panel B. Earnings (N=Workers*Months)** | | | |
| Earnings per hour (gross) | 15,850 | 12.19 | 2.40 |
| Customer service representatives | 12,736 | 11.81 | 1.05 |
| Sales representatives | 3,114 | 13.78 | 4.65 |
| Fixed earnings per hour (gross) | 15,850 | 11.20 | 1.17 |
| Customer service representatives | 12,736 | 11.58 | 0.92 |
| Sales representatives | 3,114 | 9.62 | 0.64 |
| Variable earnings per hour (gross) | 15,850 | 1.00 | 2.68 |
| Customer service representatives | 12,736 | 0.22 | 0.63 |
| Sales representatives | 3,114 | 4.16 | 4.75 |
| **Panel C. Worker Mood (N=Workers*Days)** | | | |
| Worker logs into platform = {0, 1} | 232,292 | 0.35 | 0.48 |
| *Conditional on logging into platform…* | | | |
| Worker answers mood question = {0, 1} | 81,106 | 0.44 | 0.50 |
| *Conditional on answering mood question …* | | | |
| % who feel Frustrated | 35,715 | 0.07 | 0.26 |
| % who feel Exhausted | 35,715 | 0.07 | 0.25 |
| % who feel SoSo | 35,715 | 0.17 | 0.37 |
| % who feel Good | 35,715 | 0.36 | 0.48 |
| % who feel Unstoppable | 35,715 | 0.34 | 0.47 |
| Mood score (1 to 5) | 35,715 | 3.84 | 1.17 |

Notes: Panel A displays the mean and standard deviation of daily-level productivity measures (one observation per day and per worker). # calls per hour = total number of daily calls divided by total hours at work. % "unproductive" time = % time not spent on the phone with customers or not spent being available to receive phone calls. Customer satisfaction score calculates the average daily customer satisfaction score for each worker (score 1 to 10). This variable is missing if none of the customer were asked to fill the survey and/or none of the customers answered the survey. Panel C presents information on earnings per hour at the monthly level (one observation per month and per worker), separately for customer service representatives and sales representatives. Panel D displays the mean and standard deviations of daily-level mood data. Upon logging into an online platform, workers are asked the mood question: "How do you feel today: Frustrated, Exhausted, So so, Good or Unstoppable?" The question is asked maximum one time per day. The worker has the option of answering the mood question or skipping it. We report here the mood distribution conditional on answering the mood question (coding the no responses as missing). The mood score takes value 1 to 5 where 1 is "feeling frustrated" and 5 is "feeling unstoppable."

variable is recorded only for a subsample of the workers (the sales representatives).

**Mood Data** Mood is measured through an online "mood questionnaire" which the workers are encouraged to fill out: see Figure 1. Individual answers are anonymous; each call center manager is provided with monthly summary statistics aggregated at the call-center level. The questionnaire is presented to the worker upon logging into a particular software platform and is asked only once per day. Logging in is required to access a number of HR functions including tracking their pay information, accessing online training, setting one's quarterly goals, and giving and receiving performance feedback. Accordingly, we assume that the login choice is largely determined by considerations other than mood and we restrict our sample to the 81,106 worker-days in which the worker logged in the platform. We provide evidence in support of the assumption in Table 6 (Column 1) where we show that our weather and sports instruments (which are related to mood) have no effect on the login choice.

Conditional on logging into the platform, a worker answers the mood question 44% of the time, while skips the question – by pressing an "exit" button – the rest of the time (see Table 1, Panel C). This requires taking a stand on how to code non-responses. In our main results, we follow the most conservative approach and code the non-responses as missing observations, thus effectively dropping non-responses and reducing the sample. Importantly, we show that the results are consistent regardless of how the missing responses are coded: they hold if we assume that "no answer" means "bad mood" (frustrated).[7] or if we impute intermediate mood scores. Reassuringly, our instruments (weather and sport) do not affect the likelihood of non-response (Table 6, Column 2).

Conditional on answering the mood question, 70% of respondents report feeling either "good" or "unstoppable", while only 14% report feeling "exhausted" or "frustrated." Mood score (which takes value 1 for "frustrated", 2 for "exhausted, 3 for "so so", 4 for "good" and 5 for "unstoppable") takes an average value of 3.8 among the respondents. As a validation check of our mood data, we correlate reported mood with "days of the week" in Table A.2 (Column

[7]In personal communication with one HR manager, the authors learned that workers may be uneasy reporting bad mood despite the organization's assurance of anonymity of survey results. This may explain why "bad mood" is under-reported.

1). As one would expect, mood is higher on Fridays and lower on Sunday (consistent with the notion that employees do not like to working on Sunday). Importantly, the variation in mood score exists both *between* workers (s.d. 1.36) and also *within* workers (s.d. 0.88). The within-worker portion of the variation is sizable. Because we use worker fixed effects, identification will come from within-worker variation: we compare the productivity of a given worker in days in which she is in good mood to days in which she is not.

# 4 OLS results: negative correlation between positive mood and productivity

This section reports the correlation between mood and productivity in the entire sample of call-center workers. As explained above, we have daily-level individual mood and productivity data. The panel structure of the data allows us to include worker fixed effects, thus controlling for any endogeneity that may arise across workers and is fixed through time. We also add day-of-the-week fixed effects, month*year fixed effects, and control for worker tenure.[8] In Table A.3, we show that our results persist in more demanding specifications that include day*month*year fixed effects (Panel A) or if we allow for autocorrelation at short horizon by clustering standard errors at the call-center*week level (Panel B). Finally, our results also do not change if we use alternative coding strategies for the mood question such as imputing no-response with bad mood ("frustrated"), neutral mood ("so-so"), or positive mood ("unstoppable"). See Table A.4.

In Table 2 Column 1, we find that a higher mood score is *negatively* correlated with productivity: a one unit increase in mood decreases the number of calls per hour by 7.3pp. The correlation is relatively linear across the different moods: the highest the mood score, the lowest the number of calls per hour (see Table A.2, Column 2). The correlation between mood and "the proportion of *unproductive* time" and customer satisfaction is very small (at least in these OLS regressions). See Table 2, Column 2.

While not causal, these results indicate that within-worker variation in mood is *negatively*

[8] We do not include workers' position and call-center fixed effects as these are fixed within a worker, and are thus redundant.

**Table 2:** Mood and Productivity, OLS Results

| | (1) | (2) |
|---|---|---|
| Dep. Var. | # calls per hour | % unproductive time |
| Mood Score (1 to 5) | -0.073*** | -0.001*** |
| | (0.014) | (0.000) |
| Observations | 35,368 | 35,368 |
| Mean Dep. Var. | 7.117 | 0.094 |

Notes: OLS regression. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1. % "unproductive" time = % time not spent on the phone with customers or not spent being available to receive phone calls.

correlated with productivity (as measured as "calls per hour") for our workers. Is this negative correlation true in other work settings? We can answer this question for more than 20,000 sales associates in more than 500 retail stores covering the entire US who used the same online platform from September 2013 until August 2015.[9] Unlike call-center workers, we cannot link individual mood with individual performance, but we can link store-level productivity (at the monthly level) with average store-level mood in that month. Controlling for store fixed effects, month*year fixed effects and for the number of workers in the store, Table A.5 shows that the correlation is negative: higher mood score is associated with lower average store profits and revenues. This shows that the negative correlation observed among our call center workers generalizes to a larger and more representative pool of workers.

A limitation of OLS estimates is that they are subject to potentially large endogeneity, reverse causality and measurement error. Because of these concerns, we turn to an IV strategy

[9]The proportion of workers who answer the mood question conditional on logging in and the average mood score among sales associates is very similar to the one of call-center workers, with a similar distribution of answers. Workers answered the mood question in 52% of the days. Conditional on answering the question, the average mood score is 3.99 (6% feel frustrated, 6% feel exhausted, 12% feel so-so, 38% feel good and 39% feel unstoppable).

in the next section. We focus on the call-center dataset as the store-level data are not granular enough to perform any analysis beyond a simple OLS.[10]

# 5 IV estimates: negative effect of positive mood on productivity

There are two reasons to believe that OLS estimates may underestimate the size of the effect of mood on productivity. First, reverse causality: a worker who happens to be highly productive may feel happier because of that. To provide suggestive evidence of a feedback effect of work environment on our mood variable, we analyze worker response to a question they were asked after answering the mood question: "What contributed the most to your mood?" Workers could identify the source of their mood as work-related ("boss," "work environment," "co-workers," etc.); or "non-work related." We believe that work-related mood is more likely to be subject to reverse causality. Indeed, work-related mood turns out to be *positively* correlated with productivity, whereas non-work-related mood is not.[11] Therefore, there is reason to believe that OLS estimates are significantly attenuated by reverse causality. The second reason to believe that OLS estimates underestimate the impact of mood is classical measurement error in the mood variable. Mood is intrinsically hard to measure, especially when captured through surveys.

Due to these concerns about downward bias of the OLS estimates, we now present IV estimates based on two separate instruments for *daily* mood: daily weather and professional sports events. Both instruments yields quantitatively similar estimates for the effect of mood.

## 5.1 First-stage results

**Weather instrument** We use weather as an instrument for worker mood, because we expect bad weather to cause worse mood. The existing literature offers support for this notion. Seasons are known to affect mood: in some people, the winter months bring bad mood and depression

[10] Productivity data are aggregated at the store level and does not vary at the daily level.

[11] Only a subset of the workers who answered the mood question also answered this second question. Results are available upon request.

(seasonal affective disorder). Higher-frequency weather (daily or weekly, rather than seasonal) has also been found to affect mood (Keller et al. 2005, Braga et al. 2014, Otto and Eichstaedt 2018, Bellet et al. 2019).

The weather data come from the National Oceanic and Atmospheric Administration (Global Historical Climatology Network-Daily Dataset). The data contain four weather variables at the daily and zipcode levels: precipitation, maximum and minimum temperatures, and snowfalls. As an instrument, we choose the weather variable that is found to be most positively correlated with mood: whether it rains or not during the day, i.e., whether precipitations are strictly positive, which is known to correlate with sunshine. As shown in Table 3 Column 1, the "rain dummy" negatively affects mood with an F-statistics of 13.8. Using all four weather variables as instruments for mood, or using "rain precipitation" (in ml) alone leads to lower F-statistics (see Table A.6, Columns 1 and 2) and hence we prioritize "rain dummy" as our instrument. In our sample, 30% of the days were rainy with considerable variation across days (s.d. 0.26). Rain varies within a locality across days and within a day across our 9 localities (located in different states of the US).

**Professional sports games instrument** For each call center, we collected information on whether the local sport team (football, baseball, basketball, or hockey) played, and whether they won or lost on any given day.[12][13] Our sport instrument takes one of three values: 0 if the team did not play on day *t-1*, 1 if the team played and won on day *t-1*, and -1 if the team played and lost on day *t-1*. We choose this coding strategy because the correlation between mood on day *t* and the local team losing (winning) a game on day *t-1* is negative (positive) in the raw data. With this sport instrument, the F-statistic of the first stage is 33.3 (Table 3,Column 2). Combining the sport and the rain instruments leads to a joint F-statistic of 22.5 (Table 3,Column 3).

[12] We obtained sports outcomes of all regular and post-season games played by teams of Major League Baseball (MLB), National Football League (NFL), National Basketball League (NBA) and National Hockey League (NHL). For one of the call centers, none of the four leagues has a team. For this location, we obtained sports outcomes from NCAA Baseball, Football and Basketball teams of the local university. The data was collected from the website Sports Reference (www.sports-reference.com). At the time of collection, College Baseball data was not available to download from Sports Reference and the data were collected directly from the team's website instead

[13] A number of other existing papers use outcomes of sport games as unexpected mood shocks (e.g., Edmans et al. 2007, Eren and Mocan 2018).

**Table 3:** Mood and Weather/Sport, First Stage Results

| | (1) | (2) | (3) |
|---|---|---|---|
| | Mood score (1 to 5) | | |
| Rain | -0.037*** | | -0.036*** |
| | (0.010) | | (0.010) |
| Sport | | 0.032*** | 0.031*** |
| | | (0.005) | (0.005) |
| **Fstat first stage** | **13.80** | **33.34** | **22.45** |
| Observations | 35,368 | 35,368 | 35,368 |
| R-squared | 0.616 | 0.616 | 0.616 |
| Mean Dep. Var. | 3.835 | 3.835 | 3.835 |

Notes: OLS regressions (IV first stage). Rain takes value 1 if it rains on day t. Sport takes value 1 if the team won on day t-1, value -1 if the team lost on day t-1 and value 0 if the team did not play in t-1. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1.

## 5.2 Second-stage results

Our second-stage estimates are presented in Table 4. As for the OLS result, our main specification controls for: worker fixed effects, day-of-the-week fixed effects, month*year fixed effects and worker tenure. When we use the rain instrument, we find that a one unit increase in mood score reduces the "number of calls per hour" by roughly 1.37, equal to 9% of the average. This result holds when we alternatively use the sport instrument, or the sport and the rain instrument combined: a one unit increase in mood reduces the "number of calls per hour" by 0.92 and 1.07 respectively. These estimates survive with the day*month*year fixed effects (Table A.3, Panel A), with standard errors clustered at call-center*week level (Table A.3, Panel B), or with alternative coding strategies (Table A.4).[14]

A reduction in the "number of calls handled per hour" can be explained by two possible

[14]While the exact coefficients change from one coding strategy to another, the coefficients are consistently negative and large in magnitude.

**Table 4:** Mood and Productivity, Second Stage IV Results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var. | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time |
| | IV: Rain | | IV: Sport | | IV: Rain and Sport | |
| Mood Score (1 to 5) | -1.327* | 0.054** | -0.920* | 0.034* | -1.071** | 0.041*** |
| | (0.717) | (0.027) | (0.524) | (0.018) | (0.420) | (0.015) |
| Observations | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 |
| Mean Dep. Var. | 7.117 | 0.094 | 7.117 | 0.094 | 7.117 | 0.094 |
| F-stat first stage | 13.80 | 13.80 | 33.34 | 33.34 | 22.45 | 22.45 |
| Sargan p-value | | | | | 0.644 | 0.509 |

Notes: Second stage IV regressions. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1. % "unproductive" time = % time not spent on the phone with customers or not spent being available to receive phone calls.

channels: either calls become longer or workers spend less of their time on the phone. Table 4 shows that the latter is at play. A one unit increase in the mood score increases the proportion of "unproductive time" (downtime, i.e., time not spent on the phone with customers or not spent being available to receive phone calls) by 3 to 5 percentage points depending on the instrument. This corresponds to an increase of between 36.1% to 57.4% of the unproductive time. Table A.7 shows that mood neither affect the average call duration, nor it affects customer satisfaction scores.

The overall picture, then, is one of fewer number of calls per hour, and a reduction in "productive working time." Our conclusion is that an exogenous increase in mood causes productivity to decline and this decline seems to be explained by an increase in downtime.

### 5.3 Concerns regarding the exclusion restriction

The size of the IV estimates are consistent across the different instruments, and we have provided supporting evidence that rationalizes why it is larger than the OLS estimates. Nevertheless, threats to the exclusion restrictions must be considered. Therefore, in this section we investigate different threats to the exclusion restriction.

**Hours worked** A first potential concern is that hourly productivity might conceivably be affected by the number of hours an employee shows up at work. The latter, in turn, might be affected by weather or by whether the sports team played the day before. E.g., rain may increase traffic and reduce hours worked, or, alternatively, rain may increase hours worked by shifting leisure into work (see Connolly 2008). Similarly watching a sports game the night before, may increase the number of workers late at work the day after. A direct effect of our instruments on hours worked may violate the exclusion restriction if working more hours negatively affects productivity, even *per hour*.[15] To alleviate this concern we first show that the second-stage results do not change if we control for the number of hours an employee was at work (see Table 5). Second, we show that our rain and sports instruments have no direct effect

[15]The raw correlation between these two variables is presented in Table A.1 and is negative. So, if anything working fewer hours should result in more calls per hours rather than less.

on the number of hours at work (intensive margin) and no effect on the number of workers who are present at work (extensive margin); see Table 6, Columns 3 and 4. Finally, we find that the results hold if we restrict the sample to workers who live less than 10km from the workplace and who are therefore less likely to be delayed by weather-related traffic in getting to work (Table A.8, Panel B).

**Demand** A second potential concern is that demand might be correlated with local weather, as would be the case for a number of jobs (farmers, taxi drivers, physical sales positions). Similarly, demand may be higher or lower the day after a local sports team plays. In our setting (call centers), the demand our workers face is national, as calls from all over North America are first aggregated and then distributed across call centers. Accordingly, we see that "number of calls incoming to a call center" is uncorrelated with weather in that call center or with local sports games the day before (Table 6, Column 5). The absence of confounding variation from the demand side is a key advantage of a call-center setting. Finally, Table 5 shows that the results are robust to controlling for the "number of calls incoming."

**Seasonality and pollution** One may worry that the time effects we include in our main specification (day-of-the-week and month*year) are not enough to control for rain seasonality. In Table 5, we control for the historic amount of rain in each calendar day (average in the past 5 years) and the results are unchanged. Moreover, as we have shown earlier, the results also hold in a specification with day*month*year fixed effects (Table A.3, Panel A).

Another concern is pollution. Pollution has been shown to reduce worker productivity in call-center settings (Chang et al. 2016) and may correlate with rain. In Table 5, we show that the results hold if we control for temperature (which is related with daily pollution).[16]

Note that seasonality and pollution are unlikely to be confounders for our sports instrument.

**Others** A final set of potential concerns (for the rain instrument mostly) is that rain might have a direct effect on call-center working conditions independent of mood. Two possibilities come

[16]We also collected data on air pollutants (i.e., Nitric Oxide and Ozone). Unfortunately, the data are missing for one third of the sample. But the results hold in this smaller sample too. Results available upon request.

**Table 5:** Mood and Productivity, Second Stage IV Results with Extra Controls

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | IV = Rain | | | | | IV = Sport | | | IV = Rain and Sport | | |
| **Panel A. Dependent variable = # calls per hour** | | | | | | | | | | | |
| Mood score (1 to 5) | -1.327* | -1.313* | -1.139* | -1.130* | -1.119 | -0.920* | -0.936* | -0.933* | -1.071** | -1.077*** | -1.010** |
| | (0.717) | (0.702) | (0.682) | (0.682) | (0.719) | (0.524) | (0.513) | (0.508) | (0.420) | (0.413) | (0.405) |
| Extra controls: | | | | | | | | | | | |
| # of hours at work | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| # of incoming calls in call-center | | | ✓ | ✓ | ✓ | | | ✓ | | | ✓ |
| Historic rain | | | | ✓ | ✓ | | | | | | |
| Temperature | | | | | ✓ | | | | | | |
| Observations | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 |
| F-stat first stage | 13.80 | 13.88 | 13.94 | 13.92 | 12.41 | 33.34 | 33.24 | 33.23 | 22.45 | 22.41 | 22.39 |
| **Panel B. Dependent variable = % unproductive time** | | | | | | | | | | | |
| Mood score (1 to 5) | 0.054** | 0.053** | 0.052** | 0.052** | 0.054* | 0.034* | 0.035* | 0.035* | 0.041*** | 0.042*** | 0.041*** |
| | (0.027) | (0.026) | (0.026) | (0.026) | (0.028) | (0.018) | (0.018) | (0.018) | (0.015) | (0.015) | (0.015) |
| Extra controls: | | | | | | | | | | | |
| # of hours at work | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| # of incoming calls in call-center | | | ✓ | ✓ | ✓ | | | ✓ | | | ✓ |
| Historic rain | | | | ✓ | ✓ | | | | | | |
| Temperature | | | | | ✓ | | | | | | |
| Observations | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 |
| Mean Dep. Var. | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 | 0.0942 |
| F-stat first stage | 13.80 | 13.88 | 13.94 | 13.92 | 12.41 | 33.34 | 33.24 | 33.23 | 22.45 | 22.41 | 22.39 |

Notes: Second stage IV regressions. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1.

**Table 6:** The Reduced-Form Effects on Logging-in, Mood Answer, Demand and Productivity

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Logs in the platform | Answers mood question | # hours at work | # workers present at work | # daily incoming calls (in '000) | # calls per hour *(conditional on answering mood question)* | |
| **Panel A. Rain** | | | | | | | |
| Rain | 0.005 | -0.002 | -0.006 | 1.506 | 0.074 | 0.049** | |
| | (0.003) | (0.002) | (0.015) | (1.963) | (0.145) | (0.025) | |
| Lead Rain (+1) | | | | | | | -0.015 |
| | | | | | | | (0.022) |
| Observations | 231,735 | 231,735 | 231,735 | 2,403 | 2,403 | 35,368 | 35,098 |
| **Panel B. Sport** | | | | | | | |
| Sport | -0.000 | -0.000 | 0.004 | 1.980 | 0.052 | -0.029* | |
| | (0.002) | (0.001) | (0.011) | (2.007) | (0.140) | (0.016) | |
| Observations | 231,735 | 231,735 | 231,735 | 2,403 | 2,403 | 35,368 | |
| Mean Dep. Var. | 0.349 | 0.154 | 7.316 | 96.67 | 8.291 | 7.083 | |

Notes: Worker-level regressions (Col. 1-3 and 6-7) control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects with standard errors clustered (twoway) at worker & call center*date level. Call-center level regressions (Col.4-5) are collapsed at the call center level and present standard errors clustered at the call center*date level. # daily incoming calls (in '000) = the total number of calls received in the call center in a given day. The number of observations is higher in the first 3 columns than in the previous regressions because we do not restrict the analysis on workers who logged in the platform in a given day but on all workers (whether they logged in or not). The lead rain instrument takes value 1 if it rains in day t+1. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

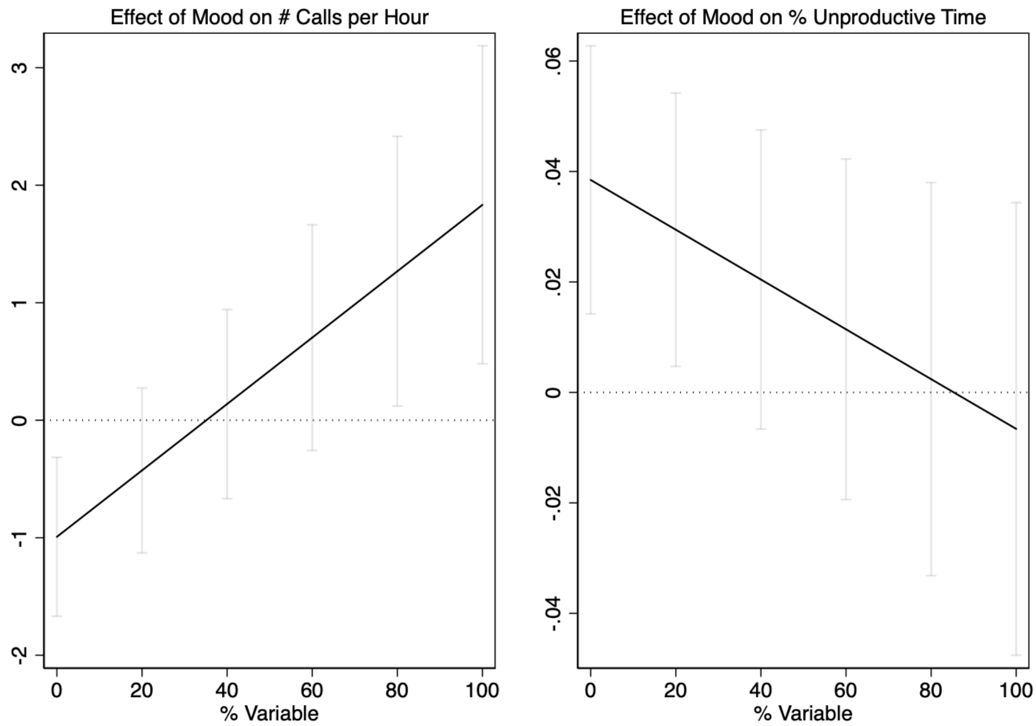
to mind. First, that weather might affect productivity through distraction-on-the-job, i.e, by looking out a window. Second, that forecasted weather might require changes in the workers' personal schedules, causing workers to waste time on the job rearranging their schedules (if rain is forecasted, cancel the BBQ, and vice versa). To guard against the first concern, we have obtained information about the prevalence of windows in different call center locations. Based on our information, one third of the call centers have no windows at all while in the others all workers see natural light. We check in Table A.8 (Panel C) whether workers in the call centers without windows are sensitive to rain-induced changes in mood (controlling for worker fixed effects). We find that they are. This indicates that the effect of mood on productivity exists regardless of the presence of a window in the workplace, and suggests that the effect of weather on mood is achieved in the time spent outside prior to reaching the workplace.

To assess the importance of the second concern (effect of forecasted weather), we regress productivity at time $t-1$ on rain at time $t$ (which we call "lead rain.") The idea is that if rain is forecasted tomorrow, a worker might have to spend some time today in order to rearrange her personal schedule. Table 6 Columns 6-7 show that the coefficient for "lead rain" is smaller than the one for "contemporary rain" and is not statistically significant. The effect of rain which we measure is thus likely not mediated by rescheduling. In contrast, rain at time $t$ significantly increases the number of calls per productive hour at $t$ by 6.2 percentage points (reduced form).

# 6 Heterogeneous effect of mood by the fraction of pay that is performance-based

We now examine the heterogeneous effect of mood on productivity by the worker's share of realized monthly compensation that is productivity-based, i.e, the fraction of their monthly pay that is recorded by the firm as "variable". To do so, we use an IV regression in which productivity is regressed on the mood score and the mood score interacted with the "fraction of pay that is variable," with the latter two variables instrumented by rain/sport and rain/sport interacted with the "fraction of pay that is variable." As before, we include worker fixed effects to

**Figure 2:** Mood and Productivity by the Fraction of Earnings that are variable




Notes: This figure presents the effect of mood score (1 to 5) on the number of calls per hour (right panel) and the fraction of unproductive time (right panel) by the fraction of earnings that are variable. Vertical bars are 90% confidence intervals.

control for time-invariant worker characteristics (such as ability), day-of-the-week fixed effects, month*year fixed effects and worker tenure.

Figure 2 (and the corresponding Table A.8 Panel A) present the heterogeneous effects of mood on productivity for different levels of the "fraction of earnings that is variable." Using the mood and sport as instruments for mood, we find that positive mood has a negative and significant effect on productivity for workers whose pay is less than 20% variable. These are the majority of our observations. Positive mood has no effect on productivity for workers whose pay is 20 to 60% variable. In the left panel – where the outcome variable is the number of calls per hour – a positive mood has a positive effect on productivity for workers whose pay is more than 80% variable.

These findings need to be taken with a grain of salt because realized compensation, even monthly, is endogenous to daily performance. Another way of cutting the data is to compare the average customer service representative (almost entirely paid a fixed rate) with the average sales representative (30% of her earnings are based on performance). Table 7 shows that the effect of mood on productivity is closer to zero for the sub-sample of sales representatives, because the coefficients on the interaction term "mood score*sales representative" has the opposite sign to the "mood score" variable.[17] These coefficients, however, are only precisely estimated for the fraction of unproductive time.Using rain as an IV for mood, it appears that the "the fraction of unproductive time" is 20% less responsive to mood for the average sales representative than for the average customer representative (Column 2). This result is stronger (although less precise) when using sports as an instrument for mood: sales representatives as 33% less responsive to mood. Overall, the findings are directionally consistent with the notion that positive mood promotes performance more for workers who are paid for performance. The fact that the level effect of positive mood on performance is negative even for sales representatives reflects the fact that for many of them the "variable" component of pay is still small (one third of those workers earn less than 10% of their earnings from the performance-based component, see Figure A.1).

This section supports the notion that positive mood decreases productivity more so for workers with low-powered incentives and, though this is more speculative, may even increase it if incentives are high-powered enough. This finding is consistent with Proposition 1 in the following section. We acknowledge, however, that workers with high-powered incentives may react differently to mood shifts because they are different types of workers (e.g., more sociable, or more ambiguity-averse) rather than because their compensation scheme is higher-powered.

# 7 Theoretical framework

Through what theoretical mechanism might short-term mood shifts affect performance? We consider two.

First, worse mood might decrease sociability, and lower sociability might increase performance. While either step has been individually documented, and so their combined action cannot be definitively ruled out even in an occupation that does not require teamwork, this

[17] Table A.6 Columns 3-5 present the first stage of the interacted IV regressions.

**Table 7:** Mood and Productivity by Incentive Structure, Second Stage IV Results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var. | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time |
| | IV = Rain | | IV = Sport | | IV = Rain and Sport | |
| Mood Score (1 to 5) | -1.290* | 0.049** | -0.898 | 0.036* | -1.069** | 0.041*** |
| | (0.679) | (0.025) | (0.550) | (0.019) | (0.416) | (0.015) |
| Mood Score* Sales Representative | 0.072 | -0.010** | -0.106 | -0.012 | 0.050 | -0.010*** |
| | (0.131) | (0.004) | (0.627) | (0.022) | (0.119) | (0.004) |
| Observations | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 |
| p-value (Mood + Mood*Sales Rep=0) | 0.052 | 0.095 | 0.152 | 0.316 | 0.010 | 0.026 |
| F-stat first stage | 9.734 | 9.734 | 11.835 | 11.835 | 12.030 | 12.030 |

Notes: Second stage IV regressions. As IV, we use rain (col.1-2), sport (col.3-4), rain and sport (col. 5-6) and the interaction of these with an indicator for being a sales representative. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1. % "unproductive" time = % time not spent on the phone with customers or not spent being available to receive phone calls. Cragg-Donald Wald F statistic presented at the bottom of the table.

theoretical mechanism does not necessarily predict the emerging pattern (so far) in the small empirical literature on mood and productivity. The pattern is that, with fixed wage, positive mood decreases productivity; but with pay-for-performance, it increases it.

The second theoretical mechanism is that worse mood might make the worker more ambiguity averse. This mechanism has also been well-documented in the literature. We now show that this mechanism, combined with standard labor-economics theory, predicts the emerging empirical pattern.[18]

We now present a model that nests two standard polar cases of interest: the fixed-wage model where incentives come from efficiency wages, and the pay-for-performance model. We build on a classic efficiency wage model (Rebitzer and Taylor 1995, henceforth RT), and introduce pay-for-performance wages in it.

A worker can exert effort $e \in \{0,1\}$. Worker output is a nonnegative random variable $Y(e)$ such that:

$$Y(1) \succsim Y(0),$$

where the relation $\succsim$ denotes first-order stochastic dominance. Thus exerting high effort improves the chances of good performance. The cost of exerting high effort is $c > 0$. The wage function:

$$w(Y) = a + bY,$$

where $a$ represents the base salary and $b$ the commission rate, transforms output into compensation. The fixed-wage case obtains when $b = 0$. Denote a worker's subjectively-expected wage by:

$$w(e) = \mathbb{E}(a + bY(e)),$$

where the expectation is taken over the worker's subjective probability. As in RT, we denote by $r$ the discount rate, by $D < 1$ the worker's subjective probability that shirking is detected (in which case the worker is terminated), and by $s$ her subjective probability of exiting unemployment.

[18]Other psychological theories exists that might counteract this effect. The mood maintenance theory states that people in a good mood becomes more loss averse because they are afraid of losing their current feelings of good mood. If this effect dominates, happier workers would become more productive because they might be more afraid of losing their jobs of they shirk.

The workers' value from not shirking, shirking, and being unemployed, solve:

$$V^N = w(1) - c + \frac{1}{(1+r)} V^N \tag{1}$$

$$V^S = w(0) + \frac{1-D}{(1+r)} V^S + \frac{D}{(1+r)} V^A \tag{2}$$

$$V^A = \frac{s\overline{V} + (1-s) V^A}{(1+r)} \tag{3}$$

These equations are directly comparable with equations (2-4) of RT, except that wages are allowed to depend on effort. Equation (3) specifies the value to a worker who separates: an unemployed worker receives a flow utility of zero, and transitions with subjective probability $s$ to a job in the local economy that yields a flow utility $\overline{V}$. We keep the subjective probability that shirking is detected equal to $D$, independent of performance, for comparability with RT.

The no-shirking condition is $V^N \geq V^S$. In Deserranno et al. (2020) we show that this condition is equivalent to:

$$\underbrace{w(1)}_{\substack{\text{efficiency-wage} \\ \text{incentive channel} \\ \text{(from RT)}}} + \underbrace{\frac{r}{D}\left[w(1) - w(0)\right]}_{\substack{\text{piece-rate} \\ \text{incentive channel} \\ \text{(new)}}} \geq \omega + \left(1 + \frac{r}{D}\right) c, \tag{4}$$

where:

$$\omega = \frac{rs}{(1+r)(r+s)} \overline{V},$$

is the discounted value of being unemployed $V^A$.

**Fixed wage model**

If $b = 0$, that is, if pay is independent of performance, then $w(1) = w(0) = a$, and condition (4) reduces to:

$$a \geq \omega + \left(1 + \frac{r}{D}\right) c. \tag{5}$$

This condition is directly comparable with condition (5) in RT. This the efficiency wage model, where the worker's incentives come entirely from the efficiency wage channel.

**Pay-for-performance model**

We define a pay-for-performance model as one where all the incentives to exert effort come from the wage schedule, and none from being fired for lack of effort. If $D \to 0$ (i.e., no-one is ever fired for lack of effort), the efficiency-wage channel vanishes and condition (4) converges to:

$$\mathbb{E}\left[Y(1)\right] - \mathbb{E}\left[Y(0)\right] \geq \frac{c}{b}, \tag{6}$$

which means that the worker's incentives come entirely from the piece rate.

## 7.1 Modeling the behavioral effect of mood

We model the effect of mood as changing the workers' attitudes toward ambiguity. Consistent with the experimental literature, we assume that a worse mood makes the worker more ambiguity-averse (or, which is the same, a better mood makes the worker more ambiguity-loving).

In our model, only four quantities are unobserved by the worker at the time of choosing $e$, and thus potentially ambiguous: $\omega$ and $D$ in eq. (5), and $Y(1)$ and $Y(0)$ in eq. (6). A more ambiguity-averse worker will evaluate these quantities more pessimistically, specifically, at levels denoted by: $\underline{\omega}, \overline{D}$, $\mathbb{E}\left[Y(1)\right] = \underline{y}(1)$, and $\mathbb{E}\left[Y(0)\right] = \underline{y}(0)$ (low value when unemployed, high probability of being detected if shirking, low productivity whether or not effort is exerted). A less ambiguity-averse (or more ambiguity-loving) worker will evaluate these quantities at more optimistic levels: $\overline{\omega} \geq \underline{\omega}, \underline{D} \leq \overline{D}, \overline{y}(1) \geq \underline{y}(1)$, and $\overline{y}(0) \geq \underline{y}(0)$.

Thus, an ambiguity-loving worker will:

- perceive the RHS in eq. (5) to be larger, compared to an ambiguity-averse worker, and thus be *more* inclined to shirk.
- perceive the LHS in eq. (6) to be larger, compared to an ambiguity-averse worker, if and

only if $\bar{y}(1) - \bar{y}(0) \geq \underline{y}(1) - \underline{y}(0)$, and in this case be *less* inclined to shirk.

The above condition can be re-written as follows.

**Assumption 1.** ***(ambiguity aversion is more impactful with high effort)***

$$\bar{y}(1) - \underline{y}(1) \geq \bar{y}(0) - \underline{y}(0).$$

This is a reasonable assumption. On either side of the above inequality, we have a measure of how much ambiguity aversion impacts subjective perception of performance. The assumption says ambiguity aversion has a larger impact on subjective perception with high effort, than with low effort. This is reasonable if objective performance variability grows with its mean, such that there is more risk (including subjective risk) when the mean is higher (more effort).

The above discussion is summarized in the following proposition.

**Proposition 1.** *With a fixed wage, more ambiguity-averse workers will be* more *inclined to shirk. With pay-for-performance, they will be* less *inclined to shirk provided Assumption 1 holds.*

The intuition for this proposition is as follows. Under pay-for-performance, risk is associated with the carrot; under a fixed wage, instead, risk is associated with the stick. Accordingly, a mood-induced increase in ambiguity aversion decreases the power of the carrot and increases the power of the stick.

# 8 Conclusions

A causal link between good mood and productivity, if established, would have profound consequences for economic theory and for business practice. In this paper we contribute to the emerging literature exploring this important link.

We leveraged a call-center dataset to explore the *causal* effect of mood on their productivity in the field through an IV strategy. The call center setting is ideal to investigate the causal effect of mood because variation in demand (a likely confounder of productivity) is national, and thus independent of our instruments – rain and sports events the day before. We find that better mood actually *decreases* our call-center workers' productivity. The effect of mood is more muted for the subset of call-center workers whose compensation depends on productivity (high-powered incentives).

We have ruled out a number of threats to the exclusion restriction: that our instruments might affect productivity through higher demand, lower pollution, more hours at work, or more time spent rearranging the workers' personal schedules. Still, a number of caveats are in order. Our results concern short-term mood shifters only. In addition, we do not study worker retention empirically. Finally, our findings relate to a specific workplace environment: call centers, where performance is mostly individual and not teamwork.

Conceptually, we have argued that a worker's productivity might be influenced by mood through risk attitudes differently depending on the shape of the compensation contract. By increasing the perceived salience of termination risk, negative mood might increase the incentives to exert effort when the wage is fixed. We want to stress that this argument does not imply that a firm should strive to worsen their workers' mood, even if they are paid a fixed wage. Among other reasons, this is because if a single firm were to artificially and permanently depress mood in its own establishment, then the workers would seek alternative employment. This effect is absent in our study because our mood variation is very short-term, and because it affects equally all establishments in a given local labor market.

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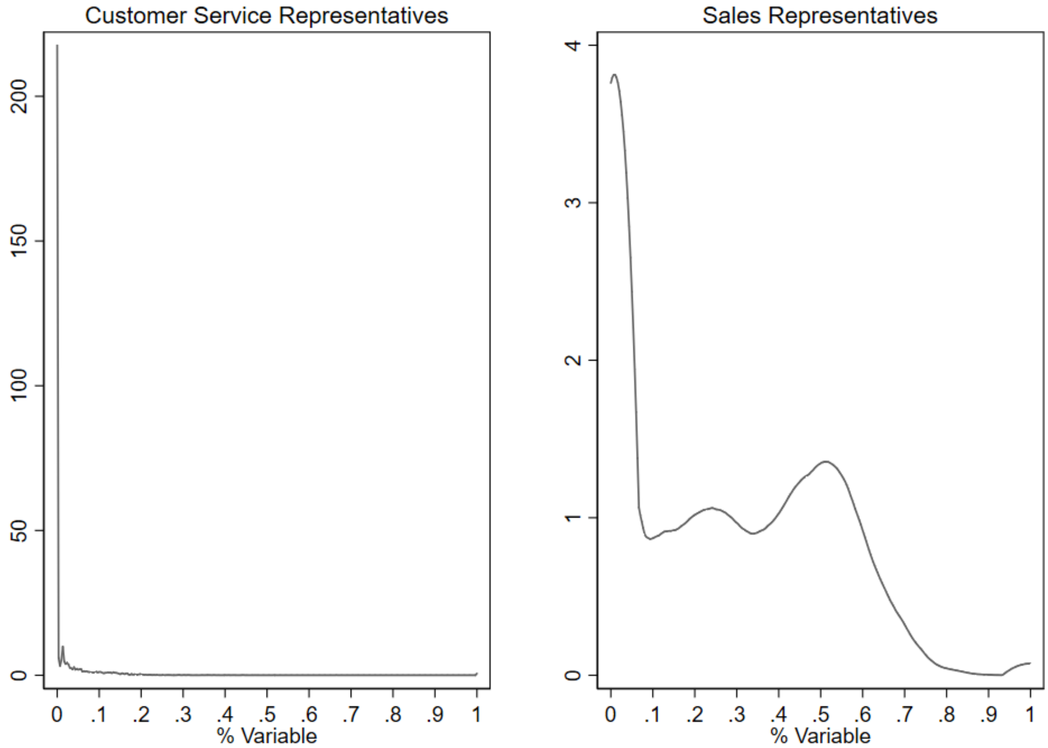
# A Appendix Tables and Figures

**Figure A.1:** Distribution of the Fraction of Earnings that is Variable




Notes: This figure presents the kernel density of the fraction of earnings that is variable – i.e., monthly variable earnings / (monthly variable earnings + monthly fixed earnings) – for customer sales representatives (left panel) and for sales repsentatives (right panel).

**Table A.1:** Correlations between Daily Productivity Measures

| | # calls per hour | # hours at work | % unprod-uctive time | Average call duration |
|---|---|---|---|---|
| # calls per hour | 1 | | | |
| # hours at work | -0.0160* | 1 | | |
| % unproductive time | -0.2700* | -0.0382* | 1 | |
| Average call duration | -0.6846* | 0.0648* | 0.1579* | 1 |
| Average customer satisfaction | 0.1763* | -0.0113* | -0.0385* | -0.1931* |

Notes: Simple pairwise correlations. *p-value<0.05. N=Workers*Days

**Table A.2:** Correlations between Mood, Weekday and Productivity

| | (1) | | (2) |
|---|---|---|---|
| Dependent Variable | Mood Score (1 to 5) [*conditional on answering mood question*] | Dependent Variable | # calls per hour [*conditional on logging in*] |
| Monday | 0.053 | Mood=Frustrated | 0.051 |
| | (0.041) | | (0.053) |
| Tuesday | 0.062* | Mood=Exhausted | 0.004 |
| | (0.036) | | (0.048) |
| Wednesday | 0.062* | Mood=So so | -0.078* |
| | (0.033) | | (0.044) |
| Thursday | 0.044 | Mood=Good | -0.114*** |
| | (0.033) | | (0.042) |
| Friday | 0.093*** | Mood=Unstoppable | -0.234*** |
| | (0.033) | | (0.044) |
| Saturday | 0.053** | | |
| | (0.025) | | |
| Observations | 35,425 | | 80,866 |
| Mean Dep.Var. | 3.8 | | 7.117 |

Notes: Sunday is the omitted group in Col. 1. "No answer to the mood question" is the omitted group in Col. 2. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1.

**Table A.3:** Mood and Productivity, Alternative Specifications

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dep. Var. | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time |
| | OLS | | IV: Rain | | IV: Sport | | IV: Rain and Sport | |
| **Panel A. Controlling for date (day*month*year) fixed effects (standard errors as in the main specification)** | | | | | | | | |
| Mood Score (1 to 5) | -0.071*** | -0.001*** | -1.170 | 0.064 | -0.965* | 0.036* | -1.025** | 0.044** |
| | (0.014) | (0.000) | (1.037) | (0.043) | (0.556) | (0.022) | (0.496) | (0.020) |
| Observations | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 |
| F-stat first stage | | | 5.725 | 5.725 | 13.40 | 13.40 | 11.57 | 11.57 |
| **Panel B. Standard errors clustered at worker & call center*week level (fixed effects as in the main specification)** | | | | | | | | |
| Mood Score (1 to 5) | -0.073*** | -0.001*** | -1.327** | 0.054** | -0.920 | 0.034* | -1.071** | 0.041*** |
| | (0.014) | (0.001) | (0.649) | (0.027) | (0.606) | (0.018) | (0.433) | (0.014) |
| Observations | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 | 35,368 |
| F-stat first stage | | | 21.07 | 21.07 | 29.27 | 29.27 | 13.86 | 13.86 |

Notes: OLS regressions. Robustness checks vary the specification (restricting to workers who answer the mood questions). *** p<0.01, ** p<0.05, * p<0.1.

**Table A.4:** Mood and Productivity, Alternative Coding

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dep. Var. | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time |
| | OLS | | IV: Rain | | IV: Sport | | IV: Rain and Sport | |
| **Panel A: Non-Response = Bad Mood [Exhausted]** | | | | | | | | |
| Mood Score (1 to 5) | -0.055*** | -0.000 | -1.439** | 0.052** | -1.491 | 0.014 | -1.452** | 0.043** |
| | (0.010) | (0.000) | (0.672) | (0.021) | (1.195) | (0.030) | (0.574) | (0.017) |
| Observations | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 |
| F-stat first stage | - | - | 14.29 | 14.29 | 5.969 | 5.969 | 9.896 | 9.896 |
| **Panel B: Assuming that not answering mood question = Neutral Mood [So-so]** | | | | | | | | |
| Mood Score (1 to 5) | -0.080*** | -0.001** | -2.144** | 0.077** | -1.410 | 0.013 | -1.825*** | 0.049** |
| | (0.013) | (0.000) | (0.967) | (0.031) | (1.071) | (0.028) | (0.691) | (0.021) |
| Observations | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 |
| F-stat first stage | - | - | 17.27 | 17.27 | 19.01 | 19.01 | 18.24 | 18.24 |
| **Panel C: Assuming that not answering mood question = Good Mood [Unstoppable]** | | | | | | | | |
| Mood Score (1 to 5) | -0.026** | -0.001*** | -4.202 | 0.151 | -1.338 | 0.012 | -2.004** | 0.045* |
| | (0.012) | (0.000) | (2.620) | (0.092) | (1.059) | (0.027) | (0.959) | (0.026) |
| Observations | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 | 80,866 |
| F-stat first stage | - | - | 4.002 | 4.002 | 17.02 | 17.02 | 10.05 | 10.05 |

Notes: OLS regressions. Robustness checks vary the assumption on how to code non-response in the mood question (using the main specification in the paper). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table A.5:** Mood and Productivity, OLS Results for the "Stores Dataset"

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Revenues | Gross margin | Ebitda | Revenues per employee-hour | Gross margin per employee-hour | Ebitda per employee-hour |
| Average Employee Mood Score (1 to 5) | -0.318*** | -0.119*** | -0.058** | -0.061*** | -0.025*** | -0.008 |
| | (0.075) | (0.030) | (0.026) | (0.018) | (0.006) | (0.005) |
| Observations | 17,407 | 17,407 | 17,407 | 17,407 | 17,407 | 17,407 |
| R-squared | 0.933 | 0.898 | 0.632 | 0.834 | 0.733 | 0.525 |
| Mean Dep. Var. | *Hidden for anonymity reasons* | | | | | |

Notes: The outcome variables vary at the store*month level. All values are in 00,000 USD. All regressions control for the total number of workers in the store, store fixed effects and month*year fixed effects. Robust standard errors clustered at store*date level are presented in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Average mood score =average mood in a store-month across workers who answered the mood question. "Gross margin" is store revenue minus cost of goods sold."'Ebitda" is store's earnings before interest, taxes, depreciation and amortization for the month. "Revenue per employee-hour" is total revenues divided by the sum of all employee hours. "Ebitda per employee-hour' is ebitda divided by the sum of all employee hours.

**Table A.6:** Mood and Weather/Sport, More First Stage Results

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Mood score (1 to 5) | | | | | | | |
| Precipitation | -0.001** | -0.001* | | | | | | |
| | (0.000) | (0.000) | | | | | | |
| Snowfall | | -0.001 | | | | | | |
| | | (0.001) | | | | | | |
| Minimum Temperature | | 0.001 | | | | | | |
| | | (0.002) | | | | | | |
| Maximum Temperature | | 0.002 | | | | | | |
| | | (0.001) | | | | | | |
| Rain | | | -0.053*** | | -0.053*** | -0.041*** | | -0.041*** |
| | | | (0.013) | | (0.013) | (0.011) | | (0.011) |
| Rain * Sales Representative | | | 0.059** | | 0.060** | | | |
| | | | (0.025) | | (0.025) | | | |
| Sport | | | | 0.031*** | 0.031*** | | 0.034*** | 0.034*** |
| | | | | (0.007) | (0.007) | | (0.006) | (0.006) |
| Sport * Sales Representative | | | | 0.001 | 0.001 | | | |
| | | | | (0.014) | (0.014) | | | |
| Rain * % Variable | | | | | | 0.420 | | 0.436 |
| | | | | | | (0.450) | | (0.452) |
| Sport * % Variable | | | | | | | -0.383 | -0.392 |
| | | | | | | | (0.417) | (0.419) |
| **F-stat first stage** | 4.212 | 2.068 | 35,368 | 16.72 | 11.75 | 7.059 | 16.65 | 11.28 |
| Observations | 35,368 | 35,368 | 0.616 | 35,368 | 35,368 | 35,306 | 35,306 | 35,306 |
| R-squared | 0.616 | 0.616 | 3.835 | 0.616 | 0.616 | 0.616 | 0.616 | 0.616 |

Notes: OLS regressions. Rain takes value 1 if it rains on day t. Sport takes value 1 if the team won on day t-1, value -1 if the team lost on day t-1 and value 0 if the team did not play in t-1. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table A.7:** Mood and Productivity, More Outcome Variables

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dep. Var. | Average call duration (minutes) | Average customer satisfaction (1 to 10) | Average call duration (minutes) | Average customer satisfaction (1 to 10) | Average call duration (minutes) | Average customer satisfaction (1 to 10) | Average call duration (minutes) | Average customer satisfaction (1 to 10) |
| | OLS | | IV: Rain | | IV: Sport | | IV: Rain and Sport | |
| Mood Score (1 to 5) | 0.066*** | -0.001 | 0.880 | -0.114 | -0.151 | 0.217 | 0.233 | 0.183 |
| | (0.015) | (0.026) | (0.661) | (2.399) | (0.542) | (0.924) | (0.403) | (0.858) |
| Observations | 35,368 | 16,005 | 35,368 | 16,005 | 35,368 | 16,005 | 35,368 | 16,005 |
| Mean Dep. Var. | 7.300 | 7.973 | 7.300 | 7.973 | 7.300 | 7.973 | 7.300 | 7.973 |
| F-stat first stage | | | 13.80 | 13.80 | 33.34 | 33.34 | 22.45 | 22.45 |

Notes: Col.1-2: OLS regressions. Col.3-8: Second stage IV regressions. All regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects. Standard errors are clustered (twoway) at worker & call center*date level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Customer satisfaction score calculates the average daily customer satisfaction score for each worker (score 1 to 10). This variable is missing if none of the customer were asked to fill the survey and/or none of the customers answered the survey.

**Table A.8:** Mood and Productivity, Other Heterogeneity Effects

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var. | # calls per hour | % un-productive time | # calls per hour | % un-productive time | # calls per hour | % un-productive time |
| | IV = Rain | | IV = Sport | | IV = Rain and Sport | |
| **Panel A. Heterogenous effects by the fraction of earnings that are variable** | | | | | | |
| Mood Score (1 to 5) | -1.252* | 0.053** | -0.448 | 0.017 | -0.992** | 0.038*** |
| | (0.702) | (0.026) | (3.116) | (0.105) | (0.410) | (0.015) |
| Mood Score* % Variable | 2.893*** | -0.049** | 54.028 | -1.776 | 2.825*** | -0.045** |
| | (0.763) | (0.023) | (378.278) | (12.617) | (0.742) | (0.021) |
| Fstat first stage | 8.680 | 8.680 | 0.448 | 0.448 | 11.640 | 11.640 |
| Observations | 35,306 | 35,306 | 35,306 | 35,306 | 35,306 | 35,306 |
| p-value (Mood + Mood*%Var.=0) | 0.088 | 0.893 | 0.888 | 0.890 | 0.026 | 0.791 |
| Mean Dep. Var. | 7.117 | 0.094 | 7.117 | 0.094 | 7.117 | 0.094 |
| **Panel B. Sub-sample of workers living < 5km from work** | | | | | | |
| Mood Score (1 to 5) | -1.518** | 0.033 | -0.051 | 0.030 | -0.868* | 0.032* |
| | (0.713) | (0.027) | (0.641) | (0.024) | (0.447) | (0.017) |
| F-stat first stage | 11.57 | 11.57 | 13.86 | 13.86 | 10.41 | 10.41 |
| Observations | 7,736 | 7,736 | 7,736 | 7,736 | 7,736 | 7,736 |
| **Panel C. Sub-sample of call-centers with no window** | | | | | | |
| Mood Score (1 to 5) | -1.559* | 0.062* | -1.063* | 0.041** | -1.235*** | 0.049*** |
| | (0.822) | (0.032) | (0.556) | (0.020) | (0.453) | (0.017) |
| Observations | 30,042 | 30,042 | 30,042 | 30,042 | 30,042 | 30,042 |
| F-stat first stage | 11.1 | 11.1 | 30.63 | 30.63 | 19.8 | 19.8 |
| Mean Dep. Var. | 7.117 | 0.094 | 7.117 | 0.094 | 7.117 | 0.094 |

Notes: Second stage IV regressions. Regressions control for worker tenure, worker fixed effects, month*year fixed effects and day of the week fixed effects, and standard errors are clustered (twoway) at worker & call center*date level. *** p<0.01, ** p<0.05, * p<0.1.