Self-Detrimental Avoidance of Rest *

Alexandra V. Schubert[†] Jenny M. Wang [‡]

Link to current version

November 22, 2024

Abstract

Across many cultures, resting instead of working is viewed as a barrier to higher earnings. This belief is also reflected in many canonical economic models. Recent empirical evidence highlighting the productivity benefits of rest challenges this belief. Yet, existing work tends to ignore individuals' demand for restful activities and whether it aligns with their returns. In the context of an online labor market experiment in South Africa, we explore whether workers capitalize on the returns to short rest periods. After eliciting demand for rest, we estimate returns to rest for the same individuals and find that mandated rest boosts productivity by 0.3 standard deviations, thus making up for forgone earnings from resting. At the same time, only 19% of workers voluntarily choose to rest. Contrary to the notion of selection on returns, workers with high financial returns to rest do not select into rest. We provide suggestive evidence that misperceived financial returns are driving the disconnect between demand for and returns to rest. Our results provide proof-of-concept evidence that individuals may be misallocating effort between resting and working and could reach higher overall utility by working less. This highlights the importance of understanding misperceptions around rest, especially in light of the economic burden of long-term costs of overworking such as burnout.

Keywords: labor-leisure trade-off, rest, productivity, demand, misperceptions, production functions, gig economy

*Formerly circulated as "Give Me a Break: Misperceived Returns to Rest Among Online Workers in South Africa". Acknowledgments: We are grateful for the generous advising and comments by Sandro Ambuehl, Lorenzo Casaburi, Frank Schilbach, Roberto Weber, and David Yanagizawa-Drott. We also thank Abhijit Banerjee, Andrew Caplin, Ana Costa Ramon, Esther Duflo, Ernst Fehr, Ronak Jain, Dominic Legett, Michel Maréchal, Sendhil Mullainathan, Rohini Pande, Joachim Voth, Mia Lu, Judah Newman, Cristine von Dessauer, and participants at MIT's behavioral lunch, UZH's BLM, UZH's development lunch, and UZH's labor lunch, as well as seminar and conference participants at Williams College, the University of Virginia, UMass Amherst, Boston College, the SEA Meetings, UCSD-NHH Spring school, ESA Helsinki, and AFE London for helpful comments. We gratefully acknowledge funding from the George and Obie Shultz Fund at MIT, the UBS Center for Economics in Society at UZH, the Swiss Re Fund for Development Economics, the Zurich Graduate School of Economics Director's Grant, and David Yanagizawa-Drott's research funds. This project would not exist without the Sloan-Nomis Summer School for Cognitive Foundations in Economics. The pre-registration for the experiment can be found under AEARCTR-0013388, and IRB approval was obtained from MIT's Committee on the Use of Humans as Experimental Subjects (E-5819).

[†]PhD Candidate, University of Zurich. E-mail: lexi.schubert@econ.uzh.ch (Job Market Paper)

[‡]PhD Candidate, Massachusetts Institute of Technology. E-mail: wangjm@mit.edu

1 Introduction

The neoclassical labor-leisure model suggests a tractable trade-off: if a worker allocates more time toward labor, this leads to higher earnings, which can be used to purchase consumption. However, this comes at the cost of enjoying less leisure time. Recently, concerns have surfaced that by forgoing leisure time, workers might be forgoing more than just non-pecuniary utility. Research has drawn attention to the perils of working too much, with Nekoei et al. (2024) estimating the cost of worker burnout to be 2.3% of labor income in Sweden. Likewise, in public discourse, proposals for four-day work weeks have emerged across several high-income countries. Additionally, recent evidence in economics highlights the benefits of restful activities such as napping, exercising, or meditating for academic performance and work productivity (Bessone et al. 2021; Cappelen et al. 2017; Cassar et al. 2022; Giuntella et al. 2022; Shreekumar and Vautrey 2024). This would suggest that the opportunity cost of leisure also encompasses pecuniary returns to resting. If workers are not aware of these costs, they may work too much. By taking more breaks, they could increase their leisure without reducing output.

The existing work in economics has begun to document the benefits of restful activities; however, studies typically do not consider the demand for self-care activities or individuals' beliefs about the opportunity costs of rest.[1] In the context of choices around resting at work, this paper asks: What are the productivity returns to rest? Is there demand for rest? And does demand align with individual returns? We conduct an online labor market experiment with 832 lower-income workers in South Africa where we elicit workers' demand for breaks and measure both actual and perceived returns to breaks. By first eliciting choices from all workers around resting and then randomizing the vast majority of workers into two different work schedules–with and without a break, we can (i) compare workers' perceived to actual returns to breaks, (ii) test whether break decisions (on average) maximize earnings, and (iii) whether those who benefit the most from breaks sort into taking breaks.

Our experimental design and analysis are guided by a simple conceptual framework that captures a richer notion of rest encompassing both pecuniary and non-pecuniary returns. This framework can accommodate the neoclassical hypothesis underlying the canonical labor-leisure model: as more time is spent resting, less income is earned. We can test the neoclassical hypothesis empirically. The rational benchmark suggests individuals choose "rest" when its overall net returns—the sum of pecuniary and non-pecuniary returns—are positive. Under the assumption of positive non-pecuniary returns to rest, we can test two related hypotheses of optimal demand for rest: First, workers choose rest when the pecuniary returns are positive. Second, if workers do not choose to rest, their pecuniary returns are negative. If we do not find optimal demand for rest, misperceptions of the pecuniary returns can rationalize mistakes according to the neoclassical benchmark.

Our experiment provides a proof-of-concept in a well-defined setting designed to understand how workers make choices around resting and working. Workers make meaningful choices over working and resting within a time frame of approximately one hour, divided into five smaller periods ("segments") of 10 minutes each. Workers face an attention-demanding task in which performance decays quickly as mental fatigue

1. The latter is important in the context of many self-care interventions that hinge on voluntary uptake, as their impact will depend on the alignment between perceptions and returns.

accrues.[2] After completing two work segments, we elicit workers' preference to work or take a break during the third segment. To uncover the causal effect of assigning rest on productivity, the majority of workers are randomly assigned to either a work or a break condition regardless of their choice. This feature allows us to estimate the counterfactual performance of a given worker holding their break preference fixed.[3] Participants who take a break listen to a brief, restorative audio script designed to promote rest. To ensure compliance, there is a small monetary reward conditional on attending to the audio script.[4] Finally, all workers complete two more work segments, which serves as a measure of post-break performance. When choosing between resting and working in the third segment, workers thus face a clear trade-off: taking a break may be restful and increase their earnings in the last two segments through increased focus, but it comes at the cost of foregone earnings during the third segment.

We document three key findings. First, we find evidence against the neoclassical assumption of negative pecuniary returns to breaks, both in terms of "per-segment earnings" and "overall earnings". Randomly assigned rest significantly increases average post-break earnings—in the fourth and fifth segments—by 23% relative to the control mean, or 0.3 standard deviations ($p < 0.01$).[5] This increase in productivity compensates for the loss of output during the break. Workers who rested in segment 3 and thus only worked in segments 4 and 5 earn as much as those who worked for all three segments. That is, despite having one fewer work segment to earn income, workers who took breaks did not experience a reduction in total work earnings compared to those who worked for all three segments. If we include the small payment that break-takers could earn for attending to the break, we even find significantly higher earnings of £0.3 among those who were assigned to take a break. Viewed through the lens of our conceptual framework, the positive average effect of breaks on earnings implies that workers should opt for rest to maximize their utility.

Second, we test if workers' demand for rest aligns with the positive earnings effect of rest. Contrary to the neoclassical benchmark prediction, only 19% of workers opt to take a break despite positive earnings returns. The remaining 81% of workers prefer to work during the third segment.[6] Break-skipping behavior is hard to predict with most observable characteristics. However, individuals with a strong work ethic, lower household income, higher social desirability concerns, higher performance in earlier segments, and lower levels of fatigue were *less* likely to opt for rest. The average positive treatment effect could, of course, be masking heterogeneity in returns to breaks. If some workers have higher returns to breaks than others, taking

2. We use a Sustained Attention Release task (SART) that quickly induces cognitive fatigue by requiring quick and accurate responses. This task has also been used in recent work in economics to induce cognitive fatigue (Brown et al. 2022).

3. To incentivize truth-telling, workers are told that picking their preferred option increases the odds of being assigned said schedule. A small subset of workers was randomly chosen to receive their preferred option. The remaining 95% were randomly assigned. All 95% of workers that are randomly assigned are made aware of their random assignment such that those that receive their initial choice–but only through randomization–know it was because they were randomized.

4. We report earnings with and without the break payment, and the main finding is robust to this. During breaks, the work task stops, and the software is programmed such that there is no way for individuals to continue working. A restorative audio script (non-sleep deep rest/ yoga nidra, explained in more detail in Section 3), plays automatically. We instruct participants during the breaks to encourage genuine rest, as we want to avoid participants looking for other, less-restful occupations in the meantime.

5. An increase of 23% relative to the control mean is enough to compensate for forgone break earnings because later segments have higher stakes attached to them. This is outlined in Section 3 and Figure 2.

6. Since attentive break-taking behavior in the experiment is incentivized with a small monetary reward, we consider the low demand for rest of 19% to be the upper bound.

breaks may only be a positive-net-utility choice for a subset of workers. For individuals with negative returns, taking a break may be suboptimal. We thus turn to studying heterogeneity in returns to rest.

Third, we test whether workers' choices about breaks are maximizing their earnings. We split the sample by workers' preference to rest or work and investigate the effect of randomly assigning a break on total earnings in segments 3 through 5. We use total earnings that include the break bonus payment in this regression as the latter is payoff-relevant for workers' choices about rest. Contrary to the notion of selection on returns, workers who actively opted out of breaks could have increased their earnings by 8.47% or 0.12 standard deviations ($p = 0.059$) with a break. Even the marginal significance is noteworthy because a null effect means that earnings are the same even though time spent working was not. This suggests that workers made costly mistakes by forgoing rest. The sample of workers who wanted to take a break is too small to conclude whether they benefited more from resting. The estimated effect of the interaction is large and positive, albeit insignificant. To explore the robustness of the finding that the majority of demand is misaligned with returns, we use Lasso to investigate whether other dimensions of heterogeneity might be driving selection on returns. We find that few characteristics are predictive of positive returns.

These findings raise questions about why demand for rest is low despite high returns and why demand for rest is uncorrelated with returns. The neoclassical benchmark suggests that workers choose breaks when overall utility returns are positive. We have estimated pecuniary returns to be positive, and we have assumed non-pecuniary returns to be positive. If this assumption does not hold, it may be optimal for workers to avoid rest. In the context of our experiment, sources of non-pecuniary utility–or disutility–could be, for instance, the cost of effort of working, the joy of resting, self-image concerns about slacking off, joy of working, or boredom while resting. On average, we find that overall self-reported happiness is the same across treatments, suggesting that workers are not made worse off by resting. Additionally, we do not find evidence of self-signaling using self-reported emotions experienced around the time the random assignment decision was announced. Using measurements of reservation wages, we can also rule out that resting led to greater disutility of the task. When we survey workers at the end of the experiment about the reasons underlying their rest choices, most report hoping to maximize their earnings. Only 28% agree with the statement that they did not believe they would enjoy the break. We can repeat our previous analysis about the effect of randomly assigning rest on the subsample of 72% of workers who did not choose a break, albeit reporting it to be a pleasant activity. We again find a positive earnings effect of rest. This finding corroborates that these workers could have increased their overall utility by choosing to rest.

If the aversion to breaks is not driven by non-pecuniary elements in the production, an alternative explanation is misperceived financial returns to rest. Systematic misperceived returns can rationalize suboptimal decision-making. The intuition is the same as with any investment scenario: if, for instance, the returns to capital are misperceived, it is unlikely that the optimal amount will be invested. In favor of misperceptions among workers in our experiment, we find that a large number of workers motivate their break-skipping choice with a desire to earn more. Using posterior data on incentivized earnings predictions of the two work schedules, regardless of the treatment assignment or initial choice, we show that the average worker systematically underestimated the effect of rest on working ($p < 0.001$). To study misperceptions of the returns, we focus on the "control" group, i.e., workers who were not assigned to take a break during the experiment. On average, workers who did not experience a break believe resting would decrease overall earnings by 4.97%. These perceived negative returns stand in stark contrast with the causally estimated increase of 9.26% (t-test, $p < 0.001$). Misperceptions of the returns to rest are less pronounced among workers who were assigned to take a break. While these differences are suggestive, we cannot detect statistically significant belief updating as a response to the treatment. The causes of these misperceptions about the returns to rest could be manifold, including lack of information about one's own performance decay, skill acquisition, and the benefits of rest. Likewise, it is plausible that stress biases the perception of returns to rest.

Our results have significant implications for policy and future research. We provide a proof-of-concept that workers' demand for rest is misaligned with their returns in a well-defined, short-term setting.[7] While the exact costs and benefits of rest may vary across contexts, we posit there are many situations—outside of the context of our online labor market experiment—where this misalignment between the returns to and demand for rest is likely to arise as well, for example, workers who do cognitive-demanding, piece-rate sewing work in textile firms. On the returns side, we hypothesize that positive financial *net* returns to rest are likely to appear in contexts where performance decays quickly but can be recovered with rest and where compensation is tied to meeting performance thresholds. An example of this would be attention-demanding piece-rate work tasks. On the demand side, more research is needed to understand how misperceptions about the returns to rest arise and are sustained, but stress is a potential contributor. Outside of our autonomous freelancer setting, managers may also influence worker behavior, which warrants additional research. We document that workers fail to capitalize on the returns to rest in a short-term context. In a longer-term setting, additional costs are likely, including delayed costs such as burnout from consistently overworking and underinvesting in rest. This potential economic burden highlights the need for additional research to examine the determinants of self-detrimental behavior and investigate policies that may counteract it, such as correcting misperceptions or mandating breaks.

Our study is related to recent papers that have used randomized controlled trials (RCTs) or natural experiments to examine the impact or determinants of restful activities like sleeping, meditating, or exercising. Oftentimes, these studies will use exogenous variation to uncover the (positive) causal effect these activities (Bessone et al. 2021; Cappelen et al. 2017; Cassar et al. 2022; Gibson and Shrader 2018; Giuntella et al. 2022; Shreekumar and Vautrey 2024). These studies utilize exogenous variation–often encouraging individuals through the use of incentives–and reveal a causal positive effect of these activities on productivity or academic performance. While assigning people to different conditions identifies the productivity effects very cleanly, these returns are not 'net' returns. That is, they do not account for the (perceived) costs that an individual may face when deciding whether to engage in a restful activity and how individuals weigh them. Given that benefits are positive, a key next step is understanding and characterizing demand for these activities (Rao et al. 2021). Research by Avery et al. (2022) has studied the behavioral determinants behind low demand for

7. We study worker's behavior in a gig-economy context, which allows us to abstract away from concerns like social signaling to employers and to isolate how workers perceive the returns to rest. We believe it is plausible that these conclusions transfer to settings with an employer or manager if workers have some autonomy over their schedule. Further work is needed to explore how these dynamics around the demand for rest would change.

sleep but does not link it to individual-level returns. We bridge this gap between the two lines of work and elicit demand and returns to rest simultaneously. This allows us to document a misalignment of the two at the individual level.

By examining how workers allocate time as a factor in their own production function, we also connect to a larger literature on perceptions of production functions. Previous work has documented that people are often unaware of how to allocate resources most productively. This has been studied in agricultural contexts (Bold et al. 2017; Hanna et al. 2014), among managers in lab experiments (Caplin et al. 2023), and as well as among workers who avoid investing in protective gear (Dean 2024). Building on these insights, we extend this work in the direction of the labor-leisure trade-off and focus on an often overlooked factor: rest. We document misperceptions of the returns to and misallocation of rest in a context where workers can autonomously decide how much to invest in rest.

The dimension of effort allocation at work has also been studied from the angle of procrastination and self-control, often focusing on real-effort provision and poverty (Augenblick et al. 2015; Kaur et al. 2015; Schilbach 2019). Existing work has documented a tendency among workers to engage in breaks to either underprovide or procrastinate uncomfortable, effortful work tasks due to self-control issues. We also find misallocation of effort at work–however, in the opposite direction–showing financially-inefficient overworking behavior among lower-income individuals.

Section 2 provides a conceptual framework for perceived returns and choices about rest. Section 3 outlines the experimental design that allows us to study demand for and returns to breaks. Section 4 discusses our main findings and section 5 considers potential mechanisms for the low uptake of rest, and Section 6 concludes.

2 Conceptual Framework

This section describes a simple conceptual framework to assess how individuals make choices regarding rest. Our focus is on understanding who opts to take a break and whether these choices maximize monetary payments and well-being. For simplicity, we are agnostic about the exact underpinnings through which breaks influence individuals' work capabilities.

2.1 Returns to Rest

We consider a representative agent who derives their overall utility u from two different sources, pecuniary utility y and non-pecuniary utility v.[8] An example of pecuniary utility could be earnings from a piece-rate wage. An example of non-pecuniary utility could be the joy derived from engaging in a pleasant restful activity or the mental cost of effort while working.

Both sources of utility depend on the extensive-margin break variable b that captures whether the individual takes a break as part of their work period. If $b = 0$ the individual works the entire work period

8. We assume that pecuniary utility can be observed by the experimenter and that subjects form beliefs about it. Non-pecuniary utility cannot be directly observed by the experimenter but is perceived accurately by workers.

without taking a break. If $b = 1$, the individual takes a break as part of their work period. Hence if a break b is taking place, less time can be allocated toward work. It is important to note that we hold the overall time fixed, and b is just a binary indicator signaling how the overall time is split up.

$$u_i(b) = y_i(b) + \nu_i(b)$$

We define the causal effect of an exogenously assigned break on overall utility Δu as the difference between these two work schedules b. We can decompose the overall effect Δu into an *earnings effect*, Δy, and a *non-pecuniary effect*, $\Delta \nu$.

$$\begin{aligned} \Delta\, u \equiv\ & u(b=1) - u(b=0) \\ =\ & \underbrace{\Delta y}_{\text{earnings effect}} + \underbrace{\Delta \nu}_{\text{non-pecuniary effect}} \end{aligned}$$

A key assumption of our framework is that leisure is considered a form of consumption, and thus we assume that the non-pecuniary returns to resting are weakly positive, $\Delta \nu \geq 0$. Another way of interpreting $\Delta \nu \geq 0$ is that non-pecuniary utility may consist of many things, but on average, the net returns to resting will be positive. For instance, cost of effort of working and joy from resting might outweigh any losses from resting such as missing out on the psychosocial value of work or any self-image concerns about resting. Overall, this means there is negative non-pecuniary utility derived from working.[9]

Assumption 1: Non-negative Non-Pecuniary Returns to Rest

The non-pecuniary returns to rest are weakly positive:

$$\Delta \nu \geq 0$$

The neoclassical labor-leisure model posits a clear trade-off between labor and leisure. Labor is defined as time that is spent working and producing output. This output in return generates income for consumption. Conversely, leisure is any time not allocated to labor. According to this canonical model, any additional time spent on leisure implies less time worked. In return, more leisure time results in lower income earned. Thus, the neoclassical model predicts that the returns to resting are negative and forms the basis for our first hypothesis.

Hypothesis 1: Negative Pecuniary Returns to Rest (Neoclassical Model)

The pecuniary returns to rest are negative:

$$\Delta y < 0$$

9. We acknowledge that $\Delta \nu \geq 0$ need not hold for every work task. In our experiment, we can shut down the psychosocial channel, and we discuss evidence that self-image concerns are unlikely to be driving our results in Section 5.

We can test this conjecture empirically by comparing the earnings between workers randomly assigned to the two schedules, and we will provide evidence in Section 4 that it does not hold in the context of our study.

2.2 Demand for Rest

To study the demand for restful activities, we consider workers' binary choices $\theta \in 0,1$ over taking a break. $\theta = 0$ if a worker chooses to work the entire period; $\theta = 1$ if a worker prefers to take a break as part of this period. The Neoclassical benchmark posits that a worker will take a break if the overall net returns on utility (Δu) are non-negative, and will avoid taking a break if the effect is negative.

$$\theta = \begin{cases} 1 & \text{if } \Delta\, u \geq 0 \\ 0 & \text{if } \Delta\, u < 0 \end{cases} \tag{1}$$

Equation 1 can be rearranged to capture the trade-off between pecuniary and non-pecuniary utility gains. The last line indicates the trade-off that is stipulated by the neoclassical model.

$$\begin{aligned} \Delta\, u &\geq 0 \\ \Rightarrow \Delta \nu &\geq -\Delta y \\ \Rightarrow \quad \underbrace{\nu(b=1) - \nu(b=0)}_{\text{non-pecuniary utility gain of resting}} &\geq \underbrace{y(b=0) - y(b=1)}_{\text{financial gain of \underline{not} resting}} \end{aligned} \tag{2}$$

Equation 2 implies that a worker will choose to take a break $\theta = 1$ if the non-pecuniary utility derived from resting outweighs the earnings gain of working. The latter is synonymous with the earnings loss of taking a break.

Following Equation 1, we consider different combinations of measurable pecuniary and immeasurable non-pecunicary returns to understand how this maps into demand for rest.

$$\theta = \begin{cases} 1 & \text{if } -\Delta y \leq \Delta \nu \\ 0 & \text{if } -\Delta y > \Delta \nu \end{cases}$$

Since $\Delta \nu \geq 0$ by Assumption 1, combining the rational benchmark Equation 1 with the definition of $\Delta u = \Delta y + \Delta \nu$ the sign of the pecuniary returns Δy will determine an individual's demand for rest θ. If $\Delta y < 0$, we would need to know how the magnitude of $\Delta \nu$ compares to the magnitude of Δy. In this case, since $\Delta \nu$ is challenging to measure in the same currency as Δy, we cannot evaluate the optimality of any observed choices about breaks. In contrast, if $\Delta y \geq 0$, Hypothesis 2a posits that individuals should demand breaks $\theta = 1$ regardless of the magnitude of Δv as long as $\Delta v \geq 0$. The overall utility derived from resting will always be positive as both (pecuniary and non-pecuniary) components are positive.

Hypothesis 2a: Optimal Demand for Rest

Non-negative pecuniary returns implies positive demand for breaks:

$$\Delta y \geq 0 \;\Rightarrow\; \theta = 1$$

Next we ask about the converse: What can we infer from observed demand (or lack thereof) for rest about the returns to rest? If we see a worker choosing a break, we cannot conclude much about the pecuniary returns Δy. Large non-pecuniary returns $\Delta \nu$ could cancel out smaller negative pecuniary returns Δy. Similar to before, we would need to measure the exact magnitude of the inobservable $\Delta \nu$, which is challenging.

However, Hypothesis 2b posits that, if we see a worker not choosing a break, we know that they expect the impact of breaks on their overall utility (Δu) to be negative. Under Assumption 1 that $\nu \geq 0$, this implies a negative earnings effect $\Delta y < 0$:

Hypothesis 2b: Optimal Demand for Rest

No demand for rest implies negative pecuniary returns to rest:

$$\theta = 0 \;\Rightarrow\; \Delta y < 0$$

So far, we assumed no worker heterogeneity. However, analysis of aggregate data may be misleading if returns are heterogeneous. Individuals may still be demanding breaks optimally but may select into rest or work according to private information about idiosyncratic returns. If we relax the assumption of a representative agent, Hypothesis 2 still holds at the individual level.

2.3 Potential Mechanisms of Suboptimal Demand for Rest

We will test Hypotheses 2a and 2b in the context of our experimental setting. If we do not observe optimal rest-taking demand according to our Optimal Demand Hypothesis, this implies that individuals must *perceive* their overall returns to resting to be different from what we observe. This misalignment according to Hypothesis 2 can have two non-exclusive causes: (i) negative non-pecuniary utility or (ii) misperceived pecuniary utility. If an individual chooses not to rest, this must be because they believe the overall utility effect rest to be negative. If the pecuniary returns to resting are positive $\Delta y \geq 0$ (as we will document empirically in Section 4), then the break-taking condition in Equation 2.2 suggests that either non-pecuniary utility must be negative or individuals must hold wrong beliefs about the pecuniary returns to rest.

First, Assumption 1—non-pecuniary effects of rest are non-negative—need not hold. If $\Delta \nu < 0$, we can no longer claim that a positive earnings effect of rest implies positive demand for rest $\theta = 1$. We provide empirical proxies in favor of the positive non-pecuniary utility assumption in Section 5.

Second, individuals may hold biased perceptions of the pecuniary effects Δy. We denote perceptions of variables using a tilde. For example, if individuals view the earnings effect of rest to be large and negative, from their perspective, it is optimal to avoid resting. The choice of a break thus depends on individuals' *perceived* returns to rest, and equation 1 turns into equation 2.3.

$$\theta = \begin{cases} 1 & \text{if } -\widetilde{\Delta y} \leq \Delta v \\ 0 & \text{if } -\widetilde{\Delta y} > \Delta v \end{cases}$$

Misperceived financial returns to rest can explain a misalignment between demand for rest and its returns as stated in Hypothesis 3.

Hypothesis 3: Misperceived Pecuniary Returns Relative to Non-Pec. Returns *(Untestable)*
Under A1, if there is no demand for rest and pecuniary returns are positive, negative perceived pecuniary returns must outweigh non-pecuniary returns.

$$\textit{If} \;\; \theta = 0 \;\; \textit{and} \;\; \Delta y \geq 0 \;\; \Rightarrow \;\; \Delta v < -\widetilde{\Delta y}$$

However, to pin down the misperception mechanism, we would need to measure non-pecuniary returns. Without the magnitude of misperceived returns, we cannot determine whether negatively perceived utility returns outweigh any positive non-pecuniary returns. We thus use a modified Hypothesis 3 as a proxy for misperceptions.

Modified Hypothesis 3: Underestimated, Negative Pecuniary Returns to Rest *(Proxy)*
1. Perceived pecuniary returns to rest are smaller than true returns.

$$\widetilde{\Delta y} < \Delta y$$

2. Perceived pecuniary returns are negative.

$$\widetilde{\Delta y} < 0$$

2.4 Framework Summary

To summarize, our model generates the following insights and hypotheses.

1. The randomized assignment of breaks b allows us to sign the causal effect of rest on earnings y.
2. Under the assumption that non-pecuniary returns to resting are positive, we can test whether non-negative pecuniary returns imply positive demand for rest.
3. Considering heterogeneity in returns, we can test if negative demand for rest predicts negative pecuniary returns to rest.
4. If demand is negative albeit pecuniary returns are positive, we can test whether returns to resting are systematically underestimated.

3 Experimental Design

3.1 Experimental Design

To study the impact of and demand for rest, we recruit low-income workers from South Africa to perform an attention-demanding real-effort task for a work period that lasted approximately one hour. The work period was split into five segments, each approximately 10 minutes in duration on average.[10] Participants first work for two segments, then face a choice about the third segment, and then work for another two segments. After the last work session, we collect measures of well-being and beliefs.

Figure 1 provides an overview of our experimental design, where θ represents preferences over breaks and b represents break realizations. Our design around the choice is similar to the selective trials framework described in Chassang et al. (2012). We use a simplified binary version. All workers begin by completing the first two work segments of the five-segment block. This allows them to get experience with the work task. Participants then express a preference over taking a break or working in the third segment. We tell participants that choosing their preferred option will increase the odds of receiving this option. We then implement workers' choices for a randomly selected subset of 5% of participants implemented via Qualtrics. The remaining participants (95%) were randomly assigned with equal probability to either take a break or to work during the 3rd segment.[11] After the third segment, in which participants are either working or taking a break, everyone works for the remaining two segments. At the end of the five segments, subjects answer a brief endline survey about their beliefs and work period experience.

The real-effort task that subjects engage in during the work period is designed to mimic an air traffic control software, using the same images and general task structure as in Waldfogle et al. 2019. The task is also known as a "sustained attention release task" (SART) or "go no-go" task in the psychology literature. We use this task as it requires constant attention and is very cognitively-demanding without requiring any special skills or expertise. The constant attention always implies that we can observe at the 2-second level if participants are doing the task or doing something else. Since attention is a finite resource in the short term, this task also has an automatic performance decay built in as recently documented by Brown et al. (2022).

During the task, workers are shown a sequence of images, each depicting two flight trajectories. For each image, workers then decide whether the two flight trajectories shown are "safe" (meaning the flights are not about to collide) or "not safe" (meaning the flights are about to collide).[12] For every image, they have two seconds to decide whether it is safe or not-safe. If it is safe, workers are instructed to click the "safe" button. If it is unsafe, they are instructed to *not* click the "safe" button and instead let the image lapse after the two-second timer is up.

10. Segment length varied due to lags in the Qualtrics server and Internet speed. To account for these lags, we set the overall time constraint of 65 minutes based on a conservative estimate of the time it would take to finish the work period (from piloting). We also accounted for this at the beginning of the study by telling subjects upfront that the exact time of the study varies and cannot be influenced by them.

11. To address concerns of behavioral responses to not receiving their first choice, we first inform everyone who was part of the 95% randomly allocated subset that they were randomly assigned to a treatment by the computer. This is meant to reduce behavioral differences in frustration between people who received their preferred outcome and those who did not.

12. Example images of a safe and a not safe flight trajectories are in Figure A.1 in Appendix A.1.

Workers evaluate 300 images in each work segment. Of those, 280 are safe and 20 are not safe. Only one image is shown at a time, and the order of safe and not-safe images is random. The disproportionately large share of safe images makes it easy to get into a habit of constantly clicking, which is part of the original intention for these types of attention-demanding tasks. The idea is that this imbalance in image types and intended response behaviors requires constantly paying attention to withhold the impulse to click on "not safe" flight trajectories. This constant attention uses up available attention resources and leads to decays in performance over time.[13] This, in turn, provides scope for breaks to enhance performance as they may allow workers to replenish their attention resources.

The pay schedule is summarized in Figure 2. Subjects are compensated with a guaranteed £8 base pay for a 75-minute experiment for participating in the study. Additionally, subjects can earn bonus payments for successful completion of work segments. In the first three segments, bonus payment is £1 per successfully completed segment. In the last two segments, bonus pay increases to £3 per successfully completed segment. Higher earnings in the last two segments serve the purpose of highlighting the importance of being attentive and performing well toward the end. This should guide participants toward making optimal choices about resting and working and might signal that resting can have positive productivity effects. These increasing incentives are comparable to low-stakes midterms and high-stakes final exams or to surge prices that Uber drivers might face at night.

A segment is considered successfully completed if the following criteria are all satisfied: (i) at most 2 not-safe flights are missed, (ii) more than 75% of all flights are correctly identified, and (iii) it is completed within the work time window of 65 minutes. The first constraint is what makes the task challenging. It forces workers to pay attention to these not-safe flights that are rare and easy to miss by always clicking out of habit. This is the key margin along which performance differs across subjects over time. The second constraint is a basic attendance constraint. We aim to ensure that individuals are actively engaging with the task throughout the work segment. If we would not enforce some measure of getting both types of flights correct, workers could game the task by always clicking or never clicking. The third constraint prevents individuals from pausing the task on their own and equalizes working conditions across subjects.

By choosing an all-or-nothing payment structure, we mimic piece rates that are common in lower-income work settings. It also simplifies the trade-off between taking a break and working for workers. Thus the opportunity cost of a 10-minute break is well-defined and lessens the burden on the worker in terms of carefully thinking about how many images they expect to get correct, which would be the case if workers would be paid in pennies for every correctly identified flight. It also makes it easier to create a bundle of critical and non-critical flights, which allows us to ensure the attentiveness of the workers, as mentioned before.

Participants who take a break earn a flat payment of £0.5. They earn this payment as long as they actively engage with the break that we "provide". During the break, the work task is inaccessible, and the program auto-plays an audio script, which subjects are asked to listen to. The audio script focuses on certain types of breathing, also known as yoga nidra or non-sleep deep rest that have been shown to have calming effects

13. These performance decays have been documented in psychological studies using these sustained attention release tasks.

(Balban et al. 2023).[14] We check compliance with the audio-scripted break by asking one question at the end of the experiment that asks about the general content of the audio script. When facing the choice, workers know about the potential break payment as well as its contingency on attending to the break.[15] Workers do not receive feedback on their performance in the task. This applies to both the performance in the main work period and attending to the audio script during the break. Thus the focus lies on workers understanding their own performance of their "production function," as a result of their factor inputs.

Besides the "official" break, there were two additional ways in which workers could take breaks "naturally." First, any worker could, at any point in time, not continue with the task and do something else in the meantime. Because the flight images flicker across the screen automatically, and because they necessitate constant responses, we observe when a worker does this. Second, any worker can pause on the confirmation page in between segments. These small pauses, however, mean that workers will have less time to complete all segments. They are informed that segments take 8 to 13 minutes and that duration can vary due to lags. Segments that are not completed within 65 minutes will not be remunerated. Thus, pauses here are not "free" either because they imply less time to complete the remaining work segments. We also consider engagement with these types of natural breaks in Appendix A.4.

To ensure a high-data-quality sample of online workers, individuals had to successfully complete an online training and correctly answer questions about the instructions during the training in order to be eligible to be hired for the main work period. Training included a description of the incentive scheme, instructions for the task, and a preview of the break choice they would have to make during the study. We also collected basic demographics, including gender, state, education, employment, and language, as well as unincentivized measures of baseline initial task performance during this training.[16] This also gave individuals a chance to practice and gain experience with the task before they decided on whether to participate in the full work study. We select lower-income individuals with a per-household-member income of less than ZAR 6,000 per month (approx. $330).[17]

Participants who passed the screener were then invited to the main study. The invitations was sent out a couple of hours after participants completed the training, and participants could take the study at a time of their choosing as long as it was within one sitting. Before the work period starts, participants respond to questions from the Marlow-Crowne Social Desirability Scale (Reynolds 1982; Dhar et al. 2022) and the World Value Survey about work ethic.[18]

During the work period, we observe performance (in the form of mistakes, which translate into bonus

14. We use a script from the website `nsdr.co` from a point in time when the website and its audio scripts were still free.

15. Workers know that they will be asked questions about their experience, but we keep the details vague to avoid that workers game the system.

16. As part of this task training, participants first practice with feedback. Afterwards, they practice without feedback. The latter allows them to experience what the work task will be like.

17. For comparison, senior citizens with monthly income below ZAR 6550 are eligible for social assistance from the government. We focus on this demographic as we are interested in individuals who are financially constrained and for whom this online survey income represents a significant source of income. Some of these individuals also work in gig-economy type settings where they do image labeling tasks similar to our air traffic control task.

18. We choose items 39-41 from the World Value Survey, Wave 7 (Haerpfer et al. 2022) and elicit these items alongside a multitude of questions to minimize experimenter demand bias

payments), self-reported fatigue after Segments 1 and 5, as well as individuals' preferences for breaks (for themselves and for others). After the work period, we elicit individuals' beliefs about the number of mistakes in the last segment as well as self-reported happiness and task satisfaction. We also ask for incentivized predicted earnings by treatment. This provides us with a measure of perceived returns to rest. Lastly, we collect qualitative data about their break choice and engagement with the break audio script.

The South African online setting lends itself well for this experiment since online gig work is very prevalent in lower-income countries. Workers on cloud gig platforms may engage in tasks that are similar to our air traffic control task e.g., image labeling for AI companies. Moreover, we believe that our results are relevant for gig economy workers who have autonomy over their schedules. Thus the decision whether to work one additional segment or whether to take a break translates well to the context of accepting another "human intelligence task" (HIT) or taking a short break.

In sum, the collected data will allow us to understand, first, how breaks affect productivity, defined as average earnings per segment worked, and well-being by comparing the 95% of the sample that were randomly assigned. Second, incentivized choices between work and a break provide information about the demand for breaks. Third, we can uncover the treatment effect on the treated and untreated by comparing individuals assigned to breaks or no breaks among the subgroup of those either who preferred a break or did not prefer a break.

3.2 Sampling Procedures

We invited N=1,577 English-speaking participants in South Africa to participate in an initial training session for a study on performance in attention-demanding work tasks. This training functions as a screener. Participants know that upon successful completion they may be invited to participate in the 75-minute long main study. Among all those who were interested, 83% (N=1,313) subjects passed our screener and were eligible for the study. The 10-minute screener consists of basic demographic questions, the instructions of the experiment a task trial period with feedback (to give participants an opportunity to learn), a task trial period without feedback (to mimic the real study), and a quiz about the instructions including the incentive structure and the break as well as an audio sound check (to ensure the audio script could be played during the break). Of those who passed, N=1,035 people met our "lower-income" criteria.[19] We invite all these online workers to participate in the main study. For our analysis, we restrict the sample to participants who only took the survey once, and N=906 unique participants followed the invitation.[20] Of those, 834 participants finish all segments of the work task. We focus on this sample for our main analysis. Of those who completed

19. Although there is no way for us to verify self-reported income, it was unlikely that participants were aware of our income selection criteria, since the income questions appeared among many other demographic questions. Income was elicited in categories, which we then top-coded and divided by the number of household residents. If this imputed value was below ZAR 6,000 we invited the worker to participate. Households knew from the beginning that not everyone who passed the training would be able to participate, but they were not informed explicitly about the income eligibility criterion.

20. Some participants took the study multiple times–even though the instructions clearly stated that this was not allowed and would not be remunerated. We cannot distinguish between participants facing technological issues and restarting (exogenous shocks) and participants who would like to have a better second attempt and stop and restart the survey (endogenous). So we discard all these observations for our analysis. Participants were rewarded for their time nonetheless.

the work period, 826 finish the entire study, including the post-experiment survey questions. Finally, since we only randomly assign 95% of all observations, we restrict our analysis to those N=790 randomly assigned participants out of the 834 who completed the work session and post-session survey.

4 Results

4.1 Details about the Experimental Context

Accumulation of Mental Fatigue in Control Group. Performance in the task could be influenced by skill acquisition (improved performance over time) and mental fatigue (worse performance over time). Our data do not allow us to differentiate between the two forces, and we can only observe net improvements or decreases in performance. Since participants have ample opportunities to practice with the task in the initial training as well as before they start, we believe learning is unlikely to still be taking place during the main work period. To test empirically whether the air-traffic-control task (known as sustained attention release (SART) task in psychology) induces mental fatigue, we track the number of "critical mistakes made" by individuals in the control group across time. In this case, critical mistakes refer to missing "not safe" flights missed by participants.[21] Figure 3 illustrates an upward trend of mistakes. The mean number of mistakes, as indicated by the horizontal blue lines in a segment, is higher in later segments relative to earlier segments. As Table 2 showcases, we can reject that workers make fewer mistakes in earlier segments relative to the fifth and last segment ($p < 0.0001$). A similar trend holds for the number of mistakes made in the penultimate fourth segment relative to previous segments, except for segment two, where the difference is not statistically significant. While there is a noticeable increase in mistakes between the first and the second segment (0.7 more mistakes, $p < 0.0001$), performance improves in the third segment relative to the second segment (0.5 fewer mistakes, $p < 0.0001$). The improvement between 2 and 3 could reflect that participants were able to recharge a little bit in the couple of minutes that they spent making a choice about taking a break. Additionally, the majority of workers had hoped to work during the third segment in order to earn more money. Heightened attention could also reflect a temporary motivational boost and excitement about being given the opportunity to earn more.

"First-Stage": Compliance with Break Treatment. Participants assigned to take a break were instructed to listen to an audio script. To ensure compliance and prevent survey hopping, we told workers upfront that they would be asked incentivized questions about the break experience at the end of the work period. At the end of the study, 94% of participants reported attending to the audio script. Of those, 65% correctly answered a question about the breathing technique used in the audio script.[22] Among the 35% who self-report using NSDR but incorrectly answer the question, a large majority still claimed to have listened to the script in an

21. There were 20 "not safe" flights randomly interspersed across the 300 total flights in a given segment. If participants missed more than 2 of these flights, they would not get the bonus in a given segment.

22. Among the 6% who self-report not engaging with the audio script, 62% get the question right. Thus, in the overall sample, 64% earn the £0.5 break attendance bonus.

ex-post open text question. Importantly, having an initial preference in favor of (or against) a break was not correlated with higher audio script compliance.

4.2 Empirical Strategy

For our primary analyses of assigning breaks on earnings, we run an ANCOVA regression and control for baseline performance in Segments 1 and 2 before the randomization took place in Column 1.[23] Additionally, we control for gender, education, employment status, year of birth, province, and per-capita household income in Column 2 to increase precision.[24] Our preferred specifications include control variables and we use the following equation to study the effect of randomly assigned rest on outcome variables of interest:

$$y_i = \beta_0 + \beta_1 \text{RandBreak}_i + \delta_1 \text{Bonus}_1 + \delta_2 \text{Bonus}_2 + X_i' \lambda + \varepsilon_i \tag{3}$$

where y_i is the outcome of worker i. RandBreak$_i$ is a binary indicator for whether an individual was randomly assigned to rest in the third work segment. The binary variables δ_1 and δ_2 reflect whether an individual earned a bonus in Segment 1 and 2 and reflect baseline performance.[25] The key coefficient β_1 represents the average treatment effect of randomly assigning a worker to take a break in the third segment. This sign of this coefficient allows us to test Hypothesis 1 in our model in Section 2. A negative sign is in line with the neoclassical model, while a positive sign would reject the neoclassical model.

In addition, in a supplementary analysis, we control for workers' choices and study the interaction effect between choices and treatment. We use the following specification:

$$\begin{aligned} y_i = &\beta_0 + \beta_1 \text{RandBreak}_i + \gamma \text{ChoseBreak}_i + \xi \left(\text{RandBreak}_i \times \text{ChoseBreak}_i\right) \\ &+ \delta_1 \text{Bonus}_1 + \delta_2 \text{Bonus}_2 + X_i' \lambda + \varepsilon_i \end{aligned} \tag{4}$$

where y_i is the outcome of worker i. RandBreak$_i$ is a binary indicator for whether an individual was assigned to rest in the third work segment, ChoseBreak$_i$ is a binary indicator for whether an individual asked to rest in the third segment. The binary variables δ_1 and δ_2 reflect whether an individual earned a bonus in Segment 1 and 2 and reflect baseline performance. By including the interaction between assignment and demand for breaks, ξ captures the treatment effect of rest among workers who preferred to take a break.

23. We discuss the ANCOVA specification and differences in baseline performance in Appendix A.3.

24. All empirical analyses of the effects of rest are restricted to the 95% sample of workers who were randomly assigned to one of the two work schedules. The 5% of workers whose choices were implemented are discarded from any analyses. We further limit the sample to individuals who completed the entire work segment and have no duplicate entries.

25. We use bonus payments–as opposed to mistakes–as measurements of baseline performance since the outcome variable is also earnings in GBP. In Segments 1 and 2, the bonus payment was £1 per segment. Thus binary receipt is equivalent to binary monetary earnings for a given individual in a given segment.

4.3 Effects of Rest on Productivity and Earnings

Our analysis of the effect of rest on income revolves around three outcome variables: (i) post-break earnings, (ii) work earnings in Segments 3 to 5, and (iii) total earnings in Segments 3 to 5, including any break payments. First, we investigate the impact of randomly-assigned (mandated) rest on post-break earnings.[26] Any differences between the two groups may reflect a mix of two dimensions: first, increased focus due to the restorative audio script, and second, the lower focus due to accumulated fatigue from not resting.

Figure 4 plots the average earnings per segment by treatment group among workers who were randomly assigned. While the magnitudes of the differences between groups are not large due to imbalance issues discussed in Appendix A.3, the figure provides suggestive evidence that individuals who were assigned to take a break in the third segment earn more in Segments 4 and 5 on average. Since the segment earnings of an individual are all-or-nothing, the higher average across all subjects in the break groups reflects a higher propensity to earn the bonus payment.

For the corresponding regression analysis in Table 3, we sum up the earnings of the post-break Segments 4 and 5 and regress them on random assignment to the break treatment. Equation 3 underlies these regressions. We use an ANCOVA specification and control for baseline performance in Segments 1 and 2 before the randomization took place in Column 1. We control for gender, education, employment status, year of birth, province, and per-capita household income in Column 2. The latter column is our preferred specification.

We find clear evidence that the break increased worker productivity. Individuals randomly assigned to rest, on average, earn £0.72 more across all post-break segments holding past performance and individual characteristics constant (Table 3, Column 2). In other words, in each segment after the break, individuals assigned to rest earn £0.36 more. This number is 12% of the potential max earnings per segment and represents a post-break earnings increase of 23% relative to the control group mean, equivalent to 0.3 standard deviations ($p < 0.001$). These results of the productivity-enhancing effect of short restorative breaks complement the existing literature around restful activities (Bessone et al. 2021; Cappelen et al. 2017; Cassar et al. 2022; Giuntella et al. 2022).

Second, we quantify how the increased post-break productivity compares to the monetary cost of resting. That is, do the higher earnings in Segments 4 and 5 among "break takers" make up for the forgone earnings of Segment 3? This allows us to test the neoclassical labor-leisure model, which predicts that working less decreases earnings. As outlined in Hypothesis 1 in Section 2, this model would predict a negative coefficient β_1 of randomly assigned rest on overall earnings. Table 4 investigates Hypothesis 1 by regressing total *work* earnings in Segments 3 through 5 on random assignment to rest.[27] These work earnings in Columns 1 and 2 only include bonus payments from completing work segments and exclude any break payments earned for attending to the break.

Contrary to Hypothesis 1, we find no significant difference between the total earnings between the two groups. Randomly assigning a break increases earnings by £0.02, controlling for initial performance

26. Post-break earnings automatically reflect a measure of productivity as well. Productivity is commonly defined as output over input. In this case, output would be the sum of post-break earnings and input would be two segments. The input is the same across all subjects and thus productivity is simply a scalar of post-break earnings.

27. We focus on Segments 3 to 5 as Segments 1 and 2 took place before the randomization.

and demographics, with mean work earnings of £3.8 for the no-break group in Segments 3 through 5. The coefficient estimate is not precise but close to zero with standard errors of approximately £0.15. A null effect implies that workers across both treatment groups earn the same on average even though workers assigned to the break group only worked for two segments while workers assigned to the no-break group worked for three segments.[28] This finding demonstrates that in the context of our experiment, breaks pay for themselves and workers are just as well off monetarily with taking a break as without.[29] These first two columns of Table 4 focus on work earnings, akin to earnings from producing output; they do not include the small payment that workers earned for attending to the break. In Columns 3 and 4 of Table 4, we consider overall earnings including the break payment. We now regress total work and break payment earnings from Segment 3 through 5 on random assignment to rest. The small break payment is pay-off relevant from the perspective of a worker, and thus, the effect of breaks on the total payment earned by workers is important when studying choices. We see statistically significantly higher total earnings for those who were randomly assigned to rest than for those who were assigned to work during that segment. On average, workers earned £0.35 more in Segments 3 to 5 if they were assigned a break, holding baseline performance and demographics constant (p=0.034). This is equivalent to a 9.26% increase relative to control group earnings. A comparison of columns 2 and 4 in Table 4 indicates that the significant benefit is driven by the break bonus payment. These positive returns to rest provide additional evidence that allows us to reject Hypothesis 1 from Section 2. Since this payment is part of workers' compensation, the returns to resting in this experiment are positive. In return, according to Hypothesis 2a, we would expect workers to choose breaks to maximize their overall earnings.

4.4 Demand for Rest

Despite the finding that workers earn significantly more under the schedule with a break, demand for breaks is low in our experiment. Only 19% of workers prefer to take a break when given the choice after finishing the first two work segments (immediately before the implementation of the potential break in Segment 3). Consequently, when making this choice, workers have experience with the task at the moment of deciding and have built up fatigue.[30] Given the positive benefits of rest, the low take-up of breaks contradicts our Hypothesis 2a, i.e., that workers demand rest if the returns pecuniary returns are positive.

We next study whether choosing rest can be predicted by individual-level characteristics. Figure 5 displays coefficient estimates from a regression of break preference on individual characteristics including demographic variables, values, and past performance. Two of the World Value Survey (WVS) questions meaningfully predict workers' preferences to take breaks. On average, agreeing one point more with the statements on "work being a duty to society" and "work should always come first" (on a Likert scale from 1

28. By working three segments, workers in the no-break group could have earned up to £7 while workers in the rest group could have earned at most £6.

29. Using only work earnings can be regarded as output that a firm or an employer might care about. Our results thus suggest weakly positive pecuniary returns to rest $\Delta y \geq 0$ in our model.

30. As outlined in Section 3, when facing the choice workers have full information about earnings schemes for both work schedules (including the break payment and the higher bonus rates in later segments) and the choice implementation.

to 5) is associated with a 3pp and 4pp lower propensity to demand a break. We also find that lower work performance in the baseline period significantly predicts higher demand for breaks. We find that higher self-reported fatigue after the first segment predicts a higher likelihood of preferring a break. We discuss mechanisms that may underlie these results in Section 5.

Besides the "official" breaks, workers could pause informally by no longer completing the work task or by pausing on confirmation pages between segments. We find little evidence of either and discuss this in Appendix A.4.

4.5 Do Choices Over Breaks Maximize Earnings?

The previous regressions presented in Section 4.3 pooled all workers and analyzed the average returns. However, evaluating choices for rest based on average returns could be misleading if there is heterogeneity in returns and if individuals select into rest based on private information about idiosyncratic returns. As we state in Hypothesis 2b in Section 2, we would expect individuals who selected out of the break in Segment 3 to experience negative pecuniary returns to rest. We test this hypothesis by splitting our sample into two groups based on workers' choices about rest and repeat our previous analysis of total earnings.

In Columns 1 and 2 of Table 5 we regress total earnings on assignment of rest among workers who did *not* choose the break. Column 2 estimates that these workers earn £0.34 more if assigned the break controlling for initial performance and demographics constant. The effect is marginally significant at the 10% level and equivalent to an 8.46% increase relative to the no-break group among "no-break choosers." It is noteworthy that already an insignificant result would have suggested that people are better off taking a break: if overall earnings are the same, there are no pecuniary losses from resting. Furthermore, under the assumption of additional positive non-pecuniary returns to rest, people are better off when working less, earning the same, and deriving non-pecuniary gains. We can reject Hypothesis 2b with this evidence.

Columns 3 and 4 of Table 5 repeat the previous exercise for workers who chose a break. As before, we regress total earnings on random break assignment in this subgroup. The resulting point estimate of £0.4 in Column 4 is large, albeit insignificant ($p = 0.391$). Mathematically, this represents an increase of 13.1% and 0.13 standard deviations relative to the no-break group among "break choosers". Given the relatively small sample of N=149 individuals who chose a break and who supplied demographic characteristics, these regressions are relatively underpowered. We find no statistically significant evidence of a treatment effect for those who chose to rest. Similarly, we cannot reject the hypothesis that the impact of rest is the same for those who chose a break and those who did not.

Columns 5 and 6 of Table 5 pool both groups and include an interaction term for the initial choice. Thus, we regress total earnings on a break choice dummy, a break assignment dummy, and an interaction of the two as outlined in Equation 4. Across all workers who choose not to take a break, the random assignment of breaks increases post-break earnings of workers by £0.32, 7.72%, or 0.11 standard deviations at the 10% level, controlling for baseline performance, and demographics.[31] The negative coefficient on the choice variable captures the correlational relationship between break choice and performance and suggests that *preferring* a

31. This coefficient estimate is different from the subsample regression due to interactions with the control variables.

break is on average associated with lower performance. The interaction between a preference for a break and being assigned a break is positive with £0.21 but not significant. Hence, we fail to reject the hypothesis that individuals who select into rest benefit significantly more than individuals who don't. However, as with the subgroup analysis in Columns 3 and 4, this may reflect low power. Under the assumption that there is no negative non-pecuniary utility from resting and that individuals aim to maximize their earnings, Table 5 allows us to conclude that choices to avoid breaks are not maximizing utility.

We complement this exercise by testing whether there might be different dimensions of heterogeneity that rely on other characteristics and not choices. In Appendix A.6, we use Lasso to predict whether any demographics can predict the gain in productivity from rest and find that few variables do so. Taken together, our results suggest that there may be similar cognitive responses to fatigue and rest across individuals. We next turn to investigating what can explain the low demand for rest.

5 Why Is the Demand for Rest Low?

The results in Section 4 highlight the contrast between positive returns to rest and low uptake of rest. Per the framework we presented in Section 2, demand for breaks depends on the overall utility effect of rest, which encompasses pecuniary and non-pecuniary utility. To rationalize a preference for working instead of taking a break, individuals must believe their overall return to taking a break is negative. This could happen via two non-exclusive channels that we will discuss below. First, our initial assumption about the sign of non-pecuniary returns to rest may be wrong. Second, individuals may misperceive the pecuniary returns to resting.

5.1 Negative Non-Pecuniary Utility from Rest

Assumption 1 in Section 2 states that the non-pecuniary returns to resting are positive. This assumption is important as large negative pecuniary returns to rest could outweigh pecuniary gains and rationalize avoiding rest. Examples of positive non-pecuniary returns to rest include the positive cost of effort, i.e., expending energy while working is costly, and thus, individuals derive a positive utility benefit from not working because they do not have to pay this cost. Another option is that workers may innately enjoy resting, e.g., they may derive utility from closing their eyes and refocusing, or outside the context of our experiment, they may enjoy a break where they drink coffee or go for a walk.

However, the non-pecuniary utility effects of resting need not be positive. First, one could imagine that individuals also enjoy working, e.g., because they derive psychosocial benefits from working (Hussam et al. 2022; Macchi and Stalder 2024), because they enjoy "getting things done" or solving a complex task, or because they derive meaning from another dimension like helping others (Ashraf et al. 2024). Second, they may <u>not</u> enjoy chatting with colleagues during a coffee break or may find a non-sleep deep rest break boring. Third, while a worker might not enjoy the task and might enjoy resting more, they might derive non-pecuniary utility from signaling to themselves that they are hard-working, that they are not slacking off, that they are stronger than people who need to rest, and that they are capable of using every minute of the day productively (Bénabou and Tirole 2016).

Contrary to the first argument, we believe that it is unlikely in our context that individuals derive positive non-pecuniary utility from the task itself. There is no social dimension, thus shutting down the psychosocial channel. Since no feedback is provided about performance and the task is quite repetitive, we also believe it is unlikely that participants derive any innate utility from that. While it is framed as an air traffic control task, which may be a meaningful service task, the lack of feedback and realism make it unlikely that people find the work meaningful. Lastly, one might be concerned that after experiencing a pleasant break, workers enjoy the task significantly less. We can also rule out that this is the case. As shown in Table 8, they have marginally lower reservation wages at the end of the experiment. That is they need to be remunerated slightly less in order to work an additional 10 minutes on the task.[32] Additionally, Columns 3 and 4 in Table 6 report that task satisfaction collected at the end of the experiment is the same across groups.

Second, if individuals truly do not enjoy the content of the break that is provided by them, but are aware that not working increases their earnings, they would be free to engage in a different form of a break. Additionally, it is unlikely that relative to completing a repetitive task, an individual would find closing their eyes and taking a couple of minutes to restore less pleasant. Among individuals who did not choose the break, 71% reported that they thought they would enjoy the break.

Lastly, if self-image concerns were to drive these results, we would expect workers to feel secretly relieved about being assigned a break–because they get to enjoy a break without having to actively choose it. To understand this dimension, we collected data at the end of the experiment, where we asked participants to reflect back on how they felt when they learned about their random assignment and rate it on an emoji scale. The distribution of these responses is displayed in Figure 6. 25% of participants who did not want to take a break report that they felt happy when they first found out about their assignment. 44% reported feeling unhappy, and the remainder did not report any strong views. While self-reported emotional data comes with caveats, we take this as indicative that participants did not want to choose breaks to send a signal while secretly wanting to rest.

These hypotheses about no negative effects of rest on overall utility are also reflected in self-reported measurements of well-being. At the end of the experiment, we ask individuals to self-report whether they feel rather happy or rather unhappy at the moment. This variable is rather coarse and may encompass both pecuniary and non-pecuniary utility–although people did not know their earnings by the time they answered this question. In either case, as shown in Column 1 of Table 6, we do not uncover any statistically significant differences between groups. This suggests that breaks do not induce any disutility. Furthermore, after segment 1 in the experiment (before randomization) and after segment 5 (after the experiment), we ask people to report if they feel "rather tired" or "rather alert." We find that workers assigned to take a break are significantly less likely to report feeling tired holding constant levels of baseline fatigue.

As we allowed for heterogeneity in pecuniary returns to rest, there might be heterogeneity in non-pecuniary returns. For a subset of workers who do not enjoy working less (e.g., because they do not enjoy

32. The differences are only suggestive but reflect that workers who were assigned to rest on average require £0.1 less for two segments of work. Such associations may reflect lower levels of fatigue or task disutility if taking a break in between.

listening to audio scripts or sitting still), the breaks can indeed represent a suboptimal choice if the pecuniary utility they derive from higher earnings is less than the non-pecuniary utility cost from resting. However, measuring both forms of utility in the same currency can be challenging. Thus, we cannot confidently ascertain whether individuals who do not enjoy breaks would be better or worse off by taking a break. However, we can focus on a subgroup of workers that disagree with the statement "I did not think I would enjoy the break." Approximately 71% of the participants who chose "work" believed they would have enjoyed the break. We collect this qualitative data at the end of the experiment when we ask individuals to explain their choices in favor of or against breaks. We believe that for this group, the positive non-pecuniary returns assumption is valid, and as a robustness check, we repeat the previous exercise about the effect of randomly assigning a break among this subsample. Table 9 suggests that this subsample also would have earned more by resting. Thus, the data suggest that these workers' choices were mistakes.

5.2 Misperceived Pecuniary Returns to Rest

5.2.1 Beliefs about Returns to Rest

The previous section suggests that choices are unlikely to be driven by negative non-pecuniary utility derived from rest. Another option is that even if pecuniary returns are positive, individuals *perceive* them to be negative. In that case, it may be a rational action for them to choose to avoid rest, given their beliefs. This hypothesis is also in line with qualitative survey evidence, which suggests that individuals primarily chose breaks to maximize their earnings.[33]

We focus on our analysis of misperceptions around pecuniary returns as non-pecuniary utility is realized and experienced instantaneously.[34] (Mis)perceived pecuniary returns $\widetilde{\Delta y}$ are defined as the perceived difference in total earnings when a break was taken versus when a break was not taken. At the end of the experiment, we ask all workers to predict the average overall earnings of both schedules.[35] This means that for every worker, we observe which treatment they were assigned to (break or no-break) as well as a posterior prediction of the average earnings of workers in the break and no-break group. Since beliefs are collected after the treatment has been implemented, they are posterior beliefs. That said, we consider the predictions of the no-break group about the break schedule to be proxies of prior beliefs as these workers did not experience our audio-script break. To correct for any individual misestimations of the levels and to cleanly isolate the changes due to rest, we subtract the two predictions at the individual level. This provides us with our measure of the perceived pecuniary return to rest. To encourage accurate responses, we incentivize these beliefs with a small reward if correct.

33. First, qualitatively, the factor most frequently cited by workers as driving their choice was earnings considerations. 46% of workers who chose to forgo the break mentioned that not taking a break would maximize their earnings during the work period, whereas other factors were mentioned much less frequently (33% preferred choosing their break schedule for themselves; 21% reported not liking to take breaks, 17% did not wish to be seen as lazy, and 17% were skeptical of engaging in the NSDR script during the break). Second, quantitatively, we find that beliefs about the earnings return to breaks are strongly correlated with and predictive of break choice.

34. For example, a worker will have done the task and will, at the time of the decision, know how much they enjoy it or how tired they feel.

35. Since the break payments were payoff-relevant for workers, we asked them to include them in their predictions of the earnings.

Table 10 breaks down the perceived returns by different treatment groups. First, we compare the mean perceived pecuniary return of the no-break group, which is £-0.23 with the causally estimated return of 0.35 from Column 4 of Table 4. As shown in Table 11, we can reject that the two values are the same. This means that workers significantly underestimated the returns to resting.[36] Second, within the control group in the first column of Table Table 10, we can compare the perceived pecuniary returns by break preference. Workers who wanted to take a break were significantly more optimistic about the pecuniary effects of rest than workers who did not want to take a break, reinforcing the notion that perceptions of pecuniary returns are correlated with choices.

5.2.2 Belief Updating in Response to Treatment Assignment

If beliefs are incorrect, we would expect that introspective workers update their beliefs in response to new information. Since the data are collected ex-post, this means that we would expect the break group to have beliefs that are closer to the true return than the no break group. We fail to reject the statistical test that the two means are the same; however, the data are suggestive that workers who were assigned to take breaks view returns to rest more positively. It is possible that we fail to reject the two-means test due to statistical power. Additionally, we acknowledge that another potential confound is that these data were collected ex-post when workers were potentially differentially tired to due treatment assignment. Even though we collect data on fatigue at the end of the study, we cannot include it as a control variable since it is affected by the treatment and could rise to bad control bias.

To better understand the role of fatigue, we conduct a mediation analysis and add controls for baseline performance and endline fatigue. The difference becomes marginally significant at the 10% level suggesting that individuals who were assigned to the rest group believe that earnings on average associate £0.2 higher earnings with being assigned a break. The fact that the fatigue variable, which we control for, was determined after the treatment can give rise to collider bias.

5.2.3 Potential Sources of Misperceptions

These misperceptions around the returns to rest may have arisen due to several reasons. We discuss lack of information from knowledge or experience and cognitive distortions due to stress, which we deem relevant in our experiment.

Lack of information from knowledge or experience: An obvious source of wrong beliefs about returns to rest is lack of information. This may be because the knowledge wasn't accessible or because participants did not have experience with the decision situation. Since the perceived returns that we measure are a net construct, the lack of information could appear in different cases. First, workers may not be aware of the decay in performance and of their fatigue. Second, workers may not be aware of the benefits of resting. Third, workers may overweight the benefits of skill acquisition with practice. All of these could explain why the pecuniary returns to resting are perceived to be negative. However, since the decision to rest or work

36. We can also pool perceived pecuniary returns across both treatment arms. We can again reject the hypothesis that the perceived mean effect of rest is the same as the causally estimated effect of rest.

appears after workers gain experience with the task, they should be aware of their worsening performance and their level of fatigue. It also seems reasonable to assume that workers would be aware that resting would not reduce fatigue further. 15% of the workers in our sample report knowing non-sleep deep rest or yoga nidra techniques. Among this subsample of N=126, the share of individuals choosing to rest (13.5%) is even slightly lower than across the entire sample (19.2%). We can also verify that among workers who are familiar with the break but do not choose it, 68.8% believe they would enjoy taking a break. Workers may have held the belief that they would get better by practicing more–and thus improve their chances of earning bonus payments in later segments–however, after 600 images, they should also have a sense of how good their performance is and how they feel in that moment. Thus we would argue that inexperience with the task and the decision context is unlikely to be driving these results. Future research could pin this down further by (i) providing participants with information about pecuniary and non-pecuniary returns to rest, or by (ii) studying how experience affects these decisions over time.

Cognitive Distortions due to Stress: Beliefs might be systematically biased due to biopsychological factors. An emerging literature has studied the implications of stress and other mental distress on decision-making and productivity. In the context of our experiment, participants are explicitly put under a fair amount of time stress. Additionally, many workers face financial constraints. Literature from neuroscience has shown that stress can alter our perceptions and may lead to decision-making based on heuristics (Schwabe and Wolf 2009), including reward-bias such as being more likely to pick larger options (Mather and Lighthall 2012; Treadway et al. 2013). We hypothesize that this might be driven by some form of financially-induced scarcity or stress-distorted perception. A financially constrained worker may feel compelled to work more to earn more, simply because they feel like they cannot afford to take a break.

We do not have explicit data on stress, but we can proxy for stress with income. Indeed, workers with lower household incomes are less likely to take breaks, as shown in Figure 5. The psychology literature suggests that stimuli may be more noisily perceived under time pressure (Schwabe and Wolf 2009). If pecuniary returns to leisure are more noisily perceived than pecuniary returns to working (e.g., because there is a posted wage), it is plausible that financially constrained people will hold more misperceptions about returns to rest than returns to working. However, unless there is a bias, we would expect the misperceptions and errors to go in both directions since one can under- and overperceive. If there is a bias such that people systematically underestimate the returns to resting relative to working, this could explain why rest is chosen less than optimally. It is conceivable that determining the returns to resting feels complex or effortful, thus preventing people from engaging in this estimation and choosing to work.

5.3 Robustness

5.3.1 Experimenter Demand Effects, Social Desirability Bias, and Career Concerns

A natural concern is that workers avoid taking (very observable) breaks because of experimenter demand effects or social desirability bias. We elicit measurements of social desirability bias (Dhar et al. 2022) at the beginning of the survey and find that individuals who are more prone to behave in socially-desirable ways are more likely to opt for rest (Figure 5). Tightly linked to experimenter demand effects are career concerns that workers might face. They may want to signal a strong work ethic to a potential employer, which would be the experimenter. However, we make it clear to participants that this is a one-time opportunity, and we will not hire them again afterward. In addition, the payment for the break could be seen as an endorsement of rest of the employer. Endorsing and remunerating rest is likely to increase demand for it.

5.3.2 Projection Bias

Projection bias describes the notion that people "falsely project their current preferences over consumption onto future preferences" (Loewenstein et al. 2003). Choices about resting are made immediately before taking a break. Thus, the forecasting scope is minimal in terms of (i) utility gains from consuming rest and (ii) current fatigue and the need to rest. We cannot rule out that individuals underestimate how much more tired they will be after working through the 3rd segment and how this may affect their earnings. It is possible that the misperceptions that we document in Section 5.2 are projective in nature (Zhang 2023).

5.3.3 External Validity

Our experiment is conducted in a rather artificial context. While many components are designed to mimic an online gig economy setting, future field research is needed to better understand the dynamics at play. We use a mentally-fatiguing task and a restorative break. The returns to and the demand for rest may be different if this is not the case. For example, if the task would not induce fatigue and performance were constant, the returns to resting might be negative. In contrast, a different type of break content may have slightly lower positive returns if it is less restorative. On the other hand, it may be in higher demand if individuals consider it to be significantly more joyful. The pay schedule that features high stakes at the end, as well as the piece-rate type payment, can also affect demand and returns in unique ways. More research is needed to understand how these results would translate to a linear pay scheme or different magnitudes. However, the analysis of the mistakes underlying the payments suggests that cognitive fatigue increases over the experiment and resting reduces this fatigue. Our setting also abstracts away from the effects that direct managers may have on break uptake and future research is needed to better understand this.

6 Conclusions

This study provides strong evidence that taking breaks significantly improves productivity and overall earnings in a controlled experimental setting. Participants who were randomly assigned to take a break experienced a substantial increase in per-segment earnings post-break. The productivity gains from taking breaks were large enough to offset the time spent resting, as total earnings for participants who rested were comparable or slightly higher than those who did not.

Despite these positive effects, only 19% of participants chose to take a break, highlighting a notable disconnect between the actual benefits of rest and workers' demand for it. This low uptake suggests that many workers may undervalue the gains from taking breaks, likely due to misperceptions about returns to rest. Workers reporting higher levels of fatigue or lower baseline performance were more likely to opt for a break, indicating that perceptions of personal performance and well-being influence the decision to rest. Our results suggest that individuals who chose not to take a break could have earned more during the study had they rested. There appears to be little heterogeneity in the effect of rest on earnings, which suggests that break benefits may, in part, be biological. These findings also imply that mandated breaks could improve both productivity and worker well-being, which can have important policy implications for freelancers and workplaces.

This misalignment between the demand for and returns to rest is likely not limited to this particular experimental context. The positive pecuniary returns to rest we observe hinge on a rapid performance decay, which is then "outperformed" by the recovery from resting that leads to earnings gains. In other contexts, such as jobs where performance decay does not directly affect earnings, the benefit of rest may be weaker. This points to the fact that the biological need for rest in cognitively-demanding tasks may be universal, but the monetary trade-offs for rest will vary depending on the incentive structure in different work environments. Further research is needed to explore whether the misperceptions we document are specific to rest or reflect broader misunderstandings about one's productivity over time.

Our findings are particularly relevant for freelance workers, such as those in the gig economy or self-employment, who have full autonomy over their work and break schedules. This ensures that they actively weigh the trade-off between resting and working. While mandated breaks may be an interesting policy for traditional workplaces, enforcing such policies is difficult in unsupervised work environments. For instance, while platforms like Uber and Lyft limit consecutive driving hours, anecdotal evidence suggests that drivers switch between platforms to bypass these limits, continuing to work without resting. More research is needed to understand how these work and break dynamics manifest in "managed" work environments. However, one could imagine that there are many jobs, such as piece-rate jobs in lower-income countries, where workers have some flexibility over their schedules and how many small breaks they take. This environment would be comparable to our experimental design and the results may transfer. Addressing the gap between workers' perceptions and the actual benefits of rest is a crucial challenge for policy and management.

Our results raise questions about the sources of the suboptimal demand for rest. Assuming that breaks do not induce a strong disutility, misperceived returns to rest are the most likely source of low demand. We find preliminary evidence of misperceptions by studying differential updating with respect to posterior returns about the effects of breaks across treatment groups. Such initial misperceptions could stem from, for example, a sheer lack of information about the positive returns to rest, systematic overconfidence about one's ability to perform well, scarcity of cognitive resources and poor decision-making under financial stress, or feeling guilty about resting. Further research could explore these avenues along with investigating how individuals best learn about their "own" production function over time.

7 Main Text Figures

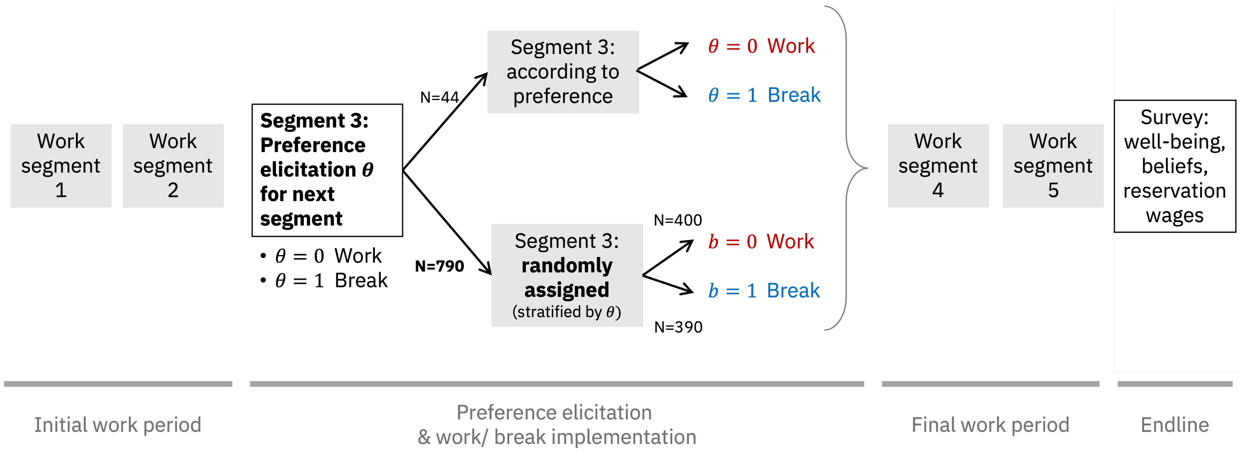

Figure 1: Experimental Design

Notes: This figure outlines the design of the online work experiment. All workers begin by working two segments. This allows them to get experience with the work task. Participants then express a preference over taking a break or working in the third segment. We tell participants that choosing their preferred option will increase the odds of receiving this option. We then implement workers' choices for a randomly selected subset of 5% of the participant pool. The remaining participants (95%) were randomly assigned with equal probability to either take a break or to work during the 3rd segment. Any worker who was part of the 95% randomly-allocated subset was first informed that they were randomly assigned to a treatment by the computer. This is meant to reduce behavioral differences in frustration between people who received their preferred outcome and those who did not. After the third segment, in which participants are either working or taking a break, everyone works for the remaining two segments. At the end of the five segments, subjects answer a brief endline survey about their beliefs and work period experience.

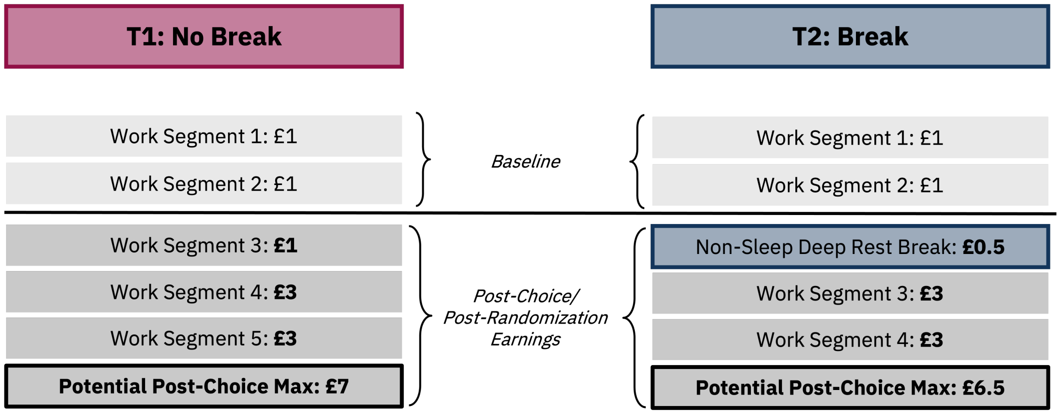

Figure 2: Potential Earnings by Schedule Assignment

Notes: This figure displays the maximum possible earnings that could be achieved in each schedule. During work segments, a bonus payment could be earned if (i) participants correctly identified more than 75% of all flights, and if (ii) they did not missed more than 2 not-safe flights. During the rest segment, participants had to attend to the audio script (which was verified via attention questions afterwards).

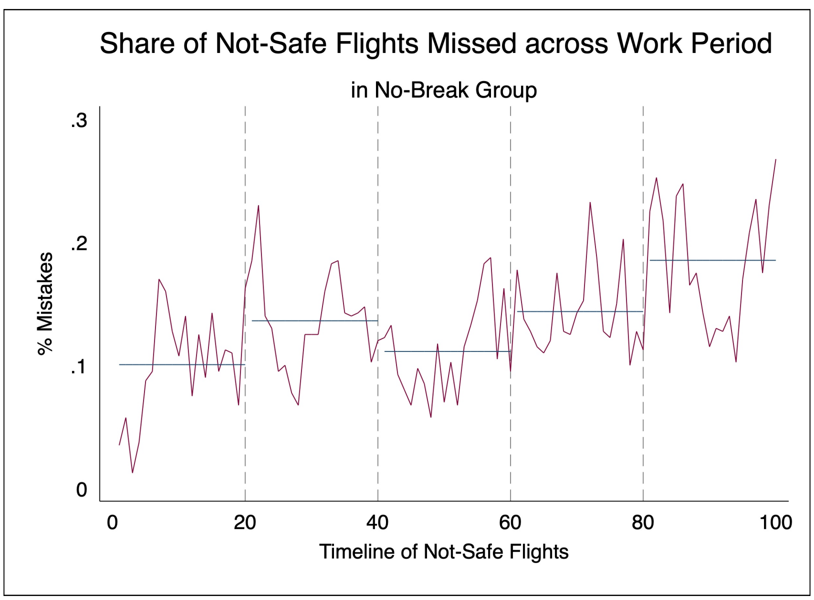

Figure 3: Realized Earnings Per Segment (including break compliance payments)

Notes: Observations restricted to individuals from the no-break group without duplicate entries and that completed the entire work period. The red line traces out the share of workers that missed a not-safe flight over the course of a segment across all five segments. Dark blue lines indicated the mean share of mistakes in a given segment. Dashed gray lines distinguish between segments. The increasing trend across all segments and flight images is indicative of cognitive fatigue induced by the task.

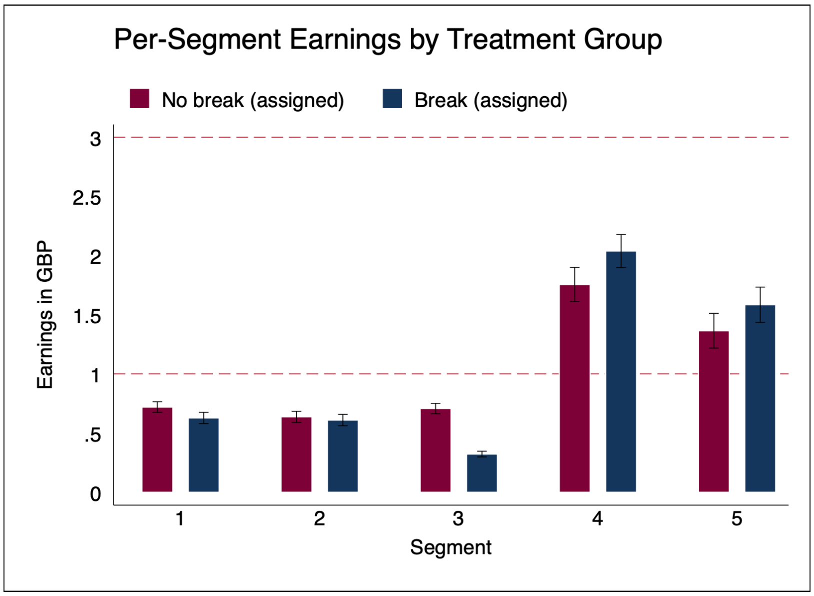

Figure 4: Realized Earnings Per Segment (including break compliance payments)

Notes: Observations restricted to individuals without duplicate entries and that completed the entire work period. Black bars indicated 95% confidence intervals. This figure plots the average realized earnings of workers in a given segment by treatment assignment. Dark red bars indicate the no-break group; blue bars indicate the break group. In Segments 1 and 2, workers could earn £1 for every successfully completed segment. In segment 3, workers who were assigned to work could earn £1 if they successfully completed the segment as indicated by the horizontal dashed line at $y = 1$; workers who were assigned to rest could earn £0.5 if they attended to the break audio script. In Segments 4 and 5, workers could earn £3 for every successfully completed segment as indicated by the horizontal dashed line at $y = 3$.

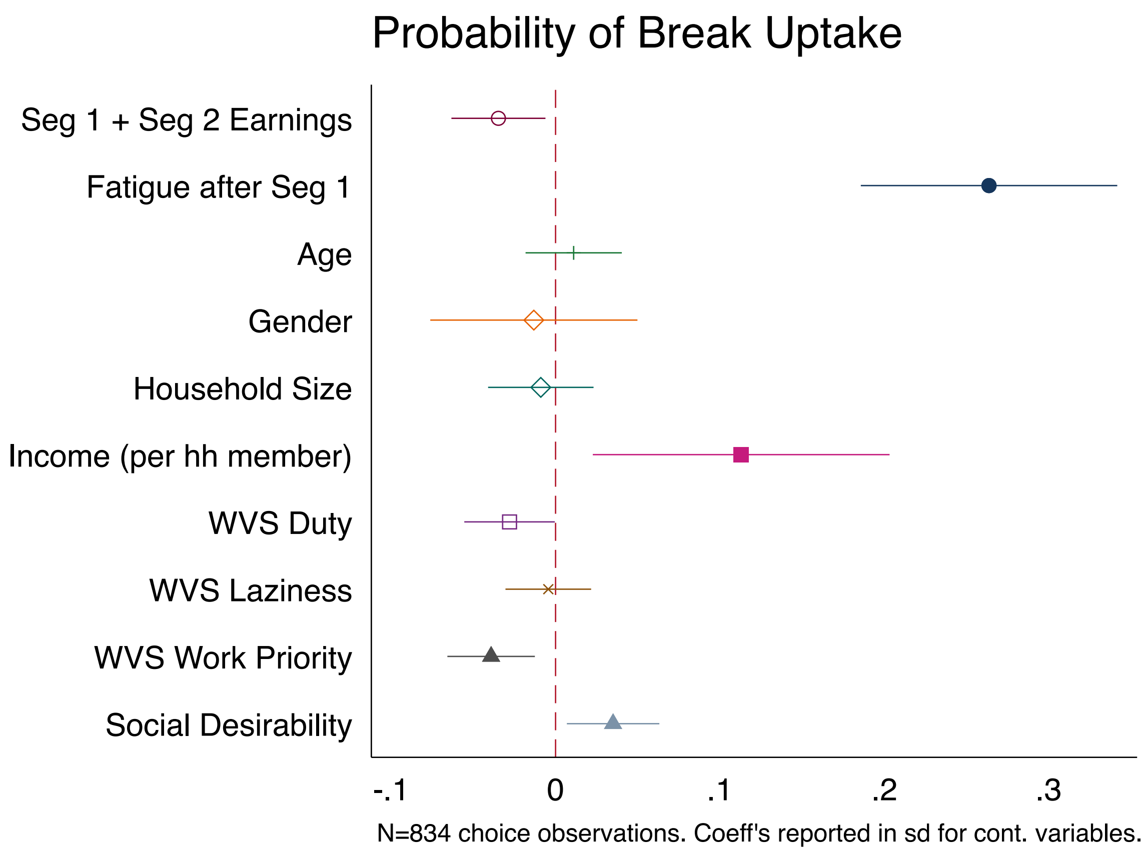

Figure 5: Correlates of Demand for Break in Segment 3

Notes: This figure plots standardized coefficient estimates for bivariate regressions of the preference to take a break on various covariates. Bars represent standard errors. Observations are restricted to any individuals without duplicate entries and individuals who completed the entire work period. The number includes individuals whose choices were implemented and not just individuals who were randomly assigned. The outcome variable Seg 1 + 2 earnings sums together earnings from the first two segments. Fatigue after Seg 1 measures self-reported, binary fatigue after Segment 1. Income per hh member takes the household income and divides it by the household size. WVS Duty, Laziness, and Work Priority Refer to World Value Survey measurements of work ethic "Work is a duty toward society," "People who don't work turn lazy," and "Work should always come first, even if it means less spare time." Social desirability is measured using the Marlow-Crowne index of social desirability.

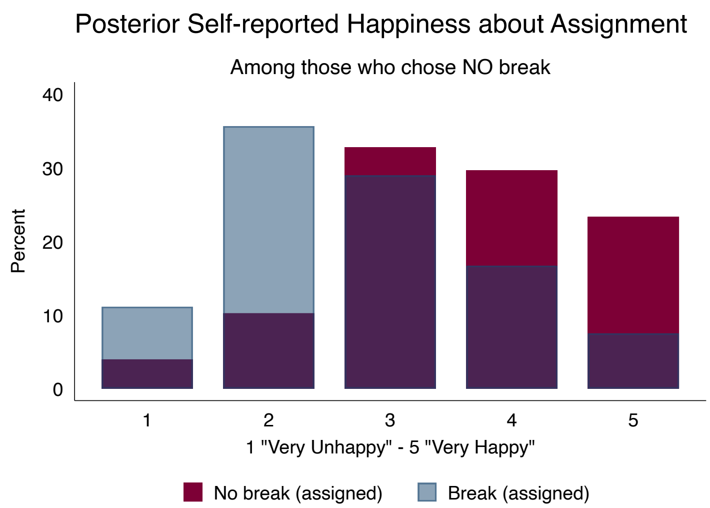

Figure 6: Self-Reported Happiness about Schedule Assignment in No-Break Group

Notes: This histogram plots the self-reported happiness about the assigned work schedule among participants who chose not to take a break by assigned work schedule, i.e., treatment. Red bars indicate workers who were assigned to the no-break schedule. Blue bars indicate workers who were assigned to the break schedule. The bars overlap in purple-shaded areas. On average, we see higher levels of self-reported happiness among workers who received the no-break schedule. The values were collected at the end of the experiment, and participants were asked to think back to how they felt when they learned about their assignment.

8 Main Text Tables

Table 1: Balance Table

	(1) No Break (assigned)		(2) Break (assigned)		(1)-(2) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
Social Desirability	400	7.362 (0.097)	390	7.364 (0.100)	790	-0.002
WVS Laziness	400	0.198 (0.062)	390	0.190 (0.063)	790	0.008
WVS Duty	400	0.745 (0.049)	390	0.754 (0.048)	790	-0.009
WVS Work Priority	400	-0.282 (0.061)	390	-0.233 (0.061)	790	-0.049
Education	371	4.854 (0.050)	363	4.917 (0.048)	734	-0.063
Age	371	29.588 (0.362)	363	30.512 (0.450)	734	-0.925
Gender	371	1.725 (0.024)	363	1.722 (0.024)	734	0.003
Household Size	371	4.296 (0.078)	363	4.515 (0.097)	734	-0.219*
Income (per hh member)	371	2826.754 (77.536)	363	2766.905 (79.887)	734	59.849
Share Seg 1 Bonus	400	0.720 (0.022)	390	0.628 (0.025)	790	0.092***
Share Seg 2 Bonus	400	0.637 (0.024)	390	0.610 (0.025)	790	0.027

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

Notes: Balance by assignment to break treatment. Observations restricted to individuals without duplicate entries and that completed the entire work period. Not every individual responded to the demographic characteristics survey, which leads to a lower sample size for these data points.

Table 2: Critical Mistakes in Control Group

Segment s	Mistakes	$H_0 : m_s < m_4$	$H_0 : m_s = m_5$
1	2.0	$p < 0.0001$	$p < 0.0001$
2	2.7	$p = 0.1404$	$p < 0.0001$
3	2.2	$p < 0.0001$	$p < 0.0001$
4	2.9	.	$p < 0.0001$
5	3.7	.	.

Notes: This table computes the number of critical mistakes among N=400 individuals in the control group who were assigned to work for all five segments. In a given segment, there were 20 not-safe flights and, thus, 20 opportunities for participants to make this mistake. To earn a bonus payment, participants were not allowed to miss more than two flights in a given segment. The second column reports the mean number of mistakes in a given segment s. The third column reports the p-value from a one-sided t-test that tests whether the mean number of mistakes in said segment is lower than in segment 4. The fourth column reports the p-value from a one-sided t-test that tests whether the mean number of mistakes in said segment is lower than in segment 5.

Table 3: Post-Break Earnings

	(1)	(2)
Break (assigned)	0.693***	0.721***
	(0.151)	(0.159)
Observations	790	734
No-Break Mean	3.120	3.081
Seg 1 & 2 Performance	Yes	Yes
Demographics	No	Yes

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

Notes: Robust standard errors in parentheses. Observations restricted to individuals without duplicate entries and that completed the entire work period. Participants without data on demographic control variables are dropped in Column 2. This table regresses total earnings in post-break segments 4 and 5 on whether an individual was randomly assigned a break. All columns control for baseline performance in Segment 1 and Segment 2, capturing the number of bonuses an individual receives. Demographic controls in Column 2 include age, providence, education level, gender, household size, per-person household income, and employment.

Table 4: Total Earnings (Segment 3-5)

	(1)	(2)	(3)	(4)
Break (assigned)	0.003	0.028	0.322**	0.354**
	(0.156)	(0.165)	(0.158)	(0.167)
Observations	790	734	790	734
Break Pay	Excl.	Exck.	Incl.	Incl.
No Break Mean	3.828	3.828	3.828	3.828
Performance	Yes	Yes	Yes	Yes
Demographics	No	Yes	No	Yes

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

Notes: Robust standard errors in parentheses. Observations restricted to individuals without duplicate entries and that completed the entire work period. Participants without data on demographic control variables are dropped in Columns 2 and 4. This table regresses total work earnings in segments 3 through 5 on whether an individual was randomly assigned a break. Columns 1 and 2 do not include any payments from the break. For workers assigned to the "no break" group, the total earning outcome variable sums earnings from Segments 3, 4, and 5. The maximum possible earnings for workers in the "no break" group are £7. For workers in the "break" group, the total earning outcome variable sums earnings from Segments 4 and 5 exclusively. The maximum possible earnings for workers in the "break" group are £6. Columns 3 and 4 do include payments from the break. For all workers, the total earnings outcome variable sums work and/ or break bonus earnings from Segments 3, 4, and 5. The maximum possible earnings for workers in the "no break" group are £7 and for workers in the "break" group £6.5. All columns control for baseline performance in Segment 1 and Segment 2, capturing the number of bonuses an individual receives. Demographic controls in Column 2 include age, providence, education level, gender, household size, per-person household income, and employment.

Table 5: Total Earnings by Break Choice *with* Break Payment (Segment 3-5)

	(1)	(2)	(3)	(4)	(5)	(6)
Break (assigned)	0.306*	0.343*	0.528	0.395	0.281*	0.319*
	(0.169)	(0.181)	(0.403)	(0.459)	(0.169)	(0.181)
Break (chosen)					-0.533	-0.487
					(0.323)	(0.337)
Break (assigned) × Break (chosen)					0.233	0.215
					(0.438)	(0.455)
Observations	635	585	155	149	790	734
Break Preference	No	No	Yes	Yes	N/A	N/A
Control Mean	4.015	3.994	3.316	3.441	3.828	3.790
Seg 1 & 2 Performance	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	No	Yes	No	Yes	No	Yes

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

Notes: Robust standard errors in parentheses. Observations restricted to individuals without duplicate entries and that completed the entire work period. Participants without data on demographic control variables are dropped in Columns 2, 4, and 6. This table regresses total earnings in segments 3 through 5 on whether an individual was randomly assigned a break. The earnings outcome variable includes compliance payments earned for break attendance among the "break group". For all workers, the total earnings outcome variable sums work and/or break attendance earnings from Segments 3, 4, and 5. The maximum possible earnings for workers in the "no break" group are £7 and for workers in the "break" group £6.5. Columns 1 and 2 restrict the sample to workers who did not want to take a break. Columns 3 and 4 restrict the sample to workers who wanted to take a break. Columns 5 and 6 pool all workers regardless of their break preference. All columns control for baseline performance in Segment 1 and Segment 2, capturing the number of bonuses an individual receives. Demographic controls in Columns 2, 4, and 6 include age, providence, education level, gender, household size, per-person household income, and employment.

Table 6: Self-reported "Utility"

	Happiness		Task Satisfaction		Fatigue	
Break (assigned)	0.005	0.006	0.017	0.019	-0.068**	-0.055
	(0.023)	(0.024)	(0.026)	(0.027)	(0.034)	(0.036)
Observations	788	733	788	733	790	734
Constant	0.893	0.600	0.777	0.341	0.595	0.748
InitialFatigue	Yes	Yes	Yes	Yes	Yes	Yes
Performance	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	No	Yes	No	Yes	No	Yes

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

Notes: Robust standard errors in parentheses. This binary-dependent variable OLS regression reports the effects of being randomly assigned a break on self-reported well-being measurements. The measurements are binary and are collected as "rather happy" or "rather unhappy", "rather satisfied" or "rather unsatisfied," "rather tired" or "rather alert." The column header suggests which outcome was chosen to be equal to one. Observations restricted to individuals without duplicate entries and that completed the entire work period. Observations without demographics dropped on Columns 2, 4, and 6. Demographics: age, providence, education, gender, household size, income, employment status.

Table 7: Reason for Break Avoidance

Reason	% No Break Choice
Maximize earnings	64.5%
Autonomy over work schedule	46.2%
Disutility from audio script	28.8%
Fear of stigma	23.6%
Skepticism about audio script	23.3%
Other	5.0%
	N=654

Notes: Participants who chose not to take a break were asked to explain their choice at the end of the experiment. They could select as many of the answer options as they wanted or propose their own via an "other" box. This table provides the frequency of how often an answer was selected by N=654 participants who chose not to take a break.

Table 8: Reservation Wage for Working 2 Extra Post-Experiment Segment

	(1)	(2)
Break (assigned)	-0.100*	-0.106*
	(0.055)	(0.058)
Observations	767	713
Constant	1.043	1.886
Seg 1 & 2 Performance	Yes	Yes
Demographics	No	Yes

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

Notes: Robust standard errors in parentheses. Observations are restricted to individuals without duplicate entries. We regress random assignment to rest on workers' (incentivized) reservation wages in £to work two extra segments at the end of the experiment. We elicit these wages by asking workers for the bonus payment they would need to be paid to be willing to accept work.

Table 9: Total Earnings (Seg 3 - Seg 5) among "Enjoy Break" & "No Break Choice"

	(1)	(2)
Break (assigned)	0.433**	0.491**
	(0.200)	(0.216)
Observations	455	420
Constant	1.058	2.301
Performance	Yes	Yes
Demographics	No	Yes

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

Notes: Robust standard errors in parentheses. Observations are restricted to individuals without duplicate entries that completed the entire work period and who do not disagree with the statement "I did not think I would enjoy the break." (This is elicited in an ex-post survey about break choices.) This subsample represents approximately 71% of the sample. Observations without demographics dropped in Column 2. Demographics: age, providence, education, gender, household size, income, employment status

Table 10: Perceived Returns to Rest by Random Assignment and Initial Choice of Rest

Break Choice θ	**Treatment Assignment b**		Pooled Choice
	No Break $b = 0$	Break $b = 1$	
No Break $\theta = 0$	-0.28	-0.15	-0.22
Break $\theta = 1$	-0.01	0.25	0.11
Pooled Assigned	-0.23	-0.07	-0.15

Notes: This table reports workers' perceived returns to taking a break in the context of our experiment. Incentivized beliefs for average earnings of both work schedules are collected at the end of the experiment and used to compute the perceived pecuniary return to resting at the individual level. The table breaks down the perceived return by choice of break and assignment to breaks. A negative value means that participants, on average, perceived the schedule without a break to earn more than the schedule with a break. A value of 0 means no difference. A positive value means that the schedule with a break is perceived to have higher earnings.

Table 11: Hypothesis Tests of Misperceived Financial Returns to Rest

Worker Group	$\widetilde{\Delta y}$	N	$H_0 : E[\widetilde{\Delta y}] = 0.35$
Chose no break	-0.23	669	$p < 0.001$
Assigned no break	-0.23	399	$p < 0.001$
Entire sample	-0.17	785	$p < 0.001$
True return	0.35		

Notes: This table reports the mean perceived returns for a subsample of workers indicated in the left column and the results from t-tests. These t-tests evaluate the null hypothesis that the workers' perceived returns are the same as the true causal return of rest of 0.35. We can reject the t-test for any of these cases.

References

Ashraf, Nava, Oriana Bandiera, Virginia Minni, and Luigi Zingales. 2024. *Meaning at Work.* Technical report. Working Paper. https://www.dropbox.com/scl/fi/76ne58id9boy0e6qccwxq/ABMZ-MeaningatWork.pdf?rlkey=lyf5otknw82sru8jo3grzr4dq&e=1&dl=0.

Augenblick, Ned, Muriel Niederle, and Charles Sprenger. 2015. "Working over time: Dynamic inconsistency in real effort tasks." *The Quarterly Journal of Economics* 130 (3): 1067–1115.

Avery, Mallory L, Osea Giuntella, and Peiran Jiao. 2022. *Why Don't We Sleep Enough? A Field Experiment Among College Students.* Working Paper, Working Paper Series 30375. National Bureau of Economic Research, August. https://doi.org/10.3386/w30375. http://www.nber.org/papers/w30375.

Balban, Melis Yilmaz, Eric Neri, Manuela M Kogon, Lara Weed, Bita Nouriani, Booil Jo, Gary Holl, Jamie M Zeitzer, David Spiegel, and Andrew D Huberman. 2023. "Brief structured respiration practices enhance mood and reduce physiological arousal." *Cell Reports Medicine* 4 (1).

Bénabou, Roland, and Jean Tirole. 2016. "Mindful economics: The production, consumption, and value of beliefs." *Journal of Economic Perspectives* 30 (3): 141–164.

Bessone, Pedro, Gautam Rao, Frank Schilbach, Heather Schofield, and Mattie Toma. 2021. "The economic consequences of increasing sleep among the urban poor." *The Quarterly Journal of Economics* 136 (3): 1887–1941.

Bold, Tessa, Kayuki C Kaizzi, Jakob Svensson, and David Yanagizawa-Drott. 2017. "Lemon technologies and adoption: measurement, theory and evidence from agricultural markets in Uganda." *The Quarterly Journal of Economics* 132 (3): 1055–1100.

Brown, Christina L, Supreet Kaur, Geeta Kingdon, and Heather Schofield. 2022. *Cognitive endurance as human capital.* Technical report. National Bureau of Economic Research.

Caplin, Andrew, David J Deming, Søren Leth-Petersen, and Ben Weidmann. 2023. *Allocative Skill.* Working Paper, Working Paper Series 31674. National Bureau of Economic Research, September. https://doi.org/10.3386/w31674. http://www.nber.org/papers/w31674.

Cappelen, Alexander W, Gary Charness, Mathias Ekström, Uri Gneezy, and Bertil Tungodden. 2017. "Exercise improves academic performance." *NHH Dept. of Economics Discussion Paper,* no. 08.

Cassar, Lea, Mira Fischer, and Vanessa Valero. 2022. *Keep calm and carry on: The short-vs. long-run effects of mindfulness meditation on (academic) performance.* Technical report. IZA Discussion Papers.

Chassang, Sylvain, Gerard Padró i Miquel, and Erik Snowberg. 2012. "Selective trials: A principal-agent approach to randomized controlled experiments." *American Economic Review* 102 (4): 1279–1309.

Dean, Joshua T. 2024. "Noise, Cognitive Function, and Worker Productivity." *American Economic Journal: Applied Economics,* ISSN: 1945-7782, accessed September 21, 2024. https://doi.org/10.1257/app.20220532. https://www.aeaweb.org/articles?id=10.1257/app.20220532&from=f.

Dhar, Diva, Tarun Jain, and Seema Jayachandran. 2022. "Reshaping Adolescents' Gender Attitudes: Evidence from a School-Based Experiment in India." *American Economic Review* 112, no. 3 (March): 899–927. https://doi.org/10.1257/aer.20201112. https://www.aeaweb.org/articles?id=10.1257/aer.20201112.

Gibson, Matthew, and Jeffrey Shrader. 2018. "Time use and labor productivity: The returns to sleep." *Review of Economics and Statistics* 100 (5): 783–798.

Giuntella, Osea, Silvia Saccardo, and Sally Sadoff. 2022. *Improving Educational Achievement through Better Sleep Habits: The Effect of Technology-Based Behavioral Interventions.* Technical report. AEA RCT Registry. https://doi.org/10.1257/rct.3235-2.0.

Haerpfer, Christian, Ronald Inglehart, Alejandro Moreno, Christian Welzel, Kseniya Kizilova, Jaime Diez-Medrano, Marta Lagos, Pippa Norris, Eduard Ponarin, Bjorn Puranen, et al. 2022. "World values survey: Round seven-country-pooled datafile version 5.0." *Madrid, Spain & Vienna, Austria: JD Systems Institute & WVSA Secretariat* 12 (10): 8.

Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein. 2014. " Learning Through Noticing: Theory and Evidence from a Field Experiment *." *The Quarterly Journal of Economics* 129, no. 3 (June): 1311–1353. ISSN: 0033-5533. https://doi.org/10.1093/qje/qju015. eprint: https://academic.oup.com/qje/article-pdf/129/3/1311/30629812/qju015.pdf. https://doi.org/10.1093/qje/qju015.

Hussam, Reshmaan, Erin M. Kelley, Gregory Lane, and Fatima Zahra. 2022. "The Psychosocial Value of Employment: Evidence from a Refugee Camp." *American Economic Review* 112, no. 11 (November): 3694–3724. https://doi.org/10.1257/aer.20211616. https://www.aeaweb.org/articles?id=10.1257/aer.20211616.

Kaur, Supreet, Michael Kremer, and Sendhil Mullainathan. 2015. "Self-control at work." *Journal of Political Economy* 123 (6): 1227–1277.

Loewenstein, George, Ted O'Donoghue, and Matthew Rabin. 2003. "Projection bias in predicting future utility." *the Quarterly Journal of economics,* 1209–1248.

Macchi, Elisa, and Jeremia Stalder. 2024. *Work Over Just Cash: Informal Redistribution among Employers and Workers in Kampala, Uganda.* Technical report. Working Paper. https://elisamacchi.github.io/files/macchi-stalder-work-over-cash.pdf.

Mather, Mara, and Nichole R Lighthall. 2012. "Risk and reward are processed differently in decisions made under stress." *Current directions in psychological science* 21 (1): 36–41.

Nekoei, Arash, Jósef Sigurdsson, and Dominik Wehr. 2024. *The Economic Burden of Burnout,* 4827359, Rochester, NY, May 14, 2024. Accessed August 1, 2024. https://doi.org/10.2139/ssrn.4827359. https://papers.ssrn.com/abstract=4827359.

Rao, Gautam, Susan Redline, Frank Schilbach, Heather Schofield, and Mattie Toma. 2021. "Informing sleep policy through field experiments." *Science* 374 (6567): 530–533.

Reynolds, William M. 1982. "Development of reliable and valid short forms of the Marlowe-Crowne Social Desirability Scale." *Journal of clinical psychology* 38 (1): 119–125.

Schilbach, Frank. 2019. "Alcohol and self-control: A field experiment in India." *American economic review* 109 (4): 1290–1322.

Schwabe, Lars, and Oliver T Wolf. 2009. "Stress prompts habit behavior in humans." *Journal of Neuroscience* 29 (22): 7191–7198.

Shreekumar, Advik, and Pierre-Luc Vautrey. 2024. *Managing Emotions: The Effects of Online Mindfulness Meditation on Mental Health and Economic Behavior.* Technical report. Tech. Rep., MIT.

Treadway, Michael T, Joshua W Buckholtz, and David H Zald. 2013. "Perceived stress predicts altered reward and loss feedback processing in medial prefrontal cortex." *Frontiers in human neuroscience* 7:180.

Waldfogle, Grace E, Michaela R Hagerty-Koller, Lindsey R Lane, Allison E Garibaldi, and James L Szalma. 2019. "Exploring sex differences in vigilance performance with knowledge of results." In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* 63:1321–1325. 1. SAGE Publications Sage CA: Los Angeles, CA.

Zhang, Sili. 2023. *Projective Misperceptions and Misinferred Time Preferences.* Technical report. Working Paper. https://www.dropbox.com/s/y8zmud6iyoqpxd9/ProjectionTime_Zhang2023.pdf?dl=0.

A Appendix

A.1 Appendix: Experimental Design

Figure A.1 illustrates the screen layout that participants encountered during the work task. Additionally, Figure A.2 presents the mobile version of the task interface. The following URL can be used for a short video demonstration: https://www.dropbox.com/scl/fi/rov4abxjvm4u5rucx1a7i/task_movie.mov?rlkey=ebelfil0jrdvgxlst6c1ubslm&dl=0

A.2 Appendix: Attrition

In Table A.2, we trace out how attrition evolves over time in our experiment. We cannot tell whether a participant opened/ started the survey multiple times due to technical difficulties or because they were hoping to benefit disproportionally. We also do not observe why a person attrited and whether they wanted to leave the experiment or whether they faced technological issues, but we did receive some reports of technological issues. We exclude any duplicate IDs from the analysis sample. The column "unique IDs" restricts the sample to participants whose ID only appears once. The column "unique IDs (rand)" focuses on the subset of unique participants that were randomly assigned to breaks, i.e., disregarding those 5% of the sample whose initial choice was implemented.

To understand if our treatment differentially affected people's propensity to stay in the experiment, we break down the number of participants who were still part of the experiment at the end of each segment in Table A.1. Attrition is not statistically different by treatment. For the main analyses in this paper, we only include participants who complete the entire work period.

A.3 Appendix: Treatment Imbalance

The distribution of the treatment is balanced except for two characteristics as shown in Table 1. First, household size is marginally different in the treatment and control groups, with the no-break group having 0.2 household members fewer on average ($p < 0.1$). We control for household size in any specifications that include demographic controls. Second, the average baseline performance is statistically significantly lower in Segment 1, while the treatment is only assigned later, namely in Segment 3. On average, 72% of workers in the no break group earn the bonus payment in segment 1. In contrast, only 63% earn the payment among workers who will later be randomly assigned to take a break. This difference of 9p.p. is statistically significant at $p < 0.01$. Using an ANCOVA specification, we control for baseline performance (both segment 1 and segment 2) in all specifications about earnings to increase power and precision. The randomization was implemented using Qualtrics. We stratified the treatment by initial choice. Due to the computational intensiveness of evaluating the task, we could not stratify the treatment assignment by baseline performance. To assign people to treatments, we randomly assigned every individual an embedded data value via a survey block in Qualtrics and used the Qualtrics randomizer to randomly and evenly assign workers to the two treatments stratified by choice.

A.4 Appendix: Natural Breaks

Besides the "official" break, there were two additional ways in which workers could take breaks "naturally." First, any worker could, at any point in time, not continue with the task and do something else in the meantime. Because the flight images flicker across the screen automatically, and because they necessitate constant responses, we observe when someone does this. We find that only 1 worker in our sample is once completely absent for an entire segment (segment 4). Some workers are absent for periods of time but even this is rare. In Table A.3, we report the number of workers out of 790 who missed more than 100 clicks in a given segment (which consisted of 300 images of which 280 necessitated a click). Table A.4 documents the share of absent safe flights at the 75th and 95th percentile of all workers in a given segment.

Second, any worker can pause on the confirmation page in between segments. Participants laded on these pages automatically at the end of a segment. Each page also featured a time stamp of their start time as well as a reminder that segments completed within 65 minutes would not be remunerated. Participants had to click a continue button to start the next segment. These small pauses, however, mean that workers will have less time to complete all segments. They are informed that segments take 8 to 13 minutes and that duration can vary due to lags. Segments that are not completed within 65 minutes will not be remunerated. Thus, pauses here are not "free" either because they imply less time to complete the work segments. We report the 25th, 50th, 75th, and 95th percentile of the seconds spent on those pages by segment in Table A.5. The majority of workers only spent a couple of seconds on a given page. It is plausible that the median 10 seconds that we commonly observed were used to re-read that message about the time stamp. The regular pause and confirm screen for Segment 2 comes right after the end of Segment 2 and before participants make a choice about resting. We denote this as 2a. There is an additional confirmation screen after the break choice. We denote this by 2b. There is no pause after segment 5 since the experiment ends there

We do not find statistically different pause times by break treatment in Segment 4. We do find a significant difference of 12 seconds after segment 3. The longer time in the no-break group is likely driven by the fact that workers prefer a short moment to regroup before starting a new segment, while workers in the break group have been relaxing the entire last segment.

A.4.1 Appendix: Compliance with Non-Sleep Deep Rest Breaks

Our design captures both the causal intent-to-treat (ITT) effect of non-sleep-deep-rest breaks (more narrow) and the causal intent-to-treat (ITT) effect of mandated rest (more broad). As previously mentioned, we choose non-sleep deep rest to provide participants with a restful task and to avoid the issue of them engaging in other tiring or stressful tasks such as other surveys. However, we cannot isolate the causal treatment effect of these non-sleep-deep-rest breaks. Depending on assumptions about what non-treatment-complying individuals are doing, ITT estimates are often considered to capture the lower bound or upper bound of the treatment effect. If we were only interested in the ITT of NSDR, the interpretation of the treatment effects would depend on assumptions about whether the other activities that non-compliers are engaging in have positive or negative effects on productivity. The same is true for the rest, however, the discussion needs to be slightly more nuanced.

Suppose the rest that we assigned people to is the best possible rest in terms of positive returns. In that case, non-compliance means that some people are engaging in rest activities with lower returns. Hence, we would be estimating the lower bound of the treatment effect of rest (and NSDR).

Suppose the type of rest that we assign people to is *not* does not have the highest possible returns, and non-compliers would be exclusively engaging in restful activities with higher returns for productivity. In that case, we would again be estimating a lower bound of rest since compilers could have reaped higher returns by not complying. In that scenario, we would be overestimating the ITT effect of NSDR.

Suppose again the type of rest that we assign people to is *not* does not have the highest possible returns and allows non-compliers to engage in restful activities with both higher and lower returns. In that case, our estimates would still be capturing the ITT of rest, and they would simply be more imprecise similar to measurement error and attenuation bias.

Since the primary focus of our paper lies on understanding the effects and perceptions of rest, and non of non-sleep deep rest, we acknowledge that imperfect compliance may lead to mismeasurement, but we posit that it does not threaten the qualitative interpretation of the results.

Conducting our previous analysis with only compliers to estimate the causal effect of non-sleep deep rest break compliance on performance is impossible since we have no way of identifying compliers in the control group. We can only identify them in the treatment group, where we ask questions toward the end of the study that gauge whether people attended to the break. We suspect that compliers differ from non-compliance in unobservable ways, and hence, simply comparing compliers in the treatment group with the entire control group would lead to biased estimates.

A.5 Appendix: Back of the Envelope Calculations

Without break payments: We find that earnings are virtually the same even though individuals worked less. If we assume this effect is constant over the course of the workday, we should see workers who take a break every two segments work 160 minutes less than workers who work for an entire 8-hour workday without taking breaks–yet earnings would be the same. This would result in higher earnings of 50% per hour actively worked.

With break payments: We find effects on earnings of approximately £0.35 for an approximately 1hour task. We now speculate how taking breaks consistently throughout the workday may affect overall earnings. We assume that a worker works for 8 hours a day split across two 4-hour workbooks with a longer, fully restorative break in between. It is plausible that the benefits of breaks may diminish over the course of the workday as fatigue accumulates. However, fatigue would likely also accumulate in the group without breaks–hence we posit that the relative benefit will stay the same. To stick with the existing rhythm, a worker would need a break every two segments. There would be approximately 8 blocks of 2 work segments and 1 break in one morning, and another 8 in the afternoon. If the returns to rest are constant, this would imply higher earnings of approximately £5.6 in a given day.

A.6 Appendix: Lasso

To understand if any other observable characteristics predict who may benefit more or less from rest, we focus on post-break productivity. We compute this by summing up the earnings from the post-break segments 4 and 5 and dividing those by 2 to get a measure of earnings-per-segment-worked.

We use LASSO to select variables in a regression of post-break productivity on the break assignment, baseline performance, age, providence, education categories, gender, household size, income, and employment dummies. Given the design of the experiment and the initial imbalance, we force the break assignment and baseline performance to be part of the model.

LASSO selected one of the South African Providences, two of the education categories, and gender as predictive variables.

Table A.6 displays the post-selection coefficients from a regression of post-break productivity on these earnings. Besides baseline performance, none of these coefficients have magnitudes that are larger than the break treatment. The slightly bigger effect for women is interesting, however, we do not find any significant interactions of gender and treatment when we include this in a regression. We also do not see any difference in terms of gender with respect to break uptake.

B Appendix Figures

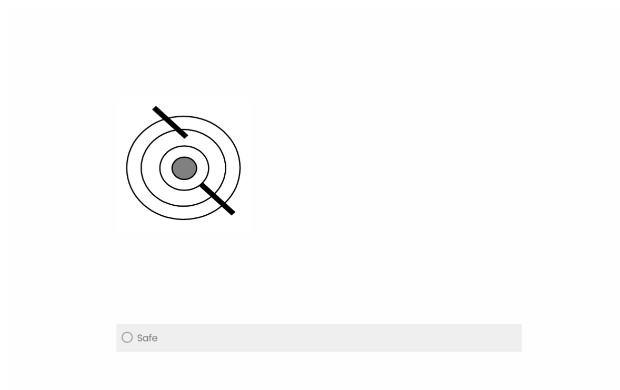

Figure A.1: Example Flight (Participant View, Desktop)

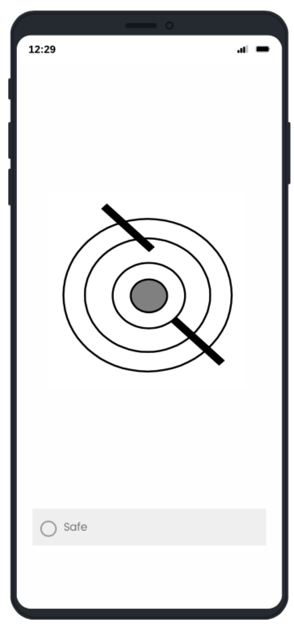

Figure A.2: Example Flight (Participant View, Mobile)

A Appendix Tables

Table A.1: Attrition by Treatment

Seg	All Obs		Unique IDs (all)		Unique IDs (rand)	
	No break	Break	No break	Break	No break	Break
1	569	526	451	414	412	409
2	569	526	451	414	412	409
3	544	508	448	410	409	405
4	519	485	443	401	404	396
5	493	464	440	395	401	390

Notes: The following table breaks down attrition by treatment for various degrees of "sample restrictiveness." Participants who attrited before the end of Segment 2 are not included in this table because the treatment was randomly assigned after segment 2. (Hence the first two rows are the same.) We cannot observe whether a participant attrited because they wanted to leave the experiment or because they faced technological issues. In our study, we only include participants who complete the entire work period.

Table A.2: Overall Attrition

Segment	All Obs	Unique IDs (all)	Unique IDs (rand)
1	1158	885	841
2	1196	866	822
3	1052	858	814
4	1004	844	800
5	962	835	791

Notes: This table follows "overall" attrition of observations. The columns "all observations" includes anyone who ever opened the link–including duplicate attempts. We cannot tell whether a participant opened/ started the survey multiple times due to technical difficulties or because they were hoping to benefit disproportionally. We exclude any duplicate IDs from the analysis sample. The column "unique IDs" restricts the sample to participants whose ID only appears once. The column "unique IDs (rand)" focuses on the subset of unique participants that were randomly assigned to breaks i.e. disregarding those 5% of the sample whose initial choice was implemented.

Table A.3: Count of Workers with Safe-Flight Misses ≥ 100

Segment	Count ≥ 100	Total N
1	23	790
2	8	790
3	4	400
4	11	790
5	14	790

Notes: This table documents how many workers missed more than or equal to 100 "safe" flights in a given segment. Safe flights required a click on the safe button for a correct response. These misses do not need to occur consecutively, but often do.

Table A.4: Count of Workers with Safe-Flight Misses $\geq$ 100

Segment	% missed at p75	% missed at p95
1	5	28.2
2	2.5	13.9
3	3.6	14.3
4	2.8	13.9
5	2.8	15.4

Notes: This table lists the percent of *safe* flights missed as part of the 280 safe flights encountered in a given segment for a given percentile of the overall distribution. Column 1 describes this at the 75th and column 2 at the 95th percentile among all flights missed.

Table A.5: Seconds spent on pause screen between segments

After Segment ...	p25	p50	p75	p95
1	12	16	22	68
2a	9	14	27	125
2b	3	5	7	15
3	6	9	16	82
4	5	9	18	112

Notes: This table documents the number of seconds spent on a pause/confirmation screen between segments. 2a denotes the screen right after segment 2. 2b denotes the screen after the break choice and before segment 3.

Table A.6: LASSO Selected Coefficients

LASSO-Selected Variable	**Coefficient Value**
Break Assignment	0.37
Seg 1 Performance	0.7
Seg 2 Performance	
Province: Western Cape	0.16
Education: Secondary School Graduate	0.27
Education: Some College/ University	-0.18
Gender: Male	0.12

Notes: This table reports the coefficents from using LASSO with 10-fold cross-validation with 100 lambdas with $N = 734$. The underlying regression is linear and regresses post-break per-segment earnings on break treatment, baseline performance, age, providence dummies, education categories dummies, gender dummies, household size, income, and employment dummies. We force the model to incorporate the break treatment and baseline performance.