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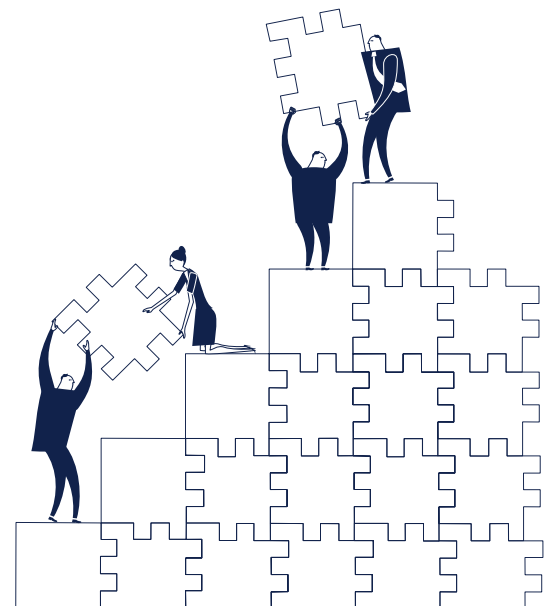
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# DOES EMPLOYEE HAPPINESS HAVE AN IMPACT ON PRODUCTIVITY?\*

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October 14, 2019

## Abstract

This article provides quasi-experimental evidence on the relationship between employee happiness and productivity in the field. We study the universe of call center sales workers at British Telecom (BT), one of the United Kingdom's largest private employers. We measure their happiness over a 6 month period using a novel weekly survey instrument, and link these reports with highly detailed administrative data on workplace behaviors and various measures of employee performance. We show that workers make around 13% more sales in weeks where they report being happy compared to weeks when they are unhappy. Exploiting exogenous variation in employee happiness arising from weather shocks local to each of the 11 call centers, we document a strong causal effect of happiness on labor productivity. These effects are driven by workers making more calls per hour, adhering more closely to their workflow schedule, and converting more calls into sales when they are happier. No effects are found in our setting of happiness on various measures of high-frequency labor supply such as attendance and break-taking.

JEL: D03; J24; M5; I31

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# 1 Introduction

What explains the large differences in labor productivity that are typically observed between firms and individuals? Historically, theoretical and empirical work seeking to understand such differentials has mostly focused on monetary aspects of motivation (e.g. [Lazear, 2000](#)). However, a more recent stream of economic research has begun to broaden this focus to also include non-monetary aspects of work, such as intrinsic motivation, social preferences, meaningfulness of tasks, and social comparisons (e.g. [Benabou and Tirole, 2003](#); [Cassar and Meier, 2018](#); [DellaVigna and Pope, 2017](#); [Gneezy and Rustichini, 2000](#); [Ichniowski and Shaw, 2003](#)). In this paper, we add to this growing literature by studying the productivity effects of a typically-overlooked aspect of workers' lives: their day-to-day happiness.

A recent trend has seen a growing number of employers at least claiming to care about the happiness of their employees, and beginning to invest in management practices and services aimed at creating and maintaining a happy workforce.<sup>1</sup> At least one reason for this is the expectation that happier workers will be more productive in their jobs.<sup>2</sup> However, it remains unclear whether this belief is based on sound empirical evidence or is, rather, a case of “management mythology”.

We build on a long history of work, largely outside of economics, on employee well-being and performance. A large initial stream of research examined the association between measures of self-reported job satisfaction and worker performance, typically in field settings, and has generally found a modest positive correlation between the two (see [Judge et al., 2001](#), for a review). However, there is a general lack of causal research on the issue, and the best existing evidence relies principally on within-worker estimates. A more recent stream of research—arising largely out of cognitive psychology—has moved away from evaluative assessments of employee satisfaction, in order to study people's affective or emotional states in the workplace ([Brief and Weiss, 2002](#); [Tenney et al., 2016](#)). One benefit of studying emotional states is that they are more readily manipulable in laboratory settings, allowing for more clearly causal research designs. A recent pioneering paper in economics, for example, influences happiness in a laboratory setting to show a robust causal effect on a stylized, piece-rate productivity task ([Oswald et al., 2015](#)).<sup>3</sup> However, it remains unclear whether these effects translate into real-world employment settings.

In this paper, we present evidence of a causal effect of workers' week-to-week happiness on their productivity, in a field context at one of the United Kingdom's largest private employers. We study the universe of around 1,800 sales workers at British Telecom (BT), a large telecommunications firm in the UK. Employees are distributed across 11 call centers, where their job is predominantly to take incoming calls from new and existing customers, and seek to sell them various products such as broadband internet contracts, cell and landline phone deals, and television packages. We observe the happiness of these workers on a weekly basis over a six month period. We match this self-reported happiness data to detailed administrative data on a number

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<sup>1</sup>Companies such as Google or Zappos, for example, have even appointed “Chief Happiness Officers” to this end ([Knowles, 2015](#)).

<sup>2</sup>Other motivations may also include a desire to attract and retain high quality workers, the enhancement of firms' reputation among customers, as well as concerns to do with corporate social responsibility.

<sup>3</sup>For earlier work in psychology showing the effects of positive mood on task performance in a non-incentivized setting, see [Erez and Isen \(2002\)](#). See also [Isen and Reeve \(2005\)](#).

of workplace behaviors and performance outcomes. Whereas much of the prior literature on worker well-being and performance has been forced to rely on subjective outcomes—such as managerial performance evaluations—the benefit of studying a call center population is that we are able to study a range of objective, quantitative performance metrics that are measured routinely by the firm. For our main outcome measure, we focus on the number of weekly sales made by each employee. In order to investigate channels through which any effect of happiness may translate into sales, we also study fine-grained measures of labor productivity, namely i) minutes per call, ii) the percentage of calls converted to sales, and iii) the extent to which workers “adhere” to their scheduled workflow.

The use of high-frequency panel data allows us to purge from our estimates any unobserved heterogeneity between workers. However, there remain reasons to believe our within-worker estimates could still be biased. First, our survey measure of happiness may be a noisy measure of workers’ happiness, and this measurement error is likely to bias any estimate downward. Second, there is a concern of reverse causation, and here the direction of the bias is theoretically ambiguous. On the one hand, strong performance could increase the mood of workers if they derive enjoyment from the success of making sales. But on the other hand, if tasks are not in themselves enjoyable or fulfilling then doing more of them could produce unhappiness.<sup>4</sup> We present evidence more in line with the latter — suggesting that in more routine work settings the causal effect of happiness on performance is likely to be greater in magnitude than the initially observed within-worker association.

We study adverse local weather shocks in order to set up a natural experiment wherein we are able to estimate the causal effect of happiness on productivity. We instrument for employees’ weekly happiness using local weather conditions. Using weather station data local to each of our 11 call centers we construct a Bad Weather Index, which is the weekly total incidence of fog, rain and snow close to each call center. This has a strong (“first-stage”) negative effect on worker happiness, which we show ultimately leads to fewer weekly sales in two-stage IV models.

Our key identifying assumption is that weather patterns have an effect on sales only through variation in worker happiness. We explore in detail at least two principal threats to this assumption. First, there is a possibility that weather will also affect product demand, either directly or indirectly through the mood of customers. It is worth noting here that demand is national, and that calls are allocated to call centers based on call type and operator availability. In all of our models, we include both worker and *week* fixed effects, such that our key piece of identifying variation in the data comes from differences across call centers (which are very widely dispersed geographically across 3 countries, from the south coast of England to the north of Scotland) within any given week, and not from seasonal movements in national weather from week-to-week.

Second, it may be that weather shocks affect how much people work. For example, poor weather could influence commuting patterns, or induce sickness among workers causing them to attend less. Equally, it weather could affect the opportunity cost of leisure compared to work (see [Connolly, 2008](#)), and have effects on attendance. One of the key benefits of studying workers in a call center setting is that employees enjoy very little—if any—discretion over their day-to-

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<sup>4</sup>Equally, higher volumes of work related to making more sales could also lead to stress.

day work hours, making it an ideal population in which to cleanly measure labor productivity effects.

In line with this, when examining channels, we find null effects on various fine-grained measures of labor supply such as attendance, sickness leave, overtime, or length of paid and unpaid breaks. Instead, leveraging detailed data on high-frequency labor productivity, we show that the effect of happiness on sales is driven largely by employees both working faster (i.e. making more calls per hour) and also converting more of their calls into sales during weeks when they feel happier. The latter channel suggests that the effects of happiness are likely to be strongest in service industry settings, where work is directly customer-facing. Happiness may in this sense be beneficial to people's social skills, the importance of which have been shown to be increasing in the labor market (Deming, 2017). Underscoring the importance of happiness as an aid to social skills, we show that the effects are greater for upgrade and re-contracting sales—where there is more leeway for inter-personal connection, persuasion, and negotiation—than they are for more routine order-taking. We also discuss the contribution of alternative psychological mechanisms such as intrinsic motivation and cognitive processing.

The findings contribute to various strands of research in economics, psychology, sociology, and industrial relations. First, as noted above, the analysis relates directly to a large and long-standing literature in economics on the determinants of productivity (Syverson, 2011).

Second, the results contribute to a large body of work outside economics, which has a long history of examining the relationship between employee well-being and performance. In studying well-being in a field setting, our work is closely related to research on job satisfaction and performance. But in studying a measure of positive affect, our findings are also closely related to a largely more laboratory-based literature on emotional states in determining work-related outcomes (see Walsh et al., 2018, and citations within for an extensive review of the evidence arising from both streams of work).<sup>5</sup>

Third, our findings provide micro-foundation for work showing that firms listed in the “100 Best Companies To Work For In America” outperform industry benchmarks in terms of long-run stock returns (Edmans, 2011), as well as for research suggesting a positive link between firm-level employee satisfaction and financial performance (Böckerman and Ilmakunnas, 2012; Bryson et al., 2017; Krekel et al., 2019). Fourth, and relatedly, the findings are in line with an experimental literature at the individual level, largely in psychology, showing in non-incentivized laboratory settings that induced happiness has effects on processes like motivation, cognitive flexibility, negotiation, and problem solving skills (see Isen, 2001, for a review).

Fifth, the results contribute to work in economics that implies the existence of mood effects on workplace behaviors, but is unable to measure them directly. Heyes and Saberian (2019) show, for example, that temperature has significant effects on the decision-making of judges in high-stakes court cases, while work by Eren and Mocan (2018) suggests that judges' decisions can be swayed by college football results. Equally, behavior in stock markets is affected by sunshine and daylight hours (Hirshleifer and Shumway, 2003; Kamstra et al., 2003) and national soccer results (Edmans et al., 2007). While none of these papers is able to measure mood directly,

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<sup>5</sup>In a paper relatively close in nature to ours, Rothbard and Wilk (2011) study the mood and performance of a sample of 29 call center workers in an insurance firm, and present within-worker estimates of the relationship between affect and task performance.

all explicitly tell a story in which emotional states causally affect workplace behaviors. Our analysis contributes to this literature by more directly measuring the effects of happiness and unhappiness on performance.

Finally, our study also ties in to an emerging field-experimental literature showing that the improvement of management practices can have simultaneously positive impacts on i) employee happiness and satisfaction as well ii) as productivity (e.g. [Gosnell et al., 2019](#)). [Bloom et al. \(2014\)](#) show, for example, that allowing call center employees to work from home improves their productivity while also enhancing happiness and satisfaction, and an intervention by [Breza et al. \(2017\)](#) shows that pay inequality has negative effects on morale while also depressing productivity.<sup>6</sup> Each of these papers suggests that employee happiness may be one channel through which workplace organization feeds through to productivity. In this paper, we isolate this channel more clearly in order to show a positive causal relationship between happiness and employee performance.

## 2 Data and Institutional Setting

We collect data from a large telecommunications company based in the United Kingdom. We focus our analysis on the firm's 11 call centers located across England, Scotland and Wales that have a large number of workers concentrating predominantly on sales. We use administrative data obtained from the firm on worker characteristics, work schedules and productivity, and combine these data with an original survey instrument we implemented to measure workers' psychological well-being over a six month period.

### 2.1 Psychological Well-Being Survey

The use of "happiness" data in economics has grown substantially over the past decade (see, e.g, [Aghion et al., 2016](#); [Benjamin et al., 2012](#); [Haushofer and Shapiro, 2016](#); [Kahneman et al., 2004](#); [Luttmer, 2005](#)). Subjective well-being is typically divided into two separate components that measure i) how people feel as well as ii) how they think about their lives ([Kahneman and Krueger, 2006](#)).<sup>7</sup> *Evaluative* measures of psychological well-being typically comprise answers to global, cognitive judgements like the extent to which people are satisfied with their job or their life overall. *Affective* measures of well-being – which are often also referred to as 'hedonic' or 'experienced' measures – refer, on the other hand, to the extent to which people experience positive and negative emotional states (like happiness, enjoyment, stress and worry) in the course of their day-to-day lives.

Whereas much of the existing literature on well-being in the workplace focuses on evaluative measures of job satisfaction, which are typically slow-moving overall cognitive assessments, we focus instead on employees' experienced well-being as it varies week-to-week. In doing so, we build on a small experimental literature that manipulates positive and negative affect in

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<sup>6</sup>Similarly, [Moen et al. \(2017\)](#) show that improving worker autonomy has a positive effect on well-being and also decreases turnover (see also [Moen et al., 2016](#)). The authors are unable, however, to observe productivity in their IT firm setting.

<sup>7</sup>A third component is increasingly also identified, which comprises meaningfulness or "eudaemonia" (see, e.g., [Ariely et al., 2008](#)).

Figure 1: Happiness Survey Email

## Overall, how happy did you feel this week?



\* Your answer will always remain anonymous.  
Find out more

*Note: Screenshot of the happiness survey, which was sent weekly over a six month period to all workers. Respondents had to click a face within the email for their response to be registered. See text for more details.*

the laboratory in order to examine effects on economic outcomes like productivity (Oswald et al., 2015), time preferences (Ifcher and Zarghamee, 2011), and behavior in ultimatum and trust games (Capra, 2004). For ease of exposition, we use the terms ‘happiness’, ‘positive mood’, ‘affect’, ‘affective state’, ‘emotional well-being’ and ‘emotional state’ interchangeably throughout the paper.<sup>8</sup>

In designing our survey instrument, the firm followed the OECD’s measurement guidelines, which they provide largely for the benefit of national statistical offices seeking to measure population subjective well-being for policy purposes (see OECD, 2013).<sup>9</sup> Employees were asked “Overall, how happy did you feel this week?”<sup>10</sup> Following Kunin (1955) and decades of subsequent work in the psychological literature, we offer five response categories as a Faces Scale that ranges from very sad to very happy androgynous faces.<sup>11</sup> The use of faces in this way is both intuitive to respondents, and is also known to strongly pick up the affective component of well-being questions (Fisher, 2000).

The question was asked on a weekly basis for six months, beginning in July 2017. The survey was sent by email on Thursday afternoon, and is shown in Figure 1. It is important to note that we measured happiness at the end of the week, and asked employees about their happiness during that particular week. This allows us to link happiness reports and work outcomes over the same corresponding time period. An alternative option would be to ask

<sup>8</sup>Feeling states are typically categorized into moods and emotions. While emotions are discrete short-run reactions, usually to a specific stimulus, moods are more general positive or negative feeling states (Frijda, 1986). A related literature considers the effects of discrete emotions, rather than mood, on economic behavior (see Loewenstein, 2000).

<sup>9</sup>For a full discussion of the issues surrounding the measurement of subjective well-being, as well as a detailed account of the various ways in which the validity and reliability of such measures have been tested, see OECD (2013). See also Krueger and Stone (2014) and Krueger and Schkade (2008). The OECD reports that well-being measures are now being regularly collected in over 20 countries, many of which are also using them systematically in the policymaking process (Durand, 2018).

<sup>10</sup>This is (by design) very close in wording to the standard happiness question asked by the UK government’s Office for National Statistics (ONS) in all of its main household and labor force surveys. The ONS question asks: “On a 0-10 scale where 0 is not at all happy and 10 is completely happy, overall, how happy did you feel yesterday?” (see Dolan et al., 2011).

<sup>11</sup>One notable issue with the use of faces in this way is that people – men and women, in particular – have been shown to interpret the neutral face in different ways (see, e.g., Elfering and Grebner, 2010). Since our main specifications use individual fixed effects and look within-workers over time, such issues of response style are much less of a concern here.

employees at the start of the week, which would give a clearer temporal ordering between happiness and subsequent outcomes. However, this would come at the expense of not knowing workers' happiness during the period where they are actually working on those sales. Our use of happiness and sales measures that are temporally concurrent thus has significant benefits, but the contemporaneous nature of our happiness and sales measures underlines the need for an instrumental variables strategy in order to deal with potential issues of endogeneity.

In order to reduce the onerousness of the data collection on employees, and in doing so ensure as high a response rate as possible, the survey was a single-item question that could be answered simply by clicking an answer from within the email. Specifically, there was no need to click on a link through to a further webpage (as is typically the case with emailed surveys) in order to register a response. Workers were assured that their individual happiness responses would not be shared with the firm's management. Workers were also offered the opportunity to opt-out of the study at any time, via a simple email click-through.

The responses provide us with a weekly, ordinal measure of affective well-being. The distribution of responses is shown in panel (a) of Figure 2. Although we assign a numerical value to each of the responses ranging from 1 (least happy) to 5 (most happy), we are naturally hesitant to cardinalize the scale into a continuous measure of happiness – and in our main initial empirical model we introduce the response categories into our productivity equation as a set of indicator variables.

As can be seen in Figure 2, the modal response is the least happy state. If we are to use the scale in a continuous manner, the mean response is 2.6 with a standard deviation of 1.4 (a full set of descriptive statistics are shown in Table A1). Importantly for our identification using individual fixed effect models, panel (c) of Figure 2 shows that the responses vary significantly within-workers over time during the study, suggesting that we are not simply picking up a more static overall measure of evaluative job satisfaction.

## 2.2 Administrative data

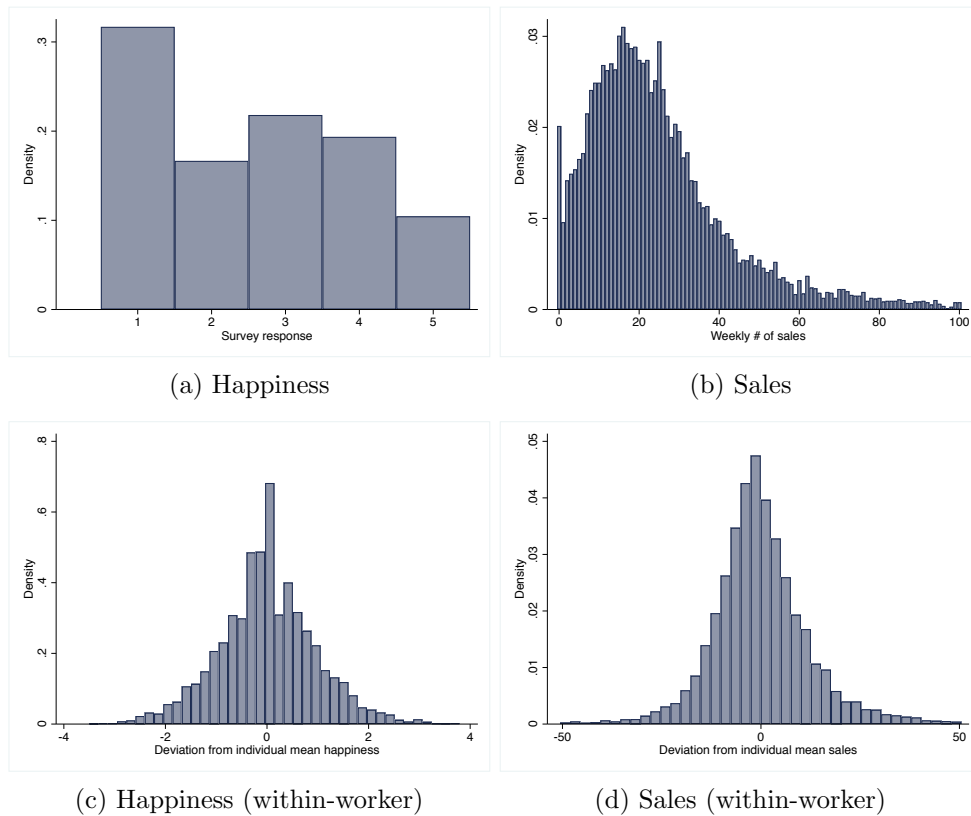
We combine the survey responses with detailed individual-level administrative data from the firm. We focus our attention on sales workers across the 11 call centers, whose job it is to sell a variety of BT products. These predominantly consist of landline and cellphone contracts, broadband internet contracts, and television subscription bundles. The vast majority of the work (91% of time and 82% of tasks) carried out by the employees in the sample are incoming calls from potential or existing customers, with the remainder consisting of outgoing calls (4% of time and 12% of tasks) and “other” activities (which includes tasks such as dealing with inbound and outbound letters, online customer chats, and incoming and outgoing SMS messaging).

Workers are observed in the data on a daily basis and are identified by their unique personal ID as well as a time-varying team ID. Workers sit individually at desks with a computer terminal and a telephone headset, and are clustered physically in the workspace by their team. Although workers are organized into teams, this largely relates to the sharing of a line manager and not to any interdependence of workflow, since the job of selling in this context is almost exclusively an independent task with very little to no teamwork involved.

At the worker-day level we observe the number of sales, which include new sales, whether to



Figure 2: Distribution of Happiness and Sales



*Note: Panels (a) and (b) show the overall distribution of happiness and sales. Each observation is a worker-week. Panels (c) and (d) show the extent to which these two variables vary within-workers over time. These latter graphs show the residuals from OLS regressions of each variable on individual fixed effects. An observation is an individual-day residual from each regression.*

a new or existing customer, as well as instances where the worker is able to retain a customer through re-contracting. The distribution of sales in our sample can be seen in panel (b) of Figure 2. As is typically the case with sales data, the distribution of this count variable is right-skewed. We also look more closely at mechanisms through which any relationship between happiness and sales may take place, and in doing so consider other work outcomes like call duration, adherence to workflow scheduling, call-to-sale conversion, and customer satisfaction. In addition, we observe daily measures of workers' scheduling. Within this, we are able to track the number of hours the employee is scheduled to work, their attendance, the number and duration of paid and unpaid breaks they take, as well as the length of time they spend working on sales (which is factored for call waiting time). Finally, using data from the Human Resources department of the firm, we observe a limited number of time-invariant characteristics of workers such as their gender, age, and tenure.

### 2.3 Sample construction and characteristics

Since our psychological well-being data is reported by worker-week, we aggregate all of the administrative data to the Monday-to-Friday week. In an appendix, we also make use of the daily nature of much of the productivity and scheduling data by constructing a full worker-by-

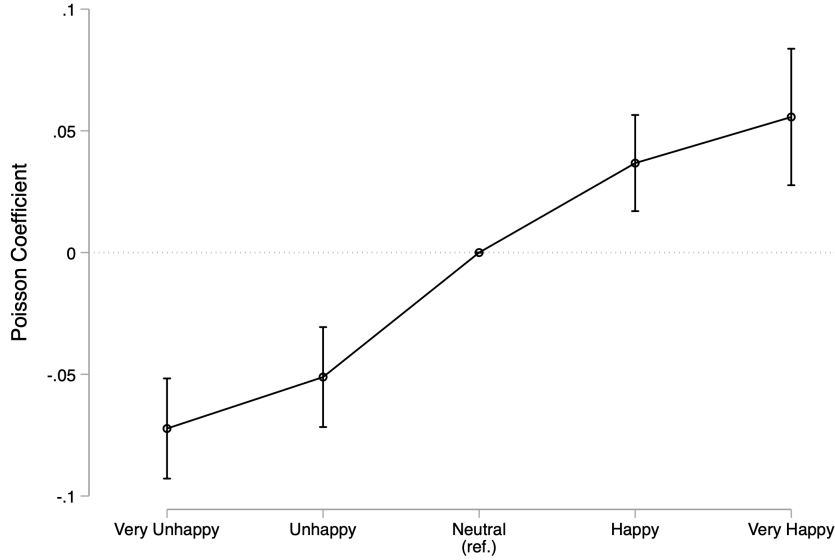
day dataset and assuming happiness to be constant throughout the days of that week (given that the question asks them specifically how happy they have felt overall during the week).

We observe 1,793 sales workers, distributed across 11 different call centers (for a map of the spatial distribution of these call centers, see Figure 4). All of these workers were invited to take part in the study and were sent weekly psychological well-being surveys. Of these employees, 1,438 (around 80%) participated by answering at least one survey over the subsequent 6 months. All of this cohort of workers were sent a weekly email, unless they had since left the organization (in which case their email survey is recorded as “bounced”). We do not follow any workers who subsequently joined the firm after the first week of the study. In the supplementary material, we assess the extent to which observable demographic characteristics and workplace performance are able to predict i) participation in the study, on the extensive margin (Table S1) and ii) the number of survey waves answered if the worker did participate, on the intensive margin (Table S2). Importantly, neither participation in the study nor frequency of response are significantly related to the average weekly number of sales made by workers during the course of the study. Mean hours of selling time is positively predictive of the number of response waves – an extra hour of mean daily sales time is associated with around a 2% increase in the number of waves responded.

We drop any participants who responded to only one survey wave, since we rely principally on within-worker variation over time in our main analysis. Also dropped from the analysis are observations that lead to statistical separation in our main individual and week fixed-effect Poisson models. This leaves us with a final sample of 1,161 employees. Summary statistics for this final sample are shown in Table A1. Around 57% are male, and the modal age category is 26-30 (with over 60% of the sample being between 21 and 35 years old). Mean tenure in the firm is about 5 years, with a large standard deviation of 7 years. Half of the workforce in our sample has been in this position for less than 2 years, and around 7% of the sample experienced turnover during the 6 months – either leaving of their own accord or having their employment terminated. Conditional on participating in the study, workers responded to a mean of 10.3 waves (with an SD of 7.1). The weekly response rate of workers who participated was on average around 37%.

Using our final sample of workers, we do not observe a fully balanced worker-week panel since we are restricted by non-response to the happiness survey instrument. Moreover, there is a significant concern that non-response to the survey is unlikely to occur randomly, and may indeed relate to our main variables of interest in ways likely to bias our estimates. For example, it may be that a worker does not respond in a given week because she is either too happy or miserable to spend time reading the email, or alternatively because she is too busy making sales. In Table S3 we regress a dummy for having responded to the survey in a given week on a number of time-varying observables like sales, selling time, and team average happiness (as well as a set of individual and week fixed effects). Reassuringly, neither weekly sales performance nor team average happiness (minus the focal worker) is significantly related to non-response within-individuals over time. It is, however, positively related to the number of hours worked during the week, suggesting that workers are less likely to respond during weeks in which they are scheduled to work less.

Figure 3: Within-worker association of happiness and sales



Note: Coefficients and 95% confidence intervals shown from a poisson model in which the number of sales are regressed on a series of happiness dummies, a full set of individual and time fixed effects, as well as scheduling controls. Full model is reported in Table A2.

### 3 Results

#### 3.1 Within-worker estimates

We are interested in whether workers’ self-reported psychological well-being has any causal impact on their weekly performance at work. We focus on sales workers so that our preferred performance measure is the worker’s number of weekly sales. We estimate a within-worker productivity equation, such that

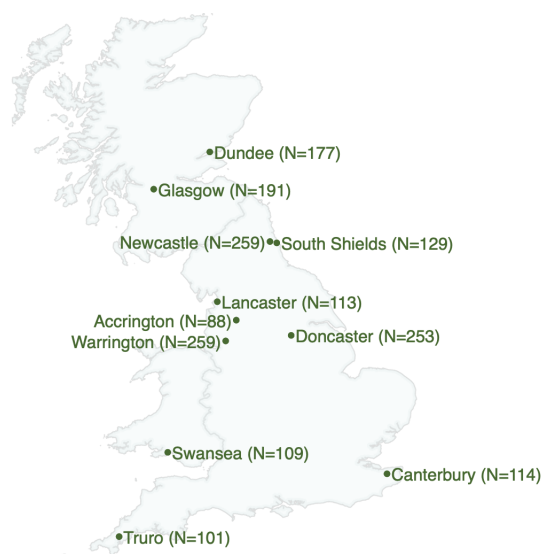
$$E[S_{ijt}|H_{ijt}, X_{ijt}] = \exp\{\beta H_{ijt} + \gamma X_{ijt} + \nu_i + \tau_t\} \quad (1)$$

where  $S_{ijt}$  corresponds to the number of weekly sales for worker  $i$  in call center  $j$  during week  $t$  and  $H_{ijt}$  is her reported happiness during that same period  $t$ . Worker fixed effects  $\nu_i$  capture any individual-specific characteristic that does not change over time, and  $\tau_t$  is a time fixed effect partialing out any shocks that may affect both well-being and sales. Finally, we include a vector of controls  $X_{ijt}$  for two major work schedule variables that may vary over time and across workers, namely the total number of selling hours during week  $t$  (and its squared value), and the fraction of time spent at work in the week on internal training.

We estimate equation (1) with a Poisson quasi-maximum likelihood model. The Poisson model is particularly relevant for count data, and also makes the interpretation of  $\beta$  intuitive, as it can be interpreted in terms of a percent change in number of sales per hour. A linear specification using logged sales per hour, which leads us to lose around 2% of our sample size due to observations with zero sales, is reported in Table S13 and gives similar estimates.

We show the results of this empirical model in Figure 3 (for full reporting of this model, see

Figure 4: Spatial Distribution of Call Centers



*Note: Map shows the location of the 11 call centers in the study, as well as the number of sales workers in each.*

Table A2). We omit the neutral third category of happiness from the regression, and show the association of happiness and unhappiness in relation to this. Each of these four (unhappiness) indicators enters significantly into the productivity equation. As can be seen, being in the most happy state (as compared to a neutral emotional state) is associated with around a 6% rise in weekly sales. Being in a negative emotional state (as compared to the neutral) is associated with around an 7% decrease in weekly sales. There is, thus, a slight asymmetry in the association of happiness and unhappiness with sales. Comparing weeks when workers report being very unhappy with weeks where they are very happy, the difference in sales is around 13%.

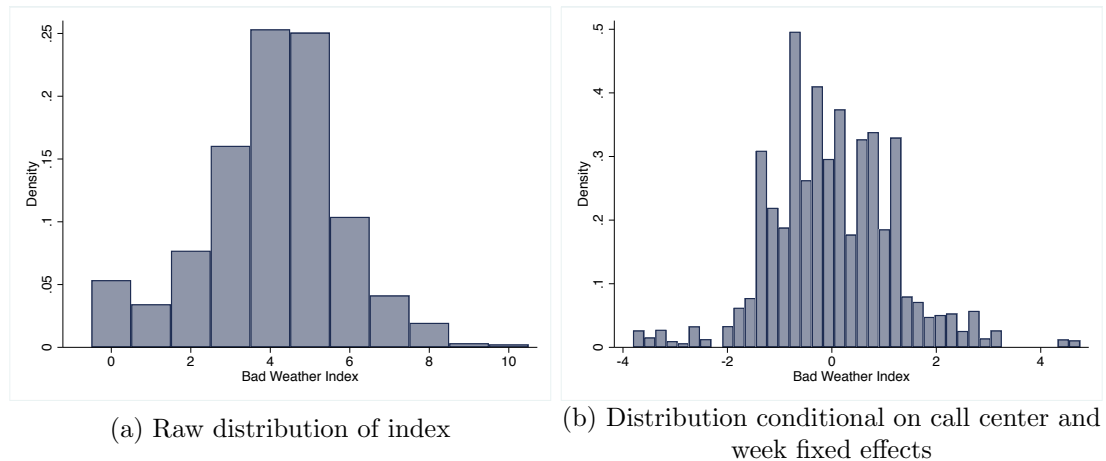
### 3.2 IV estimates

One major empirical concern is that, even within-workers over time, a change in subjective well-being may be endogenous to performance. In particular, we see two (opposing) major ways in which reverse causality may bias our coefficients. First, more productive workers can get compensated for their higher performance through financial incentives, or non-monetary rewards from their colleagues or managers, or simply enjoyment. This alone could explain their higher reported well-being, in which case the coefficient will be biased upward. Second, and conversely, higher productivity and being over-worked can lead to higher levels of stress or anxiety, which are both highly likely to be negatively correlated with happiness. Equally, doing more work may simply be more unenjoyable. In this case, the coefficient will be biased downward.

Our main strategy to deal with the endogeneity of  $H_{ijt}$  is to rely on instrumental variables  $Z_{ijt}$  that are correlated with the latter, but are independent of sales. In our case, the first stage is:

$$H_{ijt} = \omega Z_{jt} + \Gamma X_{ijt} + \nu_i + \tau_t + \eta_{ijt} \quad (2)$$

Figure 5: Variation in Weather



*Note:* Panel (a) shows the distribution of weekly bad weather across call centers. The index is constructed by summing the daily incidences between Monday and Friday of fog, snow, and rain (source: NOAA). Panel (b) shows the residuals from an OLS regression of the weather index on a set of call center and week fixed effects.

where our preferred instrument,  $Z_{ijt}$ , uses variation in local weather conditions. The inclusion of  $\tau_t$  ensures that our key piece of identifying variation, in terms of  $Z_{jt}$ , is weather shocks across call centers  $j$ , within any given week  $t$ . It is thus vital that we have a large number of call centers, which are spread widely in terms of geography. Moreover, it is important to have a geographical setting where weather does indeed vary significantly across space within any given time period. Great Britain happens to be a place with very variable weather, both across time and space, and, even within-weeks, locations vary significantly in the weather patterns they experience (see panel (b) of Figure 5).

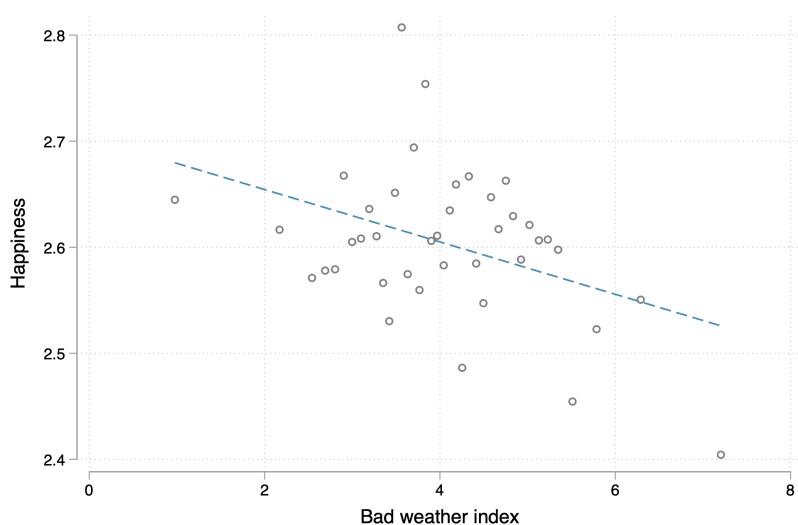
The standard two-stage least square (2SLS) estimator is appropriate in the case of linear panel models. However, when it comes to non-linear models with individual fixed effects, a fully robust approach is to rely on control function methods – that is, estimate the first stage for  $H_{ijt}$  and add the first-stage residuals as a control in equation (1) (see Papke and Wooldridge, 2008, for another application to non-linear models). We bootstrap the standard errors in order to adjust for the first-stage estimation, re-sampling across individuals 1000 times in order to account for clustering.

**Weather Instrument.** Weather data is drawn from the National Oceanic and Atmospheric Administration’s (NOAA) Global Surface Summary of the Day database. We use the address of each call center to determine its latitude and longitude, and match each center to the closest weather station in the data, which is on average 14km away. Since not all station\*days have non-missing data available, we link each call center with the closest 5 stations, and where the closest station has missing values we take the second closest, and if missing take the third closest, and so on.<sup>12</sup> Each station reports on a daily basis a separate indicator variable for whether there has been fog, snow and rain on that day.

We construct for each call center location a Bad Weather Index, corresponding to the total

<sup>12</sup>The 5th closest station, which is only very rarely used, is on average 51km away. See <https://data.noaa.gov/dataset/global-surface-summary-of-the-day-gsod> for more details of the data.

Figure 6: Weather IV First Stage



*Note: Figure shows the relationship between bad weather and happiness, adjusting for individual and week fixed effects as well as the full set of further controls. Both weather and emotion are first regressed on the full set of fixed effects and controls. The residuals from these regressions are binned across 40 quantiles and plotted as grey dots. The blue line shows the linear fit from an OLS regression using all of the data.*

number of daily incidences of fog, rain and snow during the week for which individuals reported their happiness. If it were to rain, snow and be foggy every day of the week, the index would be 15, if it rains for 2 days and is foggy for 1 day, the index would be 3, and so on. Panel (a) Figure 5 shows how this index—which in theory could lie between 0 and 15 but in reality ranges from 0 to 10—is distributed once matched to the weekly performance data. Panel (b) shows there is significant variation in the index, when conditioning on week and call center fixed effects.

**Reduced Form.** We first estimate the reduced form effects of local weather on sales performance. Column (1) of Table 1 shows a negative effect of local adverse weather conditions on sales performance. In addition, we show this at the daily-level: In table S9 we regress daily sales on daily (and weekly) weather, together with a full set of individual and date fixed effects, and our standard set of daily work schedule controls (equivalent to above). We find that poor weather in the geographic region of the call center has a negative effect on sales performance. One concern with our findings using the happiness survey is the threat of bias arising from non-response, which we discussed above. Here we are able to make a further check, and show that the effect of weather on sales is very similar for worker-days on which we have non-missing and missing (weekly) happiness data.

**First Stage.** The negative impact of bad weather on well-being is now well documented (Baylis et al., 2018; Connolly, 2013). We confirm this finding, and show in Figure 6 the first-stage relationship between bad weather and worker happiness. As can be seen, within-workers over time there is a clear negative relationship between adverse weather conditions and their happiness. This model is also shown more formally in column (2) of Table 1. The F-statistic from this linear first stage, which is around 10.5, suggests the instrument is sufficiently powerful to be valid.

Table 1: Happiness and Sales Performance: IV estimates

	Sales (Poisson)	Happiness (OLS)	Sales (Poisson)
	(1)	(2)	(3)
	Red.-Form	1st Stage	2nd Stage
Happiness (1-5)			0.2403** (0.1032)
Bad Weather Index	-0.0057** (0.0026)	-0.0247*** (0.0076)	
Observations	12,282	12,282	12,282
1st Stage F-Stat		10.47	

Notes: Columns (1) and (3) are Poisson-FE models. Column (2) reports an OLS-FE regression. Column (3) reports the second stage of a Poisson-FE control function model. Robust standard errors in parentheses, clustered on individuals in models (1) and (2). Bootstrapped standard errors reported for model (3), resampling across individuals to account for clustering. All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Second Stage.** The second stage regression, shown in column (3) of Table 1, suggests a strong causal effect of happiness on sales performance. A one point increase in the 1-5 happiness leads to around a 24% increase in weekly sales. This implied estimate is higher than in the equivalent non-instrumented analysis (see Table A2), suggesting a negative bias between well-being and productivity. This could be due to a negative reverse causality bias, noted above, wherein over-work leads to stress or where doing more work is simply unenjoyable in a job where the tasks are not greatly interesting or fulfilling, or involve interacting with angry customers. Equally, classical measurement error in our main right-hand-side variable is very likely to have biased our initial estimates downward (a point we will return to below). If anything, the positive effect found in the initial Poisson-FE specification should hence be seen as a lower bound to the true causal effect.

### 3.3 Threats to validity of IV analysis

While the data suggest a strong first-stage, the instrument will only be valid under the condition that weather has no direct impact on sales. We discuss three main threats to this exclusion restriction:

**Product Demand.** One major concern here is that weather may also have a direct impact on customer demand, or equally have an indirect effect on customer demand by affecting customers' mood. As noted above, it is important to note that we include week fixed effects in the equation. Our 11 call centers are distributed across the whole of Great Britain, from the south coast of England to the north of Scotland (see Figure 4 for a map). We are thus relying on variation in weather across call centers within any given week, rather than on movements in national weather conditions from week-to-week. Since calls come from various parts of the country and are directed to call centers based on query type and operator availability, *local* weather in the vicinity of the focal call center should be independent from customer demand. Looking more directly in the data, we show in the online appendix that the number of incoming calls to a given call center week-to-week (a proxy for demand) is not at all affected by weekly

weather that is local to that particular call center (See Table S10 of the online appendix).

**Labor Supply: Opportunity Cost of Leisure.** An additional concern is that the presence of (in)clement weather outside may change the opportunity cost of leisure time (see [Connolly, 2008](#)), leading workers to adjust their labor supply decisions. Relatedly, bad weather could have direct impacts on employee’s ability to attend, or arrive on time – for example, if rain affects their ability to commute to work. First, it is worth noting that, in our setting, workers have very little discretion over labor supply. Work hours are scheduled by management, and once workers are at their terminal during their scheduled hours they face calls as they come in. Second, we note that all of our analyses are robust to the inclusion of a control for the number of working hours done by the employee during the week (as well as other scheduling controls for internal training time). Our effects are thus conditional on labor supply. In addition to this, we also show directly in Table S10 that aggregate call center attendance is not associated with local weather conditions. We further discuss labor supply effects in the channel section, and find no effect of instrumented happiness on various fine-grained measures of labor supply.

**Labor Supply: Sickness.** A concern related to this is the possibility that adverse weather conditions may cause sickness among workers, and impair their ability to attend work. We use the fine-grained detail of our dataset to show at the call-center-by-week level that weather conditions are not related to aggregate sickness (see Table S10).

**Treatment Heterogeneity.** In the presence of treatment response heterogeneity, a valid instrument identifies a local average treatment effect (LATE), that is the effect driven by those who comply with the treatment. In our case, this may be an issue if only certain types of workers care about weather. Assuming these workers also tend to be those whose productivity reacts more strongly to happiness, this effect alone could explain the larger coefficient found in the IV case. We investigate the possibility of treatment response heterogeneity directly by looking at whether our bad weather index affects workers’ mood differently across a number of important characteristics. We look at basic demographics (gender, age and workers’ tenure), the total number of weekly sales and whether the worker reports an above median average happiness level during the entire period. Table S11 shows the first stage of our IV strategy where we interact our bad weather index with each of these five main characteristics. We find no evidence of heterogeneity across any of these dimensions.

## 4 Robustness

**Production function approach.** Our main approach used a Poisson model predicting a worker’s number of weekly sales, using her level of happiness that week. An alternative approach, is to estimate a standard Cobb-Douglas worker-specific production function of weekly sales,<sup>13</sup> augmented by our measure of worker happiness, such that

$$\ln(S_{ijt}) = \beta \ln(H_{ijt}) + \gamma \ln(X_{ijt}) + \nu_i + \tau_t + \epsilon_{ijt}.$$

We show in Table A2 that our main within-worker estimates are similar when doing so.

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<sup>13</sup>See [Black and Lynch \(1996, 2001\)](#) or [Attanasio et al. \(2015\)](#) for a similar estimation on the impact of human capital on productivity.



The poisson coefficient on log happiness is .077 (.008), suggesting that a 10% increase in our happiness scale increases weekly sales by a bit less than 1%. When instrumenting log happiness with our adverse weather index, we show in Table S6 the robustness of our findings to this alternative approach. In this specification, the first stage is slightly stronger, with an F-statistic of 12. The resultant second stage coefficient on log happiness of .505 (.217) suggests that a 10% increase in happiness has a positive impact on weekly sales, increasing them by around 5%.

**Heterogeneity.** We look for potential sources of heterogeneity across gender, age, average level of happiness, or length of tenure but find no robust evidence of heterogeneity along these dimensions (see Table S14 in online appendix). When doing so, we find very few differences in the association of happiness and sales across any of the sub-groups of workers we identify.

**Linear Estimates.** Our results are very similar if we use a linear OLS model (with individual and week fixed effects) instead of a Poisson model, as shown in Table S13.<sup>14</sup> By logging the weekly sales, we lose around 2% of the sample, since these observations have zero sales. However, our results remain robust when doing so.

Whereas the use of a poisson model, to account for sales being a count variable, led us to use a two-stage control function approach in order to estimate our instrumented equations, the use of logged sales on the left-hand-side of the equation means we are instead able to estimate a more straightforward two-stage least squares (2SLS) equation. Here again we find consistent results (see Table S13).

**Daily Estimates.** Although our happiness data is measured at the weekly level, our productivity data is reported largely at the daily level. In our main analysis, we aggregated performance data to the weekly level, but it is also possible to produce daily estimates. Here we assume that responses to the happiness question, which is asked on Thursday and refers specifically to “this week”, apply equally to each of the weekdays. We again estimate poisson regressions predicting the number of daily sales, and include a set of individual and date (that is, day\*week) fixed effects as well as daily controls for selling time and internal training time. As can be seen in Table S12 in the appendix, results are very similar when we carry out this exercise – both in terms of our within-worker estimates as well as our instrumented estimates using local weather shocks in order to set up a natural experiment.

**Measurement Error.** Given the nature of our weekly happiness survey instrument, our estimates are highly likely to be affected by measurement error. Our IV estimates above help to deal with this. However, in order to investigate the issue more fully, we also construct an alternative instrument that uses the average happiness of workers within teams in any given week (excluding the worker’s own survey response). In the presence of emotional spillovers between colleagues (Barsade and Knight, 2015), or any common happiness shock, this measure should positively relate to own happiness.

In the first stage of the instrumented analysis shown in column (2) of Table S4, we find that co-worker happiness is strongly related to own happiness over time. The second stage regression, shown in column (3) of Table S4, again suggests a strong effect of happiness on sales performance. The estimate is higher than in the non-instrumented analysis, suggesting that our initial estimates are likely to be strongly biased downward due to measurement error in our

<sup>14</sup>Equation (1) hence becomes  $\ln(S_{ijt}) = \beta H_{ijt} + \gamma X_{ijt} + \nu_i + \tau_t + \epsilon_{ijt}$ .

survey.<sup>15</sup>

**Customer Satisfaction.** A further concern is that even if happier workers are able to extract more sales from customers, this may come at the cost of lower customer satisfaction (and potentially fewer customers in the long-run). Assuming customers are rational, they should only accept offers whose marginal cost does not exceed their marginal utility. Taking customer satisfaction as a proxy for customer surplus, a higher surplus (hence satisfaction) may occur if more customers are buying.

To investigate this issue further, the firm provided us with data on customer satisfaction, since after each call customers are asked by text or phone to report the extent to which they would recommend BT to others, on a 0 to 10 scale. This measure is somewhat noisy, since each worker on average receives very few feedback ratings per week.<sup>16</sup> Using the weekly average response for each worker, we show in Table S5 that, within-workers over time, happiness increases customer satisfaction. Instrumenting for happiness using our weather data, however, we find little effect of employee happiness on customer satisfaction.

## 5 Channels

Having shown a robust causal effect of happiness on overall sales performance, we move on in this section to what behaviors drive this effect. We consider two possible broad categories of channel: labor supply and labor productivity.

### 5.1 Labor Supply

In our setting we observe detailed, high frequency data on workers' labor supply decisions. At the extensive margin, we observe a percentage measure of weekly attendance, which has a mean of around 93%. Here we code whether the employee recorded perfect attendance to her scheduled hours during the week.<sup>17</sup> In the second-stage of a 2SLS equation in which we instrument for happiness using adverse weather, shown in column (1) of Table 2, we find no robust evidence of any happiness effects on attendance. Equally, we find negative but non-significant coefficients for over-time working and paid vacation. If anything, increased happiness makes people more likely to take paid sick leave from the firm, though the standard error means our estimate is only weakly significant.

We also observe the number of length of paid and unpaid breaks taken by workers. Here we code the overall number of minutes taken during the week. The vast majority of breaks are unpaid (around 70% of observations for paid breaks are zero). In both cases, the coefficient is negative, suggesting that happiness increases workers' labor supply. However, in neither case is

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<sup>15</sup>While this analysis is focused principally on reducing the threat of measurement error, the use of our peer instrument should also help to mitigate endogeneity. It is worth re-iterating that call center sales are an autonomous productive task involving very few colleague interactions in the selling process, and thus other workers' mood should have little to no direct influence on the productivity of the focal worker. Nevertheless, we are unable to directly prove the non-existence of spillover effects and thus cannot fully rule out any violation of the exclusion restriction here.

<sup>16</sup>We take only instances where the worker receives two or more in a given week. We are of course also well aware that such measures suffer from a number of further limitations, including the possibility of selection bias in whether happy or unhappy customers are more or less likely to answer.

<sup>17</sup>Similar findings are found when using the continuous measure of attendance.

Table 2: Happiness and High-Frequency Labor Supply

	Attendance	Sick Leave	Overtime	Paid Vacation	Paid Breaks	Unpaid Breaks
	(100% = 1)	(Any = 1)	(Any = 1)	(Any = 1)	(Minutes)	(Minutes)
Happiness (1-5)	-0.0684 (0.1588)	0.1665* (0.0895)	-0.0866 (0.0744)	-0.1387 (0.1302)	-4.7732 (3.1381)	-19.6483 (21.3363)
Observations	12,285	12,285	12,288	12,288	12,288	12,288

*Notes: Second-stage 2SLS models reported, using adverse weather index as an IV for happiness. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects and dummies for day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .*

the estimate precise. Overall, taking each of our labor supply measures together, we find very little evidence of any robust happiness effects on labor supply decisions. This is in line with what would be expected in the context of a call center, where employees have little autonomy or freedom to decide how much they work, once they arrive and are sat at their terminal.

Overall, as we noted above in relation to the validity of our weather instrument, the very limited labor supply flexibility in our call center field site provides us with an ideal setting in which to test for the pure productivity effects of happiness in a real-world workplace setting.

## 5.2 Labor Productivity

If happier workers do not work *more*, it may well be that they work *better* or *faster*. Here we consider three main measures of labor productivity. First, workers attend and have their day's workflow scheduled for them and displayed on their terminal screen. For example, they may have the first hour scheduled as selling TV bundles, the second selling internet connections, a 15 minute break, and then an hour selling something else. The firm routinely records the extent to which employees "adhere" to this scheduled workflow. Occasional deviance from this workflow may be beneficial (if the worker has to stay on a call to complete a sale, for example), and the firm sets a loose target of 92% adherence each week. We code our outcome variable here as 1 if this target is met. We find in the second stage of a 2SLS regression (column (1) of Table 3), in which happiness is instrumented for using local weather, that happier workers adhere more closely to the workflow that has been set out for them.

Second, we observe on a daily basis the total number of minutes spent on incoming calls as well as the number of calls taken. We code the average length of each call during the week. This "speed" measure is what would typically be used as a labor productivity metric. However, in a call center setting it is not at all clear that taking more, shorter calls will be beneficial, when the goal is selling (hence the use of overall sales as our main performance metric). First, faster calls may displease customers and make them less likely to buy if the operator is too blunt or quick with them. Second, sales calls are likely to be mechanically longer, due to the time it takes to complete an order, take payment details, and so on. Nevertheless, we show in column (3) of Table 3 that in happier weeks workers do work faster. This remains true when controlling for the number of sales made, which is itself positively correlated with the length of calls.

Finally, we observe the ratio of sales to incoming calls. Here, we show in column (5) of Table 3 that in happier weeks, workers convert more of their calls to sales. Interestingly, we find in column (6) that the average length of calls is positively, not negatively, correlated with the

Table 3: Happiness and High-Frequency Labor Productivity

	Adherence (Met Target=1)		Minutes Per Call (Log)		Conversion Rate (Log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Happiness (1-5)	0.2864** (0.1413)	0.2963** (0.1477)	-0.2056** (0.0821)	-0.2156** (0.0880)	0.5432*** (0.2059)	0.6458*** (0.2163)
# Sales		-0.0030* (0.0016)		0.0026*** (0.0010)		
Minutes per call (ln)						0.6224*** (0.1162)
Observations	12,175	12,175	12,100	12,100	11,720	11,720

*Notes: Second-stage 2SLS models reported, using adverse weather index as an IV for happiness. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, and controls working hours, internal training time, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .*

conversion rate, though this does not affect the coefficient on happiness. Although in happier weeks workers work faster by making more calls per hour on the phone, this does not seem to come at a quality cost in terms of affecting their ability to convert more calls to sales.

## 6 Discussion

A long-running literature has sought to explain heterogeneity in productivity across individuals as well as firms (e.g. [Ichniowski et al., 1997](#); [Lazear, 2000](#); [Syverson, 2011](#)). We contribute to this growing body of work by showing the causal effect of a typically-overlooked aspect of workers' lives: how happy they are. We show that being in a positive mood has a significant impact on the number of sales made by employees. We find that when workers are happier, they work faster by making more calls per hour worked and, importantly, manage to convert more of these calls to sales.

### 6.1 Psychological mechanisms

While the main focus of the paper has been to assess the extent to which there is a main, causal effect of happiness on performance, our data and setting nevertheless allow us to offer some suggestive evidence on mechanisms. In this section, we draw on experimental work—largely in psychology—on the effects of induced affect for clues as to potential mechanisms. We look at three broad psychological pathways through which happiness may feed through into higher sales: intrinsic motivation, cognitive processing and emotional or social skills.

#### 6.1.1 Intrinsic Motivation

First, feelings of happiness have been shown to increase intrinsic motivation ([Erez and Isen, 2002](#)).<sup>18</sup> This effect could be particularly important in more routine work settings like ours, or in the absence of strong enough financial incentives to do good work. Because we cannot

<sup>18</sup>In this sense, our work relates to a recent literature in economics that has begun to concern itself with non-monetary forms of motivation (see, e.g. [Benabou and Tirole, 2003](#); [Gneezy and Rustichini, 2000](#)).

measure intrinsic motivation directly, we instead compare workers whose performance level may be more (versus less) *reactive* to intrinsic motivation. We rely on the presence of strong financial incentives to do good work – that is, on the nature of our sales workers’ pay-for-performance (PFP) schemes. In high performance pay settings, productivity may be less reactive to intrinsic motivation motives relative to the extrinsic incentives to sell (see, e.g. [Frey and Jegen, 2001](#)). In other words, if happiness impacts sales through intrinsic motivation, an exogenous happiness shock may have a *smaller* effect on those workers who are working under strong enough financial incentives.

In our sample of sales workers, 70% are under high performance pay: they receive a bonus amounting to 30% of their base salary if they meet their target (note that this is not an explicit piece-rate but rather a slow-moving bonus scheme). The 30% remaining workers do not benefit from this large performance pay scheme. In Table S15, we show that the performance of sales workers who do not benefit from the high performance pay scheme also seems more reactive to random unhappiness shocks, as captured by our bad weather index.<sup>19</sup> The sign of the interaction is also positive for un-instrumented happiness (but not significant).

This suggests that strong enough extrinsic motivations may limit the scope of unhappiness on performance, but that when workers perceive these incentives to be too low (or when these are simply missing), the performance costs of unhappiness can be very large. Of course, these results are only suggestive in nature. In order to make a more definite claim, one would need to rely on exogenous changes in performance pay within-workers, which goes beyond the scope of this paper.

### 6.1.2 Cognitive Abilities

A further possibility is that better mood states may improve cognitive functioning and workers’ abilities to remain focused on their daily tasks. Indeed, subjects induced into positive mood states have been shown to become better at cognitively processing information ([Estrada et al., 1997](#)) as well as better at creative problem solving tasks ([Isen et al., 1987](#)). Relatedly, it has been shown that the thoughts of unhappier people are more likely to “wander” ([Killingsworth and Gilbert, 2010](#)), a mechanism that has been formalized into an economic model in which happiness reduces the amount of time spent worrying about negative aspects of people’s lives, and thus drives productivity ([Oswald et al., 2015](#)).

Though we cannot test for cognitive abilities directly, we already saw that worker’s adherence, a proxy that captures the capacity to stay focused on a given task, increased with their happiness (see Table 3). We can further investigate this point by looking at weeks during which workers have to do other type of tasks on the top of their usual incoming calls activity (which represent 91% of their average weekly hours). Multi-tasking generally requires stronger cognitive abilities as it becomes harder to stay focused on a single task. We should therefore expect that workers who have to multi-task more in a given week should also be less productive in terms of sales. However, if happiness improves cognitive processing, the sales performance of happy multi-tasking workers should be less negative than the performance of unhappy multi-tasking

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<sup>19</sup>As we want to account for the endogeneity of our happiness measure when we discuss heterogeneous effects, we also look at interactions using our bad weather index.

Table 4: Effects of Happiness by Sales Type

	# Sales		
	(1) Phone + Internet Lines	(2) TV + Cell Phone Contracts	(3) Upgrades + Re-Contracting
Happiness (1-5)	-0.0126 (0.1807)	0.1631 (0.1782)	0.3179** (0.1599)
Observations	12,252	12,269	12,264

Notes: Second-stage Poisson-IV models reported. Bootstrapped standard errors in parentheses, re-sampling across individuals. All models include controls for the log of working hours, internal training time, and day of week dummies for response to survey. Happiness is instrumented for using local weather conditions in the first stage. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

workers.

In Table S16 we interact happiness with the fraction of weekly working hours during which sales workers were doing other tasks than responding to incoming calls. We find that weeks during which workers are asked to allocate more time to other tasks or to outgoing calls in addition to their regular activity tend to have lower sales performance. However, we do not find any evidence of this varying at different levels of happiness.

### 6.1.3 Social Skills and Emotional Labor

Finally, happiness could also augment (non-cognitive) social or emotional skills. For example, happy workers have been shown to demonstrate higher powers of self-control and abilities to manage their emotions, which is particularly useful in customer-facing industries and occupations (Goldberg and Grandey, 2007; Tice et al., 2001). One may thus think of happiness as an aid to social skills, allowing workers to better negotiate with customers and find appropriate solutions for them.

To test for this, we first examine the effect of happiness on different types of sales. Although we do not observe the amount of time spent (or number of calls) selling different products, we do observe the breakdown of realized sales. We split the sales into three categories: i) regular sales of phone lines and internet connections, which typically involve relatively simple order-taking; ii) TV and cell-phone contracts, which tend to be more complex, variable, and involve a greater amount of selling and negotiation skill; and iii) re-contracting and upgrades, which usually involve the most amount of social and negotiating skills (and also typically involve disgruntled customers).

In Table 4 we find that happiness does not have a significant effect on regular order-taking. This is consistent with the main mechanism being call-to-sales conversion rather than working faster, since line sales are largely mechanical order-taking. A positive effect is evident for TV and cell-phone contracts (though the estimate is somewhat imprecise), where there is more leeway for persuasion and negotiation. A stronger positive effect is evident for the re-contracting sales, suggesting happiness mostly impacts tasks involving the use of social and negotiating skills.

The sociological literature on *emotional labor* (see, e.g. Hochschild, 1983) has long argued that in tasks involving interactions with customers, it becomes particularly costly for unhappy

employees to leverage their social skills and manage their emotions, as they need to “fake” happiness. This is particularly the case when dealing with unsatisfied customers, as employees’ ability to empathize and “tame” customers’ negative emotions then comes at a larger psychological cost.

To further test that hypothesis, we first look at the interaction between workers’ happiness (and our bad weather index) and the BT’s overall customer satisfaction across all of our call centers in a given week. In weeks where overall customer satisfaction is low (for instance due to a network crash), the impact of being in a good (bad) mood should have a much stronger positive (negative) effect on sales. We find evidence for this effect in Table S17. The data is thus also supportive of the emotional labor hypothesis as it implies happiness mostly improves sales when interacting with unhappy customers.

There is a growing interest in the role of social skills in the labor market, and it is now well-accepted that the number of jobs requiring workers to interact socially is increasing rapidly (Deming, 2017). Our analysis, which points to a strong role for happiness in improving re-contracting and upgrade sales, in particular when workers have to deal with unsatisfied customers, suggests that the importance of employee happiness in driving productivity growth is likely to rise in the coming years.

## 7 Conclusion

Although the past few years have seen a renewed focus by employers on worker happiness, the study of employee well-being and performance does in fact have a long history that stretches back almost a century. In reaction to early scientific management theories—often loosely referred to as Taylorism—which imported tools from engineering in order to study labor productivity, the Human Relations movement sought to place human factors such as motivation and attitudes at the center of their studies of factory production (Vroom, 1964). Beginning with the Hawthorne studies of the late 1920s, this movement, and subsequent scholarship in related fields like industrial relations and organizational behavior, placed an emphasis on employee satisfaction and studied its relationship with productivity (see, e.g., Hersey, 1932; Kornhauser and Sharp, 1932, for early examples).

The large stream of research on job satisfaction in the subsequent decades produced only very mixed findings of a relationship with job performance. A more recent turn in the literature away from satisfaction measures and onto workers’ affective states has produced more robust findings, at least in laboratory settings where happiness can be manipulated in a controlled manner. As yet, however, robust causal evidence in the field of an effect of happiness on performance is lacking. In this paper we leverage variation in local weather conditions, together with a novel survey and detailed quantitative data on workplace behaviors and performance, in order to show a strong impact of employee happiness on productivity.

One limitation with the study is that while we show an effect of happiness on productivity, what we are not able to do, given our data and setting, is adjudicate as to whether investing in schemes to enhance employee happiness makes good business sense. Any such adjudication is naturally dependent on both the costs of raising worker happiness as well as the potential

benefits in terms of performance. We provide solid evidence for the latter half of the equation. A further limitation is that we are not able to observe what it is in our setting that affects workers' level of happiness and unhappiness from week-to-week (beyond variation in weather). Thus we are not in a position to make any recommendations about what firms might do in order to boost happiness and hope to gain from any productivity effects. Indeed, although we examine data from an applied setting, our study is focused principally on estimating the effect of happiness on performance.

Generally, causal evidence on the determinants of happiness in the workplace is scarce, but correlational studies suggest a number of avenues—at varying levels of expense—where employers may seek to improve well-being (see [De Neve and Ward, 2017](#)).<sup>20</sup> Higher paid workers and those in secure jobs are generally happier, for example, while those who find their job more interesting and meaningful also report higher well-being. Equally, workers who enjoy better work-life balance as well as better relationships with colleagues and managers also have higher levels of happiness.

Recent work by [Bryson and MacKerron \(2016\)](#), using high-frequency data on people's mood states in the UK, suggests that doing paid work is ranked almost the lowest in terms of happiness out of 40 activities individuals can report engaging in (only being sick in bed is associated with more unhappiness). In the USA, detailed time use surveys suggest that the most unhappy periods of people's days are when they are with their boss ([Krueger et al., 2009](#)). There thus seems to be considerable room for improvement in the happiness of employees while they are at work. While this clearly is in the interest of workers themselves, the analysis presented here suggests it may also be in the interests of their employers.

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<sup>20</sup>It is also worth noting that making comparisons between groups in terms of self-reported happiness can be problematic. As recently argued by [Bond and Lang \(2019\)](#), the comparison of group happiness requires strong identifying conditions when subjective well-being is measured on a discrete scale (namely assumptions on the latent distribution of happiness and similar reported functions between groups). Because in this study we use reported happiness as an independent variable and our preferred specification is within-workers, we are not concerned by the issue of group happiness or possible heterogeneity in reporting functions between workers.



## Appendix

Table A1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Happiness	12549	2.6	1.37	1	5
Sales	12549	25.57	19.55	0	101
Selling Time (factored for wait-time)	12549	19.89	8.21	0	52.43
Internal shrinkage	12549	10.52	13.31	0	100
Customer satisfaction	10281	7.9	2.26	0	10
Adherence	12438	92.03	5.45	0	100
Minutes per call	12549	12.43	3.34	0	33.44
Calls to Sales Conversion Rate	12105	27.14	18.4	0	100
Sickness (%)	12546	1.59	7.77	0	100
Attendance (%)	12546	92.55	14.16	0	100
Paid Breaks (mins)	12549	12.77	23.3	0	240
Unpaid Breaks (mins)	12549	213.71	93.88	0	540
Overtime (hrs)	12549	.15	.98	0	15.58
Paid Time Off (hrs)	12549	1.06	2.99	0	38
Bad weather index	12284	4.06	1.78	0	10
Age: 15-20	1161	.01	.11	0	1
21-25	1161	.22	.41	0	1
26-30	1161	.24	.43	0	1
31-35	1161	.16	.37	0	1
36-40	1161	.11	.32	0	1
41-45	1161	.09	.29	0	1
46-50	1161	.06	.24	0	1
51-55	1161	.05	.22	0	1
56-60	1161	.03	.18	0	1
61+	1161	.01	.11	0	1
Female	1161	.43	.5	0	1
Tenure (years)	1161	5.24	7.21	.09	43.79
Left the firm during study	1161	.07	.26	0	1

Table A2: Happiness and Sales Performance

	Sales		
	(1)	(2)	(3)
<b>Happiness (vs. neutral)</b>			
Very Unhappy	-0.0723*** (0.0105)		
Unhappy	-0.0511*** (0.0105)		
Happy	0.0368*** (0.0101)		
Very Happy	0.0557*** (0.0143)		
<b>Happiness (Continuous)</b>			
Happiness (1-5)		0.0349*** (0.0034)	
Happiness (ln)			0.0776*** (0.0077)
Observations	12,549	12,549	12,549
Employees	1,161	1,161	1,161
Pseudo-R <sup>2</sup>	0.626	0.626	0.626
Week FEs	✓	✓	✓
Individual FEs	✓	✓	✓

Notes: Poisson models reported. Robust standard errors in parentheses, clustered on individuals and weeks. All models include controls for the working hours, internal training time, and day of week dummies for response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

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# Supplementary Material

## Does Employee Happiness Have an Impact on Productivity?

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**For Online Publication Only**



## A Sample Characteristics and Non-Response

Table S1: Predictors of study participation: Extensive Margin

	Participated in the study = 1		
	(1)	(2)	(3)
Age: 21-25 (v. 15-20)	0.070 (0.071)	0.068 (0.073)	0.049 (0.070)
26-30	0.057 (0.076)	0.053 (0.079)	0.042 (0.074)
31-35	0.039 (0.074)	0.029 (0.078)	0.011 (0.074)
36-40	0.017 (0.079)	0.006 (0.084)	-0.018 (0.080)
41-45	0.026 (0.078)	0.013 (0.083)	-0.014 (0.079)
46-50	0.086 (0.075)	0.074 (0.082)	0.035 (0.078)
51-55	0.003 (0.091)	-0.004 (0.097)	-0.051 (0.095)
56-60	0.077 (0.092)	0.067 (0.094)	0.024 (0.084)
61+	-0.074 (0.114)	-0.082 (0.118)	-0.124 (0.119)
Female	-0.021 (0.021)	-0.020 (0.022)	-0.003 (0.022)
Left firm during study	-0.153*** (0.036)	-0.159*** (0.036)	-0.132*** (0.034)
Tenure (months)	-0.001*** (0.000)	-0.001** (0.000)	-0.000* (0.000)
Mean sales during study			-0.001 (0.002)
Mean selling hours during study			0.010*** (0.003)
Call center dummies	No	Yes	Yes
Observations	1793	1793	1793
$R^2$	0.041	0.046	0.062

Notes: Robust standard errors in parentheses, clustered on call centers. Participated =1 if worker responded to at least one survey. 1,438 workers (80.2%) participated in the study.

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table S2: Predictors of study participation: Intensive Margin

	# Waves responded to survey		
	(1)	(2)	(3)
Age (v. 15-20)			
21-25	0.006 (0.205)	-0.018 (0.196)	-0.063 (0.217)
26-30	0.012 (0.236)	-0.022 (0.223)	-0.055 (0.250)
31-35	0.056 (0.236)	0.019 (0.216)	-0.041 (0.238)
36-40	0.156 (0.226)	0.103 (0.203)	0.035 (0.230)
41-45	0.205 (0.226)	0.155 (0.204)	0.087 (0.233)
46-50	0.225 (0.251)	0.176 (0.228)	0.077 (0.253)
51-55	0.368 (0.224)	0.336 (0.206)	0.220 (0.231)
56-60	0.213 (0.217)	0.185 (0.209)	0.082 (0.240)
61+	0.119 (0.219)	0.107 (0.207)	-0.005 (0.246)
Female	-0.115*** (0.038)	-0.108*** (0.036)	-0.070** (0.033)
Left firm during study	-0.909*** (0.044)	-0.925*** (0.043)	-0.866*** (0.034)
Tenure (months)	-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
Mean sales during study			-0.001 (0.001)
Mean selling hours during study			0.024*** (0.004)
Call center dummies	No	Yes	Yes
Observations	1438	1438	1438

Notes: Robust standard errors in parentheses, clustered on call centers. Poisson models reported. Sample is all workers who participated in the study.

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table S3: Predictors of attrition/non-response

	Responded to Survey = 1			
	(1)	(2)	(3)	(4)
Sales	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Selling time	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
Bad weather index		0.001 (0.002)		0.001 (0.002)
Team happiness (excl worker)			-0.001 (0.003)	-0.001 (0.003)
Observations	33725	33725	33725	33725
$R^2$	0.436	0.436	0.436	0.436

*Notes: Robust standard errors in parentheses, clustered on individuals. Linear models reported. Unit of observation is worker\*week. Individual and week fixed effects in all models.*

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## B Measurement Error: IV Estimates using Peer Happiness

Table S4: Happiness and Productivity: IV estimates using peers' happiness

	Sales (Poisson)	Happiness (OLS)	Sales (Poisson)
	(1)	(2)	(3)
	Red.-Form	1st Stage	2nd Stage
Happiness (1-5)			0.3143*** (0.0920)
Team Happiness	0.0111*** (0.0034)	0.0362*** (0.0105)	
Observations	11,881	11,881	11,881
1st Stage F-Stat		11.97	

*Notes: Columns (1) and (3) are Poisson-FE models. Column (2) reports an OLS-FE regression. Column (3) reports the second stage of a Poisson-FE control function model. Robust standard errors in parentheses, clustered on individuals in models (1) and (2). Bootstrapped standard errors reported for model (3). All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .*

## C Customer Satisfaction

Table S5: Happiness and Customer Satisfaction

	Customer Satisfaction (z-score)			
	(1)	(2)	(3)	(4)
	OLS-FE	OLS-FE	2SLS	2SLS
Happiness (1-5)	0.0168* (0.0094)	0.0137 (0.0094)	-0.3767 (0.3185)	-0.4015 (0.3329)
# Sales		0.0034*** (0.0013)		0.0081** (0.0039)
Observations	10,062	10,062	10,062	10,062
Employees	1,082	1,082	1,082	1,082
R <sup>2</sup>	0.173	0.174	-0.173	-0.190

Notes: Columns (1) and (2) are OLS-FE models. Column (3) and (4) report Second-stage 2SLS regressions. Robust standard errors in parentheses, clustered on individuals. Weekly customer satisfaction is z-scored. All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## D Production Function Approach

Table S6: Production Function using Weather IV

	Sales (Poisson)	Happiness (OLS)	Sales (Poisson)
	(1)	(2)	(3)
	Red.-Form	1st Stage	2nd Stage
Happiness (ln)			0.5187** (0.2140)
Bad Weather Index	-0.0059** (0.0026)	-0.0117*** (0.0034)	
Observations	12,282	12,282	12,282
1st Stage F-Stat		12.06	

Notes: Columns (1) and (3) are Poisson-FE models. Column (2) reports an OLS-FE regression. Column (3) reports the second stage of a Poisson-FE control function model. Robust standard errors in parentheses, clustered on individuals in models (1) and (2). Bootstrapped standard errors reported for model (3) - see text for detail. All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table S7: Production Function: Happiness and Labor Productivity

	Adherence (Met Target=1)		Minutes Per Call (Log)		Conversion Rate (Log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Happiness (ln)	0.5590** (0.2747)	0.5610** (0.2768)	-0.3894*** (0.1500)	-0.4069** (0.1707)	1.1283*** (0.4137)	1.3529*** (0.4391)
Sales (ln)				0.0373** (0.0185)		
Minutes per call (ln)						0.6776*** (0.1006)
Observations	12,175	12,175	12,100	11,979	11,720	11,720

Notes: Second-stage 2SLS models reported, using adverse weather index as an IV for (log) happiness. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, and controls for log working hours, internal training time, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table S8: Production Function: Happiness and Labor Supply

	Attendance	Sick Leave	Overtime	Paid Vacation	Paid Breaks	Unpaid Breaks
	(100% = 1)	(Any = 1)	(Any = 1)	(Any = 1)	(Minutes)	(Minutes)
Happiness (ln)	-0.1444 (0.3347)	0.3513* (0.1850)	-0.1827 (0.1563)	-0.2926 (0.2733)	-10.0697 (6.4880)	-41.4512 (44.4289)
Observations	12,285	12,285	12,288	12,288	12,288	12,288

Notes: Second-stage 2SLS models reported, using adverse weather index as an IV for (log) happiness. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects and dummies for day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## E Reduced Form Weather Effects

Table S9: Effects of Daily Weather on Sales

	Whole Sample		Non-Missing Happiness Data Only	
	(1)	(2)	(3)	(4)
Bad Weather Index (Daily)	-0.0100** (0.0044)		-0.0103* (0.0058)	
Bad Weather Index (Weekly)		-0.0071*** (0.0020)		-0.0068** (0.0028)
Observations	79,712	80,592	40,131	40,624
Individuals	1,188	1,189	1,184	1,185
Pseudo-R <sup>2</sup>	0.473	0.473	0.430	0.431

*Notes: Poisson-FE models reported. Robust standard errors in parentheses, clustered on individuals. Robust standard errors in parentheses, clustered on individuals. All models include individual and date fixed effects, along with work schedule controls.*

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .



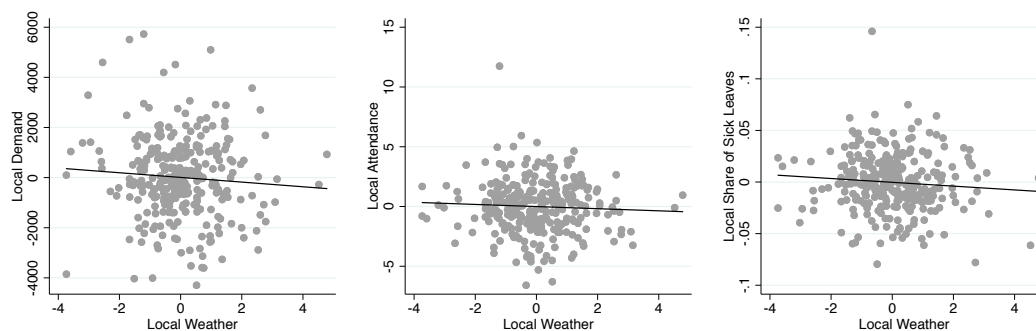
## F Weather Instrument Validity

Table S10: Weather IV Validity Test

	Local Demand	Local Attendance	Local Share of Sick Workers
	(1)	(2)	(3)
Bad Weather Index	-93.2295 (88.0944)	-0.0892 (0.0579)	-0.0018 (0.0017)
Observations	289	289	289
Call Centers	11	11	11
R <sup>2</sup>	0.915	0.666	0.326

Notes: OLS models reported. Robust standard errors in parentheses, clustered on locations. All models include week and location fixed effects.

Figure S1: Local Weather vs. Local Demand, Attendance and Sick Leaves



Note: The Figure plots the residual variation in weekly call-center total number of calls (left-panel), attendance (middle-panel) and sick leaves (right-panel) against the residual variation in local weekly weather index, after controlling for call-center and week fixed effects. Each dot represents a location  $\times$  week cell.

Table S11: Bad Weather Index and Happiness: Heterogeneous Treatment Effects

	Happiness					
	(1)	(2)	(3)	(4)	(5)	(6)
Bad Weather Index	-0.0247*** (0.0076)	-0.0175* (0.0093)	-0.0128 (0.0236)	-0.0262*** (0.0092)	-0.0294*** (0.0097)	-0.0288*** (0.0109)
<b>Bad Weather Interaction:</b>						
x Female Worker		-0.0181 (0.0143)				
x Worker's Age			-0.0003 (0.0006)			
x Worker's Tenure (Years)				0.0003 (0.0008)		
x Worker Avg Happiness > Median					0.0097 (0.0136)	
x # Sales						0.0002 (0.0003)
Observations	12,282	12,282	12,282	12,282	12,282	12,282
Individuals	1,157	1,157	1,157	1,157	1,157	1,157
R <sup>2</sup>	0.534	0.534	0.534	0.534	0.534	0.538

Notes: OLS-FE models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, work schedule controls, and day of response to survey. Column (6) also controls for weekly sales as it varies within workers.

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## G Estimates using Daily Data

Table S12: Happiness and Sales Performance: Daily

	(1)	(2)	# Sales (3)	(4)	(5)
	Poisson	Poisson	Poisson	Poisson-IV	Poisson-IV
Very Unhappy	-0.0794*** (0.0112)				
Unhappy	-0.0565*** (0.0107)				
Happy	0.0332*** (0.0107)				
Very Happy	0.0539*** (0.0155)				
Happiness (1-5)		0.0363*** (0.0036)		0.2608** (0.1027)	
Happiness (ln)			0.0814*** (0.0081)		0.5743** (0.2299)
Observations	40,624	40,624	40,624	40,624	40,624
1st Stage F-Stat				12.59	13.00

Notes: Poisson-FE and Poisson-IV models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and date fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## H Linear Estimates

Table S13: Linear Estimates

	Ln(Sales)			Ln(Sales+1)		
	(1) OLS-FE	(2) OLS-FE	(3) 2SLS	(4) OLS-FE	(5) OLS-FE	(6) 2SLS
<b>Happiness (vs. neutral)</b>						
Very Unhappy	-0.0715*** (0.0131)			-0.0687*** (0.0123)		
Unhappy	-0.0479*** (0.0134)			-0.0405*** (0.0127)		
Happy	0.0367*** (0.0131)			0.0247** (0.0126)		
Very Happy	0.0674*** (0.0175)			0.0512*** (0.0179)		
Happiness (Continuous)						
Happiness (1-5)		0.0362*** (0.0041)	0.6364*** (0.2266)		0.0310*** (0.0041)	0.6092*** (0.2277)
Observations	12,292	12,292	12,025	12,555	12,555	12,288
1st Stage F-Stat			10.51			10.30

Notes: OLS-FE and Second-stage 2SLS models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, work schedule controls, and day of response to survey.

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

# I Heterogeneity by Demographics

Table S14: Happiness and Sales Performance: Heterogeneity

	# Sales				
	(1)	(2)	(3)	(4)	(5)
Happiness (1-5)	0.0349*** (0.0034)	0.0316*** (0.0042)	0.0481*** (0.0116)	0.0372*** (0.0041)	0.0322*** (0.0050)
Happiness (1-5) × Female Worker		0.0096 (0.0068)			
Happiness (1-5) × Worker's Age			-0.0004 (0.0004)		
Happiness (1-5) × Tenure (Years)				-0.0006 (0.0005)	
Happiness (1-5) × Worker Avg Happiness > Median					0.0050 (0.0066)
Observations	12,549	12,549	12,549	12,549	12,549
Individuals	1,161	1,161	1,161	1,161	1,161
Pseudo-R <sup>2</sup>	0.626	0.626	0.626	0.626	0.626

Notes: Poisson-FE models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, work schedule controls, and day of response to survey.

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## J Mechanisms: Robustness

Table S15: Happiness and Performance-Related Pay

	# Sales			
	(1)	(2)	(3)	(4)
Happiness (1-5)	0.0349*** (0.0034)	0.0324*** (0.0072)		
Happiness $\times$ High Performance Pay		0.0031 (0.0081)		
Bad Weather Index			-0.0057** (0.0026)	-0.0168*** (0.0048)
Bad Weather Index $\times$ High Performance Pay				0.0148*** (0.0051)
Observations	12549	12549	12282	12282
Individuals	1,161	1,161	1,157	1,157
Pseudo-R <sup>2</sup>	0.626	0.626	0.617	0.617

Notes: Poisson-FE models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table S16: Happiness and Multi-Tasking

	# Sales	
	(1)	(2)
Happiness (1-5)	0.0378*** (0.0039)	
Happiness (1-5) $\times$ Other Tasks (% Working Hours)	-0.0004 (0.0004)	
Bad Weather Index		-0.0080*** (0.0030)
Bad Weather Index $\times$ Other Tasks (% Working Hours)		0.0004 (0.0003)
Other Tasks (% Working Hours)	-0.0010 (0.0013)	-0.0039*** (0.0011)
Observations	12,521	12,255
Individuals	1,159	1,155
Pseudo-R <sup>2</sup>	0.625	0.616

Notes: Poisson-FE models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table S17: Happiness and Emotional Skills

	# Sales	
	(1)	(2)
Happiness (1-5)	0.0352*** (0.0033)	
Happiness (1-5) × Weekly Customer Satisfaction	-0.0045* (0.0027)	
Bad Weather Index		-0.0038 (0.0026)
Bad Weather Index × Weekly Customer Satisfaction		0.0111*** (0.0019)
Observations	12,549	12,282
Individuals	1,161	1,157
Pseudo-R <sup>2</sup>	0.626	0.618

*Notes: Poisson-FE models reported. Robust standard errors in parentheses, clustered on individuals. All models include individual and week fixed effects, work schedule controls, and day of response to survey. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .*