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Effect of mood and worker incentives on workplace productivity†

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ABSTRACT

We study the causal effect of mood on the productivity of call-center workers. 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 negative effect of mood is attenuated for workers whose 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 rule out a number of threats to the exclusion restrictions, and discuss the mechanisms that could generate our findings (*JEL* J24, J28, M52, C26).

1. INTRODUCTION

This article studies the relationship between good mood and productivity in an observational setting. We find that the relationship is mediated by the incentive scheme: the relationship is negative for fixed-wage workers, but it is attenuated for workers whose pay depends majorly on performance.

Documenting that the effect of mood varies by incentive scheme is important because the best-identified studies in the prior literature (Oswald et al. 2015; Bellet et al. 2019) focus specifically on workers who are paid for performance. But only a small fraction of US workers are paid based on their performance—most are paid a fixed wage.[1] If the relationship

[1] Using data from the U.S. Bureau of Labor Statistics' Employer Costs for Employee Compensation (ECEC), Gittleman and Pierce (2013) report that less than 20% of hours are worked in incentive pay jobs or are rewarded with "types of nonproduction bonuses that seem to be specifically designed to align pay with performance" (page R5).

between mood and productivity differs by incentive scheme, perhaps the existing literature is less informative than might at first appear about the effect of mood in the "average job."

We observe the workers of nine call centers that are owned by a single nation-wide retailer and located in different US states. All the calls made to the retailer's single nationwide telephone number are routed to these call centers for processing. A call center worker's daily productivity is measured by the number of calls per worker/hour, and by other measures including downtime. Mood is measured through an online "mood questionnaire" which the workers are encouraged to fill out daily.[2] We use two instrumental variables for mood: local weather and win/loss of a local sports team. The panel structure of the data (i.e., workers in different locations observed for many days) allows us to use worker-fixed effects and, therefore, to leverage within-worker variation in mood. Helpfully, call-center demand is national and, thus, its variation (a likely confounder of productivity) in independent of local shocks to mood.

Across all workers, we find that better mood decreases productivity. We instrument for mood with local rain on the same day, or 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 either of the two instruments (rain or sport), or both instruments combined, the second-stage estimates show that positive mood significantly reduces the number of calls answered by the workers and increases the share of "unproductive" time workers spends off the phone and unavailable to receive a call. Mood affects neither average call duration nor customer satisfaction scores.

Looking across incentive schemes, we find that the negative effect of positive mood is strongest for workers whose entire compensation is administratively coded as "fixed pay" (these are more than 80% of the observations), and weaker for workers who receive some pay that is coded as "variable." The effect of mood even crosses into positive territory for workers whose pay is mostly variable. This finding needs to be taken with a grain of salt because the size of the variable component of pay 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 finding also holds within work description, with sales representatives who have a larger variable component reacting more favorably to positive mood than sales representatives with a small variable component.

The causal interpretation of the IV 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 United States 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 Barbeque (BBQ)). 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

2 The mood questionnaire arises from the company's desire to measure worker engagement. See Figure A1.

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 productivity? We consider two. First, worse mood might decrease sociability and increase productivity. 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 2004). Both effects have been documented in the literature.[3] We find suggestive evidence in favor of the second mechanism, but we do not have sufficient empirical evidence to reject the first mechanism.

The article proceeds as follows: Section 2 discusses the related literature on mood and productivity; Section 3 presents statistics and explains our institutional context. Section 4 identifies the correlation and the causal effect of mood on productivity: Ordinary Least Squares (OLS) and Instrumental Variables (IV) results, respectively, and discusses potential threat to the IV identification strategy. Section 5 explores the heterogeneous effect by compensation scheme and discusses the possible mechanisms underlying our results. Section 6 concludes.

2. LITERATURE ON MOOD AND PRODUCTIVITY

"Mood" in our article 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. (2016) 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. 2016: 40).[4] 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 laboratory, 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 article comes as close as possible to demonstrating that mood *causally* affects "work-like" behavior. As mentioned before, Bellet et al. (2019) is closest to our article in identification strategy, but the results are the opposite: good mood causes higher performance. We propose two theories that can account for the difference based on the fact that pay-for-performance is more prevalent in their setting.[5] 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 firm, and rationally respond by working harder quite independently of shifts in mood.

[3] See Section 5 for a description of the literature.
[4] Gallup Inc. has measured workplace well-being for decades, and has long supported the notion of a link between well-being 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."
[5] Seventy percent of their workers receive a "large performance bonus" (Bellet et al. 2019: 23).

3. DATA AND INSTITUTIONAL SETTING

Our call-center data cover 2720 workers located in nine call centers across nine different US states from January 2015 to February 2016. In total, 72% of call centers workers are females. While average tenure is high (38 months), median tenure is only 13 months, and the first quartile of the tenure distribution is only 5 months. This speaks to a skewed distribution with a few "career" employees, many "short-term" employees, and a higher termination rate.

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 Information Technology (IT) system and calls are automatically routed into her headset. A call from any location in the United States 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. Workers fill two positions: customer service representatives, which represent 82% of the workforce, and sales representatives. Customer service representatives perform three main tasks: they (1) provide information about products and services, (2) respond to customer complaints, and (3) process returns. Sales representatives also perform three main tasks, some of which overlap with customer service representatives: they (1) provide information about products and services, (2) recommend products, and (3) sell products.[6] Workers in the two positions differ in the extent to which their compensation is variable (more on this below).

Table 1 presents the summary statistics on productivity, earnings, and mood for the average call center worker (in Columns 1–3), for customer service representatives (in Columns 4–6), and for sales representatives (in Columns 7–9).

3.1 Productivity data

The IT records provide us with detailed information on the workers' daily productivity (see Table 1, Panel B). For each worker, we know the number of working hours (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 7.1) and the average call duration (7 min 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 36% of the calls; this may be because not all customers are selected to answer these questions, or because not all customers choose to answer them. In the latter case, an issue of selection arises, but we have no visibility of customer non-response, so we take these numbers at face value.

Our preferred measure of productivity is the "number of calls per hour." (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).[7] We do not focus on the number of working hours as a key outcome variable because: (1) workers are compensated hourly and (2) work 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.

[6] The call-center workers we study in this article are different from those in Coviello et al. (2022). Neither position is segregated in specific call-center locations.

[7] In Table A1, we show that 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

Sample	(1)	(2) All workers	(3)	(4)	(5) Customer service representatives (CSR)	(6)	(7)	(8) Sales representatives (SR)	(9)
	Obs.	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Mean**	**SD**
Panel A. Demographics (N = Workers)									
Female = {0, 1}	2720	0.72	0.45	2304	0.73	0.44	416	0.65	0.48
Age	2720	33.61	13.85	2304	34.17	14.08	416	30.95	12.42
Tenure (in months)	2708	37.49	57.64	2292	37.76	58.11	416	30.00	53.61
Panel B. Productivity (N = Workers * Days)									
Number of hours at work	232,292	6.30	1.94	182,125	6.32	1.93	50,166	6.24	1.98
Proportion of unproductive time (in %)	232,292	0.10	0.07	182,125	0.09	0.07	50,166	0.10	0.06
Number of calls per hour	232,292	7.08	2.85	182,125	6.75	2.95	50,166	8.29	2.06
Average call duration (in minutes)	232,292	6.95	3.25	182,125	7.16	3.54	50,166	6.18	1.65
Average daily customer satisfaction (1–10)	84,965	7.94	2.68	55,850	7.46	2.93	29,115	8.86	1.78
Sales per hour	—	—	—	—	—	—	46,988	238.51	162.04
Panel C. Earnings (N = Workers * Months)									
Earnings per hour (gross)	15,850	12.19	2.40	12,736	11.81	1.05	3114	13.78	4.65
Fixed earnings per hour (gross)	15,850	11.20	1.17	12,736	11.58	0.92	3114	9.62	0.64
Variable earnings per hour (gross)	15,850	1.00	2.68	12,736	0.23	0.63	3114	4.16	4.75
Panel D. Worker Mood (N = Workers * Days)									
Worker logs into platform = {0, 1}	232,292	0.35	0.48	182,125	0.34	0.48	50,166	0.37	0.48
Conditional on logging into platform...									
Worker answers mood question = {0, 1}	81,106	0.44	0.50	62,641	0.42	0.49	18,465	0.50	0.50
Conditional on answering mood question ...									
% who feel "frustrated"	35,715	0.07	0.26	26,473	0.07	0.26	9242	0.07	0.25
% who feel "exhausted"	35,715	0.07	0.25	26,473	0.07	0.26	9242	0.05	0.21
% who feel "so so"	35,715	0.17	0.37	26,473	0.18	0.38	9242	0.14	0.34
% who feel "good"	35,715	0.36	0.48	26,473	0.37	0.48	9242	0.33	0.47
% who feel "unstoppable"	35,715	0.34	0.47	26,473	0.31	0.46	9242	0.42	0.49
Mood scores (1–5)	35,715	3.84	1.17	26,473	3.78	1.17	9242	4.00	1.16

(continued)

Table 1. (continued)

Sample	**(1)**	**(2) All workers**	**(3)**	**(4)**	**(5) Customer service representatives (CSR)**	**(6)**	**(7)**	**(8) Sales representatives (SR)**	**(9)**
	Obs.	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Mean**	**SD**
Panel E. Worker Mood Response Behavior (N = Workers)									
% workers who never answered mood question	2720	0.37	0.48	2301	0.40	0.49	419	0.21	0.40
Conditional on answering mood question at least once . . .									
Average number of times mood question is answered in a month	1712	3.40	4.02	1379	3.39	4.01	333	3.42	4.07
% workers who answered mood question at least twice per month	1712	0.45	0.38	1379	0.46	0.38	333	0.44	0.35

Notes: Columns (1)–(3) present statistics on the full sample of workers, while Columns (4)–(6) (respectively, 7–9) is restricted to customer service representatives (respectively, sales representatives). Panel A displays the mean and standard deviation of worker-level socio-economic background. Panel B 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 (scores 1–10). 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 1–5 where 1 is "feeling frustrated" and 5 is "feeling unstoppable." Panel E displays worker-level statistics on the mood response behavior. The average number of times the mood question is answered in a month is restricted to months in which the worker is employed.

Customer service representatives work a similar number of hours per week as sales representatives and are "unproductive" the same portion of time. They typically receive fewer calls per hour (6.75 calls per hour versus 8.29 for sales representatives) but stay a minute longer on these calls on average (7.16 versus 6.18 min per call).

3.2 Earnings data

Customer service representatives are paid a fixed hourly rate (mean is 11.8 dollars per hour) and earn effectively no commission (variable pay; see Table 1, Panel C). 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."[8] In sum, relative to customer service representatives, sales representatives have a larger share of their compensation that is productivity-based: this pattern is shown in Figure A2.

3.3 Mood data

Mood is measured through an online "mood questionnaire" which the workers are encouraged to fill out: see Figure A1. Conditional on answering the mood question, 70% of respondents report feeling either "good" or "unstoppable," while only 14% report feeling "exhausted" or "frustrated" (Table 1, Panel D). The mood score takes integer value ranging from 1 for "frustrated" to 5 for "unstoppable;" and averages 3.8 among respondents. Individual responses to the mood questionnaire are anonymous: call center managers are only provided with monthly summary statistics aggregated at the call-center level. Workers know that their responses are anonymous and thus have limited incentive to misreport their mood.[9]

Importantly, variation in mood score exists both *between* workers (SD: 1.36) and also *within* workers (SD: 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.

The mood questionnaire is presented to the worker upon logging into a particular software platform and is available once per day. Logging in is required to access a number of Human Resources (HR) functions including tracking their pay information, accessing online training, setting one's quarterly goals, and giving and receiving performance feedback. A worker who logs into the platform may decline to answer the mood question by clicking an "exit" button.

Not all workers answer the mood questionnaire daily, either because they do not log in to the platform (65% of our worker $\times$ day observations are non-loggers in), or because they click out conditional on logging in (probability 56%).[10] In our main results, we follow the most conservative approach and code all non-responses as missing observations, thus effectively reducing the sample from 232,292 to 35,715 observations. The smaller sample will be referred to as the "main sample."

The selection of workers into the main sample is a potential concern. However, the main sample of workers who answer the mood question is similar to the set of all workers based

[8] We do not focus on "sales per hour" as a measure of productivity because the variable is recorded only for a subsample of the workers (the sales representatives).

[9] As a validation check of our mood data, we correlate reported mood with "days of the week" in Table A2, Column 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).

[10] The average worker in our sample answers the mood question 3.4 times per month, with 5% of workers answering the mood question more than 12 times per month. Among workers whom we observe answering the mood question at least once, 45% answered the question at least twice per month on average. See Table 1, Panel D for these statistics.

on observables—and, reassuringly, the same is true of the sample of loggers-in. Table A3, Panel A shows that workers who answer the mood question at least once (Columns 7–9), or who log into the platform at least once (Columns 4–6), look similar in terms of gender, age, and tenure, to the full worker population (Columns 1–3). Moreover, logging into the platform or answering the mood question on a specific day does not appear to correlate with daily productivity or monthly earnings (Panels B and C). Finally, Table 5 (Columns 1 and 2) shows that a worker's daily mood (proxied with our weather and sports instruments) has no effect on the worker's choice to login or to answer the mood question; this finding supports the notion that a given worker's choice to log in or to answer the mood question is largely determined by considerations other than mood. In sum, while sample selection is possible in theory, it appears to be a minor factor in the sample composition.

Later in the article, we will pursue a different approach to assessing the robustness of our estimates to selection concerns: we will impute an answer to the non-respondents. We find that the results are robust to coding "no answer" as "bad mood" (frustrated), and also to imputing an intermediate mood score.

Looking across worker positions, sales representative are more likely than customer service representatives to have answered the mood question at least once (80% versus 60%; Table 1, Panel E). To account for the difference in response frequency, we will control for it when we estimate the heterogeneous effect of mood on productivity by worker type.[11]

4. THE EFFECT OF MOOD ON PRODUCTIVITY

4.1 OLS results

The correlation between mood and productivity in the entire sample of call-center workers is reported in Table A4. 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 $\times$ year-fixed effects, and control for worker tenure. The results show that a higher mood score is *negatively* correlated with the number of calls per hour (Column 1): a one-unit increase in mood decreases the number of calls per hour by 0.073 (1%). Such correlation is relatively linear across the different moods: the higher the mood score, the lower the number of calls per hour (see Table A2, Column 2).[12]

There are two reasons to believe that these OLS estimates may underestimate the negative 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.[13] 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

[11] We thank a referee for this suggestion.

[12] The correlation between mood and "the proportion of *unproductive* time" is also negative but very small in magnitude (Table A4, Column 2).

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

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 yield quantitatively similar estimates for the effect of mood.

4.2 IV First-stage results

4.2.1 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 (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 zip code 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, that is, whether precipitations are strictly positive, which is known to correlate with sunshine. As shown in Table 2, 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 A5, Columns 1 and 2) and hence we prioritize "rain dummy" as our instrument. In our sample, 28% of the days were rainy. Importantly, the variation in rain exists both within a day *across* localities (SD: 0.1) and also *within* locality across days (SD: 0.44). The within-location portion of the variation is sizable. Because we use worker (and hence location)-fixed effects, identification will come from within-locality variation.

4.2.2 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.[14] 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 2, Column 2). Combining the sport and the rain instruments leads to a joint *F*-statistic of 22.5 (Table 2, Column 3).[15]

[14] We obtained sports outcomes of all regular and post-season games played by teams of Major League Baseball, National Football League, National Basketball League, and National Hockey League. 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 were collected from the website Sports Reference (www.sports-reference.com). At the time of collection, College Baseball data were not available to download from Sports Reference and the data were collected directly from the team's website instead. 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).

[15] Table A5 (Column 3) presents the first stage for each sport separately. The coefficient is positive and significant for each sport. This is consistent with each sport being popular in our setting.

Table 2. Mood and weather/sport, first-stage IV results

	(1)	(2) Mood scores (1–5)	(3)
Rain	−0.037***		−0.036***
	(0.010)		(0.010)
Sport		0.032***	0.031***
		(0.005)	(0.005)
Observations	35,368	35,368	35,368
Mean Dep. Var.	3.835	3.835	3.835
F-stat first stage	13.80	33.34	22.45

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 (two-way) at worker and call center*date level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 IV Second-stage results

Our second-stage estimates are presented in Table 3. 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.[16]

These estimates persist with the day×month×year-fixed effects (Table A6, Panel A) or if we allow for autocorrelation at short horizon by clustering standard errors at the call-center×week level (Table A6, Panel B). The results are also robust to using 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 A7.[17]

A reduction in the "number of calls handled per hour" can be explained by two possible channels: either calls become longer or workers spend less of their time on the phone. Table 3 shows that the latter is the case. 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 3–5 percentage points depending on the instrument. This corresponds to an increase of between 36.1% and 57.4% of unproductive time. Table A9, moreover, shows that mood affects neither average call duration nor customer satisfaction scores. Finally, mood appears to reduce the hourly sales of sales representatives (customer service representatives do not make sales) but these estimates are not precise, potentially due to a weak first stage.

16 We can alternatively estimate the effect of each discrete level of mood on productivity implementing the two stages control–function approach developed by Trezza (1987) and Vella (1993). This approach requires: in the first stage, to estimate an ordered probit model where the dependent variable is the ordinal variable mood and the instruments (and the controls) are the same as in our main estimates; in the second stage, to control for the ordered probit generalized residuals and estimate with OLS a model with four indicators for each discrete level of mood. When doing so, the results are broadly consistent with the notion that being in a better mood reduces productivity. Results available upon request.

17 Table A7 is restricted to the sample of 81,106 days in which workers log into the software platform. Table A8 replicates this robustness analysis with the full sample of 232,292 worker-days (days in which the workers log or do not log into the platform). The direction of the results is qualitatively similar, albeit less precise.

Table 3. Mood and productivity, second-stage IV results

Dep. Var.	(1) # calls per hour	(2) % unproductive time	(3) # calls per hour	(4) % unproductive time	(5) # calls per hour	(6) % unproductive time
	IV: Rain		IV: Sport		IV: Rain and Sport	
Mood scores (1–5)	−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

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 (two-way) at worker and call center * date level. % unproductive time = % time not spent on the phone with customers or not spent being available to receive phone calls.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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.

4.4 Concerns regarding the exclusion restriction

The size of the IV estimates is 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. We do this next.

4.4.1 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. For example, 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*.[18] 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 4, Column 2). Second, we show that our rain and sports instruments have no direct effect 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 5, Columns 3 and 4. Finally, we find that the results hold if we restrict the sample to workers who live less than 10 km from the workplace and who are therefore less likely to be delayed by weather-related traffic in getting to work (Table A10, Panel A).

Another related concern is that the presence of rain, or having watched a sports game the previous day, could make the worker be late for work. If a worker missed some morning hours and compensated by working more hours in the evening, and if mornings have more customer calls than evenings, being late could affect productivity *even if the total number of hours are held fixed*. This alternative story is unlikely in our context because our workers' schedules are determined one week in advance by the firm; so if a worker shows up late for work, we would expect her to work fewer hours that day. But we do not observe this in the data.

18 The raw correlation between these two variables is presented in Table A1 and is negative. So, if anything working fewer hours should result in more calls per hours rather than less.

Table 4. 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 scores (1–5)	−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 scores (1–5)	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
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
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

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 (two-way) at worker & call center*date level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. The reduced-form effects on logging-in, mood answer, demand, and productivity

	(1) Logs in the platform	(2) Answers mood question	(3) # hours at work	(4) # workers present at work	(5) # daily incoming calls (in '000)	(6) # calls per hour (conditional on answering mood question)	(7)
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	2403	2403	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	2403	2403	35,368	
Mean Dep. Var.	0.349	0.154	7.316	96.67	8.291	7.083	

Notes: Worker-level regressions (columns (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 (two-way) at worker and call center*date level. Call-center level regressions (columns (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 three 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). Rain (respectively, lead rain) is a dummy variable that takes values 1 if it rains at time t (respectively, $t+1$).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.2 *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, and 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 5, Column 5). The absence of confounding variation from the demand side is a key advantage of a call-center setting. Finally, Table 4 shows that the results are robust to controlling for the "number of calls incoming."

4.4.3 *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 4, 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 A6, Panel A). Another concern is pollution. Pollution has been shown to reduce worker productivity in call-center settings (Chang et al. 2019), and it may correlate with rain. In Table 4, we show that the results hold if we control for temperature (which is related with daily pollution).[19]

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

[19] 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.

4.4.4 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 to mind. First, that weather might affect productivity through distraction-on-the-job, that is, 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). 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 A10 (Panel B) 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. Columns 6 and 7 of Table 5 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 (reduced form).

5. AN EXPLORATION OF POSSIBLE MECHANISMS

Section 4 has shown that better mood decreases worker productivity. This section explores possible mechanisms. First, we examine the heterogeneous effect of mood on productivity by the worker's share of realized monthly compensation that is productivity based, that is, the fraction of their monthly pay that is recorded by the firm as "variable." Then, we use this evidence to tentatively illuminate the possible mechanisms underlying the results.

5.1 Heterogeneous effects by "fraction of variable pay"

We seek to assess whether the adverse effect of positive mood on productivity depends on the compensation structure. To this end, 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," and instrument these two variables with rain/sport and rain/sport interacted with the "fraction of pay that is variable." As before, we include worker-fixed effects to control for time-invariant worker characteristics (such as ability), day-of-the-week-fixed effects, month$\times$year-fixed effects, and worker tenure. Because the "fraction of pay that is variable" correlates with other job$\times$worker characteristics, we further control for tenure, gender, and the number of times the worker answered the mood question in the average month—and their interactions with the instruments.[20] The IV first-stage results are presented in Table A11 (Columns 1–3).[21]

Figure 1 (and the corresponding Table A10, Panel C) presents the second-stage heterogeneous effects. Using rain 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

[20] We chose this list of controls because they differ substantially between sales representatives (whose pay is mostly variable) and customer service representatives (whose pay is mostly fixed). See Table 1.

[21] We find no significant heterogeneous effects of our instruments on mood by "fraction of pay that is variable." The coefficients for "rain$\times$% variable" and "sport$\times$%variable" are not statistically significant. The F-statistic is above 10 in all regressions.

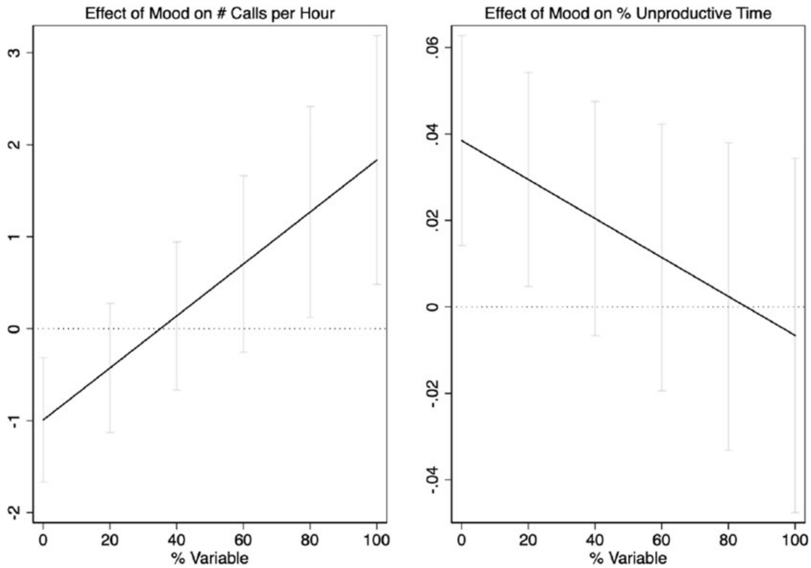

Figure 1. Mood and productivity by the fraction of earnings that are variable.

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

for workers whose pay is 20%–60% variable. In the left-hand panel—where the outcome variable is the number of calls per hour—positive mood even attains a positive effect for workers whose pay is more than 80% variable.[22]

The heterogeneous effects by "fraction of variable pay" are similar when we restrict the analysis to the sub-sample of sales representatives: see Figure A3, left panel.[23] This indicates that the heterogeneous effects do not arise solely from differences in tasks across occupations. In addition, for sales representatives, worker productivity can also be measured with "sales per hour:" Figure A3 (right panel) shows that the heterogeneous effects are similar for this variable also.

In sum, the adverse effect of positive mood on productivity is mostly restricted to workers who are on fixed wage. These findings need to be taken with a grain of salt because realized compensation, even though measured at the monthly level, is endogenous to daily performance. One way to ameliorate this endogeneity concern is to compare workers across occupational categories. Customer service representative is paid almost entirely based on a fixed wage, whereas sales representative is partly compensated based on performance (30% of their earnings are based on performance). Table 6 shows that the effect of mood on productivity tends to be less negative for the subsample of sales representatives. Indeed, the coefficients on the interaction term "mood score×sales representative" have opposite sign to the "mood score" variable in all columns except Column 3. These interaction coefficients, however, are only precisely estimated for the fraction of unproductive time (Columns 2 and 6). Using rain as an IV for mood, it appears that the "the fraction of unproductive time" is 25% 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

[22] Note that the mass of workers with variable pay above 80% is small in our data and this is why standard errors are wide.

[23] We cannot restrict the analysis to the sub-sample of customer service representatives as the variable portion of their pay is nearly always zero (see Figure A2).

Table 6. Mood and productivity by incentive structure, second-stage IV results

Dep. Var.	(1) # calls per hour	(2) % unproductive time	(3) # calls per hour	(4) % unproductive time	(5) # calls per hour	(6) % unproductive time
	IV = Rain		IV = Sport		IV = Rain and Sport	
Mood scores (1–5)	−0.818*	0.025	−0.806	0.033	−0.820**	0.028**
	(0.454)	(0.017)	(0.510)	(0.020)	(0.335)	(0.013)
Mood score* sales representative	0.020	−0.008**	−0.138	−0.012	0.017	−0.008**
	(0.107)	(0.003)	(0.630)	(0.022)	(0.107)	(0.003)
Observations	35,316	35,316	35,316	35,316	35,316	35,316
p-value (mood + mood*sales rep = 0)	0.071	0.266	0.141	0.436	0.015	0.098
Mean Dep. Var.	7.117	0.094	7.117	0.094	7.117	0.094
F-stat first stage	14.023	14.023	10.155	10.155	12.504	12.504

Notes: Second-stage IV regressions. As IV, we use rain (Columns (1)–(2)), sport (Columns (3)–(4)), rain and sport (Columns (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. They also control for the interaction between the IV(s) and worker tenure, being a male, and the number of mood questions answered in a month. Standard errors are clustered (two-way) at worker and call center*date level. % 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

instrument for mood: sales representatives as 63% less responsive to mood.[24] Overall, this cross-occupation comparison confirms that the negative effect of positive mood is mostly restricted to workers who are paid a fixed wage.

5.2 Possible mechanisms

Overall, this section has shown that the negative effect of mood on productivity is moderated by the workers' compensation scheme: the more pay depends on performance, the more the relationship between positive mood and productivity improves, ultimately becoming positive for the few workers whose variable portion of compensation is the highest, though this is more speculative given the small sample size.

These findings are consistent with at least two behavioral models. The first model is one where the key channel is sociability: with fixed pay, better mood increases sociability (time around the water cooler) which, in turn, decreases productivity; with variable pay, time is money for the worker, and so no-one hangs around the water cooler, regardless of their mood.[25]

The second behavioral model is based on the worker's incentives to exert effort. With fixed wages, the only incentive to exert effort is the fear of being fired; but when wages are variable, the incentives come from the rewards to high productivity. Mood affects these two incentive schemes differently. We posit that a worse mood makes the worker more ambiguity-averse, that is, more prone to focus on the most negative risk realizations—on the worse-case scenario.[26] In a context like ours—with a high turnover rate and a large fraction

[24] The first-stage results are presented in Table A11 (Columns 4–6). The sport instrument equally affects the mood of both types of workers (i.e., the interaction term "sport×sales representative" is small and not significant). The effect of rain on mood is negative for both types of workers, but less so for sales representatives than customer service representatives (i.e., the interaction term "rain×sales representative" is positive and significant). The *F*-statistic is above 10 in all regressions.

[25] Inducing a better mood experimentally has been shown to increase subjects' vulnerability to distractions (Pacheco-Unguetti and Parmentier 2016), and to increase sociability (see Cunningham (1988) and the literature cited therein).

[26] 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 and Smith (2008) summarize this literature as follows: "In general, induced positive

of workers with very little tenure (see Section 3)—it is likely that the worker's worse-case scenario is being fired. Since fixed-wage workers are motivated solely by the fear of being fired, we expect these workers to work less when their mood is better. This is because they are momentarily less ambiguity-averse—and thus less fearful of being fired. By contrast, workers on variable pay are less motivated by the fear of being fired. Instead, these workers are partly motivated by the chance of being highly productive. In this context, ambiguity averse workers may fear that no matter how hard they work, nature will ensure that their output is low, and so will be demotivated. But when hit by a better mood, these workers may believe that nature is fair and thus they will become more motivated.[27] Thus, it is possible that good mood may increase the motivation of workers who are paid for performance.

Adjudicating between these two models is beyond the power of our data. However, there are two pieces of evidence that point slightly toward the incentive model. First, Figure 1, as well as the existing literature (Oswald et al. 2015; Bellet et al. 2019) find a positive effect of positive mood on variable pay workers, which is inconsistent with the sociability channel but consistent with the incentive/ambiguity channel. Second, the negative effect of positive mood on the number of calls exists exclusively for the sample of short-term employees, who presumably fear termination more than career employees who are more established. This, too, is consistent with the notion that the fear of termination moderates the effect of mood on productivity.[28]

6. CONCLUSIONS

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

We leverage a call-center dataset to explore the *causal* effect of mood on individual worker productivity. 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 instrumental variables for mood—rain, and previous-days sporting events. 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 rule 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.

We discuss two mechanisms through which short-term mood shifts might affect productivity. First, a worse mood might increase productivity by decreasing sociability. Second, a worse mood might make the worker more ambiguity averse. We find suggestive evidence in

mood produces increased risk taking." Otto and Eichstaedt (2018) use very similar instruments to ours (sunny days and wins by the local sport team). They document that, at the city level, positive mood is associated with risk taking (lottery participation).

[27] Refer to the model in Appendix B.

[28] Figure A4 shows the heterogeneous effect of mood by the "fraction of pay that is variable" for "short-term employees" (with tenure below the median of 13 months) versus "career employees" (with tenure above the median). In line with the ambiguity aversion channel, the negative effect of mood on the number of calls exists exclusively for the sample of short-term employees.

favor of the second mechanism, but we do not have sufficient empirical evidence to reject the first mechanism.

We want to stress that our findings do 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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APPENDIX A

Figure A1. Screenshot of mood questionnaire.

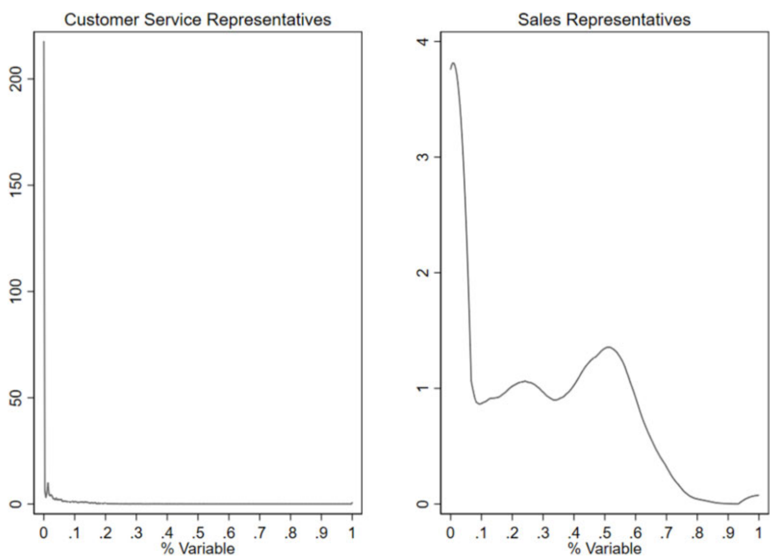

Figure A2. Distribution of the fraction of earnings that is variable.

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

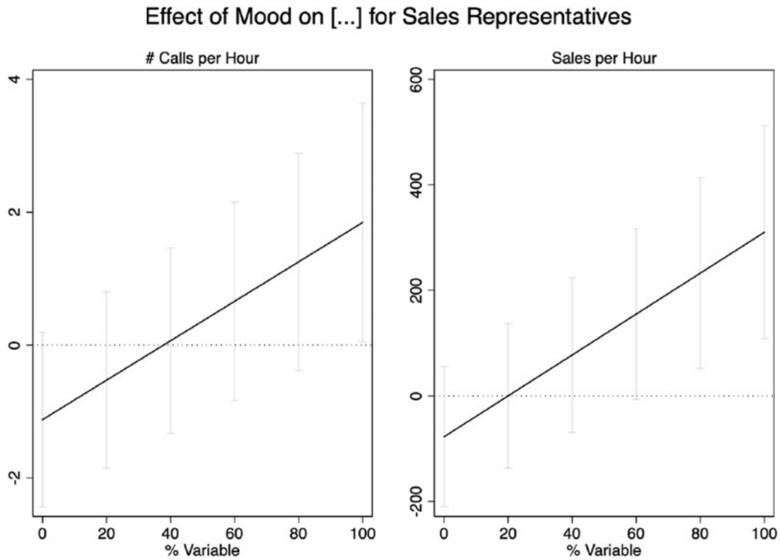

Figure A3. Mood and productivity by the fraction of earnings that are variable—sample of sales representatives.

Notes: Sample restricted to sales representatives. This figure presents the effect of mood scores (1–5) on the number of calls per hour (left panel) and sales per hour (right panel) by the fraction of earnings that are variable. Vertical bars are 90% confidence intervals.

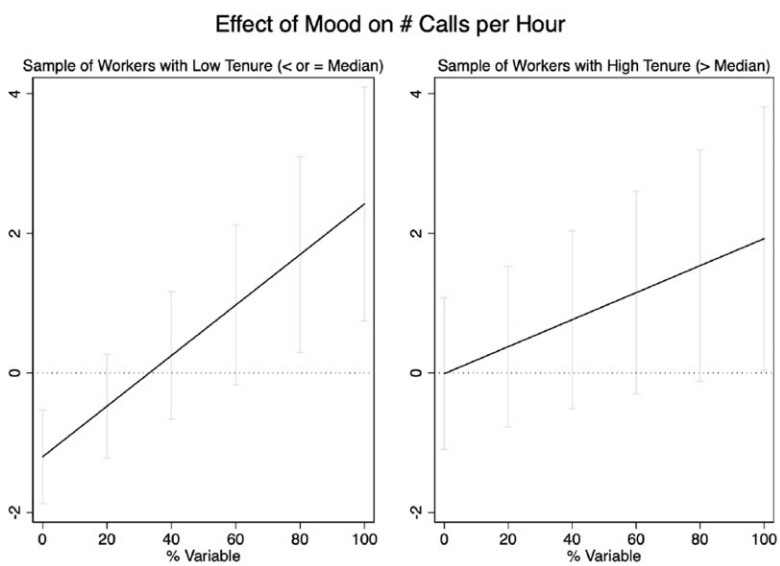

Figure A4. Mood and productivity by the fraction of earnings that are variable—low versus high tenure workers.

Notes: This figure presents the effect of mood scores (1–5) on the number of calls per hour by the fraction of earnings that are variable for (i) low tenure workers (left graph) and (ii) high tenure workers (left graph). Vertical bars are 90% confidence intervals. In both panels, the overwhelming majority of the observations lie at the extreme left of the horizontal axis (recall that 80% of the observations have negligible variable pay). In line with the ambiguity aversion channel, the effect of mood on the number of calls is negative only in the left panel, that is, exclusively for the sample of short-term employees.

Table A1. Correlations between daily productivity measures

	# calls per hour	# hours at work	% unproductive time	Average call duration	Average customer satisfaction
# 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*	1
Sales per hour	0.2998*	0.1701*	−0.0157*	−0.1604*	0.1822*

Notes: Simple pairwise correlations. N = Workers * Days. The variable "sales per hour" is available for sales representatives only.

* $p < 0.01$.

Table A2. Correlations between mood, weekday, and productivity

Dep. Var.	(1) Mood score [conditional on answering mood question]	Dep. Var.	(2) # 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 Column (1). "No answer to the mood question" is the omitted group in Column (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 (two-way) at worker and call center * date level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3. Summary statistics by log-in and mood response behavior

Sample:	(1)	(2) All observations	(3)	(4)	(5) Conditional on logging into the platform	(6)	(7)	(8) Conditional on answering the mood question	(9)
	Obs.	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Mean**	**SD**
Panel A. Demographics (N = Workers)									
Female = {0, 1}	2720	0.72	0.45	2127	0.72	0.45	1712	0.72	0.45
Age	2720	33.61	13.85	2127	33.12	13.59	1712	32.68	13.37
Tenure (in months)	2708	37.49	57.64	2125	32.57	52.17	1710	30.54	50.49
Panel C. Earnings and Termination (N = Workers * Months)									
Number of hours at work	232,292	6.30	1.94	81,106	6.49	1.84	35,715	6.46	1.88
Proportion of unproductive time (in %)	232,292	0.10	0.07	81,106	0.09	0.06	35,715	0.10	0.06
Number of calls per hour	232,292	7.08	2.85	81,106	7.12	2.89	35,715	7.06	2.86
Average call duration (in minutes)	232,292	6.95	3.25	81,106	7.30	3.29	35,715	7.43	3.32
Average daily customer satisfaction (1–10)	84,965	7.94	2.68	36,899	7.97	2.64	16,363	8.10	2.56
Panel C. Earnings (N = Workers * Months)									
Earnings per hour (gross)	15,850	12.19	2.40	10,324	12.24	2.71	6088	12.23	2.84
Fixed earnings per hour (gross)	15,850	11.20	1.17	10,324	11.05	1.11	6088	11.00	1.10
Variable earnings per hour (gross)	15,850	1.00	2.68	10,324	1.19	3.04	6088	1.24	3.15

Notes: Columns (1)–(3) present statistics on the full sample of observations, while Columns (4)–(6) (respectively, 7–9) are conditional on logging into the platform (respectively, conditional on answering the mood question). Panel A displays the mean and standard deviation of worker-level socio-economic background. Panel A columns (4)–(6) (respectively, 7–9) restrict the sample to workers who logged into the platform (respectively, answered mood question) at least once in our data. Panel B 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 (scores 1–10). 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.

Table A4. Mood and productivity, OLS results

Dep. Var.	(1) **# calls per hour**	(2) **% unproductive time**	(3) **Average call duration (minutes)**	(4) **Average customer satisfaction (1–10)**	(5) **Sales per hour [Sample = Sales representatives]**
Mood scores (1–5)	−0.073***	−0.001***	0.066***	−0.001	2.453
	(0.014)	(0.000)	(0.015)	(0.026)	(1.726)
Observations	35,368	35,368	35,368	16,005	12,362
Mean Dep. Var.	7.117	0.094	7.300	7.973	179.8

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 (two-way) at worker and call center * date level. % unproductive time = % time not spent on the phone with customers or not spent being available to receive phone calls. The customer satisfaction score calculates the average daily customer satisfaction score for each worker (scores 1–10). This variable is missing if none of the customer were asked to fill the survey and/or none of the customers answered the survey. The variable "sales per hour" is available for sales representatives only.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5. Mood and weather/sport, more first-stage IV results

	(1)	(2) **Mood scores (1–5)**	(3)
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)	
Sport: Baseball			0.017**
			(0.007)
Sport: Hockey			0.044***
			(0.014)
Sport: Basketball			0.032**
			(0.013)
Sport: Football			0.045**
			(0.022)
Observations	35,368	35,368	35,368
F-stat first stage	4.212	2.068	9.698

Notes: OLS regressions. In Column (3), sport takes value 1 if the team (in each specific league) 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 (two-way) at worker and call center*date level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6. Mood and productivity, alternative specifications

Dep. Var.	(1) # calls per hour	(2) % un-productive time	(3) # calls per hour	(4) % un-productive time	(5) # calls per hour	(6) % un-productive time	(7) # calls per hour	(8) % 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 scores (1–5)	−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 and call center*week level (fixed effects as in the main specification)								
Mood scores (1–5)	−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 A7. Mood and productivity, alternative coding

Dep. Var.	**(1) # calls per hour**	**(2) % un-productive time**	**(3) # calls per hour**	**(4) % un-productive time**	**(5) # calls per hour**	**(6) % un-productive time**	**(7) # calls per hour**	**(8) % un-productive time**
	OLS		**IV: Rain**		**IV: Sport**		**IV: Rain and Sport**	
Panel A: Non-Response = Bad Mood [Exhausted]								
Mood scores (1–5)	−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			22.91	22.91	5.969	5.969	9.896	9.896
Panel B: Non-Response = Neutral Mood [So-so]								
Mood scores (1–5)	−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			24.26	24.26	19.01	19.01	18.24	18.24
Panel C: Non-Response = Good Mood [Unstoppable]								
Mood scores (1–5)	−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			5.112	5.112	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). Sample restricted to days in which a worker logs into the software platform.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8. Mood and productivity, alternative coding—full sample

Dep. Var.	**(1) # calls per hour**	**(2) % un-productive time**	**(3) # calls per hour**	**(4) % un-productive time**	**(5) # calls per hour**	**(6) % un-productive time**	**(7) # calls per hour**	**(8) % un-productive time**
	OLS		**IV: Rain**		**IV: Sport**		**IV: Rain and Sport**	
Panel A: Non-Response or Non-Login = Bad Mood [Exhausted]								
Mood scores (1–5)	−0.026***	−0.000*	−1.099	0.042	−2.817	0.021	−1.325	0.039
	(0.006)	(0.000)	(1.006)	(0.030)	(3.022)	(0.072)	(0.927)	(0.027)
Observations	231,735	231,735	231,735	231,735	231,735	231,735	231,735	231,735
F-stat first stage			17	17	1.791	1.791	5.464	5.464
Panel B: Non-Response or Non-Login = Neutral Mood [So-so]								
Mood scores (1–5)	−0.022***	0.000***	−0.735	0.028	−2.403	0.018	−0.877	0.027
	(0.005)	(0.000)	(0.664)	(0.019)	(2.712)	(0.061)	(0.627)	(0.018)
Observations	231,735	231,735	231,735	231,735	231,735	231,735	231,735	231,735
F-stat first stage			33.60	33.60	1.845	1.845	8.745	8.745
Panel C: Non-Response or Non-Login = Good Mood [Unstoppable]								
Mood scores (1–5)	−0.010***	0.001***	−0.552	0.021	−2.094	0.015	−0.652	0.021
	(0.004)	(0.000)	(0.516)	(0.015)	(3.065)	(0.055)	(0.502)	(0.014)
Observations	231,735	231,735	231,735	231,735	231,735	231,735	231,735	231,735
F-stat first stage			28.10	28.10	0.766	0.766	4.651	4.651

Notes: OLS regressions. Robustness checks vary the assumption on how to code non-response or non-login in the mood question (using the main specification in the paper). Sample includes days in which a worker logs into the software platform and days in which she does not.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9. Mood and productivity, second-stage IV results, more outcome variables

Dep. Var.	(1) Average call duration (minutes)	(2) Average customer satisfaction (1–10)	(3) Sales per hour [Sample = Sales representatives]	(4) Average call duration (minutes)	(5) Average customer satisfaction (1–10)	(6) Sales per hour [Sample = Sales representatives]	(7) Average call duration (minutes)	(8) Average customer satisfaction (1–10)	(9) Sales per hour [Sample = Sales representatives]
	IV: Rain			IV: Sport			IV: Rain and Sport		
Mood scores (1–5)	0.880	−0.114	−241.666	−0.151	0.217	−31.685	0.233	0.183	−50.364
	(0.661)	(2.399)	(391.244)	(0.542)	(0.924)	(75.813)	(0.403)	(0.858)	(77.476)
Observations	35,368	16,005	12,362	35,368	16,005	12,362	35,368	16,005	12,362
Mean Dep. Var.	7.300	7.973	179.8	7.300	7.973	179.8	7.300	7.973	179.8
F-stat first stage	16.93	1.955	0.568	33.34	17.18	6.375	22.44	9.468	3.902

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 (two-way) at worker and call center*date level. The customer satisfaction score calculates the average daily customer satisfaction score for each worker (scores 1–10). This variable is missing if none of the customer were asked to fill the survey and/or none of the customers answered the survey. The variable "sales per hour" is available for sales representatives only.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10. Mood and productivity, other heterogeneous effects

Dep. Var.	**(1)** **# calls per hour**	**(2)** **% unproductive time**	**(3)** **# calls per hour**	**(4)** **% unproductive time**	**(5)** **# calls per hour**	**(6)** **% unproductive time**
	IV = Rain		**IV = Sport**		**IV = Rain and Sport**	
Panel A. Sub-sample of workers living < 5 km from work						
Mood scores (1–5)	−1.518**	0.033	−0.051	0.03	−0.868*	0.032*
	(0.713)	(0.027)	(0.641)	(0.024)	(0.447)	(0.017)
Observations	7736	7736	7736	7736	7736	7736
Mean Dep. Var.	7.117	0.094	7.117	0.094	7.117	0.094
F-stat first stage	16.11	16.11	13.86	13.86	10.41	10.41
Panel B. Sub-sample of call-centers with no window						
Mood scores (1–5)	−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
Mean Dep. Var.	7.117	0.094	7.117	0.094	7.117	0.094
F-stat first stage	11.1	11.1	30.63	30.63	19.8	19.8
Panel C. Heterogeneous effects by the fraction of earnings that is variable						
Mood scores (1–5)	−0.805*	0.028	−1.145	0.040	−0.792**	0.028**
	(0.459)	(0.017)	(3.373)	(0.111)	(0.338)	(0.013)
Mood score* % Variable	2.729***	−0.039**	95.355	−3.073	2.707***	−0.038*
	(0.704)	(0.020)	(1108.831)	(36.055)	(0.705)	(0.020)
Observations	35,254	35,254	35,254	35,254	35,254	35,254
Mean Dep. Var.	7.117	0.094	7.117	0.094	7.117	0.094
F-stat first stage	12.975	12.975	0.168	0.168	11.846	11.846

Notes: Second-stage IV regressions. Regressions control for worker tenure, worker-fixed effects, month*year-fixed effects, and day of the week-fixed effects. Panel C also controls for the interaction between the IV(s) and worker tenure, being a male, and the number of mood questions answered in a month. Standard errors are clustered (two-way) at worker and call center*date level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11. Mood and productivity by incentive structure, first-stage IV results

	(1)	(2)	(3)	(4)	(5)	(6)
			Mood scores (1–5)			
Rain	−0.085***		−0.083***	−0.093***		−0.092***
	(0.021)		(0.021)	(0.022)		(0.021)
Rain * % Variable	0.135		0.148			
	(0.470)		(0.473)			
Rain * Sales Representative				0.052**		0.053**
				(0.026)		(0.026)
Sport		0.053***	0.052***		0.053***	0.052***
		(0.012)	(0.012)		(0.013)	(0.012)
Sport * % Variable		−0.293	−0.303			
		(0.424)	(0.429)			
Sport * Sales Representative					−0.000	−0.000
					(0.014)	(0.014)
Observations	35,254	35,254	35,254	35,316	35,316	35,316
R-squared	0.615	0.616	0.616	0.616	0.616	0.616
p-value (Rain + Rain * Sales Rep = 0)				0.161		0.180
p-value (Sport + Sport * Sales Rep = 0)					0.000	0.000
Mean Dep. Var.	3.835	3.835	3.835	3.835	3.835	3.835
F-stat first stage (from second-stage regression)	14.023	14.023	10.155	10.155	12.504	12.504

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. They also control for the interaction between the IV(s) and worker tenure, being a male, and the number of mood questions answered in a month. Standard errors are clustered (two-way) at worker and call center*date level. The *F*-stat first stage at the bottom of the table is the Cragg–Donald Wald *F*-stat for the joint significance of the instruments in the two first stages (Mood and Mood * Sales Representative).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

APPENDIX B

B.1 Theoretical framework

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

First, worse mood might decrease sociability, and lower sociability might increase productivity. 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 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.[29]

We 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

[29] Other psychological theories exist 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.

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

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

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

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

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

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

These equations are directly comparable with Equations (2)–(4) of RT, except that wages are allowed to depend on effort. Equation (B.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 $V^N \geqslant V^S$. This condition is equivalent to:

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

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 (B.4) reduces to

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

This condition is directly comparable with condition (5) in RT. This is 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 (B.4) converges to

$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \geqslant \frac{c}{b}, \tag{B.6}$$

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

B.2 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: ω and D in Equation (B.5), and $Y(1)$ and $Y(0)$ in Equation (B.6). A more ambiguity-averse worker will evaluate these quantities more pessimistically, specifically, at levels denoted by: $\underline{\omega}, \overline{D}$, $\mathbb{E}[Y(1)] = \underline{y}(1)$, and $\mathbb{E}[Y(0)] = \underline{y}(0)$ (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: $\overline{\omega} \geqslant \underline{\omega}, \underline{D} \leqslant \overline{D}, \overline{y}(1) \geqslant \underline{y}(1)$, and $\overline{y}(0) \geqslant \underline{y}(0)$.

Thus, an ambiguity-loving worker will:

perceive the RHS in Equation (B.5) to be larger, compared with an ambiguity-averse worker, and thus be *more* inclined to shirk.

perceive the LHS in Equation (B.6) to be larger, compared with an ambiguity-averse worker, if and only if $\overline{y}(1) - \overline{y}(0) \geqslant \underline{y}(1) - \underline{y}(0)$, 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).

$$\overline{y}(1) - \underline{y}(1) \geqslant \overline{y}(0) - \underline{y}(0).$$

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 *less* inclined to shirk. With pay-for-performance, they will be *more* 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.

DATA AVAILABILITY

The paper makes use of confidential administrative data from an individual company. The data sharing agreement does not permit us to provide data directly to interested researchers. However, our do files are available on the journal's website.

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