Sleepless in Chennai: The Consequences of Increasing Sleep among the Urban Poor

Pedro Bessone† Gautam Rao Frank Schilbach
Heather Schofield Mattie Toma

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Abstract

This paper measures the prevalence and consequences of sleep deprivation among the urban poor in India. Low-income adults in Chennai sleep 5.6 hours of objectively-measured sleep per night, despite 8 hours in bed. Providing improvements to sleep environments, information, and encouragement increased sleep by over 30 minutes per night over the course of three weeks. Increased night sleep had no detectable effects on cognition, productivity, decision-making, or psychological and physical well-being, and led to small decreases in labor supply. In contrast, offering afternoon naps at the workplace improved cognition, psychological well-being, and productivity. Naps also reduced inattention to incentives and increased patience, as measured by a real-effort task and financial savings. Taken together, our results provide a possible explanation for the persistence of widespread sleep deprivation and the relatively high prevalence of afternoon naps in many developing countries.

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†Bessone: MIT (tepedino@mit.edu); Rao: Harvard and NBER (grao@fas.harvard.edu); Schilbach: MIT and NBER (fschilb@mit.edu); Schofield: UPenn (hschof@wharton.upenn.edu); Toma: Harvard (mattietoma@g.harvard.edu)
1 Introduction

A third of the US population is classified as sleep-deprived (Walker, 2017). Sleep deprivation may be even more common in cities in developing countries, where poor living conditions and environmental irritants such as heat, noise, mosquitoes and physical discomfort abound. Sleep experts warn of severe cognitive and health impacts from sleeping fewer than 7 hours per night (Watson et al., 2015). However, we know little about sleep patterns in the developing world or about the real-world economic impacts of increasing sleep in any context.

This paper reports results from the first large-scale field experiment on sleep in a developing country. To precisely measure the impact of sleep on labor-market outcomes, we recruited 452 low-income workers in urban India for a full-time data-entry job for one month each. As self-reports of sleep are notoriously noisy and biased, all study participants wore wristwatch-like devices that infer sleep from motion to objectively measure sleep.

After a one-week baseline period, we introduced two types of interventions to increase sleep. A random subset of study participants were offered items to improve their home sleep environments (e.g. mattresses, ear plugs, eye shades), information about their sleep, and verbal encouragement to sleep more at night. Another group received both this intervention and modest daily financial incentives to sleep more at night. The control group did not receive any such intervention.

In addition to these nighttime sleep treatments, a cross-randomized treatment group was offered a daily opportunity to nap in the afternoon during a consistent 30 minute period in comfortable nap cabins in the office. A control group was not offered access to the nap cabins, and was randomized within person to either receive a break of 30 minutes or to work through the nap period.

Baseline sleep. We document two novel findings regarding sleep among urban low-income workers. First, when measured objectively, the majority of workers in our sample are severely and chronically sleep-deprived. Despite spending about 8 hours in bed each night during the baseline period, they sleep on average 5.6 hours per night, well below levels recommended by sleep experts and estimates of objectively measured sleep in US populations (6.25 to 6.5 hours per night) (Hirshkowitz et al., 2015; Walker, 2017).

\[ \text{To avoid mechanical differences in income effects across groups, participants in other groups received identical streams of daily payments, but not conditioned on their sleep.} \]
Second, these findings imply a strikingly low average sleep efficiency — sleep time divided by time in bed — of about 70 percent in our study population, substantially lower than the sleep efficiency of healthy sleepers of the same age in rich countries (85 to 95 percent) and comparable to those with sleep disorders such as sleep apnea (Yoon et al., 2003; Carrier et al., 2001; Cole et al., 1992; Walker, 2017). Importantly, this low sleep efficiency implies a high opportunity cost of time of increasing night sleep.

**Impacts on sleep.** The night-sleep interventions led to sizable increases in sleep during the three-week treatment period. Individuals who were offered night-sleep devices and encouragement slept an average of an additional 21 minutes (standard error: 3.4 minutes) per night. When additionally provided with financial incentives, night sleep increased by 35 minutes (se: 3.8) relative to the control group. This increase was driven by greater time spent in bed — on average 32 and 48 minutes more per night, respectively — rather than an improvement in sleep efficiency.

Naps were effective at increasing sleep. Each afternoon during the 30-minute nap period, over 88 percent of individuals in the Nap Group fell asleep at some point and, average unconditional nap length was 13 minutes. Crowd-out of sleep from the interventions was modest: on average, the nap treatment crowded out 6 minutes of night sleep the following night, while those assigned to night-sleep treatment groups napped just as much as others when offered naps.

Taken together, our results suggest that improvements in sleep efficiency may be difficult to achieve without more substantial changes in sleep environments, but individuals do have some ability to adjust their total sleep time. However, these adjustments come at a relatively high time cost, given the low sleep efficiency in this population.

**Work outcomes.** Increasing sleep increased productivity meaningfully. The night-sleep treatments and naps increased productivity by 1.3 percent (se: 1.2) and 2.3 percent (se: 1.0), respectively. These impacts are sizable, both compared to piece-rate variation—quadrupling the piece rate increases productivity by 11 percent—and compared to interventions in other studies such as offering commitment devices (Kaur et al., 2015) or exposing workers to considerable environmental noise (Dean, 2018).

Absent increases in sleep efficiency, increased time asleep mechanically reduces time spent on other activities. Indeed, we find that the night-sleep treatment group reduced labor supply by about 9 minutes per day, largely due to arriving at work later in the morning. Combining

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2This draft reports p-values without correcting for multiple hypothesis testing. We are in the process of implementing such corrections controlling for Family-Wise Error Rates using a permutation approach, which will be report in future versions of this paper.
the productivity and labor-supply impacts, the night-sleep treatments reduced earnings by 2.7 percent (se: 1.8).

Taking a nap increased earnings by 4 percent (se: 1.8) compared to taking a break during the nap period, but reduced earnings by 8.3 percent (se: 1.8) compared to working through the break, due to a 23 minute reduction in labor supply. This negative impact on earnings declined over the course of the treatment period, with equal earnings (despite lower labor supply) between the groups that took a nap and worked through the break by the end of the study. Regular naps may thus increase productivity enough to maintain earnings despite reductions in labor supply.

Taken together, we find no evidence that increased night sleep raises earnings, in contrast to non-experimental work on the wage and educational attainment impacts of sleep in the long run (Gibson and Shrader, 2018; Jagnani, 2018). Our results are also contrary to predictions elicited from sleep experts and economists, who predicted an increase in output of 8 percent on average from the night sleep treatments.3

Attention. Economists have shown that limited attention distorts reactions to taxes, prices, news, and attributes of goods (Chetty et al., 2009; Allcott and Taubinsky, 2015). Some argue that limited attention underlies a range of behavioral biases (Gabaix, 2019). Work by sleep scientists suggests sleep may impact attention and vigilance (Lim and Dinges, 2010). We study impacts on attention in two ways. First, we deploy a standard laboratory test of sustained attention and reaction time sleep scientists frequently use. Naps improved performance in this task by 0.1 standard deviations (se: 0.02), while, in contrast to laboratory-based studies that deprive healthy subjects of their sleep, the night-sleep treatments had no effect.

Second, we built a test of limited attention into the daily data-entry work. We created variation in piece-rate incentives within participants over time and additionally randomize the visual salience of the changes in these incentives. We can thus estimate the degree of inattention to non-salient incentives by comparing the elasticity of output under non-salient incentives to the full-attention benchmark across treatment arms. In the control group, individuals exhibit limited attention; they are 15 percent away from the full-attention benchmark on average. The night-sleep group has similar levels of inattention. However, the nap group is only 5 percent away from the full-attention benchmark, an effect driven predominately by improved (attention in the afternoon (post-nap). Our two measures of attention thus paint a consistent picture: naps increase attention while the night-sleep treatments do not.

3Experts in both domains were provided with information on the design of the study, baseline levels of sleep, and the treatment effect of the intervention and were then asked to report their beliefs on the impact of those changes on a subset of experimental outcomes.
Preferences and decision-making. We next investigate whether increased sleep affects time preferences. First, we measure present bias following Augenblick et al. (2015) by eliciting incentivized choices of how many pages of data entry participants would like to do at different piece rates and time horizons. We structurally estimate individual-level present bias, and find an average level of present bias of $\beta = 0.925$ in the control group (where $\beta = 1$ corresponds to no present bias). The night-sleep group exhibits a similar level of present bias, while we find significantly less present bias on average in the nap group: $\beta = 0.981$ (se: 0.03). Thus, naps may reduce self-control problems.

We also measure patience in another economically important domain: savings. We offered participants an opportunity to save money in an account at the study office with daily interest rates randomized across individuals and ranging from 0 percent to 2 percent a day. We find that the nap treatment increased average daily deposits by economically meaningful amounts (14 percent of control-group savings) although, given the noisy outcome measure, the estimated coefficients are only statistically significant in some specifications. Consistent with the estimated present-bias parameters, the night-sleep treatments did not affect savings.

In contrast to the effects of naps on time preferences, we find no effects of either naps or night-sleep treatments on standard incentivized laboratory measures of risk preferences (risk and loss aversion) and social preferences (dictator, ultimatum, and trust games).

Well-being and health. Finally, we measured impacts on psychological and physical well-being. First, the nap treatment increased an index of psychological well-being by 0.13 standard deviations (se: 0.05), particularly through increased happiness and a greater sense of life satisfaction and life possibilities. Night-sleep treatments had no effect on psychological well-being.

Neither naps nor increased night sleep had significant impacts on physical activity or physical health. These findings are consistent with the medical literature, where modest or no measurable improvements in health have been observed in the short run (Aggarwal et al., 2019; Bravata et al., 2003). However, the longer-run effects could be larger due to the cumulative and gradual nature of many chronic conditions.

Summary. This paper provides evidence on sleep and its consequences in a variety of domains. First, low-income individuals in Chennai sleep little compared to existing guidelines. Their low levels of sleep are closely related to strikingly low sleep efficiency, which also increases the opportunity cost of sleep. Our sleep treatments (devices with encouragement, incentives, and naps) all increased night sleep substantially, but did not increase overall sleep efficiency. Increasing night sleep did not result in clear short-run improvements in the domains measured. In contrast, afternoon naps proved to be an effective intervention
in improving productivity, attention, psychological well-being, present bias and savings.

Taken together, our findings provide a possible explanation for the persistence of widespread sleep deprivation. The costs of increasing night sleep are immediate and salient: individuals have fewer hours available for work or leisure, with no accompanying payoff in terms of earnings, happiness or even health over the course of a few weeks. These non-effects of increased night sleep may be specific to the low quality of night sleep in the setting we study, as evidenced by its low efficiency and large number of sleep disturbances. Future research might explore interventions to improve the quality and efficiency of sleep, which may have more powerful effects on economic outcomes without the associated opportunity costs of time.

Our results are also consistent with the greater prevalence of naps in developing countries, since naps appear to provide a variety of immediate and clear benefits in terms of psychological well-being, productivity, and decision-making in our sleep deprived population. Our findings are consistent with a large body of research in sleep medicine which concludes that naps are effective in countering the cognitive effects of sleep deprivation (Lovato and Lack, 2010; Dinges, 1992).

The remainder of this paper proceeds as follows: Section 2 describes key background information. Section 3 describes the experimental design. Section 4 provides data on baseline levels of sleep in the study population and the effect of the interventions on sleep. We describe sleep’s impact on productivity and labor supply, savings, and health results in Section 5. Section 6 discusses the findings and concludes.

2 Background

2.1 Measuring Sleep

Self-reported levels of sleep are notoriously unreliable and often only correlate moderately with objective sleep measures. Because it is difficult to report on a partially conscious state, individuals instead tend to report the hours spent in bed, frequently leading to over-reporting of sleep duration (Lauderdale et al., 2008). In an experimental context, the interventions themselves can create demand effects (i.e. people may over-report sleep to satisfy the experimenter) or may bias reports in other ways (e.g. treated participants may pay more attention to sleep disturbances). Given these potential sources of error, objective measures of sleep are essential to measure sleep rigorously in experimental trials.

Sleep labs feature polysomnography (PSG), a gold-standard technology which records brain waves, eye movements, and other measures such as pulse to determine sleep/wake cycles.
as well as stages of sleep (Marino et al., 2013; de Souza et al., 2003). However, this technology is impractical for field studies, as it is bulky and requires multiple wire attachments to the participant each night (potentially altering sleep patterns). As a result, existing experimental sleep research has largely been conducted in hospital settings or sleep laboratories, often featuring small sample sizes and short study lengths due to cost considerations.

Recent technological advances in sleep-measurement techniques, known as actigraphy, greatly facilitate experimental field studies. These wristwatch-like devices measure sleep rigorously by inferring wake/sleep patterns from movement. Actigraphs can be used to objectively and passively measure sleep in individuals’ natural home environments. Comparisons between actigraph and PSG measures show high degrees of accuracy and sensitivity in sleep-wake detection, with total sleep time and sleep efficiency showing no significant differences across the two measurements (Kushida et al., 2001; Marino et al., 2013; Sadeh et al., 1995; Ancoli-Israel et al., 2003; Sadeh, 2011).

While actigraphs provide accurate data on sleep quantity and sleep efficiency, they do not measure sleep stages, in particular REM sleep, or sleep disorders. Actigraphs do provide some measures of sleep quality by capturing the number of sleep disturbances, i.e. the periods of movement during sleep. In addition, the devices are able to predict whether an individual is in bed, but not yet/still asleep. Hence, while the primary focus of sleep measurement in our study is sleep quantity, we are also able to report on sleep efficiency — time asleep divided by time in bed. Finally, participants are also asked to self-report their sleep daily allowing us to compare the objective and subjective measurements.

### 2.2 Sleep Deprivation Around the World

Few representative studies feature objective sleep measurements. The existing evidence, mostly from high-income countries, suggests that sleep deprivation is common around the globe, relative to the sleep science consensus view on optimal sleep habits (Watson et al., 2015). In the United States, sleep deprivation is often considered a public health epidemic (Walker, 2017). Similarly, in the United Kingdom the Mental Health Foundation finds that only 38 percent of adults are “good sleepers” (UK National Health Services, 2011).

The available evidence on sleep patterns is even more limited in developing countries and relies almost exclusively on self-reports or non-representative samples. The WHO-SAGE multi-country study with over 40,000 adults from rural areas in 8 countries documents a moderate overall prevalence of sleeping problems (16.6 percent), with large variation across countries and a higher prevalence of sleeping problems among female, older, and lower-
education individuals (Stranges et al., 2012; Gildner et al., 2014). In the Indian component of this study, self-reports by 4,500 older Indian adults show a relatively high self-reported average sleep duration of 7.1 hours (Gildner et al., 2014). However, even in this sample, about 30 percent of individuals report sleeping six or fewer hours per night (Selvamani et al., 2018).

Given that individuals tend to substantially overestimate their own sleep, such self-reported measures likely underestimate the true extent of sleep deprivation (Lauderdale et al., 2008). Additional challenges to sleep among the urban poor – including heat, noise, light, crowding, or physical discomfort – suggest a higher prevalence of sleep deprivation in urban areas than in the rural areas covered by WHO-SAGE.

Consistent with this hypothesis, the objective sleep measures in our urban sample reveal a much higher prevalence of sleep deprivation. While individuals in our sample self-report similar amounts of sleep to individuals in developed countries and in the WHO-SAGE data (7.2 on average), objective measures show an average sleep duration of 5.6 hours. By current medical standards, this figure implies severe sleep deprivation among the majority of study participants and strikingly low sleep efficiency in this context, as described in more detail below.

3 Experimental Design and Empirical Framework

Figure 1 provides an overview of the experimental design and timeline of the study. We recruited 452 workers to participate in the study for a total of 28 work days each. Enrollment took place on a rolling basis and occurred over 18 months. The experiment took place in a study office located in central Chennai, which contains computer work-stations for data-entry, a break room, gender-separated nap stations on a separate level, and stations for surveys and additional experimental tasks. Given the high ambient temperatures in Chennai, the office was mildly air-conditioned throughout the study to prevent the computers from overheating.

3.1 Interventions to Increase Sleep

Two cross-randomized sets of treatments were administered to increase sleep: (a) two interventions to increase night sleep among individuals in their usual home environments and (b) an intervention to increase daytime sleep by offering individuals the opportunity to nap at their workplace.
Night-sleep treatments. At the end of day 8 of the study, each individual was randomized into one of three night-sleep treatment groups of equal size, stratified by baseline productivity and sleep to ensure balance on these key covariates.

1. **Sleep Devices**: Participants in this group were provided with a bundled intervention to increase their night sleep. Surveyors offered individuals: (i) loaned devices to improve their sleep environment, (ii) information regarding the benefits of sleep (in particular, health benefits), and (iii) encouragement to increase their sleep as well as daily feedback on the total duration of their previous night’s sleep as measured by the actigraph. The devices offered included eye shades, earplugs, a cot, a mattress, sheets, pillows, and a fan (see Figure 2a). Participants were permitted to take more than one of each device, as piloting had suggested that the devices were often shared with family members.

2. **Sleep Devices + Incentives**: Participants in this group received the same interventions as the Sleep Devices group plus linear financial incentives to increase their sleep during the treatment period relative to their objectively measured average sleep in the baseline period. Individuals were paid Rs. 1 per minute of increased sleep for up to two hours of increased sleep (Rs. 120, about $2), again, objectively measured using actigraphs.

3. **Control**: Participants in the Control group did not receive any of the sleep treatments we discuss above. A subset of individuals were offered the choice between different placebo household items unrelated to sleep to assess concerns that loaning items generated reciprocity effects or impacted reported well-being. The items were of roughly the same total value as those provided to the other groups and included items such as small kitchen devices, a chair, decorative figurines, a shoulder bag, kitchen utensils, and a flashlight.

All devices were loaned to the participants, who were asked to return the items on day 29 of the study. We then elicited participants’ willingness to pay for the devices on the following day. To avoid income effects generated by the financial incentives to sleep, equivalent payments were made to the other experimental arms as well. Members of the Control and Sleep Devices groups were each randomly and anonymously matched to a member of the Devices + Incentives group who had completed the study and received the exact same stream of payments as this matched individual.\(^4\) Accordingly, the only difference in these payments across treatment groups was that for the Incentives Group, the payments were linked to their

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\(^4\)Participants enrolled in the first few months of the study were matched to pilot participants.
sleep, while payments to members of the other two groups were exogenous. All participants also received a small daily incentive payment (Rs. 10) to wear the watch continuously.

**Nap treatment.** In addition to the treatments to increase night sleep, we cross-randomized study participants into the Nap Treatment. Starting on day 9 of the study, a random subset of individuals were given the opportunity to take a short afternoon nap between 1:30 pm and 2 pm every day at their workplace. The private nap space was located in a quiet and gender-separated area of the study office and included a bed, blanket, pillow, table fan, ear plugs, and eye shades as depicted in Figure 2b. While the vast majority did indeed sleep during their allotted nap time, study participants who were not feeling tired or who did not want to nap for any other reason were asked to sit quietly or rest in their nap area. The nap group did not have the option to work during this time.

The impacts of increased sleep crucially depend on the opportunity costs of sleeping, i.e. the relative value of activity that is crowded out by increasing sleep. In the case of naps, the natural alternatives were for individuals to work or take a break. To learn about the impacts of sleep relative to each of these options, we further randomized study participants assigned to the Nap Control group on a daily basis either to take a mandatory break or be allowed to work during the 30-minute nap period. This within-person randomization allowed us to compare the effectiveness of naps to (i) taking a break and relaxing and (ii) working through the nap period.

**Compliance.** Among the 300 participants randomized into one of the two night-sleep treatment groups, 262 participants took at least two of the offered sleep-aid devices home. However, self-reported usage of the devices varied significantly across individuals and over time. In the Nap Treatment, all participants stayed in their assigned space during the nap period.

Compliance with wearing the actigraphs was monitored by running a plastic strip through a hole in the band of the watch. The plastic strip was readily breakable so that the watch could be removed if the participant desired, but also allowed us to monitor compliance with wearing the actigraph. Compliance was high in all experimental arms, with 9 percent of participants removing the device on any given day. Participants who removed the watch lost both the daily payment for wearing and any incentive payment for sleeping.

### 3.2 Study Population, Recruitment, and Balance

The study population consisted of 452 low-income men and women aged 25 to 55 in Chennai, India. Due to capacity constraints, we conducted the study on a rolling basis over
18 months, with approximately 35 to 40 individuals enrolled at any given time during the majority of the study.

3.2.1 Recruitment and Selection

Recruitment followed two strategies: First, recruiters went to low-income neighborhoods in Chennai and spread information about the study. Advertisements for the study offered a one-month data-entry job, and recruiters provided interested individuals with additional information. Second, past participants were able to refer potential new participants to the study. In both cases, recruiters approached interested individuals to interview them and determine their eligibility to participate in the study.

Field screening. Recruiters conducted a short, unpaid field screening survey with interested individuals to determine whether the individual met the study’s eligibility criteria, which included: (i) being between 25 and 55 years of age; (ii) fluency in Tamil (the local language); (iii) the ability to read and write numbers; (iv) having worked fewer than 5 days per week in the previous month; (v) earning less than Rs. 700 per day in the previous month; (vi) living in a dwelling able to accommodate the sleep devices used in Night Sleep Treatments; (vii) ownership of fewer than four of the sleep devices being offered in the study; (viii) the intention to be in Chennai for the following 5 weeks; and (ix) no children in the household younger than 3 years.

Home screening. If a potential participant passed the initial field screening survey, a recruiter visited the participant’s home to verify the information provided regarding home sleeping arrangements and to verify that the potential participant did not already own more than three of the study-provided sleep devices. Individuals who passed the home-screening survey were then invited to come to the study office to receive further information and to conduct a final screening survey.

Office screening. In this screening, surveyors first confirmed the participant’s eligibility criteria for the study by re-asking potential subjects the questions posed in the initial recruitment and home interviews. If all answers were consistent, the surveyor then discussed in greater detail the participant’s plans to remain in the city for the next five weeks in order to minimize dropouts. Participants were required to pass all three screenings in order to enroll in the study.
**Informed consent.** All participants who passed the screening process were then asked to engage in an informed-consent process. During this process, we explained to participants that if they chose to enroll, they would also be participating in a study, and potential treatment conditions and outcome measurements were described.

**Selection.** At each recruitment and screening stage, the majority of individuals were able and willing to proceed to the subsequent stage. First, 62 percent of individuals surveyors approached on the street agreed to take the eligibility survey. Second, 57 percent of these individuals passed the initial screening test for eligibility in the study, the vast majority of which (96.3 percent) expressed interest in proceeding to the home screening. Third, 72 percent of such individuals passed the home screening and came to the study office. Finally, the vast majority of individuals (95 percent) who participated in the office screening and informed-consent process proceeded to enroll in the study.\(^5\)

### 3.2.2 Sample Characteristics and Balance Checks

Sixty-six percent of study participants were female, and the typical study participant was roughly 35 years old with 1 to 2 children (Appendix Tables A.1 and A.2). Study participants had relatively high education levels (about 10 years of education on average). While only about 32 percent of individuals had prior experience with computers, participants were eager to learn and their performance on the data entry work improved quickly during the baseline period.

We test for imbalances in baseline characteristics across the experimental conditions using the following specification:

\[
y_i^B = \beta_1 T_i^D + \beta_2 T_i^I + \beta_3 T_i^N + \epsilon_i, \tag{1}
\]

where \(y_i^B\) is an observable baseline characteristic or average of participant \(i\)’s values across the baseline period when multiple measures are available. The treatment variables \(T_i^D, T_i^I,\) and \(T_i^N\) indicate whether an individual is part of the *Sleep Devices Group*, the *Sleep Incentives Group*, or the *Nap Group*, respectively. Given the cross-randomized design of the study, we

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\(^5\)Although the workers included in this sample are selected, the selection criteria do not obviously select for either better or worse sleep than in the low-income population in general. While we did exclude individuals who already possessed the majority of devices to improve sleep and may sleep more, we also excluded the homeless and families with children below age 3, who almost surely sleep less.
show the results separately for the respective night-sleep and nap treatments.

The treatment groups were well-balanced across key characteristics, indicating that the randomization was effective. As is expected given the large number of comparisons, a few statistically significant differences across treatment groups did emerge. Most notably among those, we find differences in baseline attendance and age across night-sleep treatment groups.

3.3 Timing of Data Collection

Study participants were primarily engaged in data-entry work. Hours were flexibly chosen most days, and payment consisted of a mixture of per-minute compensation and piece-rate compensation per correct character entry (minus a penalty for incorrect characters), as described in more detail in Section 5.1. In addition to data entry, study participants completed short surveys and experimental tasks at varying frequencies. Each day, in addition to the data-entry task, study participants completed: (i) a short survey about well-being, sleep, and outside earnings, (ii) at least one of the tasks measuring cognitive function, and (iii) a savings activity which allowed individuals to save money in a personalized lockbox at the study office. Moreover, we measured participants’ blood pressure every 4 days throughout the study and steps taken were captured continuously via the actigraph.

On day 1 of the study, participants completed a baseline survey providing detailed information about their demographics, sleep patterns, alcohol and tobacco consumption, and other aspects of their lives. As part of this survey, we measured study participants’ risk and social preferences using standardized incentivized survey instruments. In addition, we elicited measures of time preferences near the beginning and end of the study using a real-effort task following Augenblick and Rabin (2019). On day 28 of the study, participants completed an endline survey paralleling the baseline survey and undertook an incentivized stationary-bike task to measure their physical performance. Participants were also weighed at both baseline and on day 28.

Finally, we collected two measures of the participants’ beliefs regarding the value of sleep at the conclusion of the study. First, we elicited participants’ willingness to pay for a subset of the devices provided in the night-sleep treatments using an incentive-compatible BDM mechanism (Becker et al., 1964). Second, we elicited participants’ beliefs regarding the impact of the Sleep Devices treatment on attention, earnings, labor supply, and savings. Additional details of each task are provided in the relevant sections.
3.4 Empirical Framework

Our primary empirical specification is an ANCOVA regression, which captures the main treatment effects while controlling for the baseline measure of the outcome as well as baseline controls and a number of fixed effects for timing.

\[ y_{itd} = \beta_1 T_{iNS} + \beta_2 T_{inap} + \beta_3 S_{it} + \gamma_1 \bar{y}_{ib} + \gamma_2 X_{it} + \delta_t + \delta_d + \epsilon_{itd}. \] (2)

We measured the outcome variable \( y_{itd} \) for participant \( i \) on her \( t \)th day in the study and on calendar date \( d \). Throughout the analysis we pool the two night sleep treatments, as in equation (2) unless otherwise stated. The average treatment effect of the nighttime and nap interventions is captured by \( \beta_1 \) and \( \beta_2 \), respectively. While nap-group participants took an afternoon nap, the remaining participants were randomized on a daily basis either to take a break or to continue working on the typing task if they so chose. The variable \( S_{it}^{W} \) is a dummy capturing whether participant \( i \) was randomized to work, denoted \( W \), at \( t \). Thus, the excluded category for the nap comparisons consists of participants taking a break during the nap period, and \( \beta_3 \) captures the impact of working through the break relative to taking a break.

Following McKenzie (2012), we condition on the average baseline value of the outcome variable \( \bar{y}_{ib} \) in all specifications, excluding the baseline days from the analysis, i.e. the regressions include observations from days \( t \in \{9, 10, ..., 28\} \). We also control for various baseline covariates, including participants’ age and gender. \( X_{it} \) also includes additional task-relevant controls specific to each outcome, as we describe below. Finally, we include day-in-study and date fixed effects, captured by \( \delta_t \) and \( \delta_d \), respectively. In some specifications, we include the interaction between the night-sleep and nap treatments.

4 Baseline Sleep and Treatment Effects on Sleep

Drawing from actigraph- and self-reported data, we used the following main measures of sleep in the study: (i) time in bed, (ii) night sleep, (iii) sleep efficiency (night sleep divided by time in bed), (iv) nap sleep, and (v) 24-hour sleep (night sleep plus nap sleep). Each of these measures was captured via actigraphy. However, participants also self-reported measures (i) through (iii). Unless otherwise noted, all sleep data refers to actigraphy-based measures.
4.1 Sleep Patterns

Figure 3 illustrates three features of the sleeping patterns of participants in our sample: (i) time in bed, (ii) time asleep, (iii) sleep efficiency (time asleep/time in bed), both self-reported (upper panel) and objectively measured using actigraphs (lower panel).

**Time in bed.** Workers in our sample reported spending considerable time in bed, as indicated by nearly identical averages of self-reports and actigraph measures of time in bed. At baseline, the average study participant spent roughly 8 hours per night in bed (Figures 3a and 3b). These averages resemble reported hours in bed in US samples: Kurina et al. (2015), for instance, found in their study of older Americans that the average time in bed is 8.4 hours, while Jackson et al. (2018), in a multi-ethnic study of adults across several US states, found that the average time in bed per night is 7.2 hours.

**Self-reported sleep.** Average baseline self-reported sleep duration in our study is 7.2 hours (Figure 3c). This average is slightly above the average of 7.1 hours found in the representative WHO-SAGE survey among the elderly in rural India described in Gildner et al. (2014). For comparison, averages of self-reported sleep duration in US range from 6.8 to 7.9 hours per night (Jackson et al., 2018; Lauderdale et al., 2008; Watson et al., 2015). Based on the self-reports, 41 percent of workers in our sample sleep fewer than 7 hours per night.

**Actigraph-measured sleep.** In contrast, the objectively measured sleep data provide clear evidence of severe sleep deprivation among the majority of workers in our sample (Figure 3d). Only 5 percent of participants slept more than 7 hours per night on average, the lower bound of recommended sleep level for adults, and 71 percent slept less than 6 hours. (Hirshkowitz et al., 2015). Consistent with the challenging environmental conditions that interfere with participants’ sleep, actigraph measures show an average sleep duration of 5.6 hours per night at baseline. Variation around the mean is modest, with an average within-person standard deviation of 0.9 hours per night. This duration is significantly lower than typical sleep durations in the US (6.25 to 6.5 hours per night, Jackson et al. (2018)).

**Low sleep efficiency.** Sleep efficiency measures the fraction of time individuals are asleep as a share of their overall time in bed. Average baseline sleep efficiency in our study population is 70 percent (Figure 3f). This strikingly low estimate is much below estimates of sleep efficiency in developed countries, e.g. between 85 to 95 percent for the US (Yoon
et al., 2003; Carrier et al., 2001; Cole et al., 1992; Walker, 2017). Low sleep efficiency in our sample is not just a result of poor sleep in the evenings and mornings. Rather, sleep efficiency remains around 70 percent even between 1 and 5 am (when almost everyone is in bed), consistent with very poor and disrupted sleep throughout the night (Appendix Figure A.1). Finally, given that self-reported levels of sleep exceed actigraph measures, self-reports overestimate sleep efficiency levels relative to actigraph measures (Figure 3e).

**Summary.** Taken together, we document several novel findings. First, we find clear evidence of severe sleep deprivation for the majority of our sample, which appears to be fairly representative of much of the low- to middle-income population of Chennai. Second, strikingly low sleep efficiency rather than little time in bed appears to be the main driver of this sleep deprivation. Third, the stark differences between self-reported and actigraph-measured sleep highlight the importance of objective sleep measurement. Finally, our data are consistent with the hypothesis that the urban poor in developing countries face challenging sleep environments. Survey responses from daily surveys highlight the importance of environmental factors in interfering with study participants’ nighttime sleep, with over half of the population indicating that cold or heat, noise, and/or light disrupt their sleep (Appendix Figure A.2).

### 4.2 Treatment Effects on Sleep

All three treatments were effective at increasing study participants’ sleep. On average, the two Night-Sleep Treatments increased night sleep by 28 minutes. The median nap duration was 15 minutes.

**Night-sleep treatments.** Both the Sleep Devices and the Devices + Incentives Treatments increased sleep markedly and immediately, as measured both by self-reports and objective sleep measurements using the actigraphs (Figure 4 and Table 1). On average, individuals in the Sleep Devices and the Sleep Incentives Treatment Groups increased their time asleep by 21 and 35 minutes compared to the Control Group, respectively (Table 1, Column 1).

The increase in time asleep was almost exclusively due to additional time in bed rather than increased sleep efficiency. Both Night-Sleep Treatment groups increased their time in bed significantly throughout the treatment period—32 minutes for the Sleep Devices Group and 48 minutes for the Sleep Incentives Group (Figure 4a and Table 1, Column 3). Given that the ratio of treatment effects on night-sleep duration and time in bed are similar to the
sleep efficiency at baseline, the two Night-Sleep Treatments did not significantly change sleep efficiency compared to the Control Group (Figure 4d and Table 1, Column 5). This result is surprising given that the Sleep Devices Treatment was designed to improve individuals’ sleep environments with the goal of increasing sleep efficiency.

Perhaps even more surprisingly, neither of the two treatments appears to have impacted sleep efficiency even in the middle of the night (Appendix Figure A.1a). Accordingly, while the treatments were effective at increasing night sleep, they entailed substantial opportunity costs of time by increasing the time individuals spent in bed. Moreover, the treatments were not able to improve the severely disrupted and fragmented sleep experienced by most individuals in our sample.

The self-reported changes in sleep are broadly consistent with the estimates based on actigraphs (Figure 4c and Table 1, columns 2, 4, 6). Participants in the Sleep Treatments report increasing their time in bed by 1 to 1.2 hours and time asleep by 0.9 to 1.1 hours. This over-estimation of treatment effects relative to the actigraph data suggests a combination of difficulties in reporting sleep accurately (possibly due to confusion between time in bed and time asleep) and potential experimenter demand effects, both of which highlight the importance of objective sleep measurement. As in the actigraph-based data, the changes in time in bed and time asleep did not result in a significant change in sleep efficiency.\footnote{Notably, at roughly 91 percent self-reported sleep efficiency is significantly higher than measured sleep efficiency.}

**Nap treatment.** The nap intervention was highly effective at increasing study participants’ daytime sleep, as intended. The vast majority of individuals (92 percent) of participants in the Nap Group self-reported falling asleep during a nap, which is confirmed by actigraph data which recorded that 88 percent of participants were able to fall asleep during their nap. The median time asleep during the nap window was 15 minutes, and the mean time asleep was 13 minutes. Although there was a small negative spillover of 6 minutes of taking a nap to nighttime sleep (Table 1, columns 1 and 2), the sleep gained during the nap was not fully crowded out (Table 1, column 7).
5 Impacts of Increased Sleep

5.1 Typing Task

Study participants were employed full-time as data-entry workers throughout the study.

Work hours. Study participants were generally free to choose their work hours, including their arrivals, departures, and break times (except those associated with the nap). On the majority of days (“regular days”), participants could arrive and depart at times of their choosing between 9:30 am and 8 pm. On a subset of days (“short days”), work hours were limited to 11 am to 5 pm, in an effort to provide clean estimates of productivity, unconfounded by potential changes in labor supply. To encourage uniform presence during these hours, we paid a bonus of Rs. 50 to anyone present during the entire (short) day. On all days, we provided participants with tea twice a day and lunch at the office.

Data-entry work. The data-entry task consisted of digitizing textual and numeric data designed to mimic a real-world, data-entry job, using the interface represented in Figure 5. The screen was divided into two panels, with the data to be digitized on the left and corresponding fields for the entries on the right. Fields had to be entered sequentially, and once the participant submitted the text in a given field, he or she could not alter the work in previous fields. Once all the fields in a page were completed, participants “submitted” the page. Participants dedicated 61 percent of their work time at the office to data-entry work, which constituted 57 percent of their earnings in the study.

Data-entry incentives. The payment for the data-entry work had two components. First, the participants received Rs. 21.60 or roughly $0.30 per hour of active typing. This time did not include time spent on other study tasks such as short daily surveys or time spent taking voluntary breaks. Any time a participant spent two consecutive minutes without typing, the software would automatically generate a screen indicating that the task was

7The data to be digitized had been artificially generated. By generating the data, we had ready access to the correct data, allowing us to measure the accuracy of the work immediately. Study participants were unaware of the artificial nature of the data. Since accuracy is often measured in “real” data-entry jobs via double-entry, and study participants had little experience with data entry prior to the study, they had no reason to doubt that their work was not “real” and useful.

8To facilitate learning, during the first three days of participation in the study, a pop-up box appeared after each page was submitted. This box informed participants of their earnings and the number of mistakes they had made on that page. After dismissing the message, the software provided a new batch of data for entry. Starting on day four, this information was no longer provided.
paused and the participant did not receive the time-based payment. However, she could dismiss the screen and immediately resume work and payment.\(^9\) Second, participants received a performance-based payment consisting of a piece-rate per correct character and penalty per mistake.\(^{10}\) Each half hour, piece-rates were randomly and independently assigned between the high value (Rs. 20 per 1,000 correct characters) and the low value (Rs. 5 per 1,000 correct characters) with equal probability. The penalty rate remained constant throughout at Rs. 1 per every 10 mistakes. Participants were informed about their current but not about their future piece-rates with variation in salience of this rate as described in Section 5.2. Payments for all study-related earnings were made daily before the participant left the study office in the evening.

5.1.1 Measures of Labor Market Performance

We focus on three key measures based on individuals' performance on the data-entry work: (i) labor supply, (ii) earnings, and (iii) productivity.

**Labor supply and earning.** We use two precise measures of labor supply: 1) time at the office and 2) active typing time. We precisely measured individuals' time at the office, i.e. the difference between their departure and arrival times. Active typing time was captured via the data-entry software by adding all periods of active typing within the day.\(^{11}\) Data-entry earnings are a combination of attendance pay and performance earnings as described above. On average, 65 percent of the typing compensation was performance pay.

**Productivity.** Our primary measure of worker productivity is output divided by hours worked. Output is the number of correct entries minus 8 times the number of mistakes, where the relative weight is derived from the ratio of the average piece-rate (Rs. 1.25) and error rate (Rs. 10) per 100 characters. We determined this ratio based on pilot data and held it fixed throughout the study. We further decompose productivity into measures of speed (number of correct entries per hour typing) and accuracy (number of correct entries per 100

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\(^9\) Each participant had her daily schedule in the study coded in the software. When participants were scheduled for another task, the screen would freeze and prevent participants from typing. This process ensured that any changes to performance on other tasks did not influence the time spent typing.

\(^{10}\) Following Augenblick et al. (2015), we measured mistakes using the distance between the text entered and the text prompted as measured by the Levenshtein distance, defined as the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one word into the other.

\(^{11}\) Any periods of inactivity greater than two minutes triggered an automatic pause in the software. Study activities other than typing were pre-programmed into the software and triggered an automatic pause of a fixed duration.
5.1.2 Impact of Sleep on Data-Entry Performance

Summary. We find evidence that both treatments increase productivity. However, increased sleep entails opportunity costs of time, which leads to reductions in labor supply in most specifications. As a result, increasing night sleep causes small reductions in earnings. Naps increase earnings relative to taking a break but not relative to working through the break.

Productivity. Individuals assigned to the Night-Sleep Treatment Groups were 1.3 percent more productive compared to their Control Group counterpart, though this estimate is not statistically significant (Table 2, column 1). The impacts of the Nap Treatment on productivity are larger than those of increased night sleep, both when compared to the group that was taking a break (2.4 percent increase) and the group that was working through the break (2.2 percent increase). We find that increased speed drives the productivity increase rather than improved accuracy (columns 7 through 9 of Table A.3).

Labor supply. The treatments had no impact on labor supply at the extensive margin (days worked). Overall attendance at the office was high (84 percent), with no discernible differences across groups (Figure A.3). In contrast, increased night sleep reduced labor supply at the intensive margin (Table 2, columns 3 and 4). Individuals in the Night-Sleep Treatment Groups worked about 9 fewer minutes compared to the Control Group. This negative treatment effect is almost entirely explained by changes in hours at the office as opposed to changes in voluntary breaks during work hours. The reduced work hours can mostly be attributed to later arrival times, presumably caused by individuals staying in bed longer in response to the Night-Sleep Treatments (Table A.3, columns 4 through 6).

By construction, the Nap Group has a 30-minute block during which they nap and cannot work. Individuals could adjust their labor supply by arriving at the study office earlier, by leaving later, or by taking fewer breaks. However, we find little evidence of such adjustments by the Nap Group in comparison to the other two groups (Table 2, columns 3 and 4). The Nap Group spent a few additional minutes at the office at the end of the day, but the estimates are small and marginally significant. Accordingly, napping at the office reduced typing time by 26 minutes (the designated nap time is 30 minutes) compared to working through
Earnings. Given the opposing impacts of increased night sleep on productivity and labor supply, the impacts of the Night-Sleep Treatments on earnings are unsurprisingly small (Table 2, columns 5 and 6). We find small but statistically insignificant negative impacts on both performance earnings (i.e. earnings based on data-entry output) and on overall earnings, i.e. the small increase in productivity is counterbalanced by the reduction in labor supply.

The impacts of naps on earnings depend on the comparison group. Compared to taking a break, naps increased overall earnings by about Rs. 11 per day, a sizable increase of 4.1 percent (Table 2, column 6). Focusing on the performance-pay dimension alone (column 5), the impact increases to 5.3 percent. However, the opportunity costs of taking time to nap lowered earnings by Rs. 23 (8.3 percent) for the Nap Group when compared to working through the break.

5.2 Sleep and Limited Attention

Recent work has shown that individuals do not pay full attention to non-salient or opaque tax rates, prices, and attributes of goods: the response to a change in a non-salient variable such as sales taxes or future energy savings is more muted than the response under a full-attention benchmark where the dimension is unshrouded (e.g. Chetty et al. (2009), Allcott and Taubinsky (2015)). Indeed, some scholars argue that limited attention may underlie a number of behavioral biases and anomalies (Gabaix, 2019). In this section, we test whether increased sleep improves direct measures of attention and improves participants’ ability to attend to important aspects of their work environment.

5.2.1 Lab Measure of Attention: PVT

Design. Each day in the office, participants completed the Psychomotor Vigilance Task (PVT), a standard measure of alertness and attention in sleep medicine (Basner et al., 2011; Basner and Dinges, 2011). Participants are asked to react to a visual stimulus shown on a computer screen by pressing the space bar as soon as they see a stimulus appear on the screen. The test measures the speed and accuracy with which subjects respond to the visual stimuli on the screen and has been shown to be highly responsive to experimentally-induced

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12 Compared to the Break Group, there is no statistically significant difference, although the coefficient points to a 1-minute increase in work time by the Nap Group.
Results. The Nap Treatment had positive impacts on PVT performance, increasing payment received on the task by 0.15 (p < 0.01) standard deviations (Table 3, Panel A, column 1). The effects were similar for other indices constructed with standardized measures of the individual components. In particular, naps affected PVT performance by reducing lapses in attention and improving inverse reaction time (Table 3, Panel A, columns 4 and 5). In contrast, perhaps surprisingly, the night-sleep treatments had no significant effect on PVT performance. Motivated by this finding, we next turn to testing whether naps correspondingly increased subjects’ attention to the incentives faced in their typing work.

Other aspects of cognition. The cognitive effects of naps appear to be concentrated on attention rather than affect other aspects of cognition. In contrast to the existing literature regarding sleep deprivation from laboratory experiments, we find no evidence of impacts of the treatment on other aspects of cognitive function (Lim and Dinges, 2010; Killgore, 2010).

5.2.2 Attention in the Work Environment

Design. To test whether sleep impacts how individuals react to non-salient incentives in their work environment, we randomized the salience of piece-rates (performance pay) across days within individuals.

In the salient condition, the current piece-rate was highlighted in a visible color and readily available to study participants at all times. As illustrated in Figure 5, a low piece-rate was highlighted by a blue bar at the bottom of the screen (panel 5b), while a high piece-rate was highlighted by a green bar (panel 5c). In addition, the entire computer screen blinked twice to indicate the beginning of a new 30-minute slot, thereby drawing attention to a possible switch in incentives. We consider this condition the “full-attention” benchmark.

In contrast, in the non-salient condition, noticing and remembering the piece-rate was more challenging. First, the bottom of the screen was uncolored for both piece-rates in the non-salient condition. In addition, the piece-rate was only visible for the first 15 seconds of

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13 For a more detailed overview of these tasks, see the appendix and Dean et al. (2019).
14 We find suggestive evidence that naps may have slightly reduced reaction times in the inhibitory control task (.14 standard deviations). However, this change was not large enough to impact overall payments for performance on the task.
a slot (as illustrated by panels 5e and 5f) and faded in and out slowly.

**Empirical strategy.** Our empirical strategy to identify attention to wage incentives follows Chetty et al. (2009). For each of the treatment groups $j$ (i.e. Night-sleep, Nap, and Control), we estimate the (average) reaction to high piece-rate under the salient and non-salient conditions for output, productivity, and labor supply, denoted by $\epsilon^S_j$ and $\epsilon^{NS}_j$, respectively. The attention parameter $\theta_j$ is defined as the ratio between the reaction to incentives under non-salient and salient conditions, i.e. $\frac{\epsilon^{NS}_j}{\epsilon^S_j}$. Importantly, we assume that the response to piece-rates under the salient condition is the full-attention benchmark, as in Chetty et al. (2009) and Allcott and Taubinsky (2015). We interpret $\theta_j$ as the deviation from the “full-attention benchmark” caused by inattention to non-salient incentives. Participants are fully-attentive even in the non-salient condition when $\theta_j = 1$ and completely inattentive when $\theta_j = 0$.

We estimate the treatment effect of the sleep interventions by comparing the attention parameter $\theta$ in each treatment group to the control group’s $\theta$. We first estimate the average reaction to incentives for each group $j$ during the full salience and non-salient periods, using the OLS regression

$$y_{iwtd} = \sum_j \mathbb{1}_{\text{Treat},=j} \cdot (\beta_1^j \text{High}_{iwnt} + \beta_2^j \text{Sal}_{it} + \beta_3^j \text{High}_{iwnt} \cdot \text{Sal}_{it}) + \delta_i + \delta_t + \delta_d + \nu_{iwtd}, \quad (3)$$

where $\mathbb{1}_{\text{Treat},=j}$ captures whether participant $i$ was in treatment group $j$, $\text{High}_{iwnt}$ captures whether the participant faced a high piece-rate during the 30-minute incentive window $w$ (as described above), and $\text{Sal}_{it}$ whether participant $i$ was randomized to the salient condition on day $t$.

This equation differs from the benchmark reduced-form regression (2) in two ways. First, rather than using an ANCOVA specification as with other outcomes, we used participant-level fixed effects given the within-person variation in salience during the treatment period. Second, the unit of observation is the 30-minute window rather than the day given the frequency of potential incentive changes. We use the OLS estimates from equation (3) to recover $\hat{\epsilon}^{NS}_j = \hat{\beta}_1^j$ and $\hat{\epsilon}^S_j = \hat{\beta}_1^j + \hat{\beta}_3^j$. Finally, we estimate the attention parameter for each group by $\hat{\theta}_j = \frac{\hat{\epsilon}^{NS}_j}{\hat{\epsilon}^S_j}$. Standard errors in equation (3) are clustered at the participant level, while standard errors for $\hat{\theta}_j$ are estimated using the Delta Method.

**Results.** Consistent with limited attention, work output of the Control Group reacted
16 percent less to high incentives when piece-rates were not salient (Table 3, Panel B, column 1). The Night-sleep Group was just as inattentive: it reacted 15 percent less to incentives when they were non-salient, consistent with the lack of effect of the night-sleep treatment on PVT performance.

In contrast, and also consistent with the PVT results, the Nap Group was nearly fully-attentive even to non-salient incentives. Specifically, we cannot reject that $\theta = 1$ for the Nap Group. The Nap Group was 10 percentage points closer to the “full-attention benchmark” than the Control Group was, highlighting the improved attentional resources provided by naps in a real-world work environment.

The results are even more stark for labor supply (column 3). Participants in the Control Group (Night-Sleep Treatment) reduced their active typing time during low incentives by 23 percent (20 percent) less on non-salient work days compared to their reaction to piece-rates in the full-attention benchmark. The Nap Group, on the other hand, did not adjust its typing time differentially in response to piece-rates on salient versus non-salient days.

**Morning vs. afternoons.** Consistent with evidence from the sleep literature that short afternoon naps boost attention, particularly during the first three hours following the nap (Lovato and Lack, 2010), the increases in attentiveness almost entirely arose in the afternoon (i.e. post nap time). The attention parameter across groups is very similar in the morning (columns 4 and 5). However, the Nap Group’s $\theta$ for output and productivity increases to 0.97 for both variables in the afternoon, with much less significant changes for the Control and Night-Sleep Groups (columns 7 and 8).

**Summary.** In summary, using both a standard lab task used by sleep scientists and a measure of attention to work incentives, we find consistent evidence that afternoon naps increase participants’ attention. These effects may serve as one of the underlying drivers of the gains in productivity in the Nap Group. In contrast, increases in night sleep have no detectable effect on attention, either as measured via the standardized laboratory task or in the work environment.

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15 Labor-supply responses here are driven by voluntary breaks or pauses in work.
5.3 Preferences

5.3.1 Time Preference: Savings Task

Measuring savings. We measured savings behavior by offering individuals the opportunity to save money in a lockbox at the study office at a favorable interest rate, as in Schilbach (2019). This approach allows a precise measure of individuals’ savings by encouraging individuals to save in a well-measured environment (since self-reported savings are often noisy and biased). At the end of each work day after receiving their earnings, individuals had the opportunity to deposit or withdraw money from their savings box. Participants were randomly assigned to receive daily interest rates between 0 and 2 percent for any money saved in the lockbox.\textsuperscript{16} Deposits were capped at Rs. 600 per day in order to ensure that participants did not make enormous deposits from other sources to leverage the high interest rates.\textsuperscript{17}

Results. The Night-Sleep Treatments did not meaningfully affect savings (Table 4, Panel A). In contrast, the Nap Treatment is associated with economically meaningful increases in daily deposits and daily net savings (deposits minus withdrawals). The Nap Group deposited an additional Rs. 16 per day, a 14-percent increase relative to the Control Group. The impact of naps on daily net savings is smaller (Rs. 9). While still large in relative terms (12.5 percent), it is noisy and not statistically significant. The loss in power is in part explained by the presence of large, one-time withdrawals before the end of the study (Figure A.5). Both coefficients and power increase with the extent of winsorization to the left tail of the outcome variable distribution (columns 3 and 4). When we winsorize at 5 percent, or minus Rs. 50, the point estimate is roughly the same as that of deposits (column 4).

An alternative way to measure savings is the interest accrued over the course of the study (columns 5 to 8). This measure captures average savings during the study period and is less sensitive to large withdrawals. We consider two different versions of this variable. First, we consider the actual interest accrued (columns 5 and 6). Second, since the latter measure depends on the interest rate (which is zero for a significant fraction of the sample), we also use a hypothetical interest accrued using a constant (positive) interest rate for all

\textsuperscript{16}In the first 7 months in the study, interest rates were either 1% or 2% daily. In December 2017, we switched from computing interest only on days when we administered the savings survey to computing it every day, including weekends. In May 2018, we briefly changed interest rates to 1% and 2% weekly. Finally, in June 2018, the interest rates were changed to 0 percent to 1 percent for new participants to enable us to calculate the semi-elasticity both from 1% to 2% as well from 0% to 1%. The week fixed effects in the savings regressions absorb these changes over time.

\textsuperscript{17}The deposit ceiling was Rs. 400 for roughly the first 4 months of the study. Because participants were frequently reaching this cap, we raised the limit to Rs. 600.
participants (columns 7 and 8). As in the other specifications, the Night-Sleep Treatments

did not affect the interest accrued over the course of the study in a meaningful way. In
contrast, participants in the Nap Group accrued around 20 percent more interest relative
to the Control Group. While the point estimates are similar across specification, the estimates
using the hypothetical interest are more precise and (marginally) statistically significant
(columns 7 and 8). While similar in magnitude, the estimates using actual interest accrued
are not statistically significant (columns 5 and 6).

The impact of naps on savings cannot be explained by wealth or income effects. Given the
labor supply effects described above, study earnings in the Nap Group are in fact a bit lower

than the relevant comparison group (i.e. the Work and Break Groups combined). Similarly,
changes in risk preferences are unlikely to explain the changes in savings, given that we do
not find impacts of naps on risk preferences (Section 5.3.3). In contrast, the above impacts
appear to be at least in part explained by changes in present bias. Consistent with this
hypothesis, we find that naps reduced present bias in a real-effort task, as discussed next.

5.3.2 Time Preference: Effort Discounting

**Design.** Following Augenblick and Rabin (2019) and Augenblick et al. (2015), we mea-
ure present bias using a real-effort choices. Participants make decisions about how many
pages to type on a fixed date (referred to as “work day”) under different piece rates. Differences in choices for a future work day vs. for the same work day identify present bias. The task mimics regular data-entry work in the study, using shorter pages to allow for finer choice sets. Using effort choices elicited both at baseline and at least once during the treatment period for each participant, we structurally estimate individual-level present bias parameter \( \beta_i \) for the baseline and for the treatment period. A complete description of the task is in Appendix B.2.

**Results.** Using our preferred specification, we estimate a mean \( \beta \) of 0.92 among Control

participants (Table 4, Panel B, column 1). Reassuringly, the estimated \( \beta \) is predictive of
other behaviors related to time preference. For example, participants with a lower estimated
\( \beta \) arrive at work later and save less (Table A.5). Similar to the other outcomes we describe
above, the Night-Sleep Treatments did not significantly affect the present-bias parameter. In
contrast, the Nap Treatment increases the estimated \( \beta \) by 0.06 (column 1).\(^ {18} \)

For robustness we also consider the ratio between pages chosen for work “now” versus

\(^{18}\)For participants who did an updated version of the present bias experiment, results are even larger
(column 2), although results are non-significant for this smaller sample. See Appendix B.2 for details.
“later” as dependent variable (columns 3 and 4). The results are strikingly similar to those with the structural parameter, except that they are marginally insignificant. In that model, as well as in the structural estimate, we only keep participants for whom the structural estimator converge. When we add these additional 46 participants, the estimates fall by half.\textsuperscript{19}

5.3.3 Social and Risk Preferences

**Design.** We measure risk and social preferences via standard tasks in the behavioral economics literature. Risk preferences and loss aversion are captured via a multiple price list elicitations similar to those in Holt and Laury (2002), Sprenger (2015), and Charness et al. (2013). Social preferences are measured via dictator, ultimatum, and trust games (Camerer, 2003).

**Results.** Neither the Night-Sleep Treatments nor the Nap Treatment significantly altered risk aversion or loss aversion in the standardized tasks (Table A.6, “Risk Components” section), in contrast to findings of McKenna et al. (2007). While the results are not precise enough to detect very small effects, we are able to rule out changes greater than 0.2 standard deviations for each of these outcomes and treatments, suggesting that if effects are present, they would be small.\textsuperscript{20} We find similarly precise and null results when examining behavior in the dictator, ultimatum, and trust games, in both sender and receiver positions, where applicable (Table A.6, “Social Components” section). These results are also in contrast with earlier work, though this work uses different study populations and exploits different variation in sleep (Dickinson and McElroy, 2017; Anderson and Dickinson, 2010).

5.4 Well-Being

5.4.1 Psychological Well-Being

**Design.** We collect data on a variety of aspects of participants’ well-being, including happiness, a measure of life possibilities (Gallup Cantril Scale), life satisfaction, and self-reported stress, as described in more detail in the appendix. We examine these variables

\textsuperscript{19}Choices by dropped participants are often non-monotonic on piece rates or almost entirely at corner choices, impeding us to estimate any potential present bias.

\textsuperscript{20}These results are also robust to dropping observations with non-monotonic response patterns (results available upon request).
both as indices and individually.

**Results.** Mirroring the results described above, naps improved psychological well-being while increased night sleep did not (Table 5). The Nap Treatment increased the index of psychological well-being index by 0.08 to 0.14 standard deviations. While the estimates for all individual components of well-being are positive, napping appears to have the strongest treatment effects on happiness and life satisfaction and possibility. In contrast, the Night-Sleep Treatments did not have a positive (and possibly even a negative) impact on any measure of subjective well-being or on the overall index.

5.4.2 Physical Well-Being

**Design.** We collected a variety of measures of physical activity and physical health. The measures of physical health included: (i) performance in a stationary biking task; and (ii) steps taken (measured passively and objectively by the actigraphs). The measures of physical health were: (i) reported days of illness; (ii) self-reported pain; (iii) activities of daily living; and (iv) blood pressure. All measures of physical well-being are described in more detail in the appendix. As above, we examine these variables both as indices and independently.

**Results.** Neither the Night Sleep Treatments nor the Nap Treatment led to increases in physical activity (Table 6, columns 1 to 3). Effects of night sleep on our biking task point in a positive direction. This is offset, however, by the negative impact of night sleep on total daily steps, which appears to be driven by the fact that sleeping longer decreases the number of hours in the day, and hence constrains the opportunities to get more steps. The null result of the Nap Treatment on the biking task may be at least partially explained by the fact that this task was administered at endline, on a day when participants in the Nap Treatment did not have the opportunity to nap.

6 Conclusion

This paper provides the first experimental evidence linking sleep and its potential economic consequences. We find that the urban poor in developing countries sleep poorly: an average of only 5.6 hours per night, with sleep efficiency well below that found in the urban areas. If we look just at steps during the hours when all participants would be expected to be awake, night sleep participants accrue more steps during this time.

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21 If we look just at steps during the hours when all participants would be expected to be awake, night sleep participants accrue more steps during this time.
developed world.

Increasing sleep in this population is feasible, both through interventions that improve the home sleep environment and encourage individuals to sleep more, and via mid-afternoon naps. However, the consequences of increased sleep depend greatly on the type of sleep, as summarized in Figure 6. Improving nighttime sleep by 30 minutes per night for about three weeks did little to improve any of the outcomes measured in the study, including earnings, physical health, well-being, cognition, or decision-making (Figure 6a).

In contrast, an average of 13 minutes of napping in the mid-afternoon generated notable improvements in a variety of outcomes (Figure 6b). Naps improved productivity and enhanced psychological well-being. They improved attention, both in laboratory-style tests and to aspects of the work environment. Finally, naps reduced present bias in a real-effort task and increased savings.

This striking contrast raises the question of why some types of sleep cause meaningful impacts while others do not. In addition, these results stand in contrast to a few recent studies suggesting large impacts of sleep on economic outcomes such as wages and schooling (Gibson and Shrader, 2018; Jagnani, 2018), as well as a substantial body of evidence in the sleep-medicine literature which has found significant short-term impacts on cognition of depriving individuals of nighttime sleep.

There are many possible reasons for such differences, ranging from the economic context (e.g. the US vs. India), the level of sleep deprivation, the low efficiency and fragmentation of the induced increases in sleep, and whether sleep is being improved or impaired. Another possibility is that three weeks is too short a period of increased sleep to generate effects on economic behaviors or health outcomes. Finally, the timing of sleep, both relative to the day and to the task at hand, is likely to play a role in its efficacy.

While this study is unable to fully disentangle the relative impact of each of these factors, we can engage in some informed speculation. Experiments in sleep laboratories do find substantial and cumulative effects of restricting night sleep to 4 or 6 hours of sleep per night over the course of a few days (Van Dongen et al., 2003; Belenky et al., 2003; Lim and Dinges, 2010). Thus, while the longer-run effects of our night-sleep treatments may well be larger than those reported here, three weeks is not too short a period to find substantial effects, at least on cognitive function. We detect no such effects and can rule out relatively small effects. And while the effect of an episode of sleep may diminish over the course of a day, we generally do not find evidence that increased night sleep affects work outcomes early in the day. Thus, it seems plausible that the key reason increased night sleep does not translate into meaningful effects in our study is due to the highly fragmented and inefficient nature of
the baseline sleep, and of the additional sleep our interventions induced. Increased efficiency and reduced fragmentation of sleep may well have larger effects on economic outcomes.

Taken together, our results provide a plausible explanation for the persistence of widespread sleep deprivation and the relatively high prevalence of naps in many developing countries. The opportunity costs of sleeping more are clear and immediate, with less time available for leisure and work. Any benefits of increases in nighttime sleep among the chronically sleep-deprived appear to be difficult to detect in the short run. Detecting any effects is made harder by the fact that monitoring one’s sleep quantity or quality is, in itself, a challenge in an environment with many disruptions. In contrast, naps provide more immediate and salient changes (e.g. improved well-being and productivity) and are substantially more effective per minute invested. Given these trade-offs, many individuals may choose to enjoy additional waking and leisure hours that limit nighttime sleep while investing in naps to reap the greater per minute benefits in this environment.
References


Gildner, Theresa, Melissa Liebert, Paul Kowal, Somnath Chatterji, and Josh Snodgrass, “Associations between Sleep Duration, Sleep Quality, and Cognitive Test Performance among Older Adults from Six Middle Income Countries: Results from the Study on Global Ageing and Adult Heath (SAGE),” Sleep, 2014, 10 (6), 613–621.


7 Tables and Figures

Figure 1: Experiment Design Timeline

Notes: This figure presents an overview of the timeline and experimental design of the study. After the 8 baseline days, the 450 participants are first divided in 3 groups: Control, Sleep Devices, and Sleep Devices and Incentives. Participants in each of these groups were further randomized between a Nap Group, which was allowed and encouraged to use a nap station in the office in the early afternoon, and a No Nap Group. While all these randomizations occurred between participants, participants in the No Nap group were further randomized on a daily level either to being allowed to work during or to take a mandatory pause during the nap period. The Nap treatment ends at day 27, and the participants return the sleep devices on day 28. Finally, endline surveys occur on day 28 and a few days later.
Notes: Panel (a) of this figure displays the items offered to individuals in the Sleep Devices group. These items were loaned to the participants, who could borrow as many units of the items as they wished. The items were brought to the participant’s home on day 8 and retrieved on day 28 by surveyors. A subset of the participants in the Control Group also received household goods unrelated to sleep in order to allow us to test for (and if needed, estimate) experimental demand or reciprocity effects. Panel (b) of this figure shows the nap station where participants in the Nap Group were allowed and encouraged to sleep, for up to 30 minutes, in the early afternoon. The participants in the No Nap Group were not allowed to use this nap station, which was situated on an exclusive floor at the study office.
Figure 3: Baseline Distribution of Sleep-Related Variables

Notes: This figure shows the distribution of the participant-level baseline average of sleep-related variables. In panels (a) and (b), we plot, respectively, hours of night-sleep and hours in bed as measured by the actigraph. In panel (c), we plot self-reported night-sleep. In panel (d), we plot the series for Sleep Efficiency (Nighttime Sleep / Time in Bed) as measured by the actigraph.
Figure 4: Impacts of Night-Sleep Treatments on Sleep

Notes: This figure shows the average of different sleep-related variables for each Night-Sleep Treatment group by day in study. In panels (a) and (b), we plot, respectively, the series for hours of night-sleep and hours in bed as measured by the actigraph. In panel (c), we plot self-reported night-sleep. In panel (d), we plot the series for Sleep Efficiency (Nighttime Sleep / Time in Bed) as measured by the actigraph.
Figure 5: Data-Entry Interface with Salient and Non-Salient Piece Rates

Notes: This figure shows screen shots of the data-entry task faced by individuals. The upper panels illustrate the salient condition. The lower panels illustrate the non-salient condition. Panels (a) and (d) show the left side of the screen, which contains the data to be transcribed by individuals. The remaining panels show versions of the right side of the screen, where the data is to be entered. Panels (b) and (c) show right side of the screen under salient incentives, once for low incentives (panel (b)) and once for high incentives (panel (c)). Panels (e) and (f) show the right side of the screen under non-salient incentives. Panel (e) is taken from the very beginning of a 30-minute period when individuals can see the (non-colored) piece rate for 15 seconds. Panel (f) is taken from the remaining part of the 30-minute period when the piece rate is no longer visible.
Figure 6: Summary of Effects

Notes: This figure summarizes the treatment effects described in detail above. For each outcome, we plot the point estimates and confidence intervals with respect to Night-sleep interventions, in Panel (a), and Nap intervention, in Panel (b). All outcomes are standardized measures with the exception of “Incentives”. Outcomes with multiple components are condensed in indices. The coefficient for “Incentives” corresponds to differences between treatment and control coefficients as shown in Table 3, panel B, column 1. The coefficient for “Savings” corresponds to the one in Table 4, panel A, column 1.
### Table 1: Treatment Effects on Sleep (First Stage)

<table>
<thead>
<tr>
<th></th>
<th>Night Sleep</th>
<th>Time in Bed</th>
<th>Sleep Efficiency</th>
<th>24 Hr Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actigraph</td>
<td>Self</td>
<td>Actigraph</td>
<td>Self</td>
</tr>
<tr>
<td>Sleep Treatment</td>
<td>0.354***</td>
<td>0.913***</td>
<td>0.536***</td>
<td>1.029***</td>
</tr>
<tr>
<td></td>
<td>(0.0583)</td>
<td>(0.0678)</td>
<td>(0.0624)</td>
<td>(0.0659)</td>
</tr>
<tr>
<td>Incentives Treatment</td>
<td>0.580***</td>
<td>1.132***</td>
<td>0.797***</td>
<td>1.216***</td>
</tr>
<tr>
<td></td>
<td>(0.0626)</td>
<td>(0.0730)</td>
<td>(0.0689)</td>
<td>(0.0700)</td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>-0.0921*</td>
<td>-0.0646</td>
<td>-0.178***</td>
<td>-0.0577</td>
</tr>
<tr>
<td></td>
<td>(0.0509)</td>
<td>(0.0642)</td>
<td>(0.0542)</td>
<td>(0.0608)</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.790***</td>
<td>0.564***</td>
<td>0.601***</td>
<td>0.592***</td>
</tr>
<tr>
<td></td>
<td>(0.0301)</td>
<td>(0.0420)</td>
<td>(0.0348)</td>
<td>(0.0351)</td>
</tr>
</tbody>
</table>

Control Mean: 5.601 7.213 8.085 7.943 0.695 0.909 5.704  
Control SD: 1.221 1.345 1.381 1.324 0.113 0.0794 1.233  
N: 8430 7687 8427 7690 8427 7684 8430  
Participants: 452 452 452 452 452 452 452

*p < 0.10, ** p < 0.05, *** p < 0.01

Notes: This table considers the treatment effect of the two Night-Sleep and the Nap interventions on sleep patterns.

- Night Sleep (columns 1 and 2), Time in Bed (columns 3 and 4), and 24-Hour Sleep (column 7) are measured in hours, where 24-Hour Sleep adds Nap Sleep to Night Sleep. Sleep Efficiency (columns 5 and 6) is the ratio between Night Sleep and Time in Bed.

- The odd column measures were collected by actigraph, and the even columns are self-reports. There is no self-reported measure of 24-hour sleep because we do not collect data on self-reported nap duration.

- Each column shows the OLS estimates of equation (2) separating the two night-sleep treatments, controlling for the baseline (ANCOVA), age, female, years of education, number of children, and day-in-study and date fixed effects. Standard errors are clustered at the participant level.
Table 2: Treatment Effects on Data-Entry Work Performance

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Productivity</th>
<th>Labor Supply</th>
<th>Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Output/Hour (1)</td>
<td>Days in Office (2)</td>
<td>Hours in Office (3)</td>
</tr>
<tr>
<td>Night Sleep vs. Control</td>
<td>45.84</td>
<td>-0.17</td>
<td>-0.15***</td>
</tr>
<tr>
<td></td>
<td>(39.91)</td>
<td>(0.40)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Nap vs. Break</td>
<td>82.45**</td>
<td>0.79</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(36.33)</td>
<td>(0.49)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Nap vs. No Break</td>
<td>74.61**</td>
<td>-0.33</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(36.64)</td>
<td>(0.44)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Control Mean</td>
<td>3401.36</td>
<td>16.48</td>
<td>6.71</td>
</tr>
<tr>
<td>Control SD</td>
<td>1834.62</td>
<td>4.00</td>
<td>2.93</td>
</tr>
<tr>
<td>N</td>
<td>7350</td>
<td>452</td>
<td>7348</td>
</tr>
<tr>
<td>Participants</td>
<td>451</td>
<td>452</td>
<td>451</td>
</tr>
</tbody>
</table>

Notes: This table considers the treatment effect of the Night-Sleep and the Nap interventions on work outcomes.

- Row 1 shows treatment effects of the two Night-Sleep interventions (pooled) in comparison to the Control Group. Row 2 shows treatment effect of the Nap intervention in comparison to participants not randomized to naps who took a break during the nap time. Row 3 is analogous, but the comparison group consists of participants who worked during the nap time.

- The dependent variables are: productivity, defined as output over hours typing; labor supply outcomes capturing, respectively, the number of days present in the office, overall hours in the office, and hours actively typing; earnings from data-entry work capturing, respectively, performance earnings and overall earnings, the latter adding payments for time working to the former earnings measure.

- Each column shows the OLS estimates of equation (2), controlling for baseline values (ANCOVA), age, female, long study day, fraction of high piece-rate sessions, and day in study and date fixed effects. Standard errors are clustered at the participant level.
### Panel A: PVT

<table>
<thead>
<tr>
<th></th>
<th>Indices</th>
<th></th>
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<th>Individual Components</th>
<th></th>
<th></th>
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<th></th>
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</thead>
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<tr>
<td></td>
<td>Anderson (1)</td>
<td>Average (2)</td>
<td>Payment (3)</td>
<td>Inverse RT (4)</td>
<td>Minor Lapses (5)</td>
<td>False Starts (6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Night-Sleep Treatments</td>
<td>-0.005</td>
<td>-0.002</td>
<td>0.002</td>
<td>-0.027</td>
<td>0.013</td>
<td>-0.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.044)</td>
<td>(0.043)</td>
<td>(0.041)</td>
<td>(0.047)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>0.111***</td>
<td>0.118***</td>
<td>0.151***</td>
<td>0.104***</td>
<td>0.156***</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.056)</td>
<td>(0.051)</td>
<td>(0.058)</td>
<td>(0.052)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.446***</td>
<td>0.593***</td>
<td>0.449***</td>
<td>0.002</td>
<td>0.028</td>
<td>0.0568**</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.035)</td>
<td>(0.020)</td>
<td>(0.028)</td>
<td>(0.022)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table considers the treatment effect of the Night-Sleep Interventions and Nap interventions on attentiveness as measured by the Psychomotor Vigilance Task (PVT) and Attention to Incentives. Standard errors throughout the table are clustered at the participant level.

- Variables are standardized by the control group’s average and standard deviation, with signs flipped such that higher coefficients indicate more desirable outcomes. Columns 1 and 2 are weighted averages of the 3 standardized PVT outcomes. Column 1 averages the outcomes optimally accounting for correlation across measures (Anderson, 2008), while column 2 is a simple unweighted average of the standardized variables.
- The outcome in column 3 is payment for the PVT task, which is calculated based on the performance measures in the following columns. Column 4 displays inverse reaction time, while column 5 is the number of minor lapses (significant delays between when the signal appears and the participant acts), and the outcome variable in column 6 is the number of false starts (when the participant acts before the signal is displayed).
- Columns 3 to 6 show the OLS estimates of equation (2), controlling for baseline values (ANCOVA), age, female, years of education, number of children, fraction of high-piece-rate sessions, whether the participant was randomized to work during nap times, and day in study and date fixed effects. Standard errors are clustered at the participant level.

### Panel B: Incentives

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th></th>
<th></th>
<th></th>
<th>Morning</th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Output (1)</td>
<td>Minutes (2)</td>
<td>Output (3)</td>
<td>Minutes (4)</td>
<td>Output (5)</td>
<td>Minutes (6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Night-Sleep Treatments</td>
<td>0.85</td>
<td>0.80</td>
<td>0.83</td>
<td>0.94</td>
<td>0.85</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.13)</td>
<td>(0.05)</td>
<td>(0.54)</td>
<td>(0.04)</td>
<td>(0.12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>0.94</td>
<td>0.99</td>
<td>0.85</td>
<td>0.84</td>
<td>0.97</td>
<td>0.96</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.16)</td>
<td>(0.05)</td>
<td>(0.61)</td>
<td>(0.06)</td>
<td>(0.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>0.84</td>
<td>0.77</td>
<td>0.80</td>
<td>0.65</td>
<td>0.86</td>
<td>0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.15)</td>
<td>(0.05)</td>
<td>(0.38)</td>
<td>(0.06)</td>
<td>(0.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value NS vs Control</td>
<td>0.891</td>
<td>0.830</td>
<td>0.576</td>
<td>0.569</td>
<td>0.877</td>
<td>0.677</td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value Nap vs Control</td>
<td>0.011</td>
<td>0.110</td>
<td>0.282</td>
<td>0.710</td>
<td>0.023</td>
<td>0.060</td>
<td></td>
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<tr>
<td>N</td>
<td>71596</td>
<td>71596</td>
<td>29241</td>
<td>29241</td>
<td>42355</td>
<td>42355</td>
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<td>450</td>
<td>451</td>
<td>451</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table shows the attention parameter $\theta$ – which captures attention as the ratio of the reaction to high incentive between the non-salient and the salient conditions. Details of the definition and estimation of $\theta$ are presented in Section 5.2. Columns 1 and 2 show $\theta$ considering incentive windows for the whole day, while columns 3 to 4 and 5 to 6 consider only window incentives before nap time (morning) and after nap time (afternoon), respectively.

- We consider attention for three groups. First, the Control group, which in this regression consists of individuals in the intersection between Night-Sleep Control and Nap Control. Second, the Night-Sleep treatment group, which pools both Sleep-Devices and Incentive groups. Third, the Nap Group. The excluded group includes both participants in the Break and Work conditions.

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### Table 4: Treatment Effect on Savings and Time Preferences

#### Panel A: Savings

<table>
<thead>
<tr>
<th></th>
<th>Savings Flow (Winsorized)</th>
<th>Interest Accrued</th>
<th>1% Interest Accrued</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Deposits</td>
<td>Net Savings</td>
<td>1% (-1146)</td>
</tr>
<tr>
<td>Night Sleep Treatment</td>
<td>-3.00 (9.35)</td>
<td>-9.39 (11.85)</td>
<td>-2.02 (10.40)</td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>16.12* (8.26)</td>
<td>8.99 (11.03)</td>
<td>11.74 (9.46)</td>
</tr>
<tr>
<td>Interest Rate</td>
<td>34.41*** (8.62)</td>
<td>39.43*** (11.29)</td>
<td>36.06*** (9.53)</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.87*** (0.05)</td>
<td>0.57*** (0.08)</td>
<td>0.74*** (0.06)</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>113.29</td>
<td>71.97</td>
</tr>
<tr>
<td>Control SD</td>
<td>166.68</td>
<td>325.68</td>
<td>238.94</td>
</tr>
<tr>
<td>N</td>
<td>8574</td>
<td>8574</td>
<td>8574</td>
</tr>
<tr>
<td>Participants</td>
<td>452</td>
<td>452</td>
<td>452</td>
</tr>
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</table>

#### Panel B: Present Bias

<table>
<thead>
<tr>
<th></th>
<th>Structural Beta (β)</th>
<th>Ratio Now vs. Later</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full Sample</td>
<td>New Version</td>
</tr>
<tr>
<td></td>
<td>Restricted</td>
<td>Unrestricted</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.007</td>
<td>0.049</td>
</tr>
<tr>
<td>Night Sleep Treatment</td>
<td>0.056* (0.033)</td>
<td>0.073 (0.048)</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.037</td>
<td>0.076</td>
</tr>
<tr>
<td>Control SD</td>
<td>0.34</td>
<td>0.34</td>
</tr>
<tr>
<td>N</td>
<td>352</td>
<td>214</td>
</tr>
</tbody>
</table>

**Note:** This table considers the treatment effect of the Night-Sleep and the Nap interventions on time preferences.

- **Panel A: Savings**
  - The dependent variable in column 1 captures daily deposits (which is equivalent to winsorizing daily net savings at Rs. 0) at the study office. Column 2 shows daily net savings (difference between deposits and withdrawals). Columns 3 and 4 use the same outcome variable, winsorized at 1 percent (Rs. -1146) and 5 percent (Rs. -50), respectively. Columns 5 and 6 show daily interest accrued due to savings, with column 6 excluding individuals who were assigned zero interest rates.
  - Each column shows the OLS estimates of equation (2), controlling for the baseline (ANCOVA), age, female, daily piece rates, default amount and maximum payment from cognitive tasks.
  - Interest accrued measures the earnings from interests accrued on each day in the study.
  - Counterfactual interest accrued is constructed by calculating the interest earnings participants would have received if all faced 1% daily interest rates.

- **Panel B: Present-bias**
  - The dependent variable throughout Panel B is one of our two preferred measures of present bias parameter: either the percentage decrease in effort chosen on ‘work-days’ (OLS) or the structurally estimated $\beta$. In all columns, we present the treatment effect of the Night-Sleep and the Nap interventions on present-bias parameter, controlling for baseline present bias and other controls (See Appendix B.2 for more details).
  - The dependent variable in columns 1 and 2 is our preferred structurally-estimated present bias parameter. We exclude individuals for whom the structural estimator did not converge.
  - The dependent variable in columns 3 and 4 is the OLS present bias parameter. In this specification, we exclude the participants for whom the structural estimator did not converge.
  - The dependent variable in columns 5 and 6 is the OLS present bias parameter. Here we include all participants who completed the present bias task successfully at least once in the treatment period.
Table 5: Treatment Effects on Psychological Well-Being

<table>
<thead>
<tr>
<th></th>
<th>Indices</th>
<th>Standardized Components</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Anderson Average</td>
<td>Pre-Reg. (3)</td>
</tr>
<tr>
<td>Night-Sleep Treatment</td>
<td>-0.0225 (0.0501)</td>
<td>-0.0220 (0.0509)</td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>0.142** (0.0689)</td>
<td>0.0843* (0.0477)</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.780*** (0.0368)</td>
<td>0.723*** (0.0397)</td>
</tr>
<tr>
<td>N</td>
<td>442</td>
<td>442</td>
</tr>
<tr>
<td>Participants</td>
<td>442</td>
<td>442</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

Notes: This table considers the treatment effect of the Night-Sleep and Nap interventions on measures of psychological well-being.

- All variables are standardized by the control group’s average and standard deviation, with signs flipped when the smaller values of the dependent variable indicate greater well-being.
- The outcome variable in columns 1 and 2 are weighed averages of the 5 standardized well-being outcomes. Column 1 averages the outcomes optimally accounting for correlation across measures (Andersen 2008), while column 2 is a simple average. Column 3 is a simple average of only the three pre-registered outcomes - depression, happiness, and life possibility.
- The outcomes in columns 4 to 8 are (4) self-reported depression, at endline; (5) self-reported happiness, where a score of 1 means “not at all happy” while a score of 5 means “very happy”; (6) ladder of life possibility (Gallup Cantril Scale), where participants were asked, “Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?”; (7) life satisfaction (from Gallup Survey), where participants are asked, “All things considered, how satisfied are you with your life as a whole (0 Dissatisfied to 10 Satisfied)”; (8) self-reported stress (part of Cohen et al.’s PSS), where an answer of 1 means “none of the time” while 6 means “a lot of the time.”
- We pool the two night-sleep treatments and control for age, female, years of education, number of children, day-in-study and date fixed effects, and baseline (ANCOVA), when available. When the dependent variables comprise an index, we control for the index at baseline.
## Table 6: Treatment Effects on Physical Well-being

<table>
<thead>
<tr>
<th></th>
<th>Physical Activity</th>
<th>Physical Health</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Index (1)</td>
<td>Index 1 (4)</td>
</tr>
<tr>
<td>Night-Sleep Treatments</td>
<td>-0.0150 (0.0549)</td>
<td>0.0460 (0.0339)</td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>-0.0827 (0.0527)</td>
<td>0.0534* (0.0320)</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.511*** (0.0330)</td>
<td>-0.0443 (0.0469)</td>
</tr>
</tbody>
</table>

|                | Biking (2)        | Steps (3)       | Index 3 (6) | Illness (7) |
|                | 0.107 (0.0559)    | 0.0163 (0.0520) | 0.0144 (0.0243) | |
| Baseline        | 0.861*** (0.0144) |                 |              |              |

|                | Index 4 (8)       | Index 5 (9)     | Illness (10) | Pain (11) |
|                | Illness (6)       | Pain (7)        | Daily Act (8) | BP (9) |
| Night-Sleep Treatments | 0.0733 (0.0654)   | 0.0877 (0.0887) | 0.0985 (0.0907) | 0.0199 (0.0259) |
| Nap Treatment     | 0.0461 (0.0320)   | 0.0591 (0.0479) | 0.0641 (0.0847) | 0.119 (0.0860) |
| Baseline          | -0.00813 (0.0144) | 0.190*** (0.0358) | 0.222*** (0.0461) | 0.771*** (0.0178) |

### Notes:

- This table considers the treatment effect of the Night-Sleep and Nap interventions on physical well-being outcomes.

- All variables are standardized by the control group’s average and standard deviation, with signs flipped such that higher outcomes indicate more desirable outcomes.

- Columns 1, 2, 3, 6, and 7 are weighted averages of the 6 standardized health outcomes. Column 1 averages the physical activity outcomes optimally accounting for correlation across measures (Anderson, 2008) using Manski lower bounds to account for biking task attrition, column 2 is the same as column 1 but uses Manski upper bounds, column 3 is a simple unweighted average of the standardized physical activity outcomes. Column 6 averages the physical health outcomes optimally accounting for correlation across measures (Anderson, 2008), and column 7 is a simple unweighted average of the standardized physical health outcomes.

- The remaining dependent variables are (4) total number of daily steps, (5) biking task performance, (8) days in the last week with self-reported illness, (9) self-reported pain on a scale from 1 to 10, (10) score of days in the last week that health impaired daily activities, and (11) an average of standardized, winsorized systolic and diastolic blood pressure. More details of the health outcomes can be found in Sections 5.4.2 and B.1.

- Each column shows the OLS estimates of an equation similar to (2). In the regression, we pooled the two night-sleep treatments and controlled for age, female, years of education, number of children, day in study and date fixed effects, and baseline (ANCOVA), when available. When the dependent variable is an index, we control for the index at baseline.

N 449 369 8615 439 439 439 439 439 2214
Participants 449 369 449 439 439 439 439 443
Figure A.1: Fraction of Individuals in Bed and Asleep by Hour of Night and by Treatment Group

Notes: This figure shows the fraction of participants asleep and in bed over the course of the night. In panel (a), the lines show the fraction of participants in each Night-Sleep Intervention group that are asleep at any time during the night, as measured by the actigraph. In panel (b) the lines show the fraction of participants in each Night-Sleep Intervention group that are in bed at any given time during the night, as measured by the actigraph.
Figure A.2: Reported Factors Interfering with Study Participants’ Sleep

Notes: This figure shows the fraction of participants who reported various disturbances impacting their sleep, including environmental conditions, mental distress, and physical distress. A participant is considered to have been affected by a disturbance if they ever reported the factor bothering them.
Notes: This figure shows the fraction of participants present for each day in the study separated by treatment group. In panel (a), the solid purple line shows the fraction of participants in the pooled Night-Sleep Intervention group who were present in the study office each day, while the dashed line does the same for Night-Sleep Control participants. In panel (b) the solid green line shows the fraction of participants in the Nap Intervention group who were present in the study office each day, while the dashed line does the same for Nap Control participants.
Figure A.4: Earnings Comparison between Nap and Work Group Over Days

Notes: This figure plots coefficients of a regression of typing earnings on the indicators of Nap and Work groups following specification (2). The post-treatment period is split in groups of 3 days to highlight the dynamics of the Nap Treatment.
Figure A.5: Quantile Plot of Daily Net Savings

Notes: This figure shows the ordered values of daily net savings (difference between deposits and withdrawals) in black dots plotted against the quantiles of a theoretical uniform distribution, represented by the solid black line. The solid red line highlights the 5th percentile of the distribution, associated with a daily net savings of -50.
Table A.1: Balance Across Treatment Conditions: Demographics and Baseline Sleep

<table>
<thead>
<tr>
<th></th>
<th>Night-Sleep Treatments</th>
<th>Nap Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control</td>
<td>Devices</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Female</td>
<td>0.66</td>
<td>0.64</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Age</td>
<td>35.84</td>
<td>35.24</td>
</tr>
<tr>
<td>(0.62)</td>
<td>(0.58)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>Number of Children</td>
<td>1.42</td>
<td>1.34</td>
</tr>
<tr>
<td>(0.09)</td>
<td>(0.08)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Years of Education</td>
<td>10.35</td>
<td>10.03</td>
</tr>
<tr>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Familiar with Using A Computer</td>
<td>0.30</td>
<td>0.28</td>
</tr>
<tr>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Self-Reported Night Sleep (Hrs)</td>
<td>7.22</td>
<td>7.20</td>
</tr>
<tr>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Actigraph Night Sleep (Hrs)</td>
<td>5.57</td>
<td>5.55</td>
</tr>
<tr>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Actigraph Time in Bed (Hrs)</td>
<td>8.00</td>
<td>7.99</td>
</tr>
<tr>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Sleep Efficiency</td>
<td>0.70</td>
<td>0.70</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Number of Sleep Devices Owned</td>
<td>2.52</td>
<td>2.70</td>
</tr>
<tr>
<td>(0.13)</td>
<td>(0.15)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Number of Participants</td>
<td>152</td>
<td>152</td>
</tr>
</tbody>
</table>

Notes: This table considers any underlying differences that may exist between the randomized treatment groups.

- Columns 1 to 3 show baseline means and standard errors by Night-Sleep Treatments. Columns 4 to 6 show p-values of t-tests between columns 1 vs. 2, 1 vs. 3, and 1 vs. 2 and 3.
- Columns 7 to 8 show baseline means and standard errors by Nap Treatment Group. Column 9 shows the p-value for the t-test between No Nap Group and Nap Group.
Table A.2: Balance Across Treatment Conditions: Health, Well-Being, Cognition, Work, and Savings

<table>
<thead>
<tr>
<th>Panel C. Health, Well-Being, Cognition</th>
<th>Night-Sleep Treatments</th>
<th>Nap Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control</td>
<td>Devices</td>
</tr>
<tr>
<td>Health Index</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Well-being</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Low-Incentive PVT Pay (Rs.)</td>
<td>12.67</td>
<td>12.50</td>
</tr>
<tr>
<td>Low-Incentive HF Pay (Rs.)</td>
<td>13.48</td>
<td>13.60</td>
</tr>
<tr>
<td>Low-Incentive Corsi Pay (Rs.)</td>
<td>13.89</td>
<td>13.84</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.11)</td>
</tr>
</tbody>
</table>

Panel D. Baseline Work and Savings

| Typing Time (Hrs)                      | 4.71                   | 4.72           | 4.66       | 0.89  | 0.52  | 0.75        | 4.71   | 4.68 | 0.64 |
|                                        | (0.05)                 | (0.05)         | (0.05)     | (0.04) | (0.04) |
| Time in Office (Hrs)                   | 7.96                   | 7.95           | 7.90       | 0.88  | 0.45  | 0.62        | 7.95   | 7.93 | 0.78 |
|                                        | (0.06)                 | (0.06)         | (0.06)     | (0.05) | (0.05) |
| Typing Productivity                    | 2277.65                | 2388.86        | 2393.92    | 0.82  | 0.70  | 0.57        | 2468.81| 2202.07| 0.07 |
|                                        | (122.00)               | (137.73)       | (120.17)   | (114.83) | (90.19) |
| Earnings (Rs.)                         | 384.30                 | 390.39         | 386.61     | 0.91  | 0.84  | 0.70        | 396.35 | 377.86 | 0.08 |
|                                        | (8.86)                 | (9.76)         | (8.50)     | (8.29) | (6.31) |
| Attendance                             | 0.94                   | 0.93           | 0.92       | 0.11  | 0.04**| 0.05**      | 0.93   | 0.93 | 0.26 |
|                                        | (0.01)                 | (0.01)         | (0.01)     | (0.01) | (0.01) |
| Prior Savings (Rs.'000)                | 27.17                  | 15.95          | 33.03      | 0.12  | 0.62  | 0.76        | 27.11  | 22.92 | 0.57 |
|                                        | (5.59)                 | (4.11)         | (10.87)    | (7.63) | (3.81) |
| Savings (Rs.)                          | 93.77                  | 90.37          | 113.57     | 0.56  | 0.15  | 0.49        | 100.11 | 98.12 | 0.84 |
|                                        | (8.94)                 | (9.74)         | (10.05)    | (7.76) | (7.92) |

Number of Participants  152  152  148  226  226

Notes: This table considers any underlying differences that may exist between the randomized treatment groups.

- Columns 1 to 3 show baseline means and standard errors by Night-Sleep Treatments. Columns 4 to 6 show p-values of t-test between Columns 1 vs. 2, 1 vs. 3 and 1 vs. 2 and 3.
- Columns 7 and 8 show baseline means and standard errors by nap treatment group. Column 9 shows p-values for t-test between no nap group and nap group.
Table A.3: Decomposing Impacts on Labor Supply

<table>
<thead>
<tr>
<th></th>
<th>Labor Supply</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minutes Typing</td>
<td>Total Pause</td>
</tr>
<tr>
<td>Night Sleep vs. Control</td>
<td>-9.86***</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>(3.06)</td>
<td>(1.18)</td>
</tr>
<tr>
<td>Nap vs. Break</td>
<td>1.53</td>
<td>3.05***</td>
</tr>
<tr>
<td></td>
<td>(3.05)</td>
<td>(1.05)</td>
</tr>
<tr>
<td>Nap vs. No Break</td>
<td>-26.34***</td>
<td>29.34***</td>
</tr>
<tr>
<td></td>
<td>(3.14)</td>
<td>(1.26)</td>
</tr>
</tbody>
</table>

Notes: This table considers the treatment effect of the Night-Sleep Interventions and Nap interventions on labor supply outcomes (measured in minutes).

- The outcome variables in columns 1 to 6 are various measures of labor supply. Column 1 considers minutes spent typing, column 2 considers total pauses, and column 3 considers voluntary pauses (excluding mandatory pause for participants randomized to stop work instead of napping). Column 4 considers total minutes in office and columns 5 and 6 consider office arrival and departure times, respectively.
- The outcome variables in columns 7, 8, and 9 are measures of productivity: productivity (output/hour), typing speed, and typing accuracy, respectively.
- Each column shows the OLS estimates of equation (2), controlling for baseline values (ANCOVA), age, female, long study day, fraction of high piece-rate sessions, and day in study and date fixed effects. Standard errors are clustered at the participant level.
Table A.5: Relation between present bias ($\beta$) and behaviors involving time preferences

<table>
<thead>
<tr>
<th></th>
<th>Daily Deposits</th>
<th>Lateness</th>
<th>Voluntary Pauses</th>
<th>Night Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Beta Structural</td>
<td>39.66*</td>
<td>37.81*</td>
<td>-6.485</td>
<td>-8.256*</td>
</tr>
<tr>
<td></td>
<td>(21.11)</td>
<td>(20.71)</td>
<td>(4.474)</td>
<td>(4.297)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Control Mean</td>
<td>127.1</td>
<td>127.1</td>
<td>42.37</td>
<td>42.37</td>
</tr>
<tr>
<td>Control SD</td>
<td>121.3</td>
<td>121.3</td>
<td>25.94</td>
<td>25.94</td>
</tr>
<tr>
<td>Observations</td>
<td>351</td>
<td>351</td>
<td>351</td>
<td>351</td>
</tr>
</tbody>
</table>

Notes: This table reports correlation measures between the present bias coefficient ($\beta$) and participants’ behavior.

- The independent variable of interest is the present bias measure $\beta$, estimated via the benchmark structural estimation method, which excludes participants for whom the maximization problem in the structural estimation does not converge.
- The dependent variables are daily deposits: from the savings task; lateness: how much longer participants arrive after the office opening; voluntary pauses: length of voluntary pauses from the typing task; and night-time sleep: time sleeping during the night measured by the actigraph. All the dependent variables are study long averages (including the baseline period).
- Each column shows the OLS estimates when controlling for participant’s gender, age, and education level.
Table A.4: Treatment Effects on Inhibitory Control and Memory

<table>
<thead>
<tr>
<th></th>
<th>Inhibitory Control</th>
<th>Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Payment Frac. Correct Avg. Reaction</td>
<td>Payment</td>
</tr>
<tr>
<td>Night-Sleep Treat</td>
<td>0.0240 (0.0356)</td>
<td>0.0119 (0.0518)</td>
</tr>
<tr>
<td>Nap Treat</td>
<td>0.0439 (0.0327)</td>
<td>-0.125*** (0.0479)</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.461*** (0.0261)</td>
<td>0.526*** (0.0341)</td>
</tr>
<tr>
<td>Control Mean</td>
<td>14.98</td>
<td>0.891</td>
</tr>
<tr>
<td>Control SD</td>
<td>1.371</td>
<td>0.0970</td>
</tr>
<tr>
<td>N</td>
<td>3654</td>
<td>3654</td>
</tr>
<tr>
<td>Participants</td>
<td>449</td>
<td>449</td>
</tr>
</tbody>
</table>

Notes: This table considers the treatment effect of the Night-Sleep and Nap interventions on inhibitory control and memory.

- All variables are standardized by the control group’s average and standard deviation, with signs flipped such that higher outcomes indicate more desirable outcomes.

- The outcomes in columns 1-3 are all related to inhibitory control, measured by the Hearts and Flowers task. The outcome variable in Column 1 is the payment participants earn for completing the H&F task, where the payment is a weighted average of the fraction of correct entries and reaction time in the task. Columns 2 and 3 break apart performance, respectively, by the fraction of correct entries, out of 40, and average reaction time, or the time it takes participants to respond after seeing a stimulus.

- The outcome variable in column 4 is the payment participants earn for completing the Corsi block task, which measures working memory. Payment depends on the maximum number of blocks they can recall within the task.

- All columns show the OLS estimates of equation (2), controlling for baseline values (ANCOVA), age, female, years of education, number of children, whether participants faced high or low incentives for the task (which varied by day), and day in study and date fixed effects. Standard errors are clustered at the participant level.
Table A.6: Treatment Effects on Risk and Social Preferences

<table>
<thead>
<tr>
<th>Indices</th>
<th>Risk Components</th>
<th>Social Components</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
</tr>
<tr>
<td>Night Sleep Treatment</td>
<td>-0.046 -0.045</td>
<td>-0.083 -0.013</td>
</tr>
<tr>
<td>(0.051) (0.053)</td>
<td>(0.101) (0.091)</td>
<td>(0.104) (0.101)</td>
</tr>
<tr>
<td>Nap Treatment</td>
<td>0.048 0.052</td>
<td>0.050 0.102</td>
</tr>
<tr>
<td>(0.048) (0.050)</td>
<td>(0.094) (0.087)</td>
<td>(0.098) (0.095)</td>
</tr>
<tr>
<td>Amount Received</td>
<td>0.625*** 1.155***</td>
<td></td>
</tr>
<tr>
<td>(0.040) (0.032)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.419 0.409***</td>
<td>0.317*** 0.385***</td>
</tr>
<tr>
<td>(0.095) (0.054)</td>
<td>(0.052) (0.050)</td>
<td>(0.055) (0.055)</td>
</tr>
<tr>
<td>N</td>
<td>415 415</td>
<td>415 415</td>
</tr>
<tr>
<td>Participants</td>
<td>415 415</td>
<td>415 415</td>
</tr>
</tbody>
</table>

Notes: This table considers the treatment effect of the Night-Sleep and Nap interventions on risk and social preferences.

- All variables are standardized by the control group’s average and standard deviation, with signs flipped such that higher outcomes indicate lower risk preferences or higher social preferences.
- Columns 1 and 2 are weighted averages of the 7 standardized risk and social preferences outcomes. Column 1 averages the outcomes optimally accounting for correlation across measures (Anderson, 2008), while column 2 is a simple unweighted average of the standardized risk and social preferences outcomes.
- The remaining dependent variables are separated into two panels, which are risk preferences components and social preferences components. Risk preferences components include (3) the point at which the participant switched from the risky to safe choice in the risk aversion game and (4) the point at which the participant switched from the risky to safe choice in the loss aversion game. Social preferences components include (5) the amount of money the sender sent in the dictator game, (6) the amount of money the sender sent in the ultimatum game, (7) the amount of money the sender sent in the trust game, (8) whether the recipient received the sender’s offer in the ultimatum game and (9) the amount of money the recipient sent back to the sender in the trust game.
- We take the average of recipients’ choices across different amounts of money they received from senders when calculating indices. In contrast, we separate different recipients’ choices in component regressions.
- Each column shows the OLS estimates of an equation similar to (2). In the regression, we pooled the two night-sleep treatments and controlled for age, female, years of education, number of children, day in study and date fixed effects, and baseline (ANCOVA), when available. When the dependent variable is an index, we control for the index at baseline. When the outcomes are recipients’ choices, we control for the amount of money they received from senders, which is also standardized.
B  Detailed Description of Tasks and Outcomes

B.1  Details of Health Outcomes

We captured a battery of different outcomes relevant to participants’ health over the course of the study. These measures include:

- **Blood pressure:** Systolic and diastolic blood pressure are measured 5 times for each participant over their time in the study using a digital blood pressure monitor and set protocol to ensure consistency.

- **Alcohol and tobacco consumption and spending:** Participants are asked 8 times over the course of the study about the quantities of alcohol and tobacco they consumed the previous day, if any.

- **Stationary biking outcomes:** On the last day of the study, participants were asked to bike on a stationary bike for 30 minutes, with incentive payments for total distance. We recorded total distance covered in the 30 minutes and the maximum speed attained.

- **Absences due to illness:** When participants were absent, they were contacted and asked about why they did not come to the office. Absences due to illness (e.g., cold, hospital visit, pain, etc.) were tracked and counted.

- **Daytime steps:** In addition to tracking sleep, the actigraphs also count steps. We tracked daytime steps (defined as steps between 9am and 8pm) as a measure of physical activity.

- **Change in weight:** Participants were weighed at the beginning and end of the study, giving us their change in weight over the course of the study.
B.2 Present Bias

B.2.1 Experimental Design

**Real-Effort Experiment.** Similarly to Augenblick and Rabin (2018), participants make decisions about how many pages to type in a fixed date ("work day", henceforth) under different piece rates. The work is very similar to the data-entry work they are used to, except that the pages are shorter to allow for a less coarse choice set for the participants. This work is completed at a fixed time after the completion of their regular working day, but before they get paid.

**Choices.** Participants have to make a total of 14 decisions. On each of them, the participants is offered a $w^c$ and must choose how many pages they would like to type for that piece-rate. We impose a minimum and a maximum number of pages each participant can choose. All participants must choose to type at least 5 pages, which we impose to avoid fixed costs associated with moving from 0 pages to 1 page, as in Augenblick et al. (2015). We also impose an upper limit of pages the participants can choose. We define a participant-specific upper limit, which we determine based on the participant’s typing speed up to that point in the study. We impose this limit so every participant can easily finish the task within two hours even when they choose the maximum number of pages, avoiding considerations of risk of not being able to complete the task by lack of time from the participants.

Immediately after they make their last decision, we randomly select one of the decisions made by the participant to be the one that counts for the task they need to perform. For example, if decision $c$ is selected, the choice’s associated piece rate, $w^c$, and the participants choice, $e^c$, will be the piece rate and the output target of the participant on the work day.

**Timeline.** The decisions are made on two different dates: 7 on a day prior to the work day (prospective date), and 7 on the work day. The payment date is always at least one day after the work day. Moreover, the payment date is a function of the randomly selected choice: we designed it so the payment distance is fixed between the date of a given choice and the payment if that choice is selected. The difference in choices between the two decision dates is the base of the identification of time preferences.

Participants completed the present bias experiment once in baseline and 1 to 3 times during the treatment period.

**Earnings from the task.** Earnings from the tasks consist of a lump-sum plus $w^s \cdot e^s$, where $w^s$ is the piece rate and $e^s$ is the number of pages in the selected choice. The participant only gets paid if they complete all the committed to within 2 hours, otherwise they receive nothing from the present bias task.

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22We do that as a priori sleep could impact risk-aversion, which would then affect this trade-off. We do not find however any treatment effect in risk preferences.
Changes during the study. The major change in design during the experiment was that in the first design we repeated the same 7 piece rates on the two decision dates. However, the debriefing of participants revealed that they sometimes deliberately tried to choose the same number of pages across dates for any given piece rate for what we understood as a preference for consistency. In order to avoid that issue, we changed the piece rates so there were 7 pairs of pieces that were randomized in blocks between day 1 and day 2 of the task. All the 14 piece-rates would therefore be different, which might make it harder for choices to be guided by participants’ demand for consistency. Also, to allow more time to elapse between the two decisions, we reduced the number of times participants completed the present bias experiment from 3 to 1 in the treatment period. That was necessary since participants only have 3 weeks during the treatment period.

Experimental Integrity. All except 1 participant refused to complete the task conditional on making the full set of choices. A small share of participants never shown up for the working day, and we exclude those from the analysis. Participants who were absent on the work day but were present on the next one to two dates were allowed to complete the task. This represents less than 20% of the choices and there are no significant differences between experimental groups on that dimension.

B.2.2 Structural Estimation of Present Bias

We estimate individual-level short-term discounting parameters \( \beta \) assuming participants choose the number of pages they would like to type by maximizing the utility function\(^{23}\)

\[
U(e, w, k; t, T) = -\beta^{-D_{k, t}} \delta^{t-k} C(e, \gamma) + \delta^{T-k} U_m(e \cdot w)
\]

where \( T \) is the date of payment, \( t \) is the date of the work, \( k \) is the date of the choice, and \( D_{k, t} \) is an indicator of whether \( k = t \).

The first part of the utility function captures the cost of effort from the extra work. Following Augenblick and Rabin (2016) (AR, henceforth), we assume the cost function has a power form in our benchmark specification, i.e.

\[
c(e, \gamma) = \frac{1}{\gamma} e^\gamma
\]

In robustness checks we impose an exponential cost function, like in DellaVigna and Pope (2016), of the form:

\[
c(e, \gamma) = \frac{1}{\gamma} \exp(\gamma \cdot e)
\]

The second part of the utility function captures the utility from choosing effort \( e \) under piece rate \( r \), parameterized as

\[
U_m(e \cdot w) = \phi \cdot w \cdot e + \alpha \cdot e
\]

The first term of this function captures the utility of money. We found that some partici-
pants also appear to have an intrinsic motivation in working, which based on participants’
debriefings is often linked to either reputation building (although we are explicit that we just want to know their preferences) or gift-exchange. We capture this effect with the term $\alpha \cdot e$ above. In practice adding this term improved our fit considerably. In our benchmark specification, optimal effort is given by

$$e^* \equiv e^*(k, t, T, w) = \left( \phi \cdot w \frac{\delta^{T-t}}{\beta_{(t>k)}} \right)^{\frac{1}{\gamma - 1}} \quad \text{(FOC)}$$

Finally, we assume that we observe the data with noise and with censoring at 5 and $\max_i > 5$. Thus, for choices interior to the participant’s choice set, we assume we observe $\tilde{e} = e^*(k, t, T, w) \cdot \tilde{\epsilon}$, where $\tilde{\epsilon}$ is a log-normal error term independent across observations and from the covariates. When accounting for the possibility of censoring, we assume that the pages we observe being chosen is determined by

$$e_i = \begin{cases} 5 & \text{if } \tilde{e}_i < 5 \\ \tilde{e}_i & \text{if } 5 \leq \tilde{e}_i \leq \max_i \\ \max_i & \text{if } \tilde{e}_i > \max_i \end{cases}$$

In our benchmark specification, we estimate the utility parameters in 4 using a 2-sided Tobit model, with cost function 5 and return to effort 7. We also impose that $\delta = 1$ in our preferred specification, which improved the quality of estimation of our key parameter of interest, $\beta$.

Finally, we estimate one model per participant that completed the present bias experiment at least once during the treatment period only using data from the treatment period. We do the same for the baseline period, so we end up with one baseline and one treatment period estimate of present bias per participant. The structural estimation does not converge for 47 participants in the treatment period in our preferred specification, so we drop those from the sample. The structural estimation also does not converge to 10 participants in the baseline period. We replace those missing values with the average value across participants during baseline, since we only use this variable as a control.

### B.2.3 Treatment Effect on Present Bias

To estimate the treatment effect of the Night-Sleep and the Nap interventions, we estimate the following equation by OLS:

$$y_i = \theta_{NS} D_{i}^{NS} + \theta_{Nap} D_{i}^{Nap} + \omega X_i + \epsilon_i$$

The outcome variable in this regression is an individual-level estimate of present bias, measured by the structurally estimated $\beta$ in our benchmark specification described above. We also show results when $y_i$ is the OLS estimate $\hat{\beta}_i^{raw}$ from the following regression

$$\log e_{cit} = \beta_i^{raw} \text{Now}_{cit} + \gamma_i^0 + \gamma_i^1 \log w_{cit} + \epsilon_{cit}$$
where Now$_{cit}$ is an indicator of whether $t$ is the work date, log $e_{cit}$ is the log of pages chosen and log $w_{cit}$ is the piece-rate in choice $c$.

The coefficients of interest are $\theta_{NS}$ and $\theta_{Nap}$, the intention-to-treat estimates for the Night-Sleep and the Nap Treatments, respectively. The term $X_i$ captures control variables, including the baseline present bias parameter, estimated in the same way as the dependent variable, except using only observations from the baseline, rather than the treatment, period. We also control for participant’s gender and age, as specified in our benchmark reduced form equation in the PAP.