Noise, Cognitive Function, and Worker Productivity

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October 14, 2020

Abstract

Cognitive science research suggests the noisy workplaces common in low and middle income countries can impair workers' cognitive functions. However, whether this translates into lower earnings for workers depends on the importance of these functions for productivity and whether workers understand these effects. I use two randomized experiments in Nairobi, Kenya to answer these questions. First, I randomize exposure to engine noise during a textile training course at a government training facility. An increase of 10 dB reduces productivity by approximately 5%. In order to study what mechanism drives this effect, I then randomize engine noise during tests of cognitive function and placebo effort task. The same noise change impairs cognitive function but not effort task performance. Finally, in both experiments, I examine whether individuals appreciate the impact of noise on their performance by eliciting participants' willingness to pay for quiet working conditions while randomly varying whether they are compensated based on their performance. Individuals' willingness to pay does not depend on the wage structure; suggesting that they are not aware that quiet working conditions would increase their performance pay. This suggests workers may fail to mitigate earnings losses by either sorting into quieter jobs where they are more productive or by demanding compensating differentials.

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Workplaces in low and middle income countries can be egregiously loud. In some, factories workers can experience jet-engine-level noise daily (Nandi and Dhatrak 2008; Kimani 2011). Cognitive science research suggests noise can impair workers' task management skills like attention and working memory (Szalma and Hancock 2011; Matthews et al. 2000b; Jones and Broadbent 1991). That means that in addition to annoyance and hearing damage, these workplace environments may reduce workers' earnings by hindering their productivity. Whether this is the case depends on the importance of these skills for productivity and whether workers understand these effects. Workers who understand that they are less effective in noisy working conditions, may mitigate earnings losses by sorting into quieter jobs where they are more productive or demanding compensating differentials.

This paper uses two randomized experiments in Kenya to investigate the relationship between noise exposure and productivity. First, I estimate the reduced-form impact of noise on productivity by randomly exposing participants in a textile training course to engine noise. Second, I study the importance of cognitive function as a mechanism by randomly exposing individuals from the same population to the same engine noise while they complete a battery of cognitive tests and an effort task as a placebo.[1] Third, in both experiments I assess whether individuals understand how noise affects their productivity by offering participants the chance to pay for quiet working conditions while I randomly vary whether their pay depends on their performance. If individuals understand the impact of noise, they will be willing to pay more for quiet working conditions when they will recoup some of this investment through increased performance pay.

I demonstrate that noise can meaningfully reduce productivity in a real-work setting. While a significant body of literature considers the impact of noise on cognitive function, very little work considers how this effect might manifest itself when individuals are faced with incentivized tasks in a real-work setting (Matthews et al. 2000b). I recruited a sample of 128 manual laborers accustomed to factory noise for a two-week textile production course at a government vocational training facility outside of Nairobi, Kenya. After training the sample to complete an incentivized production task, I randomly exposed participants to engine noise while they worked autonomously for a piece rate. In order to isolate the impact of noise, I chose a task that did not involve communication, randomly varied which work location was noisy, and randomized work stations to minimize participants' familiarity with their neighbors. I estimate that increasing the noise level from that of a dishwasher to that of a vacuum cleaner (an increase of 10 dB) reduced output by approximately 5%.

Given that the task did not involve communication, the most plausible channel for this

[1] This mechanism holds particular interest because a recent literature in economics considers how conditions of poverty might affect cognitive function (Mani et al. 2013; Schilbach et al. 2016).

impact is by the effect that noise has on cognitive function, which decades of laboratory work has shown can be easily impaired by noise (Evans and Hygge 2007; Hockey 1970; Jones and Broadbent 1991; Matthews et al. 2000b; Smith 1989; Szalma and Hancock 2011). Cognitive function encompasses all of the general-purpose abilities involved in task management. This includes the ability to direct one's attention, manipulate information in memory and switch between tasks (Diamond 2013). These skills appear critical for many types of work. For example, a factory foreman requires a broad range of attention to ensure that his/her workers do not make mistakes. An auto-rickshaw driver must simultaneously drive and take directions from his/her passenger. Cognitive science research has shown stronger cognitive function is correlated with better job market outcomes, physical health and success in school (Bailey 2007; Borella et al. 2010; Crescioni et al. 2011; Duncan et al. 2007; Gathercole et al. 2004).

However, this effect could also be driven by workers choosing to reduce effort. For example, workers may resent working in an unpleasant environment and reduce effort to retaliate. To evaluate the relative importance of these two possible mechanisms, in a second experiment I randomly exposed 213 individuals from the same population to noise while they completed a wide variety of cognitive tests and an effort task where they alternated pressing the "a" and "b" keys on a keyboard for 10 minutes (DellaVigna and Pope 2018). This effort task requires all the same inputs as the sewing task (e.g. motor control and effort), except it requires minimal amounts of cognitive function.

The same engine noise reduced performance on a common factor index of cognitive test outcomes by 0.07 standard deviations, but had no impact on effort task performance. In fact, the point estimate suggests that doubling the noise level *increases* the number of key presses by 1.9 relative to a control mean of 2192, and any decrease in effort larger than 1.4% is outside of the 95% confidence interval. Combined with the evidence from the first experiment, this suggests noise in work environments can lower workers' productive abilities.

I then demonstrate that individuals neglect the productive impact of noise, suggesting they will fail to mitigate earnings losses. While a significant literature examines the disutility individuals derive from living in noisy conditions (see Navrud (2002) for an overview), no work has assessed whether individuals are aware of its productive impact. More generally, while a rapidly expanding literature suggests experiences associated with poverty might have important economic consequences by impairing cognitive function, almost nothing is known about whether individuals take actions to protect their cognition from these stimuli (Kremer et al. 2019).[2] [3] Understanding whether individuals are aware of environmental hazards to

[2]For example, there is recent work on on effects of alcohol consumption, heat, air pollution, sleeplessness and financial strain (Schilbach 2017; Adhvaryu et al. 2016b; Zivin and Neidell 2012; Bessone et al. 2019; Kaur et al. 2019).

[3]Schofield (2014) demonstrates that individuals fail to make food purchases that would improve their

their productivity is critical to predicting the real-world impact of such impediments.

In order to assess this possibility, I allowed participants in both experiments to pay for quiet working conditions and randomly varied whether they were paid based on their performance. If individuals attend to the productive effects of noise exposure, they should be willing to pay more to work in quiet when their earnings depend on their performance. Instead, I find that individuals' willingness to pay was unaffected by the wage structure.

I use my within-person variation to evaluate potential mechanisms underlying this neglect. I first assess whether individuals who were relatively unaffected by noise are driving the result. By estimating individual-level treatment effects, I show that the impact of noise on an individual's productivity does not predict the responsiveness of their demand to performance pay. Second, I show that a simple prompt to think about the productive impacts of noise also did not increase demand responsiveness. Finally, I demonstrate that responses are consistent with a failure to notice the productive impact of noise (Hanna et al. 2014; Schwartzstein 2014). In particular, individuals were able to somewhat predict their output but were unable to predict the impact of noise. Moreover, individuals appear to have realized that they did not understand the productive value of quiet and were unwilling to stake any money on their stated beliefs.

I conclude by considering the efficiency implications of this neglect for labor market sorting. If workers ignore the productive effects and sort solely based on the disutility of noise, the size of the inefficiency depends on the magnitudes of the two effects and their correlation. I find that while disutility from noise is highly heterogeneous, for most subjects it is smaller than the productivity effects. These disutility values are also uncorrelated with the productivity effects estimated using the within-person variation. Together this suggests that worker sorting is likely to be inefficient.

The remainder of this paper is organized as follows. Section 1 fixes ideas with a conceptual framework. Section 2 discusses the prevalence of noise pollution in developing cities and its effects on cognitive function, before Section 3 describes the design and results of the productivity experiment. Section 4 then presents the design and results of the cognitive experiment, Section 5 assesses whether individuals neglect the effects of noise and considers implications for efficiency, and finally Section 6 concludes.

productivity which suggests possible neglect. Also previous work in psychology on the human capacity for introspection (for example, Nisbett and Wilson (1977)) also suggests individuals in these environments might not be aware of their potential impact.

1 Conceptual Framework

To fix ideas, consider the following simple model in the style of Rosen (1986). Suppose there is an economy with two sectors: noisy and quiet. Firms with heterogeneous costs of abatement given by γ_j must choose in which sector to produce. Each firm is seeking one worker to produce a good the firm sells for a unit price.

Workers have free entry and can produce according to $Y(\eta_i, S_i, e_i) = (A - S_i\eta_i)e_i$, where $S_i = 1$ if the worker is in the noisy sector and η_i is a heterogeneous productivity loss due to noise. Workers face convex cost of effort $c(e_i)$ and are compensated with sector specific piece rates w_n and w_q. Workers then choose effort levels for each sector to equalize the marginal cost and returns to effort. In the quiet sector, this yields a constant level of effort, e^q, and output, Y^q, and heterogeneous effort, $e^n(\eta_i)$, and output, $Y^n(\eta_i)$, in the noisy sector. Workers choose which sector to enter by maximizing the following utility function where ψ_i is a heterogeneous disutility cost of noise:

$$U(S_i) = (1 - S_i)(w_q Y^q - c(e^q)) + S_i(w_n Y^n(\eta_i) - c(e^n(\eta_i)) - \psi_i)$$

Workers then enter the noisy sector if and only if,

$$w_n Y^n(\eta_i) - c(e^n(\eta_i)) - \psi_i > w_q Y^q - c(e^q) \tag{1}$$

$$w_n > \underbrace{\frac{w_q Y^q + \psi_i + c(e^n(\eta_i)) - c(e^q)}{Y^n(\eta_i)}}_{\chi_i} \tag{2}$$

Where χ_i is a random variable determined by the disamenity value of working in noise, the decreased productivity in noise, and the associated decrease in the cost of effort.

Firms make abatement decisions assuming this sorting process. A firm chooses not to abate if and only if their expected share of the output in the noisy sector, given the types of workers choosing to work in noisy environments, exceeds their share in the quiet sector less the abatement cost.

$$\mathbb{E}\left[(1 - w_n)Y^n \mid w_n > \chi\right] > (1 - w_q)Y^q - \gamma_i \tag{3}$$

$$(1 - w_q)Y^q - \mathbb{E}\left[(1 - w_n)Y^n \mid w_n > \chi\right] < \gamma_i \tag{4}$$

Because workers have free entry, w_q will be fixed such that $w_q Y^q$ is equal to the workers' outside option. The wage in the noisy sector, w_n, will then be determined by equalizing the supply of workers choosing the noisy sector and the demand from firms choosing to not abate. Letting, $F(\cdot)$ be the CDF of the random variable χ_i and $G(\cdot)$ be the CDF of γ_i gives

the following equilibrium condition:

$$F(w_n) = 1 - G\left((1 - w_q)Y^q - \mathbb{E}\left[(1 - w_n)Y^n \mid w_n > \chi\right]\right) \tag{5}$$

This implies that the wage premium and resulting allocation depends on the joint distribution of disutility, ψ_i, and productivity losses, η_i caused by noise.

Now, consider the case where a worker erroneously believes that $\eta_i = 0$ due to inattention. The worker now believes they are equally productive in noise and quiet, will choose the same level of effort in each, and will choose to sort into the noisy sector if and only if the wage premia exceeds their disutility.

$$\begin{aligned} w_n &> \frac{w_q Y^q + \psi_i + c(e^q) - c(e^q)}{Y^q} \\ Y^q(w_n - w_q) &> \psi_i \end{aligned}$$

Thus neglect not only changes the wage level by shifting worker's beliefs about how much effort they will exert and the return they will earn, but also changes the composition of workers depending on the joint distribution of η_i and ψ_i.

2 Background

2.1 Noise Pollution

Noise pollution is one of the oldest externalities documented in the written record. In the 6th century BCE, the Greek colony of Sybaris had such a noise problem that they banned potters, tinsmiths and other noisy tradesmen from working in the city (Goldsmith 2012). When the founding fathers of the United States gathered in the Pennsylvania State House in May 1787 to craft the constitution, they first spread dirt on the cobblestone streets surrounding the building to prevent the noise of passing carriages from disrupting their work (United States National Archives and Records Administration 2017). Since the industrial revolution, sources of noise pollution have proliferated at an impressive rate (Bronzaft 2002).

Given weak state capacity, it is unsurprising that noise pollution is pervasive in the rapidly urbanizing and industrializing developing world. In many cities the noise level experienced by simply standing on the street reaches dangerous levels (Wawa and Mulaku 2015; Mehdi et al. 2011; Bhosale et al. 2010). For example, areas of the central business district of Nairobi approach 85 dB (the level of noise made by a power lawn mower).

Beyond city streets, many workplaces are filled with noise. The Indian National Institute of Occupational Health reports that noise levels in most industrial occupations exceed 90

dB, a level that the United States Centers for Disease Control estimates will induce disabling hearing loss in one out of four workers exposed (Nandi and Dhatrak 2008). Similarly, an NGO in Kenya finds that 75% of metal workers are exposed to unsafe levels of noise and 22% already have disabling hearing loss (Operation Ear Drop 2010).

While comprehensive data on noise levels does not exist outside of the European Union, we can use hearing loss as a proxy for exposure. Figure 1 combines measurements of hearing ability recently collected by Mimi (2017) with data on city-level GDP from Berube et al. (2014) to show that citizens of poorer cities have substantially more age-adjusted hearing loss. The average citizen of Delhi or Mumbai has as much hearing loss as residents of New York or Tokyo who are eight years older. While there are undoubtedly many causes for this difference, for example variation in access to medical care, it suggests that citizens in poorer countries are likely exposed to more noise.

2.2 Noise and Productivity

Despite the research on the cognitive impacts of noise, we have almost no causal evidence of the impact of noise on economic outcomes in real-work settings. Weston and Adams (1935) randomized hearing protection among 20 textile workers and estimated that output was 3% higher among those with hearing protection over the next 18 months. Unfortunately, the study does not report standard errors or any statistical tests which makes it difficult to interpret this result. Broadbent and Little (1960) studied the effects of installing noise-abating materials in one room of a Kodak factory and found that the resulting noise decrease of 10 dB was associated with fewer worker errors; although, there they also found error reductions in the other factory rooms that did not receive abatement causing the authors to be concerned about what other factors may have also changed. Finally, Levy-Leboyer (1989) cross-randomized 52 workers into assembling either carburetors or air conditioners in either their typical noisy conditions or a separate quiet room. Workers assigned to assemble air conditioners in quiet were 14% faster than those in normal conditions; however, those assigned to assemble carburetors in quiet were 10% slower than their counterparts in noise. Although no study provides large-sample evidence that distinguishes the effects of noise exposure from other location-specific features, together this work suggests that noise might affect real-work outcomes.[4]

[4]Researchers have studied the impact of OSHA regulations on productivity; however, such work is unable to separate the effects of noise regulations from other safety regulations (Denison 1978; Gray 1987).

2.3 Cognitive Function and Productivity

Studies on cognitive function and productivity generally fall into one of two groups, the first of which examines how stimuli can affect cognitive function. A large psychology literature studies how a variety of factors such as heat, fatigue, sleep, and health can affect cognitive performance (see Matthews et al. (2000a) or Dean et al. (2017) for overviews). Additionally, recent literature in economics examines how conditions of poverty can impede cognitive function (Haushofer and Fehr 2014; Lichand and Mani 2016; Mani et al. 2013; Schilbach et al. 2016). These studies then generally appeal to theory, the correlational evidence mentioned above, and our intuition about the importance of cognitive abilities to make inferences about how stimuli might affect productivity.

A second group of studies examines how stimuli associated with poverty can affect productivity directly. This includes recent work in economics on how temperature, alcohol, air pollution, hunger, sleeplessness, and financial strain can affect productivity (Adhvaryu et al. 2016b; Chang et al. 2016b, 2016a; Park 2017; Schilbach 2017; Schofield 2014; Zivin and Neidell 2012; Bessone et al. 2020; Kaur et al. 2019). While these studies provide invaluable evidence on the potential for environments to affect productivity, they are unable to speak directly to the quantitative importance of a cognitive mechanism because the factors that they study generally affect productivity through multiple channels or do not have quantitative measures of cognitive function.

Finally, almost none of this work directly evaluates whether individuals understand how environments can affect their productivity via cognitive impediments (Kremer et al. 2019). If individuals appreciate these impacts, they might be able to take actions that significantly attenuate the effects estimated in controlled experiments. However, there is some reason to doubt this is the case. Schofield (2014) finds individuals do not consume calories that would improve their productivity, Adhvaryu et al. (2016b) reports that managers were surprised by the results of their study demonstrating heat reduced productivity, and research in psychology such as Nisbett and Wilson (1977) suggests individuals may not have the capacity to truly monitor their own cognitive processes. On the other hand, Adhvaryu et al. (2016a) finds evidence that managers alter worker assignments in response to air pollution induced productivity shocks. This study provides direct evidence on this question by demonstrating demand for quiet working conditions is unresponsive to incentives to increase productivity.

3 Experiment One: Noise and Worker Productivity

This experiment provides reduced-form evidence of the impact of noise on productivity. By randomly exposing workers in a textile training course to engine noise, I estimate that increasing the noise level by 10 dB (from the noise level of a dishwasher to that of a vacuum) reduces output by approximately 5%.

3.1 Experimental Design

3.1.1 Context

My survey team recruited 128 individuals for a ten-day sewing course at the Kenyan National Industrial Training Authority's Technology Development Center (TDC), a government vocational training facility located in an industrial development zone outside of Nairobi. This facility is well-suited to the experiment because it allows for significant realism. The trainers, machines and materials are all similar to what exists in a factory setting because the center's primary purpose is to train workers to then work in nearby textile factories.

We recruited our sample from groups of manual laborers who gather at the gates of nearby textile factories hoping to be hired for a day's work (see Figure A1). This population is well suited for this experiment for three reasons. First, the fact that respondents typically work in factories means that they are accustomed to significant levels of noise. Second, these participants have the opportunity to use the skills learned in the course to gain employment, which helps the experience approximate typical working conditions. Third, the sample is demographically similar to many poor communities where we are interested in the importance of cognitive function (Table B1).[5]

3.1.2 Generating Noise

Noise exposure can be manipulated at either the individual or ambient levels and by either adding or reducing noise exposure.. Ambient-level abatement is undesirable from an experimental perspective because it involves significant, location-specific investments that

[5] One less than ideal characteristic of this population is that most have very limited experience in operating sewing machines. This means that participants are learning substantially throughout the course of the experiment which creates variance in the outcome measures and raises concerns that any effects might be specific to environments where individuals are growing accustomed to the task. I deal with the former by stratifying randomization so that in each session half of workers are treated allowing me to absorb as much of the variation from learning as possible. The later I asses by examining treatment effect heterogeneity both across the two weeks and within each session. As discussed in subsubsection 3.3.5 there does not seem to be much heterogeneity on either dimension suggesting the effect does not depend on participant's comfort level with the task.

confound the reduced noise with other location-specific features. For example, a common abatement technology is to replace or pad the existing ceiling with more absorbent material. While effective at reducing noise, this means that those randomized to the room with the absorbent ceiling are necessarily also treated with the other features of that room such as temperature, humidity, and ventilation. Individual-level protection does not involve location-specific investments, but noise control experts view it as an option of last resort due to its relative ineffectiveness and the safety risks that it creates by impeding workers' ability to warn each other about hazards (Hansen and Goelzer 2001). Additionally, hearing protection not only alters the experienced noise level but also affects the physical comfort of the participants. Similarly, adding additional noise at the individual-level is undesirable because it requires subjects to wear headphones which may be unusual during production tasks or uncomfortable. For these reasons, I chose to manipulate noise by adding a new ambient noise source to the preexisting noise generated by the sewing machines.

In order to create noise representative in both the level and quality of that faced by factory workers and residents of developing countries more broadly, I chose to generate noise with a car engine that the TDC uses for auto-mechanic training classes (see Figure A2). This type of noise does not contain any informational content and is relatively consistent, but is not perfectly constant like a white noise machine. These qualities match noise pollution generated by both traffic and occupational noise generated by large industrial machines. This has two benefits: first, the effect of noise is known to depend on predictability and variability (Matthews et al. 2000b), thus the representative nature of the noise is important for external validity; and second, this type of noise is unlikely to be novel to participants, which limits concerns about whether any productivity effects are due to respondents simply changing behavior in response to a novel stimulus. The end result is that participants in the control condition experienced noise approximately equal to that of a home dishwasher running in the background, mostly due to sounds made by the sewing machines. While in the treatment condition, workers experienced noise equivalent to listening to a home vacuum cleaner.

As noted previously, the noise level experienced in many factories is sufficiently loud to pose a danger to hearing loss. For ethical reasons, this level of noise is never experienced by participants in the experiment. The American Occupational Safety and Health Administration (OSHA) requires firms to implement a hearing conservation program if workers are exposed to 85 dB(A) or more for eight hours a day or more. To stay well below this limit, the noise level was continuously monitored and exposure did not exceed 80 dB(A) for a period of six hours. This level of exposure was approved by both the MIT Committee on the Use of Humans as Experimental Subjects and the Kenyan Medical Research Institute Scientific

and Ethics Review Unit.[6]

One might be concerned that in addition to creating noise, placing an engine outside of rooms could alter other environmental conditions. For example, engine exhaust might diminish the room's air quality or annoyance with the noise might cause participants to close windows, changing the temperature inside the room. These altered environmental conditions could then have a direct effect on productivity independent of any effects of the noise level. Thus, in order to ensure that treatment only increased noise exposure, enumerators were instructed to keep the windows and doors unchanged and ensure that the exhaust pipe from the engine pointed away from the workroom doors into an open courtyard. To assess whether this was successful, I measured CO2 (as a proxy for engine exhaust), temperature, and humidity during every session.[7]

3.2 Production Task

I chose sewing pockets as the incentivized production task for several reasons. First, it is a task that can be completed relatively quickly, which allowed me to observe variation in performance over a short time period. Second, it requires many key sewing skills (e.g. sewing under control, sewing in parallel lines, hemming, and taking corners). In fact, the TDC uses this task as a tool to evaluate potential instructors for precisely these reasons. Third, these sewing skills in turn require a variety of cognitive functions. For example, sewing in a straight line requires paying close attention to how hard one presses the machine foot pedal, how quickly one moves the fabric with both hands, and exactly where the needle is puncturing the fabric being sewn at all times. These cognitive requirements are common to many production tasks that workers perform in developing contexts, which improves the external validity of the study. Third, this task does not require communication. If the task I chose for the study required participants to communicate, any observed effects would be the result of impairing both communication and cognitive function. This would then preclude me from using this experiment to explore the importance of cognitive function as a mechanism and participants' awareness of this importance. Finally, the task does not generate considerable noise. If the task I chose created significant noise (for example metal work), I would observe a mechanical positive correlation between noise and productivity.

The quality of the pockets produced was graded each hour by treatment-blind enumerators according to six criteria developed by the TDC (see Figure 3 for an example pocket

[6]The protocol numbers are 1606621783 and Non-KEMRI Protocol Number 520 for MIT COUHES and KEMRI SERU respectively.

[7]CO2 is typically highly correlated with other exhaust pollutants such as particulate matter and black carbon (Johnson et al. 2016; Abdel-Salam 2015).

with the criteria marked). In the analysis below, I use these grading data to construct three types of productivity measures. First, I use the number of pockets created per session as a pure quantity metric. Second, I combine quantity and quality by calculating the number of "points" earned across all pockets produced in a session. For example, if a subject made one pocket meeting four criteria and another meeting three criteria, they would earn a total of seven points. This is my most continuous metric where I have the most power. Finally, I report the number of pockets meeting the different possible quality thresholds per session. For example, the number of pockets meeting at least two criteria, the number of pockets meeting at least three criteria, and so on. The distribution of these outcomes is skewed suggesting any proportional treatment effect is unlikely to be well estimated in levels, but has zeros (see Figure A4). Thus, I use inverse hyperbolic sine transformations as my preferred outcomes following Burbidge et al. (1988).[8] For robustness, in each table I also present the results in levels and Table B3 presents the results of Poisson regressions for the reduced-form. All of the methods yield similar results.

3.2.1 Experiment Timing Overview

For logistical reasons, the course was repeated in four rounds with the number of respondents equally split over each round. On the first two days of the course, TDC staff taught participants how to operate a sewing machine (see Figure 2a). This included basic skills such as how to thread the machine and how to avoid breaking the sewing needle. After learning these basic skills, workers then learned how to sew a pocket. All training occurred without engine noise.

Respondents worked three sessions per day for the remainder of the experiment, sewing pockets and earning a piece rate for each perfect pocket that they created. On the last two days, respondents had the opportunity to pay to work in quiet for two sessions each day. On all days, participants worked for three two-hour sessions separated by one-hour breaks without knowing their future treatment status (see Figure 2b). These breaks allowed workers who were in the more noisy environment to decompress between sessions. Combined with the lack of knowledge about future treatment status, this allows me to isolate the contemporaneous effects of noise. This improves my power in the analysis below because it allows for the pooling of all workers within a session based on their contemporaneous treatment status, rather than having to include interactions with their previous or future

[8] An inverse hyperbolic sine transformation is defined as $f(y) = \ln\left(y + \sqrt{1+y^2}\right)$. It has the benefit that, except for values of y close to zero, $f(y) \approx \ln(2) + \ln(y)$. Thus, as long as there are not too many zeros and values are reasonably large, coefficients can be interpreted in a similar manner to a standard log transformation.

exposures.

3.2.2 Lasting Effects of Noise

While I designed this schedule to isolate the contemporaneous effects of noise, whether noise exposure has lasting effects is an important policy question. I thus also include the following decision tasks that were completed in quiet at the end of the day:

1. On every production day, participants decided how much to save in/withdraw from an account with a 1% per working-day interest rate (approximately 7% interest over the course of the experiment). This was intended to assess whether noise exposure reduced willingness to forgo current consumption by either raising the contemporaneous marginal utility of consumption or narrowing attention to the present.

2. On the fifth day, participants decided whether to buy maize flower in 5 kg bags or 1 kg bags. To test for increased inattention prices were set so that it was less expensive to buy five 1 kg bags than one 5 kg bag.

3. On the sixth day, participants decided whether to stay an additional hour and continue working for a piece rate. This was intended to assess whether noise reduced participants' willingness to exert effort.

3.2.3 Randomization

For each of the sessions following training, I randomized which participants were exposed to engine noise while working. For this purpose, I generated random schedules for each round that satisfied both of the following constraints:

- Each participant spent half of the sessions in a noisy room and half in quiet room.

- In each session, an equal number of participants (16) worked in the quiet room and in the noisy room.

I then randomly assigned each participant to one of the schedules. Thus because treatment status varies at the room by session level, I cluster all analyses at this level. For robustness, I also report randomization inference results based on re-assigning treatment status with the same code. Both inference approaches yield similar results. This randomization procedure was necessary because my piloting demonstrated significant heterogeneity in the ability to complete the production task across both individuals and time. Thus, even though simple randomization procedures would have resulted in balance in expectation, the risk of imbalance in finite samples was substantial.

In order to avoid any location-specific confounds, I randomly assigned each of two similar rooms (room "A" and room "B") to be the noisy room for half the sessions within each round (see Table B2 for balance tests).[9] Combining this randomization with the workers' noise schedule, I then created a room schedule for each participant. For each session, each participant was then told whether they were supposed to report to room "A" or room "B". Thus, workers could not anticipate whether they would be in noise or in quiet in future sessions, reducing concerns about workers intertemporally substituting effort. Finally, while participants were instructed not to talk, to further minimize the scope for communication, I randomized seating assignments within each room and session to prevent workers from becoming familiar with their neighbors. Following this randomization method, I include worker, room and session fixed effects in my regressions, which significantly improves my power.[10]

3.2.4 Compensation

On training days, all respondents received 600 Ksh (approximately $6.00) for participating. For each production session, I randomized workers to one of three wage conditions with equal probability while stratifying by participant but independent of other factors. Each wage was a combination of a piece rate paid based on the number of perfect pockets produced (5, 10 or 15 Ksh) and a flat payment calibrated so all three conditions would yield approximately 200 Ksh per session (or 600 Ksh per day).[11] Workers were informed at the start of each session of their assigned wage for that session. This allows me to benchmark the observed effect of noise against the effect of traditional incentives. Following this randomization, in all regressions I include piece-rate fixed effects.

[9] The rooms were located within walking distance of each other in the compound, but not so close that sound could travel from one to the other.

[10] I could include seat fixed effects as well, but do not since this randomization was done to ensure noise did not affect productivity by impairing communication rather than to control for factors that may influence the outcome directly.

[11] In the first round, the corresponding flat rates were 140, 160, and 180 Ksh, respectively. After participants in the first round were more productive than anticipated, the flat rates were reduced to 95, 130, and 165 Ksh to make the wage treatments as income neutral as possible. All wage fixed effects are determined based on the piece rate, which is common across all rounds.

3.3 Analysis and Results

3.3.1 Environmental Effects of Treatment

By adding the sound of the engine to the typical noise created by sewing machines, treatment increased the noise level by approximately 7 dB (Figure A3 and Table 1).[12] As noted previously, this difference is equivalent to the difference in noise between a home dishwasher and a home vacuum cleaner. Meanwhile, no other environmental variables were affected, suggesting that the pollution and temperature control procedures were effective.

3.3.2 Estimation Specifications

I estimate two different specifications. The first is the reduced-form effect of being in a treated room on productivity outcomes for individual i in room j at time t being paid wage w shown in equation (6). The regression includes individual, time, room, and wage fixed effects and has standard errors clustered at the level of randomization (room $\times$ session).

$$y_{ijtw} = \tau \cdot \text{Treatment}_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijtw} \tag{6}$$

$$y_{ijtw} = \nu \cdot \text{Noise Level}_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijtw} \tag{7}$$

To improve interpretability, I also estimate an instrumental-variables specification shown in equation (7) using an indicator for being in a treated room as an instrument for the noise level.[13] All noise levels are reported in 10s of decibels because the human ear perceives a 10 dB(A) increase as a doubling in loudness; this means all coefficients can be interpreted as the effect of doubling the perceived noise level on the outcome variable.

3.3.3 Pre-registration, deviations and piloting

While this experiment was pre-registered at the AEA trial registry under ID AEARCTR-0001500, I did not file a pre-analysis plan. In the pre-registration, filed before the first

[12] For interpretability, all noise levels in regressions are reported in 10s of decibels because the human ear perceives an increase of 10 dB as a doubling of the noise level. Thus, coefficients can be interpreted as the effect of doubling the noise level.

[13] Using only a simple indicator for treatment discards the significant variation in treatment intensity shown in Figure 5. Since this treatment intensity is quasi-randomly determined based on the noise levels at the compound and whether the engine was running smoothly or rattling, in Appendix B I use this variation to obtain more precise estimates by generating separate treatment indicators for each decile of intensity (difference in noise level between treatment and control room), Treatment_{jpt}, that are equal to one if room j was treated during a session with intensity p and zero otherwise. There are no clear relationships between session intensity and any observable characteristics besides noise (see Table B6) and the instruments yield a strong first stage (see Table B7).

experiment, I specified the primary outcomes would be "Productivity in producing the practice good, performance on cognitive tests, decisions made in three real stakes decision tasks, and willingness to pay for quiet.", but did not specify the functional forms for these outcomes. I present all functional forms considered except for $\log(1 + n)$ which was replaced with the inverse hyperbolic sign transformation because it is more standard and similarly solves the issue of skewness. No heterogeneity analyses were pre-specified and should be treated as exploratory.

I also originally planned to simultaneously collect cognitive function data during the first experiment, but this proved to be a logistically infeasible. Specifically, there was no way to collect measures of each desired cognitive function domain in a way balanced across treatment status without removing too much time from sewing. Instead I conducted the second experiment presented in this paper. An effort task was not originally going to be among the cognitive function measures, but was included in the second experiment as a method of disentangling the relative contributions of cognitive function and other mechanisms. Additionally, belief elicitations were added to the second experiment after seeing the lack of response in willingness to pay to the wage structure in the first experiment.

I ran one pilot with 32 subjects for the first experiment and no pilots for the second. I used the effect size from this pilot to determine the sample size for the first experiment. For the second, I used simulations based on the variability in the first experiment.

3.3.4 Main Results

Workers sewing in treated rooms produced approximately 3% fewer pockets (Table 2). Table B3 shows Poisson regressions yield similar results; treatment significantly decreases output by 3%. Fisher p-values shown in Table B4 yield similar inferences. Scaling this by the average noise change implies a 5% decrease in productivity for every 10 dB increase (or perceived doubling) in the noise level (Table 3).[14] In these specifications, there appears to be no effect of the noise on the number of perfect pockets. This is likely due to floor effects. During the first days of work, most participants were unable to make any perfect pockets. Because individuals cannot produce negative pockets, this attenuates the estimated treatment effect.[15]

[14] Using a larger portion of the variation by generating separate instruments for different treatment intensities yields slightly larger coefficients (see Table B8).

[15] An alternative explanation is that workers substitute their effort so that they make fewer but higher quality pockets. This is not borne out in the data. If effort substitution were occurring, we would expect the proportion of perfect pockets to be higher in treatment than in control. Table B9 shows this is not the case. Additionally, estimates of the reduced-form in the second week, although imprecise, show a larger effect on perfect pockets than on total pockets, suggesting that once individuals are capable of producing perfect pockets their production is also affected by noise exposure (Table B5).

These effects are unlikely to diminish with further exposure to noise. As noted above, the participants are already accustomed to working in large, noisy factories, and they are exposed to frequent road noise (the community sits at the intersection of two major highways from Nairobi to Mombassa and Arusha). What is less certain is how these effects map into different types of tasks. These sewing tasks were chosen explicitly because they appear to depend on cognitive function. It is unlikely that noise exposure would impede the ability of someone doing a less cognitively demanding task such as holding open a door. On the other hand, many factory employees are required to work in teams assembling complex objects, and noise would likely impede both each individual's cognitive function and the team's ability to coordinate. Another complication with extrapolating from these effects is that different sources of noise pollution vary in predictability and informational content. While the noise in this study was chosen to be representative in level and quality of major sources of noise pollution, they are by no means the only sources. Further research is needed to understand the effects of other common sources, such as your child overhearing your neighbor's television while trying to study.

3.3.5 Treatment Effect Heterogeneity

One might wonder whether this effect is driven by low-ability workers. If this is true, then a firm could eliminate the effect by firing the bad workers. To assess this possibility, I calculate each individual's performance in the control condition and split the sample at the median.[16] I then estimate the treatment effect separately for each group in a stacked regression with common fixed effects.[17] The treatment effects are equally large among better workers (Figure A5).

Another question is whether these results are specific to contexts in which individuals are learning how to perform a task or where they have not yet had the chance to adjust fully to their surroundings. I assess this possibility by estimating the treatment effect separately for each week and for the first and second hours of each session. While these regressions have lower power, the effects appear homogenous across both dimensions (see Figure A6 and Figure A7). This suggests that workers operating a sewing machine, regardless of their proficiency, must continue to engage their task management skills to prevent mistakes, and provides further assurance that the effects are unlikely to fade with longer exposure to noise.

[16] I exclude the current session from the calculation to avoid the overfitting problems highlighted by Abadie et al. (2014).

[17] This procedure is equivalent to first partialling out the fixed effects and running the regressions separately.

3.4 Lasting Effects of Noise

Some models of the effects of noise predict that exposure should generate lasting effects (Matthews et al. 2000b). While this study was designed to minimize these effects by including breaks in the schedule, I assess whether the effect of noise exposure is cumulative by regressing the inverse hyperbolic sine-transformed outcomes on a treatment indicator, a lagged treatment indicator and their interaction.[18] The results are very imprecise due to the reduction in effective sample size, so they should be interpreted with caution. Some of the coefficients are large enough to be economically meaningful, but overall the results do not provide compelling evidence that lagged treatment is important (Table B11). Additionally, treatment did not affect any of the decision tasks (Table B12). This seems to suggest that the effects of noise do not persist into later periods of quiet; however, given that the experiment was not primarily focused on this question and power in these tests is low, future work should evaluate this question directly.

3.5 Conclusions from Experiment One

To interpret these magnitudes, it is helpful to compare them to other methods of improving productivity. In this experiment, doubling the piece rate from 5 Ksh to 10 Ksh while lowering the flat rate to compensate raised output by 3%.[19] This is consistent with other recent work showing small effects of piece rates on intensive margin effort provision. For example, DellaVigna and Pope (2018) finds an elasticity of 0.03, DellaVigna et al. (2016) finds an elasticity of 0.09, and Bessone et al. (2020) finds an elasticity of 0.025.

This suggests the importance of understanding other inputs to productivity other than intensive margin effort. Kaur et al. (2015) found that offering commitment contracts increased output by 2.3%. Bessone et al. (2020) finds naps relative to taking a break increased productivity by 6%. Finally, Bloom et al. (2013) found that a five-month intensive management intervention in an Indian textile firm increased output by 9%.

Another way to interpret the size of these effects is to consider how these estimates might affect firm noise-abatement decisions. Unfortunately, it is impossible to make any general claim about cost-effectiveness because abatement costs are highly context-specific. Costs can vary by orders of magnitude depending on the noise's source, the building structure, and the production processes (Hansen and Goelzer 2001). Nevertheless, one can consider

[18] The lagged treatment indicator is set to zero for the first session of each day.

[19] Table B13 presents the full results of the piece-rate variation. Increasing the piece rate from 5 Ksh to 15 Ksh had no effect on output. One explanation consistent with this evidence is that even though we attempted to calibrate the flat rates to compensate on average, income effects began to mitigate the piece rate's effectiveness as an incentive.

whether this effect is sufficiently large to be relevant to some firms' abatement decisions. In particular, Lahiri et al. (2011) report a case study of a large computer manufacturing firm in Singapore, where reducing the noise level by 23 dB cost the firm $156 per worker per year. Combining this cost with my estimate and assuming all productivity gains would translate into increased profits implies that this firm would break even on abatement if each worker produced $1,357 per year ($5 per day) in profit. For comparison, workers at this firm were paid $100 per day. This suggests that, at least for some firms, a 5% increase in productivity is sufficient to affect abatement decisions.

Additionally, these effects are as large or larger than other environmental pollutants studied in the literature (Table B10). This suggests that as policy makers consider priorities in managing the explosive urbanization and industrialization of the developing world, they should not neglect noise pollution. Even simple regulations such as limiting the volume of car horns can prevent a race to the bottom that imposes costly externalities.

One caveat is that these estimates are necessarily specific to the noise and task combination at hand. While both were chosen in order to be representative, extrapolating to other conditions should be done with caution. For example, the effects are likely to be much larger in settings where communication is required and may be inhibited by background noise.

4 Experiment Two: Noise and Cognitive Function

While the evidence from experiment one demonstrates the potential importance of noise pollution, it does not speak to the underlying mechanisms. Understanding wether noise reduced productivity by impairing cognitive function or by reducing effort is useful for three reasons. First, a significant new literature has argued that conditions associated with poverty may impede cognitive function (Schilbach et al. 2016). Understanding whether these impediments can significantly impact productivity by themselves is helpful in interpreting this broader literature. Second, if the impact is through reduced motivation rather than impaired task management skills, firms may be able to attenuate these effects through other means of improving worker motivation. Finally, understanding the mechanism provides guidance on how to extrapolate these effects to other tasks. If the effect operates through cognitive function rather than effort, we should expect to be the most similar on tasks that use the same levels of cognitive function. I use this second experiment to provide evidence on this question by exposing individuals from the same population to the same noise change, while having them complete assessments of cognitive function and a placebo effort task.

4.1 Design Overview

In order to examine the mechanisms in a credible way, I replicated the conditions of the first experiment as closely as possible. I used the exact same recruiting procedure to recruit 213 participants split across 12 rounds (see Table B1 for a comparison of sample demographics). These subjects were then invited to come to two similar rooms less than a mile away from the TDC (see Figure A1 for a map of the locations). In the experiment I again generated random schedules that assigned participants to spend half of their time in noise and half of their time in quiet, and kept the number of participants in each room equal for each session (though fewer per room this time because of a shortage of computers to run the assessments). Which room was noisy was also randomly assigned in the same way, by ensuring each room was noisy for half the sessions in each round. Additionally, as in the first experiment, workers were compensated by randomly assigned piece rate/flat rate combinations. Noise was generated by an engine similar to the one used in the first experiment, with the same precautions to avoid other environmental changes.

The main difference between the two experiments is in the timing. Due to logistical constraints, the timing was a condensed version of experiment one (see Figure 4). Instead of coming for ten days, subjects came for two days with three, two-hour sessions per day. They spent the first session learning how to complete the cognitive tests, after which they spent the remaining sessions working autonomously on the assessments being compensated based on their performance. For the second through fifth sessions, I randomly assigned each worker to spend half the sessions in noise and half in quiet. The final session was used to elicit participant's willingness to pay for quiet working conditions (see Table B15 for balance tests).

4.2 Assessments and Measurement

Because there is no consensus among cognitive psychologists about the most important measures of cognitive function and which are most likely to be relevant in this context, I used a wide variety of tasks drawn from Dean et al. (2017), summarized in Table B14 (see Appendix C for details). I programmed each task in an open-source, python-based platform developed by Mathôt et al. (2012). The order of the tasks was randomly chosen for each individual in each session. For each task, I developed a scoring rule that is a combination of the relevant outcome measures (e.g. percentage correct and reaction time). Participants were then paid based on their performance as measured by these scoring rules in combination with their randomly assigned piece rates.

For analysis, I aggregate these individual test results into an index. Because the literature

thus far does not provide guidance on the production function mapping cognitive function to productivity, my preferred index is the first factor of a common factor analysis of the percentage correct and reaction times estimated using each individual's first control session (see Cudeck (2000) and Grice (2001) for details). This data-driven method assumes that each measure m_{ij} of individual i on test j depends on cognitive function in the following linear relationship:

$$m_{ij} = b_j \psi_i + \Sigma_{ij} \tag{8}$$

where ψ_i is the cognitive function of individual i at time t, and Σ_{ij} is a noise term. The method uses an eigenvalue decomposition to construct a set of linearly-independent factors that approximate the measures' population covariance matrix. Assuming that all Σ_{ij} are independent of ψ_i and each other, any correlations between the measures can be attributed to the latent variable ψ_i. Thus, the first factor, which explains the most covariance, is an index of the only common factor ψ_i. For robustness, I also present the effects on the standardized total number of points that served as the basis of the participants' compensation[20], the average of the standardized point totals following Kling et al. (2007), and the first component of a principal component analysis estimated on the same control data with similar results.

4.3 Results

4.3.1 Main Cognitive Results

As in the first experiment, treatment did not affect any environmental characteristics besides the noise level in the room (Table 4). Moreover, the differences in average noise level between treatment and control were also quite similar to those in experiment one (Figure 5).[21] This is useful because it allows me to use these results to understand the mechanisms at work in the first experiment without strong functional form assumptions.

My preferred specification to estimate how noise affects cognitive function is the IV using an indicator for being in a treated room as an instrument. I estimate that doubling the perceived level of noise reduces performance on my preferred index by approximately 0.07σ (Table 5).[22] This change does not appear to be driven by any particular domain

[20]Subjects' actual compensation also depended on their randomly assigned piece rate per point.

[21]Specifically, Table 1 and Table 4 show the first stage in the first experiment is 6.7 dB(A) while in the second it's 9.4 dB(A). This difference is less than the 3 dB(A) threshold commonly accepted as the minimum change in sound level detectable by humans. It is perhaps surprising that 10 dB(A) is perceived as twice as loud, but 3 dB(A) is barely noticeable. This is due to the logarithmic nature of the decibel scale in combination with the operation of human hearing.

[22]The reduced-form effect of treatment, the IV using separate instruments for different treatment intensi-

(Table B19).[23] While this effect may seem small, it is important to recognize that the size of the standard deviation is primarily driven by across-person differences (the R^2 of a regression of the index on individual fixed effects is 0.81). This implies that even substantial within-person shifts will appear small because the measure captures size relative to differences between individuals.

While we should be cautious in comparing across experiments with different sets of assessments scored and aggregated in different ways, these effect sizes are broadly comparable to those induced by other cognitive impediments. For example, Lichand and Mani (2016) find that a rainfall shock reduces performance on an index of cognitive tests by 0.041 standard deviations. Similarly, Park (2017) finds that a one standard deviation increase in temperature reduces students' exam scores by 0.052 standard deviations. However, the effect is substantially smaller than the effects observed by Mani et al. (2013), who find that once-a-year payments from sugar cane harvests increase performance by 0.67 standard deviations.

4.3.2 Alternative Mechanisms

The first potential alternative mechanism is that the noise level affects the technology of the task. For example, if the task required coordination, the increased noise level would have likely reduced productivity by impairing communication. As mentioned above, the task in experiment one was chosen precisely because it does not require any kind of listening or communication to avoid this issue. I further attempted to reduce the potential that noise could affect the technology of the task by instructing participants in both conditions not to talk to each other, and I randomized seat assignments to avoid participants becoming friendly with their neighbors.

Another possible concern is that the noise level affected other inputs to an individual's performance; for example, by reducing motivation[24] or impairing motor coordination. To assess this possibility, participants in experiment two completed a placebo task, used by DellaVigna and Pope (2018) to measure effort, where respondents had to alternate between pressing the "a" and "b" keys on a keyboard for 10 minutes.[25] This task imposes as minimal

ties, and Fisher p-values presented in Table B16, Table B17 and Table B18 yield similar inferences.

[23]This does not appear to be due to floor or ceiling effects, as most metrics generate good variation (Figure A8).

[24]There are many reasons this might be the case. For example, one might think respondents are resentful of the noise and decide to retaliate by reducing output. Alternatively, respondents might become discouraged by struggling to perform in noise.

[25]One might be concerned about the relative precision of this task measure since it is a small fraction of the total time. One way to assess this concern is to look at the within test correlation. If early performance strongly predicts the final result, then we should be less concerned that the time is too short. A regression of the final score on this effort task on the number of alterations completed at the halfway point yields an R^2 of 0.9.

of a demand on cognitive function as possible while still requiring the other inputs needed for the sewing task like motivation and physical coordination. The results presented in Table 5 show that effort did not change in response to the increase in noise. The point estimate suggests that doubling the noise level *increases* the number of key presses by 1.9 relative to a control mean of 2192, and a decrease in effort larger than 1.4% is outside of the 95% confidence interval. This level of precision is sufficient to reject many of the effects on this task found by DellaVigna and Pope (2018). For example, they find delaying payment by two weeks decreases key presses by 1.7%, a probability weighting manipulation increases key presses by 4%, and increasing the piece rate from 1 cent per 100 presses to 4 cents increases key presses by 5%. This lack of effort response is also consistent with the results of the first experiment, where being in noise did not reduce respondents' willingness to stay and work an additional hour for a piece rate (see Table B12).

4.3.3 Implied Importance of Cognitive Function for Productivity

If cognitive function is indeed the only channel through which noise affects productivity, the combined results of the experiments suggest cognitive function is an important input to productivity on this task. A relatively modest-sized, temporary shift in cognitive function is responsible for an economically significant decrease in productivity. While the importance of cognitive function to productivity varies from task to task, this implies policy makers should take other environmental factors shown to inhibit these abilities seriously.

To illustrate, it's useful to do some back-of-the-envelope calculations of what these results imply for how large the potential consequences of these other impediments might be. Suppose there was a single "return to cognitive function" parameter in the production function. If this parameter existed, and we were comfortable assuming the only effect of noise on productivity happens through cognitive function, it could be estimated with the ratio of the treatment effect on productivity to the effect on cognitive function in a split-sample IV (Angrist and Krueger 1992). In particular, for total pockets, this ratio would suggest a 79% change in productivity for every one standard deviation change in my measure of cognitive function.

5 Sorting and Efficiency

5.1 Motivation and Strategy

The combined evidence of my two experiments suggests that noise can have important impacts on productivity by impeding cognitive function; however, this is not sufficient to conclude that the effects are relevant outside of an experimental setting. Whether workers

will respond to their decreased productivity by either sorting into sectors where they are more productive, or by demanding additional compensation, depends on whether workers are aware of the impacts noise has on their productivity.

Measuring individuals' awareness of the impacts of noise also provides an opportunity to contribute evidence on the more general question of whether individuals act strategically to protect their cognitive function from environmental impediments. Without understanding this level of sophistication, it's difficult to assess the economic implications of controlled experiments demonstrating the effects of environmental stimuli associated with poverty (see Dean et al. (2017) for an overview). If individuals are generally aware of what situations impair their productivity or decision-making, the substantial effects observed in controlled experiments might be significantly attenuated by adaptation in the real-world. On the other hand, if individuals do not understand these effects, they might cause significant inefficiencies.

I assess awareness by offering participants at the end of both experiments the chance to pay for quiet working conditions and randomly vary whether their compensation will depend on their performance. Specifically, workers in the non-performance pay condition of both experiments were paid 200 Ksh for the session while workers in the piece-rate condition were paid 15 Ksh per perfect pocket in the first experiment and 4 Ksh per point in the second in addition to flat rates calibrated to yield total pay of approximately 200 Ksh.[26] If participants are aware that noise reduces productivity, they should be more willing to pay for quiet when they will recoup a portion of the investment through increased performance pay. For example, the median worker in my study can produce 18 perfect pockets in quiet during these sessions. If they realize working in noisy conditions will reduce their productivity by 3%, when they are facing a 15 Ksh piece rate they should be willing to pay 8 Ksh more to work in quiet than when facing a pure flat rate.

5.2 Elicitation Procedure

I elicit willingness to pay for quiet working conditions with a modified version of Becker et al. (1964) following the approach of Berry et al. (2015) as outlined in Figure A9 using the script in Appendix D. In this incentive-compatible task, respondents state the maximum that they are willing to pay for a good, after which a random price is drawn. If the price is below the respondent's willingness to pay, he/she purchases the good at the random price, and if the price is above the willingness to pay, the respondent does not purchase the good.

[26] In the first experiment, for each of the two days over which WTP was elicited, one of the two sessions was chosen for the worker to be compensated by 15 Ksh piece rate, flat rate combination while the other was compensated by a pure 200 Ksh flat rate. For logistical simplicity, in the second experiment individuals have their willingness to pay elicited for a single session under the possibilities of being paid a piece rate based on their score and a 200 Ksh flat rate. They are told that one of their choices will be randomly implemented.

I begin with a slight modification to the procedure by employing a binary search over the range 0-200 Ksh to identify the respondent's maximum willingness to pay rather than beginning by asking the open-ended question, "How much is the most you're willing to pay?".[27] This procedure makes the task as concrete as possible, avoids the respondent needing to engage in contingent resoning and narrows to a final number in only eight questions. In order to ensure understanding, after finalizing a maximum willingness to pay, respondents must correctly answer verification questions, and they practice the entire procedure for a lollipop. I also avoid potential issues with credit constraints, time preferences and compliance by deducting any charges from respondents' earnings in the session where they paid to be in quiet.

This elicitation procedure appears to work well in this context. In this sample, in spite of the multiple opportunities, almost no respondents ever change their willingness to pay after the binary search (fewer than 2% of respondents in the first experiment and zero respondents in the second). Additionally, the practice exercise elicits a sensible demand curve for the lollipops. Median WTP is around 5 Ksh ($0.05) in the first experiment and 10 Ksh ($0.10) in the second, and the means are 9.4 Ksh and 9.6 Ksh respectively.

Subsequent work in the same context provides further evidence of comprehension. Berkouwer and Dean (2019) use the same elicitation method and script with a sample of 1000 low-income households in Nairobi. In that sample, the mechanism is evaluated by randomizing which of two consumer goods will be used to practice the BDM at the respondent level. The good not chosen is then offered at a randomly chosen take it or leave it price. Figure A10 shows the demand curves are strikingly similar across the two different methods of elicitation and give reasonable values given the market prices of the goods. Moreover, 97% of those respondents answer two comprehension checks correctly providing further confidence in the results.

5.3 Willingness to Pay Results

The histograms presented in Figure A11 demonstrate that willingness to pay for quiet is extremely low, even before trying to separate the willingness due to productivity concerns from that due to disutility. The median willingness to pay is only 2 Ksh ($0.02) in the first experiment and 0 Ksh in the second experiment. These low levels of willingness to pay provides some assurance that workers do not appreciate the impact of noise in addition to

[27] For example, the respondent is first asked "If the random price is 100 Ksh would you want to pay to work in quiet?" If they respond no, they are then asked "If the random price is 50 Ksh would you be willing to pay to work in quiet?" If they respond no again, they're asked about a random price of 25 Ksh and so on until the search narrows to a single number.

the test using the random variation in the compensation scheme.

Nonetheless, it is possible that individuals are at least partially aware of the productivity effect and are willing to pay more for quiet when facing a piece rate. To test this possibility, I regress the level of willingness to pay, an indicator for being willing to pay a positive amount, and the level of willingness to pay after restricting to strictly positive amounts on an indicator for whether the respondent was offered a piece rate or a flat rate with standard errors clustered at the individual level.[28] Willingness to pay is essentially non-responsive to the piece rate, with any increase greater than 3.5 Ksh lying outside of the 95% confidence interval (Table 7). For comparison, the median level of productivity from the piece-rate compensated individuals in the quiet room on those days is 18 pockets, combined with the reduced form effect of a 3% decrease in productivity and a piece rate of 15 Ksh, the respondent's break-even willingness to pay should be around 8 Ksh.

There are several possible explanations for this lack of response. The first is that for many individuals the effect of noise is relatively small, so they may not notice it, or I may not be powered to detect their responses. I assess this possibility by estimating how much more each individual is likely to earn in the quiet working conditions and testing whether those with the most to gain are responsive to the wage structure. To do so, I estimate individual-level treatment effects using the following hierarchical linear model:

$$y_{it} = \rho_i + \tau_i \text{treatment}_{it} + \phi_i \text{session}_t + \beta \text{session}_t^2 + \epsilon_{it} \tag{9}$$

$$\begin{bmatrix} \rho_i \\ \tau_i \\ \phi_i \\ \mathbf{\Sigma}_i \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_\rho \\ \mu_\tau \\ \mu_\phi \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \sigma_\rho^2 & \sigma_{\rho\tau} & \sigma_{\rho\phi} & \mathbf{0} \\ \sigma_{\tau\rho} & \sigma_\tau^2 & \sigma_{\tau\phi} & \mathbf{0} \\ \sigma_{\phi\rho} & \sigma_{\phi\tau} & \sigma_\phi^2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \sigma_\epsilon^2 \mathbf{I}_t \end{bmatrix} \right)$$

In principle, instead of using this model to estimate the within-person treatment effect, one could take the simple difference between treatment and control performance within an individual. However, because I have few observations for each individual, this would lead to imprecise estimates. Imprecision is especially concerning in this context because the hypothesis of interest is whether the interaction between the wage condition and an individual's value of quiet is zero and including an imprecisely-estimated, right-hand-side variable would create attenuation bias. The hierarchical model yields more precise individual estimates by engaging in partial pooling. This is analogous to the approach used by Chetty

[28] Willingness to pay after restricting to only positive amounts is a potentially problematic outcome because it involves selecting the sample on the dependent variable; however, in this case, the specification serves to show that the subsample does not behave differently than the complete sample.

et al. (2014) and Kane and Staiger (2008) to evaluate a teacher's value added. Figure A13 shows that the model appears to fit the data well and strongly predicts the out-of-sample, realized outcomes in the willingness-to-pay sessions. To improve the interpretability of these estimates, I multiply the estimated change in productivity induced by noisy conditions by the piece rate to yield a monetary value of quiet working conditions for each individual. The distribution of estimated productive values of quiet shown in Figure A12 has significant mass beyond the 95% confidence interval of the response to the piece rate estimated above.[29]

To test for differential responses among those for whom quiet is most valuable, I re-estimate the willingness to pay regressions while interacting the individual-level estimates of the value of quiet with an indicator for being compensated with a piece rate. If individuals for whom quiet is most valuable respond more to the piece rate, the effect should manifest itself in the interaction term. Table 8 shows this is not the case. In particular, consider the benchmark case of perfectly rational, risk-neutral individuals who understand how noise affects their productivity. For these individuals, if the prediction were perfect, the interaction term should be one as switching to performance pay should increase their maximum willingness to pay by the additional amount that they will earn through increased productivity.[30] I can reject this benchmark for both experiment one and experiment two at the 10% and 5% confidence levels, respectively.[31]

Another potential explanation for this lack of response is that the possible productive gains from quiet are not "top-of-mind" for the participants so they do not consider it when making their decisions. To assess this possibility, in experiment two I elicited respondents' beliefs about their future scores if they worked in quiet and if they worked in noise following Delavande (2014). Specifically, respondents were asked to distribute ten beans across the ten bins of possible scores for each of the four possible compensation scheme and noise level combinations. Half of the respondents were randomly chosen to provide their beliefs before stating their willingness to pay, while the other half provided their beliefs afterward. If the lack of demand response is due to this simple form of inattention, then those who were forced to think through their beliefs before stating their willingness to pay should be more responsive to the piece rate. The results shown in Table 9 show that this is not the case. I

[29]It is worth noting that these estimates suggest some subjects are more productive in noise. This is possible, however, it is also possible that this is the result of insufficient observations per subject.

[30]Note that if some individuals are actually more productive in noise, we would no longer expect the coefficient to be one because individuals cannot pay less than zero. This is a potential concern for experiment two, although it is still a useful benchmark.

[31]Note that this is not the case simply because those affected by noise are generally unproductive (and thus are not concerned with the compensation scheme). The model predicts that the treatment effect is in fact more negative for those that are more productive (with a correlation coefficient of -0.52). Thus, if anything, they should care more because they both stand to lose more in a proportional sense and because this proportional loss translates into a greater monetary loss due to their greater productivity.

can reject a positive response at the 5% confidence level for the level of willingness to pay and at the 10% level for the extensive margin of being willing to pay anything.

A final possibility is that individuals have incorrect or imprecise beliefs about the impact that noise will have on their productivity. I test for this possibility using the means of the belief distributions collected in experiment two. The results are presented in Table 10. Columns 1 and 2 test whether beliefs are at least correct on average by comparing the predictive power of the mean of a respondent's relevant belief distribution to the predictive power of the model's predictions. While individuals' beliefs are reasonably predictive, they are significantly outperformed by the model. In column 3, I then compare what the data predicts an individual's income gain from working in quiet would be to what the participant predicted and find that they are essentially unrelated, suggesting individuals hold incorrect beliefs about the impact of noise on their productivity. This then raises the natural question of whether individuals were deciding their willingness to pay based on their incorrect beliefs. I test this possibility in columns 4-6 by interacting respondents' predictions of their income gain from quiet with the piece-rate indicator. I find that even those who stated that they believe they are more productive in quiet do not respond to the piece rate.[32] I can reject the benchmark case of increasing their willingness to pay one-for-one with their stated beliefs about the value of quiet at the less than 1% confidence level. Thus, the workers both had very little concept of how noise affects their productivity and, to the extent that they were willing to express beliefs, they were not willing to stake any money on those beliefs being correct.

One explanation consistent with this evidence is that respondents failed to notice the impact that noise has on their productivity (Hanna et al. 2014; Schwartzstein 2014). In this model individuals are Bayesians with two-level hierarchical beliefs about their productivity. At the higher level, individuals decide which variables to notice. Subsequently, at the lower level, individuals form beliefs about the productive impact of the variables that they noticed. The key feature of the model is that when a variable is unobserved, individuals do not attempt to infer its missing value and instead assume it to be constant. In this model, if workers fail to attend to noise, they will still have reasonably accurate beliefs about their ability, but their beliefs about the impact noise has on their productivity will be wrong. Moreover, individuals will realize that they do not understand the impact that noise has on their productivity, and they will be unwilling to stake any money on their stated beliefs. This is consistent with the pattern of effects described above.[33]

[32] Experiment one's belief data is not as detailed but is consistent with these findings (Table B20).

[33] Additionally, respondents' stated beliefs are suspiciously similar to their stated levels of annoyance (see Figure A14). This is what we would expect in a world where respondents do not understand the impact that noise has on their productivity, and instead provide something that they do understand, namely how

As with the main results, it is important to note these results may be specific to the setting. For example, in another task that requires communication, having difficulty hearing a coworker may prompt some workers to notice the effects of noise. Additionally, given that the noise levels in both rooms are less than a typical factory for ethical reasons, it's possible workers did not see the need to reduce the noise level further. A final possibility is that given more time, workers would form correct beliefs about the effects of noise on their productivity. Productivity is a relatively random outcome and it may simply be difficult for respondents to infer treatment effects over the time period of the experiment. However, in other ways the experiment is an ideal learning environment. Respondents complete the exact same task with minimal other changes to their environment besides variation in the noise level in quick succession. Given that they do not learn in this setting of experimental variation, there is reason for caution in hoping that they will learn in the real world even though their time in the experiment was relatively short. Moreover, because the sample is used to working in noisy settings, they are not beginning to learn the effects completely from scratch in the experiment. This experience should aid the learning process unless a large component of the effect of noise is task specific. If that is the case, however, we should also be skeptical that workers are sorting efficiently because learning would require extended exposure to each possible task with varying levels of noise, which seems unlikely to occur.

5.4 Efficiency Implications

As discussed in the conceptual framework, if piece-rate workers neglect the impact of noise on their productivity they will be too willing to work in noisy jobs and fail to demand additional compensation for the decrease in productivity induced by the work environment. Additionally, depending on the correlation between the disutility of noise and its productive impacts, the composition of workers sorting into the noisy sector may deviate from the efficient allocation. This sorting is particularly important because the costs of noise abatement are known to be highly heterogeneous, as are the productive effects I estimate.

To obtain an estimate of this correlation, I compare how much subjects were willing to pay for quiet when they were not being compensated based on their performance (a measure of disutility) and the estimated within-person treatment effects. Figure A15 shows the joint density of the two variables. At least in this experiment, with these measures, disutility and productivity losses appear to be unrelated. This suggests that the composition of workers sorting into noisy work environments could be significantly altered by workers neglecting the productive impact of noise.

annoying they find noise.

More generally, many of the cognitive impediments studied in the literature have both productivity and disutility components. For example, it is unpleasant to be hot and high temperatures also reduce productivity. This exercise demonstrates that in order to understand the efficiency implications of these impediments, it is important to understand the joint distribution of workplace amenities and cognitive impediments, and how workers attend to each aspect.

An additional important determinant of the welfare consequences of these results is whether firms are aware of the effects of noise and optimally abate. While assessing the degree to which this is true is beyond the scope of this paper, there are at least two reasons to be concerned this may not be the case. First, Bloom et al. (2013) demonstrates that even seemingly obvious management practices, such as sorting thread by color, is neglected by some major textile manufactures. Second, noise levels do not typically vary exogenously which makes it a difficult task for managers to infer the causal effect and adjust appropriately. Future work should assess the degree to which this is true.

6 Conclusion

This paper presents evidence that an increase of 10 dB inhibits cognitive function, but not effort, and that this results in a decrease in productivity of approximately 5%. Individuals do not seem to be aware of these effects, and those most affected are not the same as those who are the most irritated by noise. Together these results demonstrate there may be inefficiencies in the labor market surrounding noisy work environments. Workers may fail to either sort into quieter locations where they are more productive or demand additional compensation per unit of output. The composition of workers sorting into noisy occupations may deviate from the efficient optimum.

Beyond the labor market effects, these results also raise concerns about the impact of noise pollution more generally. As the developing world continues to become more urban and wealthy, noise pollution is destined to spread even further. Between 2001 and 2015, the number of cars per person in India tripled, and this growth shows no signs of slowing (Government of India 2017). While this should be celebrated as a sign of progress, it will undoubtedly bring with it even more noise pollution. The results in this paper suggest this is a potential policy problem that warrants both further research and policy makers' attention.

While eliminating noise pollution is likely an unrealistic goal, there are steps that governments can take to mitigate the problem. First, governments can follow the lead of the European Union and collect comprehensive data on noise exposure. The current state of data requires researchers and policy makers to rely on proxies, data from specific locations,

and a general sense of "loudness". Being able to quantify exposures and understand the types of people who are exposed would be a significant step forward. Second, many sources of urban noise stem from competition to be heard. For example, there is no intrinsic need for extra-loud car horns; rather, they are needed because other drivers have loud car horns. This creates an inefficient race to the bottom. Regulating these sources could likely reduce noise levels without incurring any significant efficiency costs. Finally, governments can try to raise awareness among workers and firms about the potential effects of noise on productivity. If the failure to respond to incentives is actually due to a failure to notice, calling attention to this problem is likely a way to improve outcomes at a minimal cost.

More generally, these results suggest that policy makers should take the impact that cognitive impediments can have on economic outcomes seriously. If the effect of cognitive function on productivity is as large as it seems to be, then policies and environments that tax the poor's cognitive resources may have serious economic costs. Moreover, if individuals' apparent lack of awareness of the impact of noise generalizes to other impediments, this suggests the potential for significant inefficiencies. Future research should provide estimates of these costs and how policies can be designed that account for these cognitive constraints.

References

Abadie, Alberto, Matthew M. Chingos, and Martin R. West. 2014. "Endogenous Stratification in Randomized Experiments". NBER Working Paper No. 19742.

Abdel-Salam, Mahmoud M. M. 2015. "Investigation of PM2.5 and Carbon Dioxide Levels in Urban Homes". *Journal of the Air and Waste Management Association* 65 (8): 930–936.

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2016a. "Management and Shocks to Worker Productivity". *Working Paper*.

— . 2016b. "The Light and the Heat: Productivity Co-benefits of Energy-saving Technology". Mimeo.

Angrist, Joshua D., and Alan B. Krueger. 1992. "The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables with Moments from Two Samples". *Journal of the American Statistical Association* 87 (418): 328–336.

Bailey, Charles E. 2007. "Cognitive Accuracy and Intelligent Executive Function in the Brain and in Business". *Annals of the New York Academy of Sciences* 1118:122–141.

Basner, Mathias, and David F. Dinges. 2011. "Maximizing Sensitivty of the PVT to Sleep Loss". *Sleep* 34 (5): 581–591.

Bates, Marsha E., and Edward P. Lemay Jr. 2004. "The d2 Test of Attention: Construct Validity and Extensions in Scoring Techniques". *Journal of the International Neuropsychological Society* 10:392–400.

Becker, Gordon M., Morris H. DeGroot, and Jacob Marschak. 1964. "Measuring Utility by a Single-Response Sequential Method". *Systems Research and Behavioral Science* 9 (3): 226–232.

Berkouwer, Susanna B., and Joshua T. Dean. 2019. "Credit and attention in the adoption of profitable energy efficient technologies in Kenya". Mimeo.

Berry, James, Greg Fischer, and Raymond Guiteras. 2015. *Supplementary Materials to Eliciting and Utilizing Willingness to Pay: Evidence from Field Trials in Northern Ghana*. Mimeo.

Berube, Alan, Jesus Leal Trujillo, Tao Ran, and Joseph Parilla. 2014. *Global Metro Monitor*. Tech. rep. Brookings Institution.

Bessone, Pedro, Gautam Rao, Frank Schilbach, Heather Schofield, and Mattie Toma. 2020. "The Economic Consequences of Increasing Sleep Among the Urban Poor". *Mimeo*.

Bessone, Pedro, Heather Schofield, and Mattie Toma. 2019. "Sleepless in Chennai: The Consequences of Increasing Sleep among the Urban Poor". *Working Paper*.

Bhosale, B. J., Amul Late, P. M. Nalawade, S. P. Chavan, and M. B. Mule. 2010. "Studies on Assessment of Traffic Noise Level in Aurangabad city, India". *Noise and Health* 12 (48): 195–198.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David Mckenzie, and John Roberts. 2013. "Does Management Matter? Evidence from India". *The Quarterly Journal of Economics* 128 (1): 1–51.

Borella, Erika, Barbara Carretti, and Santiago Pelegrina. 2010. "The Specific Role of Inhibition in Reading Comprehension in Good and Poor Comprehenders". *Journal of Learning Disabilities* 43 (6): 541–552.

Brickenkamp, Rolf, and Eric Zillmer. 1998. *The d2 Test of Attention*. Seattle, Washington: Hogrefe & Huber.

Broadbent, D. E., and E. A. J. Little. 1960. "Effects of Noise Reduction in a Work Situation". *Occupational Psychology* 34:133–140.

Bronzaft, Arline L. 2002. "Noise Pollution: A Hazard to Physical and Mental Well-being". Chap. 32 in *Handbook of Environmental Psychology.* Ed. by Robert B. Bechtel and Arza Churchman, 499–510. New York, NY: John Wiley & Sons, Inc.

Brunetti, Riccardo, Claudia Del Gatto, and Franco Delogu. 2014. "eCorsi: Implementation and Testing of the Corsi Block-tapping Task for Digital Tablets". *Frontiers in Psychology* 5:1–8.

Burbidge, John B., Lonnie Magee, and A. Leslie Robb. 1988. "Alternative Transformations to Handle Extreme Values of the Dependent Variable". *Journal of the American Statistical Association* 83 (401): 123–127.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016a. "Particulate Pollution and the Productivity of Pear Packers". *American Economic Journal: Economic Policy* 8 (3): 141–169.

— . 2016b. "The Effect of Pollution on Worker Productivity: Evidence from Call-Center Workers in China". NBER Working Paper No. 22328.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014. "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates". *The American Economic Review* 104 (9): 2593–2632.

Crescioni, A. Will, Joyce Ehrlinger, Jessica L. Alquist, Kyle E. Conlon, Roy F. Baumeister, Christopher Schatschneider, and Gareth R. Dutton. 2011. "High Trait Self-control Predicts Positive Health Behaviors and Success in Weight Loss". *Journal of Health Psychology* 16 (5): 750–759.

Cudeck, Robert. 2000. "Exploratory Factor Analysis". Chap. 10 in *Handbook of Applied Multivariate Statistics and Mathematical Modeling*, ed. by Howard E. A. Tinsley and Steven D. Brown, 265–296. Academic Press.

Davidson, Matthew C., Dima Amso, Loren Cruess Anderson, and Adele Diamond. 2006. "Development of Cognitive Control and Executive Functions from 4 to 13 Years: Evidence from Manipulations of Memory, Inhibition and Task Switching". *Neuropsychologia* 44 (11): 2037–2078.

Dean, Emma Boswell, Frank Schilbach, and Heather Schofield. 2017. "Poverty and Cognitive Function". In *The Economics of Asset Accumulation and Poverty Traps*, ed. by Christopher B. Barrett, Michael R. Carter, and Jean-Paul Chavas. University of Chicago Press.

Delavande, Adeline. 2014. "Probabilistic Expectations in Developing Countries". *Annual Review of Economics* 6 (1): 1–20.

DellaVigna, Stefano, John A. List, Ulrike Malmendier, and Gautam Rao. 2016. "Estimating social preferences and gift exchange at work". *NBER Working Paper Series* 53 (9): 1689–1699. arXiv: `arXiv:1011.1669v3`.

DellaVigna, Stefano, and Devin Pope. 2018. "What Motivates Effort? Evidence and Expert Forecasts". *The Review of Economic Studies* 85 (2): 1029–1069.

Denison, Edward F. 1978. "Effects of Selected Changes in the Institutional and Human Environment Upon Output Per Unit of Input". *Survey of Current Business* 58 (1): 21–43.

Diamond, Adele. 2013. "Executive Functions". *Annual Review of Psychology* 64:135–68.

Duncan, Greg J., Chantelle J. Dowsett, Amy Claessens, Katherine Magnuson, Aletha C. Huston, Pamela Klebanov, Linda S. Pagani, Leon Feinstein, Mimi Engel, Jeanne Brooks-Gunn, Holly Sexton, Kathryn Duckworth, and Crista Japel. 2007. "School Readiness and Later Achievement." *Developmental Psychology* 43 (6): 1428–1446.

Evans, Gary W., and Staffan Hygge. 2007. "Noise and Cognitive Performance in Children and Adults". Chap. 25 in *Noise and its Effects*, ed. by Linda M. Luxon and Deepak Prasher, 549–566. West Sussex, England: John Wiley & Sons, Ltd.

Gathercole, Susan E., Susan J. Pickering, Camilla Knight, and Zoe Stegmann. 2004. "Working Memory Skills and Educational Attainment: Evidence from National Curriculum Assessments at 7 and 14 Years of Age". *Applied Cognitive Psychology* 18 (1): 1–16.

Goldsmith, Mike. 2012. *Discord: The Story of Noise*. Oxford: Oxford University Press.

Government of India. 2017. *Registered Motor Vehicles per 1000 Population from 2001 to 2015*.

Grant, David A., and Esta A. Berg. 1946. "A Behavioral Analysis of Degree of Reinforcement and Ease of Shifting to New Responses in a Weigl-Type Card-Sorting Problem". *Journal of Experimental Psychology* 38 (4): 404–411.

Gray, Wayne B. 1987. "The Cost of Regulation: OSHA, EPA and the Productivity Slowdown". *The American Economic Review* 77 (5): 998–1006.

Grice, James W. 2001. "Computing and Evaluating Factor Scores". *Psychological Methods* 6 (4): 430–450.

Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein. 2014. "Learning Through Noticing: Theory and Evidence from A Field Experiment". *The Quarterly Journal of Economics* 129 (3): 1311–1353.

Hansen, Colin H., and Berenice I. F. Goelzer. 2001. "Engineering Noise Control". Chap. 10 in *Occupational Exposure to Noise: Evaluation, Prevention and Control*, ed. by Berenice I.F. Goelzer, Colin H. Hansen, and Gustav A. Sehrndt. World Health Organization.

Haushofer, Johannes, and Ernst Fehr. 2014. "On the Psychology of Poverty". *Science* 344 (6186): 862–867.

He, Jiaxiu, Haoming Liu, and Alberto Salvo. 2019. "Severe Air Pollution and Labor Productivity : Evidence from Industrial Towns in China". *American Economic Journal: Applied Economics* 11 (1): 173–201.

Hockey, G. Robert J. 1970. "Effect of Loud Noise on Attentional Selectivity". *Quarterly Journal of Experimental Psychology* 22 (1): 28–36.

Imbens, Guido W., and Donald B. Rubin. 2015. *Causal Inference in Statistics, Social and Biomedical Sciences: An Introduction*. New York, NY: Cambridge University Press.

Johnson, Karoline K., Michael H. Bergin, Armistead G. Russell, and Gayle S. W. Hagler. 2016. "Using Low Cost Sensors to Measure Ambient Particulate Matter Concentrations and On-Road Emissions Factors". *Atmospheric Measurement Techniques Discussions*.

Jones, Dylan M., and Donald E. Broadbent. 1991. "Human Performance and Noise". Chap. 24 in *Handbook of Acoustical Measurements and Noise Control*, ed. by Cyril Harris, 24.1–24.24. McGraw-Hill.

Kane, Thomas J., and Douglas O. Staiger. 2008. "Estimating Teacher Impacts on Student Achievement: An Experimental Evaluation". NBER Working Paper No. 14607.

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

Kaur, Supreet, Sendhil Mullainathan, Suanna Oh, and Frank Schilbach. 2019. "Does Financial Strain Lower Productivity?" *Working Paper*.

Kimani, John Muturu. 2011. "Evaluation of Occupational Noise Exposure Among Workers in Metal Fabricating Sector in Kamukunji Nairobi". PhD thesis, Jomo Kenyatta University of Agriculture and Technology.

Kling, Jeffery R., Jefferey B. Liebman, and Lawrence F. Katz. 2007. "Experimental Analysis of Neighborhood Effects". *Econometrica* 75 (1): 83–119.

Kremer, Michael, Gautam Rao, and Frank Schilbach. 2019. "Behavioral Development Economics". Chap. 5 in *Handbook of Behavioral Economics - Foundations and Applications, Volume 2*, ed. by B. Douglas Bernheim, Stefano DellaVigna, and David Laibson. North Holland.

Lahiri, Supriya, Colleen Low, and Michael Barry. 2011. "A Business Case Evaluation of Workplace Engineering Noise Control". *Journal of Occupational and Environmental Medicine* 53 (3): 329–337.

Levy-Leboyer, C. 1989. "Noise Effects on Two Industrial Tasks". *Work and Stress* 3 (4): 315–322.

Lichand, Guilherme, and Anandi Mani. 2016. "Cognitive Droughts". Mimeo.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao. 2013. "Poverty Impedes Cognitive Function". *Science* 341 (6149): 976–80.

Mathôt, Sebastiaan, Daniel Schreij, and Jan Theeuwes. 2012. "OpenSesame: An Open-source, Graphical Experiment Builder for the Social Sciences." *Behavior Research Methods* 44 (2): 314–24.

Matthews, Gerald, D. Roy Davies, Stephen J. Westerman, and Rob B. Stammers. 2000a. *Human Performance: Cognition, Stress and Individual Differences*. Philadelphia, PA: Taylor & Francis.

— . 2000b. "Noise and Irrelevant Speech". Chap. 10 in *Human Performance: Cognition, Stress and Individual Differences*, 177–192. Philadelphia, PA: Psychology Press.

Mehdi, Mohammed Raza, Minho Kim, Jeong Chang Seong, and Mudassar Hassan Arsalan. 2011. "Spatio-temporal Patterns of Road Traffic Noise Pollution in Karachi, Pakistan". *Environment International* 37 (1): 97–104.

Mimi. 2017. *The World Hearing Index*.

Nandi, Subroto S., and Sarang V. Dhatrak. 2008. "Occupational Noise-Induced Hearing Loss in India". *Indian Journal of Occupational & Environmental Medicine* 12 (3): 53–56.

Navrud, Stale. 2002. *The State-Of-The-Art on Economic Valuation of Noise*. Tech. rep. European Commission DG Environment.

Nisbett, Richard E., and Timothy DeCamp Wilson. 1977. "Telling more than we can know: Verbal reports on mental processes". *Psychological Review* 84 (3): 231–259. arXiv: `arXiv:1011.1669v3`.

Operation Ear Drop. 2010. *The RBA-OED Kenya Jua Kali Hearing Conservation*.

Park, Jisung. 2017. "Temperature, Test Scores, and Human Capital Production". Mimeo.

Raven, John. 2000. "The Raven's Progressive Matrices: Change and Stability over Culture and Time". *Cognitive Psychology* 41 (1): 1–48.

Rosen, Sherwin. 1986. "The Theory of Equalizing Differences". Chap. 12 in *Handbook of Labor Economics*, ed. by Orley Ashenfelter and Richard Layard, 1:641–692. Elsevier Science B.V.

Schilbach, Frank. 2017. "Alcohol and Self-Control: A Field Experiment in India". Mimeo.

Schilbach, Frank, Heather Schofield, and Sendhil Mullainathan. 2016. "The Psychological Lives of the Poor". *American Economic Review: Papers and Proceedings* 106 (5): 435–440.

Schofield, Heather. 2014. "The Economic Costs of Low Caloric Intake: Evidence from India". Mimeo.

Schwartzstein, Joshua. 2014. "Selective Attention and Learning". *Journal of the European Economic Association* 12 (6): 1423–1452.

Smith, Andrew. 1989. "A Review of the Effects of Noise on Human Performance". *Scandinavian Journal of Psychology* 30 (3): 185–206.

Stoet, Gijsbert. 2017. "PsyToolkit: A Novel Web-Based Method for Running Online Questionnaires and Reaction-Time Experiments". *Teaching of Psychology* 44 (1): 24–31.

— . 2010. "PsyToolkit: A Software Package for Programming Psychological Experiments using Linux". *Behavior Research Methods* 42 (4): 1096–1104.

Szalma, James L., and Peter A. Hancock. 2011. "Noise Effects on Human Performance: A Meta-analytic Synthesis". *Psychological Bulletin* 137 (4): 682–707.

United States National Archives and Records Administration. 2017. *Constitution of the United States - A History*.

Wawa, Enock Abe, and Galcano Canny Mulaku. 2015. "Noise Pollution Mapping Using GIS in Nairobi, Kenya". *Journal of Geographic Information System* 7 (5): 486–493.

Weston, H. C., and S. Adams. 1935. "The Performance of Weavers Under Varying Conditions of Noise". In *Industrial Health Research Board Report*, vol. 70. London: HMSO.

Wilhelm, Oliver, Andrea Hildebrandt, and Klaus Oberauer. 2013. "What is Working Memory Capacity, and How Can We Measure It?" *Frontiers in Psychology* 4 (443).

Zivin, Joshua Graff, and Matthew J. Neidell. 2012. "The Impact of Pollution on Worker Productivity". *American Economic Review* 102 (7): 3652–3673.

Figures

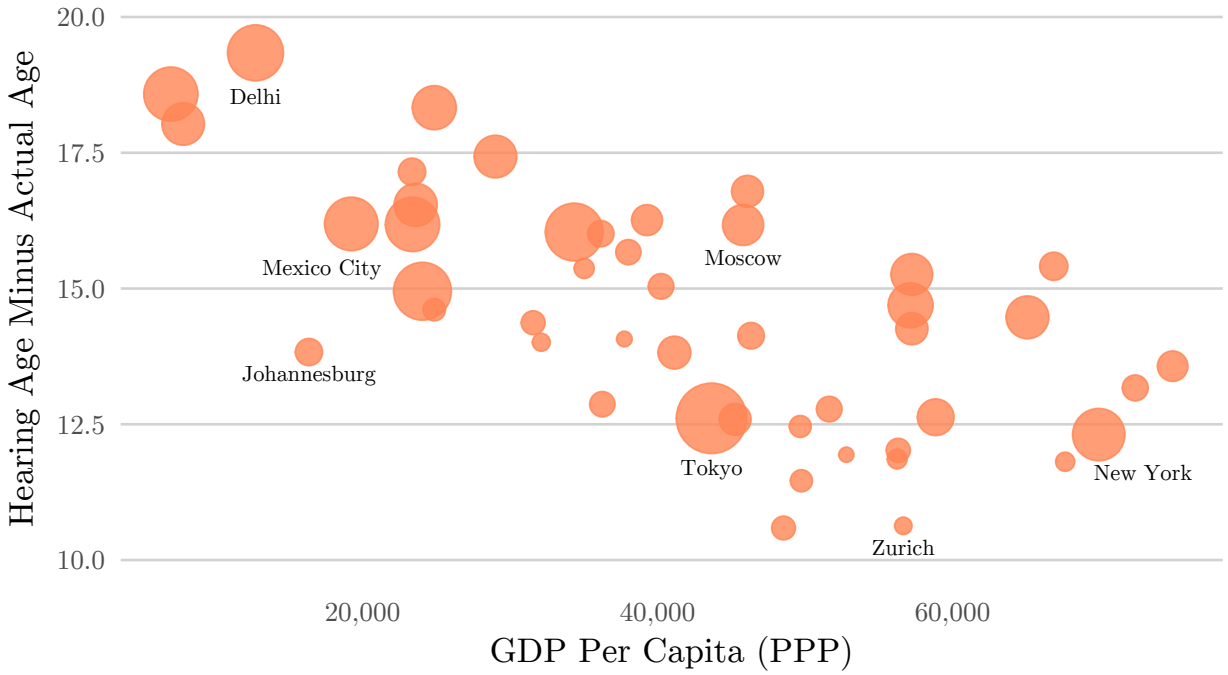


Figure 1: Average Hearing Loss in Cities by Income

Note: This figure shows the relationship between hearing loss and income at a city level. The y-axis plots years of hearing loss in excess of what would be expected based solely on age as measured by Mimi (2017). The x-axis plots the city's income per capita as estimated by Berube et al. (2014). The size of each circle is proportional to the population of each city. In the absence of representative data on noise levels, the relationship between hearing loss and income provides evidence that those in poorer cities are exposed to more noise than those in comparable richer cities.

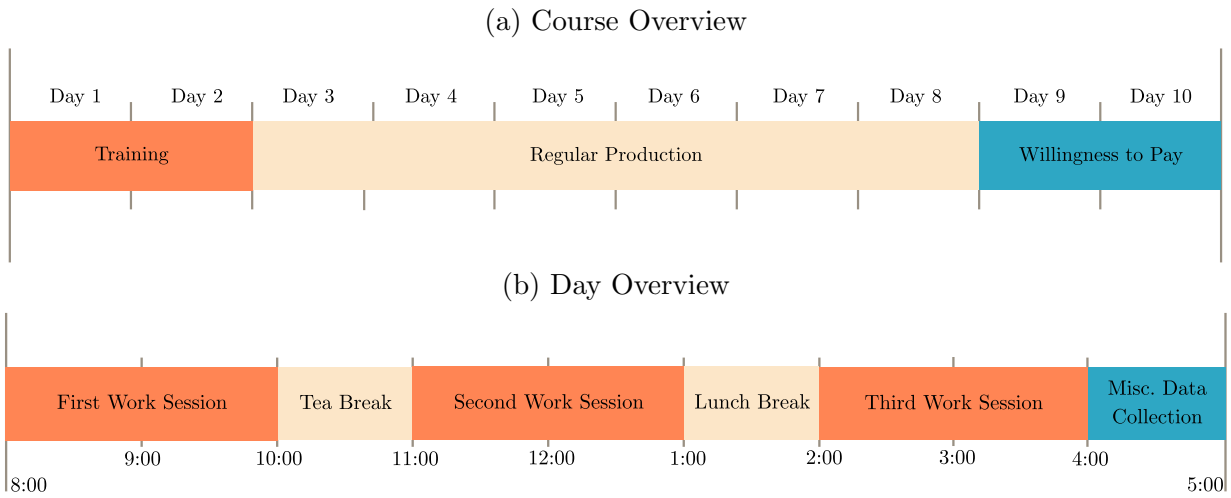


Figure 2: Experiment One Timing

Note: This figure shows the timing of the first experiment. Panel A shows the course level overview. On the first two days participants received basic training, in quiet, on how to use a sewing machine and how to sew a pocket. Over the next six days participants worked autonomously for a piece rate/flat rate combination while being randomly exposed to noise. On the last two days respondents had the opportunity to pay in order to work in quiet while I randomly varied their performance incentives. Panel B shows the day level overview. On each day participants worked for three sessions separated by breaks to isolate the contemporaneous effects of noise.

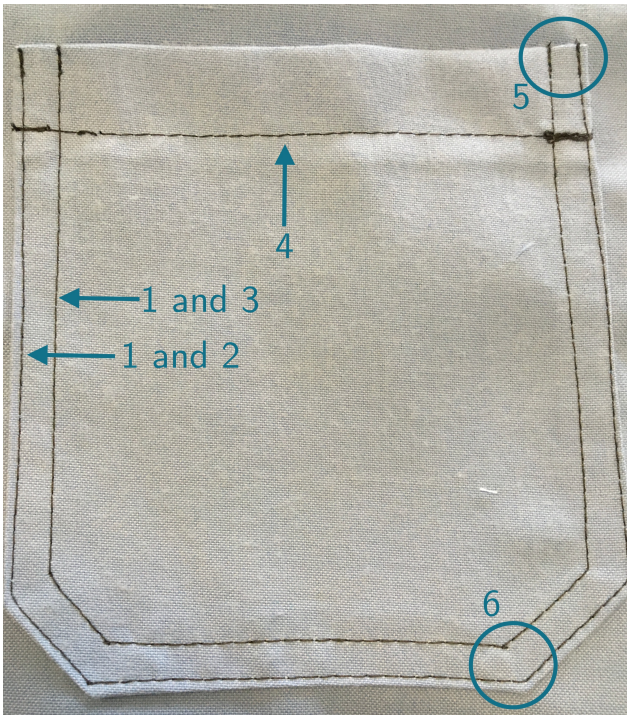


Figure 3: Example Pocket with Marked Grading Criteria

Note: This figure shows an example of the pockets produced in experiment one. Pockets were chosen as the incentivized production task because they require all of the basic skills that are needed in sewing and can be completed in a short period of time, allowing for repeated observation. In fact, the TDC uses these pockets as tools to evaluate potential hires for these reasons. Pocket quality is assessed by treatment-blind enumerators according to the following six criteria marked in the figure:

1. Are there double stitches around the pocket?
2. Is the outer stitch uniformly 1 mm from the edge?
3. Is the inner stitch uniformly 6 mm from the edge?
4. Is the top of the pocket correctly hemmed?
5. Are the ends of the seams reversed?
6. Are the corners even and continuous?

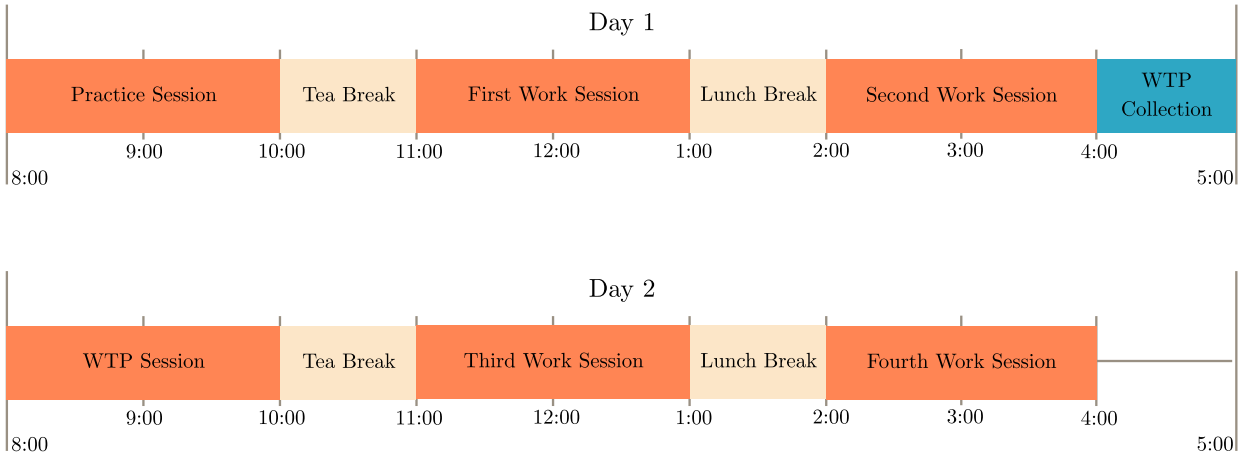


Figure 4: Experiment Two Timing

Note: This figure shows the timing outline of the second experiment. The timing was intentionally designed to follow that of experiment one as closely as possible. The one substantial departure was that instead of happening over two weeks, the second experiment happened over two days due to logistical constraints. Participants still had a training session in quiet and then worked autonomously in sessions separated by breaks.

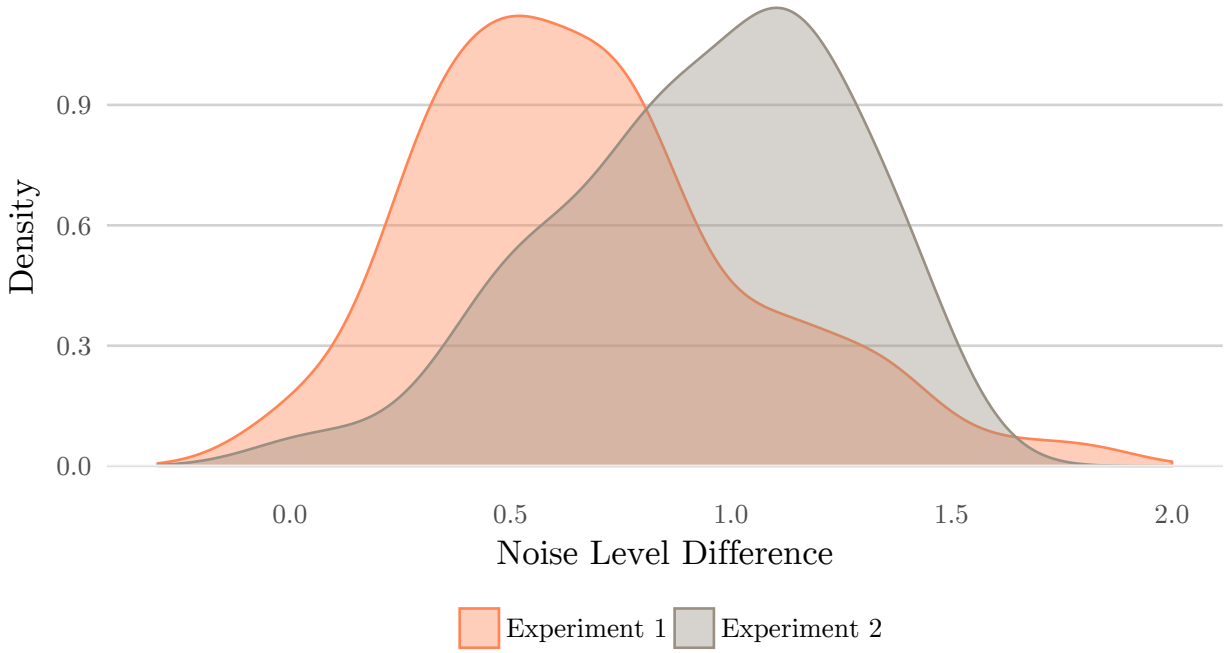


Figure 5: Difference in Noise Level Between Treatment and Control

Note: This figure shows the density of the session-level difference between average treatment and average control noise levels for both experiments. Because humans perceive a 10 dB increase as twice as loud, all noise levels are presented in 10s of decibels. The figure shows that treatment is equivalent to going from working with a home dishwasher in the background to having a home vacuum cleaner in the background.

Tables

Table 1: Environmental Effects of Treatment in Experiment One

	(1) Noise Level	(2) CO2	(3) Humidity	(4) Temperature
Treatment	0.674***	4.765	0.038	0.048
	(0.036)	(24.678)	(0.450)	(0.175)
Session FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Control Mean	6.892	624.677	42.474	26.547
Normalized Difference	2.462	0.072	0.004	0.009
Observations	157	153	153	153

Note: This table shows regressions of environmental variables on a treatment indicator, session fixed effects, and room fixed effects with robust standard errors. The normalized difference is the difference between the treatment and control means divided by the square root of the average of the treatment and control variances as defined by Imbens and Rubin (2015). Because an increase of 10 dB is perceived by the human ear as twice as loud, all noise levels are reported in 10s of decibels. CO2 is reported in parts per million, humidity is reported in raw percent, and temperature is reported in degrees Celsius. The results demonstrate that treatment only affected the noise level and that other environmental variables potentially affected by the machine such as pollution and temperature were unaffected.

Table 2: Effect of Treatment on Productivity

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
				Inverse Hyperbolic Sine Transformation				
Treatment	−0.0311***	−0.0425***	−0.0315***	−0.0378***	−0.0570***	−0.0597***	−0.0450**	−0.0137
	(0.0118)	(0.0134)	(0.0117)	(0.0113)	(0.0145)	(0.0179)	(0.0182)	(0.0189)
				Levels				
Treatment	−0.2289*	−1.1985*	−0.2184*	−0.2313*	−0.2503*	−0.2493*	−0.2061	−0.0430
	(0.1275)	(0.7199)	(0.1273)	(0.1252)	(0.1277)	(0.1273)	(0.1267)	(0.1189)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean-IHS	2.924	4.487	2.918	2.901	2.775	2.645	2.529	2.163
Control Median-Levels	10	54	10	10	10	9	9	6
Observations	2447	2447	2447	2447	2447	2447	2447	2447

Note: This table shows ordinary least squares regressions of productivity outcome variables on a treatment indicator, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The first panel shows the results for the inverse hyperbolic sine-transformed outcomes while the second panel shows the results for the untransformed outcomes. The results demonstrate that noise significantly reduced productivity. In particular, respondents in treated rooms (those working with the background noise of a vacuum instead of a dishwasher) made approximately 3% fewer pockets.

Table 3: IV Effect of Noise on Productivity – Treatment Indicator Instrument

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
				Inverse Hyperbolic Sine Transformation				
Noise Level	-0.0534^{***}	-0.0617^{***}	-0.0537^{***}	-0.0578^{***}	-0.0800^{***}	-0.0822^{***}	-0.0642^{**}	-0.0193
	(0.0161)	(0.0187)	(0.0160)	(0.0160)	(0.0202)	(0.0249)	(0.0256)	(0.0270)
				Levels				
Noise Level	-0.3969^{**}	-1.9737^{*}	-0.3876^{**}	-0.3844^{**}	-0.3935^{**}	-0.3985^{**}	-0.3305^{*}	-0.0792
	(0.1786)	(1.0172)	(0.1785)	(0.1775)	(0.1810)	(0.1786)	(0.1777)	(0.1730)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean-IHS	2.924	4.487	2.918	2.901	2.775	2.645	2.529	2.163
Control Median-Levels	10	54	10	10	10	9	9	6
Observations	2400	2400	2400	2400	2400	2400	2400	2400

Note: This table shows estimates from a two stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented with an indicator for being in a treated room. The first panel shows the results for the inverse hyperbolic sine-transformed outcomes, while the second panel shows the results for the untransformed outcomes. The results demonstrate a 10 dB change (perceived by the human ear as twice as loud) reduces productivity by approximately 5%.

Table 4: Environmental Effects of Treatment in Experiment Two

	(1) Noise Level	(2) CO2	(3) Humidity	(4) Temperature
Treatment	0.938^{***}	-47.956	-0.552^{*}	-0.041
	(0.049)	(46.633)	(0.295)	(0.113)
Session FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Control Mean	7.206	924.460	47.447	24.433
Normalized Difference	3.155	-0.154	-0.127	0.029
Observations	88	84	84	84

Note: This table shows regressions of environmental variables on a treatment indicator, session fixed effects, and room fixed effects with robust standard errors. The normalized difference is the difference between the treatment and control means divided by the square root of the average of the treatment and control variances as defined by Imbens and Rubin (2015). Noise level is reported in 10s of dB, CO2 is reported in parts per million, humidity is reported in raw percent, and temperature is reported in degrees Celsius. The results show that the noise change was similar to the change in the first experiment and that no other environmental variables were affected by treatment.

Table 5: Effect of Noise on Cognitive Function and Effort – Treatment Indicator Instrument

	Cognitive Function Tests				Placebo Effort Task	
	(1)	(2)	(3)	(4)	(5)	(6)
	Normalized Sum of Scores	Average of Normalized Scores	PCA of Percent Correct and Reaction Time	CFA of Percentage Correct and Reaction Time	Key Presses	Normalized Score
Noise Level	-0.0323^{***}	-0.0254^{***}	-0.0626^{***}	-0.0676^{***}	1.9391	0.0041
	(0.0113)	(0.0083)	(0.0150)	(0.0175)	(16.6155)	(0.0355)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.000	0.000	-0.000	0.000	2192.013	-0.000
Observations	762	762	762	762	762	762

Note: This table shows estimates from a two-stage least squares regression of cognitive outcome and placebo effort task variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by an indicator for being in a treated room. The first outcome is the normalized sum of points that participants earned on tests during a session. The second column normalizes first at the test-score level and averages across normalized scores within a session. The third outcome is the first component of a principal component analysis of percentage correct and reaction time estimated on each individual's first control session. The fourth column is my preferred outcome: the first factor of a common factor analysis of percentage correct and reaction time estimated on each individual's first control session. The results show that a 10 dB increase in the noise level (perceived as twice as loud) reduces performance on my preferred index by 0.07 standard deviations. The last two columns show that there was no effect of the same noise change on the placebo effort task. Any decrease in performance greater than 1.4% is outside of the 95% confidence interval.

Table 6: Implications for Cognitive Effects in the Literature

Source	Stimulus	Change in Stimulus	Cognitive Effect	Implied Productivity Change
Ebenstein et al. (2016)	$PM_{2.5}$	10 index units	0.017σ	1.34%
Park (2017)	Temperature	1σ	0.052σ	4.11%
Lichand and Mani (2016)	Low Rainfall	$< 30^{th}$ percentile	0.041σ	3.24%
Mani et al. (2013)	Harvest		0.67σ	53%

Note: This table combines the results of several studies' estimates of the impact of different environmental conditions on cognitive function with the estimate from my split-sample IV in order to assess what these impediments might mean for productivity. While the results should be interpreted with caution given that they involve different types of cognitive shifts and those exposed are likely doing different types of tasks, they indicate that cognitive impediments have the potential to have economically meaningful effects

Table 7: Willingness to Pay by Compensation Scheme

	Experiment 1			Experiment 2		
	(1) WTP	(2) WTP Any	(3) WTP COP	(4) WTP	(5) WTP Any	(6) WTP COP
Piece Rate	0.4202	0.0000	0.7812	0.3066	0.0377*	−3.6531
	(1.4553)	(0.0189)	(2.3519)	(1.6045)	(0.0221)	(4.2607)
Day FE	Yes	Yes	Yes	No	No	No
Outcome Mean	17.697	0.538	32.906	13.392	0.316	42.373
Observations	476	476	256	424	424	142

Note: This table shows a regression of willingness to pay, an indicator for being willing to pay a positive amount, and willingness to pay for the subsample that are willing to pay a positive amount on an indicator for whether the respondent was facing a piece rate when the willingness to pay was elicited. Because in experiment one willingness to pay was elicited on two different days, the regressions include day fixed effects. Standard errors are clustered at the individual level. The results show that individuals' willingness to pay for quiet does not depend on the wage structure. This suggests that they neglect the productive impacts of noise.

Table 8: Response to Piece Rate by Productive Value of Quiet

	Experiment 1			Experiment 2		
	(1) WTP	(2) WTP Any	(3) WTP COP	(4) WTP	(5) WTP Any	(6) WTP COP
Piece Rate	−1.5874	−0.0225	−1.4565	0.7110	0.0431*	−2.5101
	(2.5186)	(0.0311)	(3.7060)	(1.6572)	(0.0235)	(5.1276)
Model Predicted Income Gain	−0.5297	−0.0075	−0.6834	1.6734**	0.0189*	2.9648*
	(0.5794)	(0.0085)	(0.9689)	(0.7200)	(0.0111)	(1.7303)
Model Predicted Income Gain × Piece Rate	0.3746	0.0042	0.4514	−0.3504	−0.0047	−0.5879
	(0.3580)	(0.0036)	(0.6441)	(0.4441)	(0.0076)	(1.3279)
Day FE	Yes	Yes	Yes	No	No	No
Outcome Mean	17.697	0.538	32.906	13.392	0.316	42.373
Observations	476	476	256	420	420	138

Note: This table shows a regression of willingness to pay, an indicator for being willing to pay a positive amount, and willingness to pay for the subsample that are willing to pay a positive amount on an indicator for whether the respondent was facing a piece rate when the willingness to pay was elicited, how much more the model predicts the individual would make in quiet and their interaction. Because in experiment one willingness to pay was elicited on two different days, the regressions include day fixed effects. Standard errors are clustered at the individual level. The results show that even the willingness to pay of those who benefit the most from quiet is unresponsive to performance incentives.

Table 9: Testing Prompting Consideration of Noise

	(1) WTP	(2) WTP Any	(3) WTP COP
Piece Rate	3.3905	0.0667*	2.5523
	(2.3536)	(0.0339)	(6.5711)
Asked Beliefs Before WTP	5.3799	0.0601	9.0658
	(4.1393)	(0.0641)	(9.9233)
Asked Beliefs Before WTP × Piece Rate	−6.1101*	−0.0573	−11.4321
	(3.1913)	(0.0441)	(8.4494)
Outcome Mean	13.392	0.316	42.373
Observations	424	424	142

Note: This table shows a regression of willingness to pay, an indicator for being willing to pay a positive amount, and willingness to pay for the subsample willing to pay a positive amount on an indicator for whether the respondent was facing a piece rate when the willingness to pay was elicited, whether the respondent gave their beliefs before their willingness to pay, and their interaction. The results show that even when forced to think through the impact noise has on their productivity, respondents' willingness to pay is unchanged by the piece rate. This argues against the idea that willingness to pay does not respond to the wage structure because noise was simply not "top-of-mind". Standard errors are clustered at the individual level.

Table 10: Testing for Incorrect Beliefs

	(1) Realized Score	(2) Realized Score	(3) Model Predicted Income Gain	(4) WTP	(5) WTP Any	(6) WTP COP
Model Predicted Score	0.9986***					
	(0.0273)					
Participant Predicted Score		0.1535***				
		(0.0468)				
Participant Predicted Income Gain			−0.0031	0.0558*	0.0011**	0.0381
			(0.0034)	(0.0331)	(0.0006)	(0.1237)
Piece Rate				0.3796	0.0509**	−7.3685
				(1.5761)	(0.0221)	(5.1188)
Participant Predicted Income Gain × Piece Rate				−0.0042	−0.0008*	0.1936*
				(0.0143)	(0.0004)	(0.1041)
Outcome Mean	33.929	33.929	1.078	13.392	0.316	42.373
Observations	187	187	210	424	424	142

Note: Columns one and two of this table show a regression of each respondent's realized score on the model's predictions and their predictions, respectively. The results show respondents' beliefs have some predictive power over their future scores, but are not as predictive as the model. Column three shows a regression of the model's predicted value of quiet on the respondents' predicted value of quiet. The result shows that individuals' beliefs about the impact of noise on their productivity is uncorrelated with my estimates of the true impact of noise on their productivity, suggesting their beliefs are incorrect. Columns four, five, and six show regressions of willingness to pay, an indicator for being willing to pay a positive amount, and willingness to pay for the subsample willing to pay a positive amount on an indicator for whether the respondent was facing a piece rate when the willingness to pay was elicited, what the respondent believes to be his/her productive benefit from working in quiet, and their interaction. The results show that respondents are unwilling to stake any money on their beliefs. These results are consistent with a "failure to notice" form of inattention where respondents fail to learn about particular determinants of their productivity, but are aware that they do not know (Schwartzstein 2014; Hanna et al. 2014). Standard errors are clustered at the individual level.

A Supplementary Figures For Online Publication

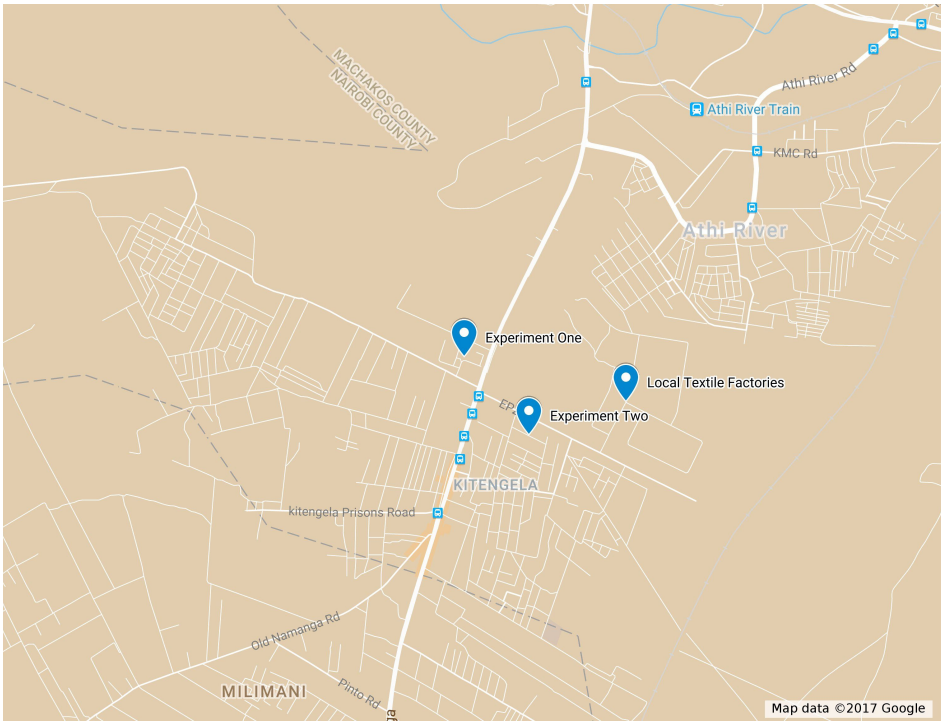


Figure A1: Experiment Locations and Surrounding Area

Note: This figure shows a map of the experiment locations and recruitment location in Kitengela, Kenya just outside of Nairobi. The experiment sites are less than a mile apart and close to the recruitment site at the gates of the local textile factories.

Figure A2: Noise Generating Engine

Note: This figure shows a picture of the car engine used to generate noise in experiment one. The engine was borrowed from an automotive mechanic training facility at the TDC. A car engine was chosen as the noise source because it is representative of important sources of noise pollution – traffic noise and large industrial machines – and leaves minimal room for experimenter manipulation.

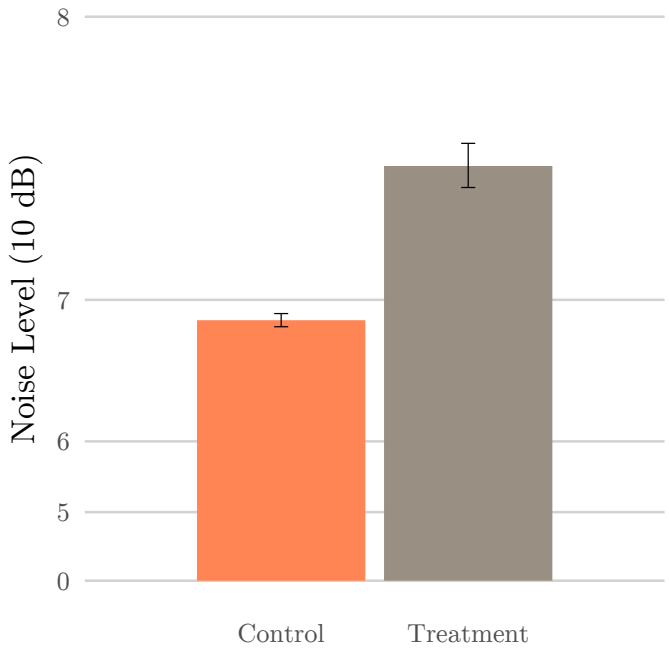


Figure A3: Noise Level By Treatment Status

Note: This figure shows the average noise level in treatment and control. A noise increase of 10 dB is perceived as twice as loud by the human year. Thus, for interpretability, all noise levels are reported as 10s of decibels and the y-axis is shown on a log scale. Treatment increased the noise level by the same amount as replacing a dishwasher running in the background with a vacuum cleaner.

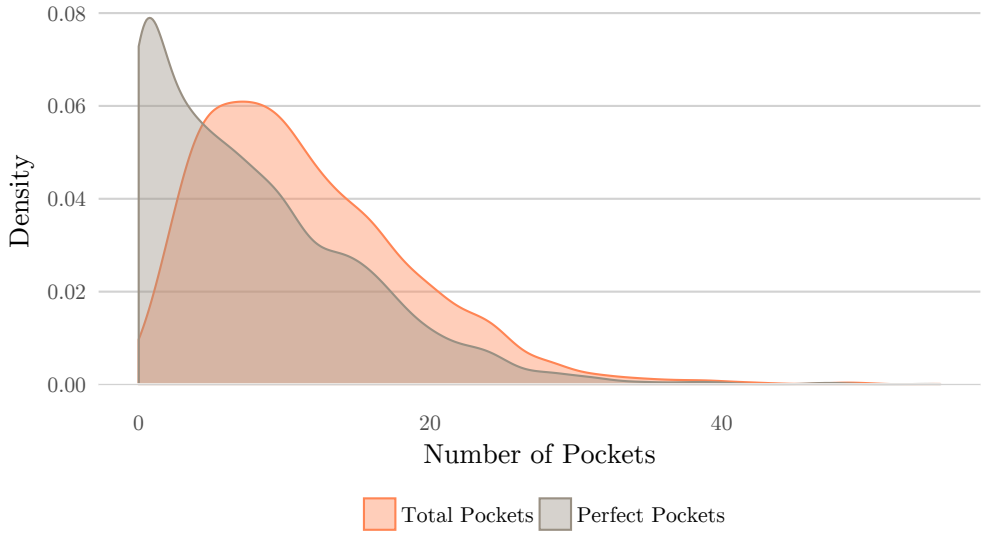


Figure A4: Output Density

Note: This figure shows the density of the number of total and perfect pockets created in experiment one. The distribution is significantly skewed, but has zeros. Thus, to increase power I present the inverse hyperbolic sine-transformed versions of the outcome variables.

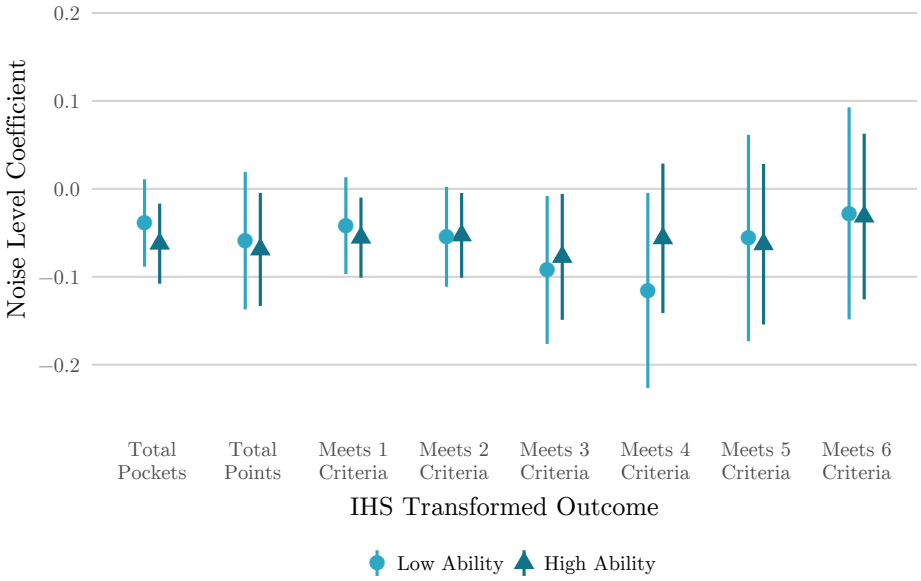


Figure A5: Instrumented Treatment Effects by Ability

Note: This figure shows coefficient estimates and their 95% confidence intervals from a two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by an indicator for being in a treated room. Before estimation, within each session the sample was split by median performance in other control sessions. Treatment effects were estimated separately for the two groups in a stacked regression. The results show that the treatment effect is relatively constant across ability levels.

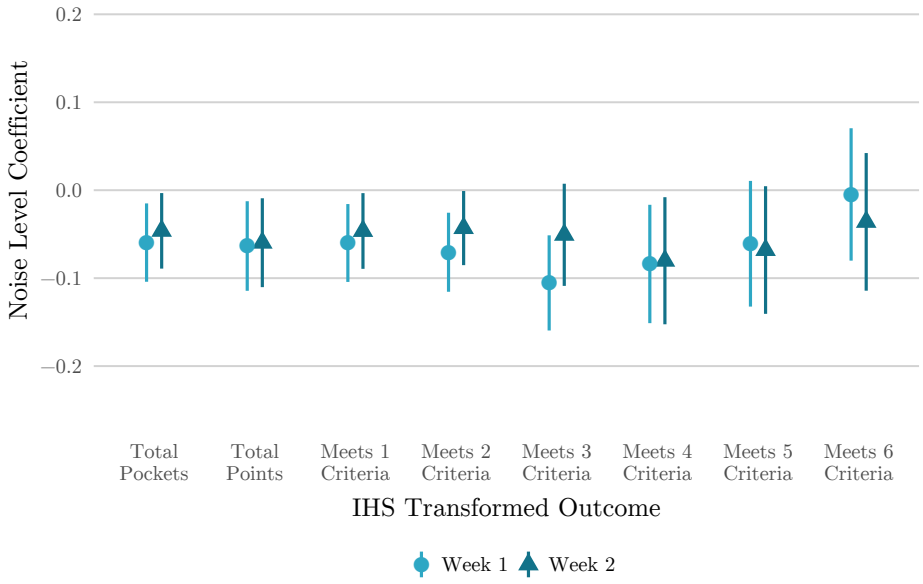


Figure A6: Instrumented Treatment Effects Over Time

Note: This figure shows coefficient estimates and their 95% confidence intervals from a two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by an indicator for being in a treated room. Before estimation, the sample was split into two groups by week. Treatment effects were estimated separately for the two groups in a stacked regression. The results show that the treatment effect is relatively constant across weeks.

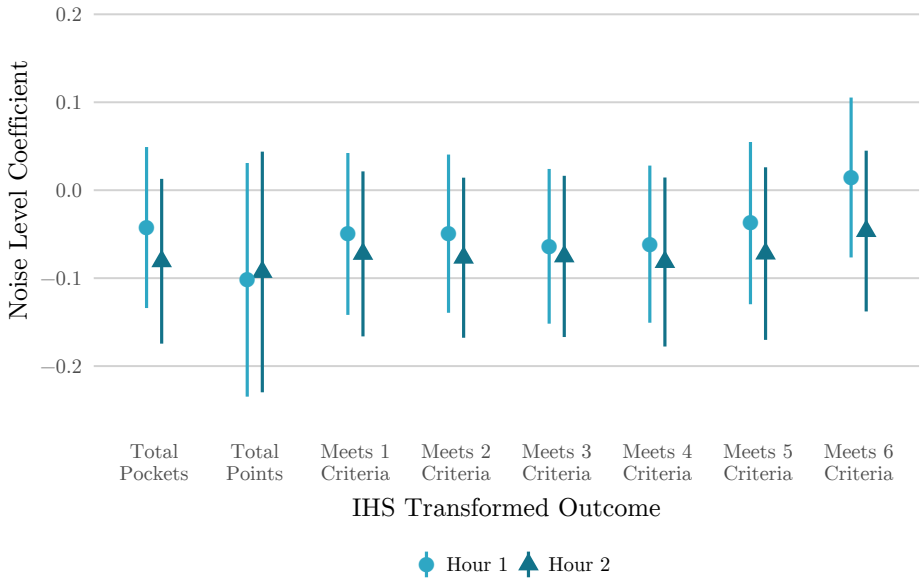


Figure A7: Instrumented Treatment Effects by Hour of Session

Note: This figure shows coefficient estimates and their 95% confidence intervals from a two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by an indicator for being in a treated room. Before estimation the sample was split into two groups by hour within each session. Treatment effects were estimated separately for the two groups in a stacked regression. The results show that the treatment effect is relatively constant across hours.

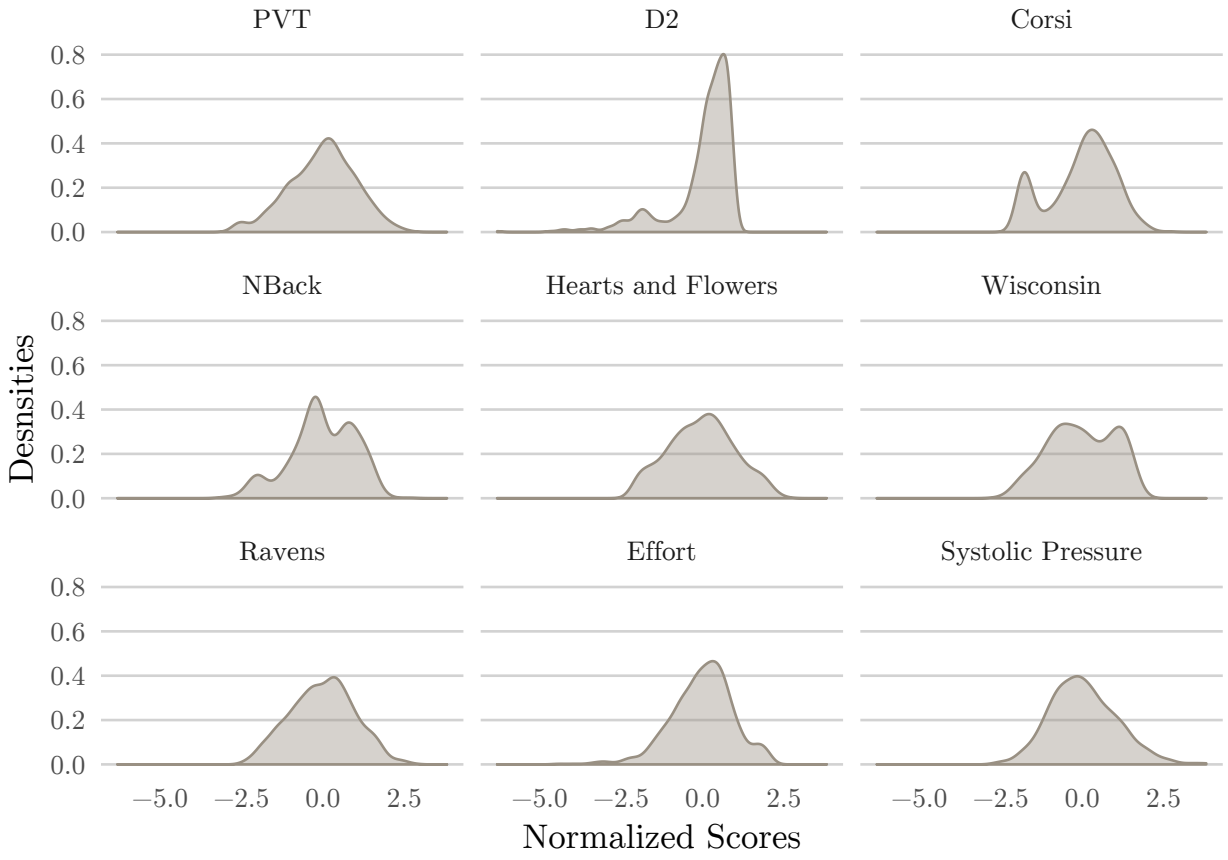


Figure A8: Normalized Test Score Variation

Note: This figure shows the density of the normalized scores for each measured outcome in experiment two. The results show that with the exception of d2, all metrics generate good variation and do not appear susceptible to ceiling or floor effects.

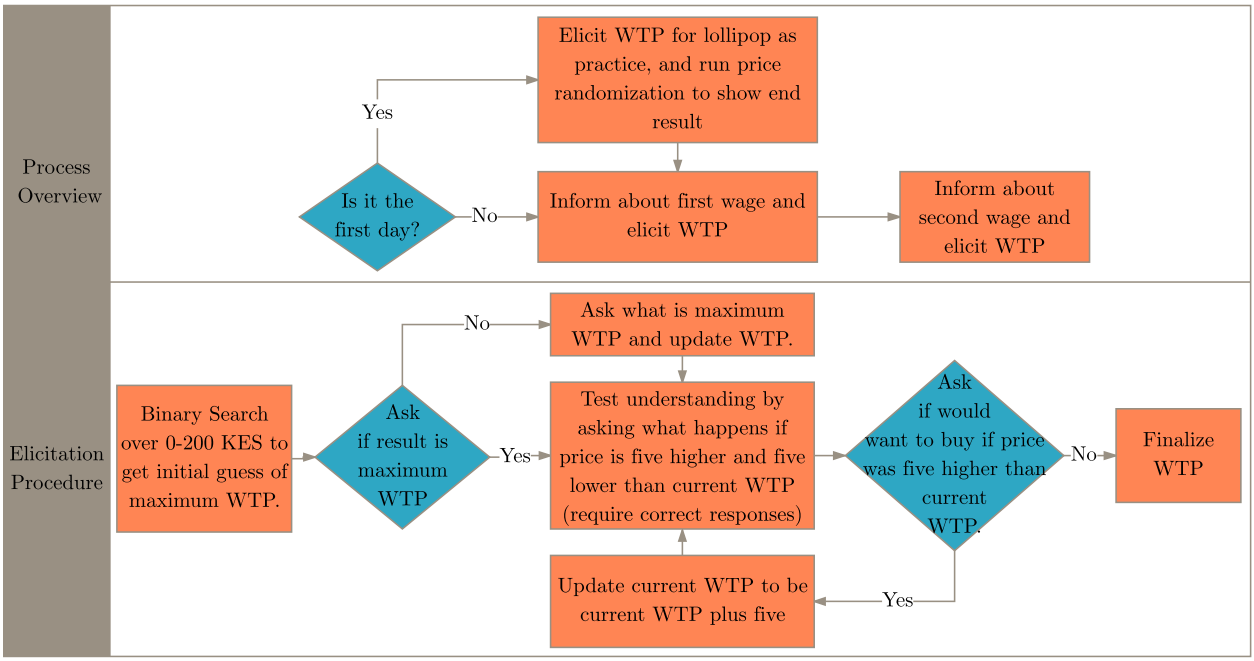


Figure A9: Willingness to Pay Overview and Elicitation Procedure

Note: The first panel of this figure shows the overview of the process of eliciting willingness to pay including when practices were conducted, and how information was timed with the elicitation. The second panel is a detailed view of how willingness to pay was elicited using a modified version of the procedure outlined in Berry et al. (2015).

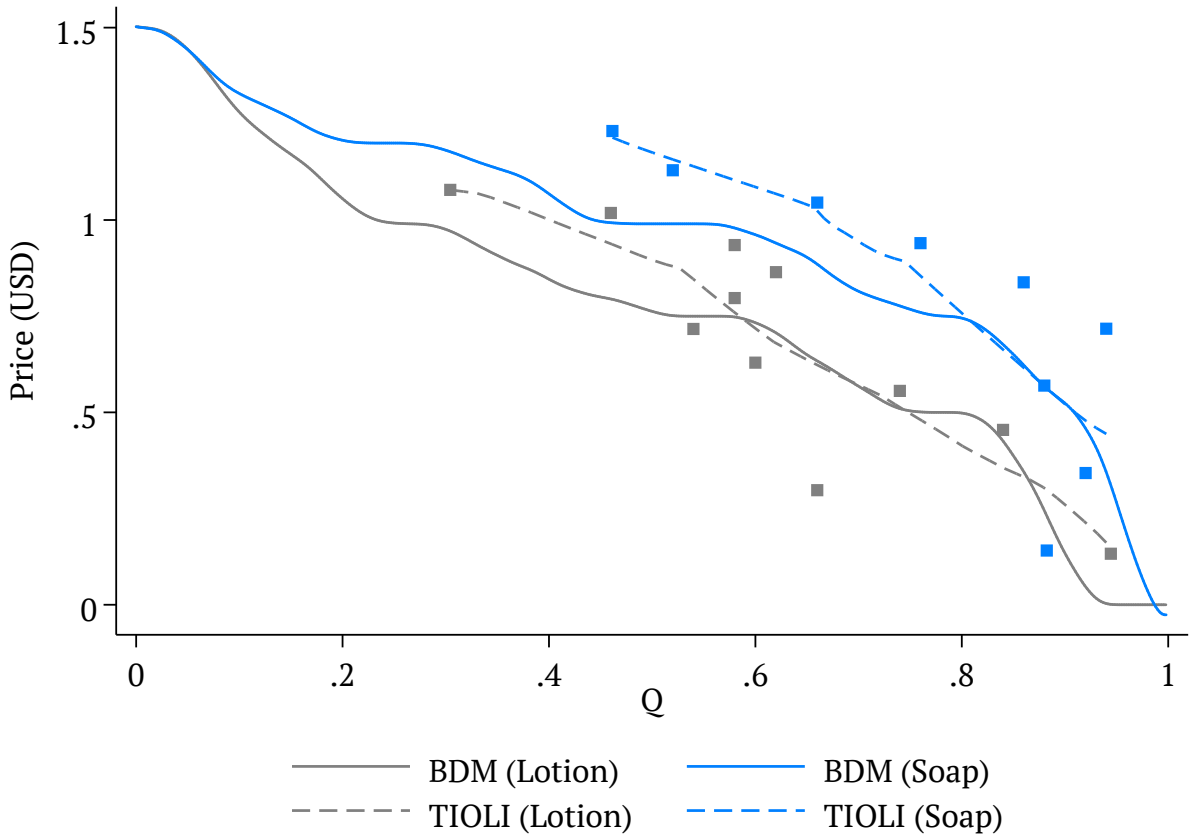


Figure A10: Comparison of BDM and TIOLI Offers from Berkouwer and Dean (2019)

Note: The figure plots the BDM procedure validation results from Berkouwer and Dean (2019). The authors use the same BDM elicitation procedure as this paper in a sample of 1000 households from Nairobi. However, instead of only having a single practice good, the authors randomly assign participants to practice the BDM for either lotion or soap. For the good not chosen as the practice good, the respondent is given a take it or leave it (TIOLI) offer at a randomly chosen price. This allows comparison of the demand curves elicited by the BDM script employed by the authors to those elicited by more traditional purchase decisions. The results show the BDM gives comparable demand curves.

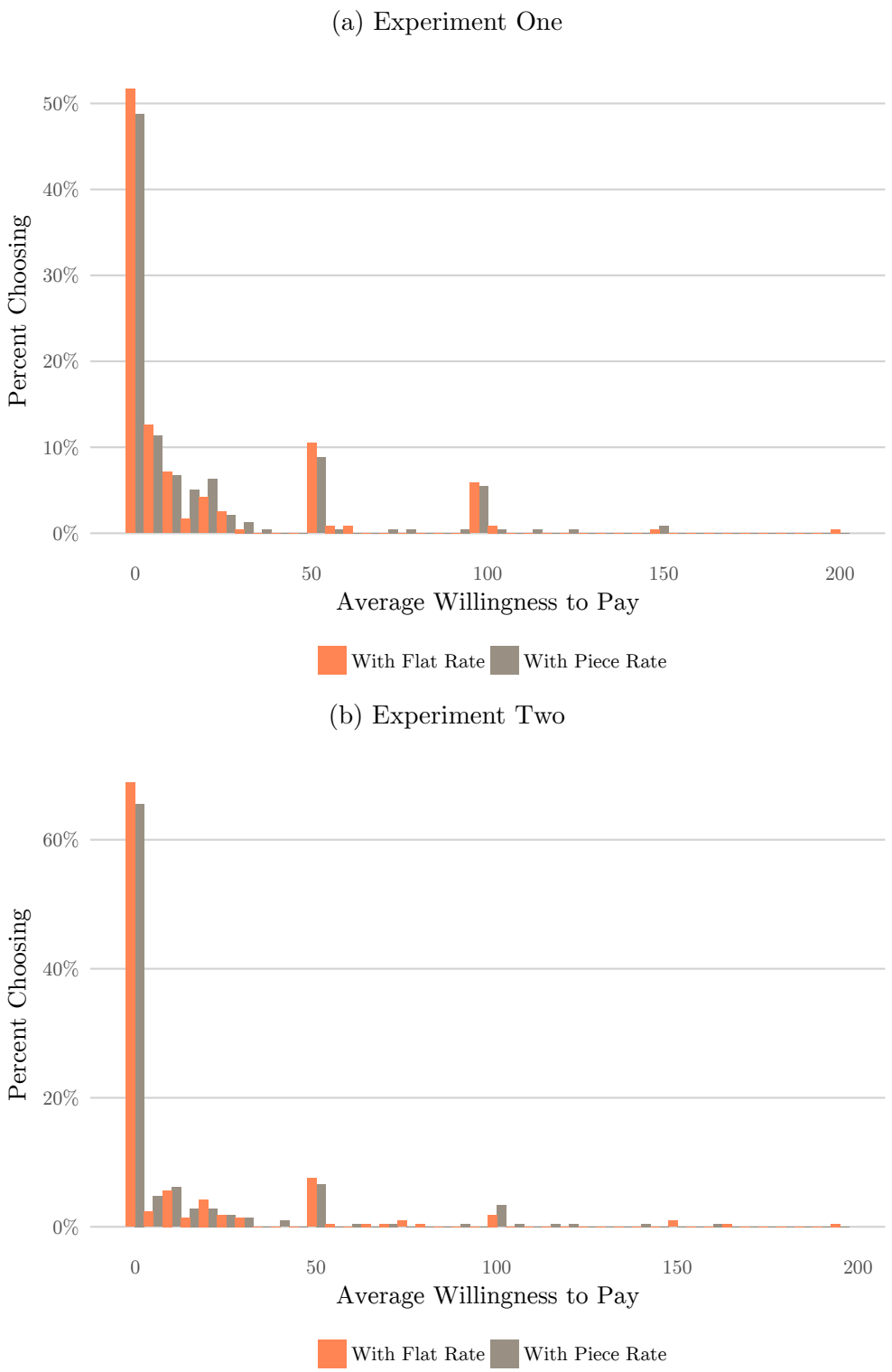
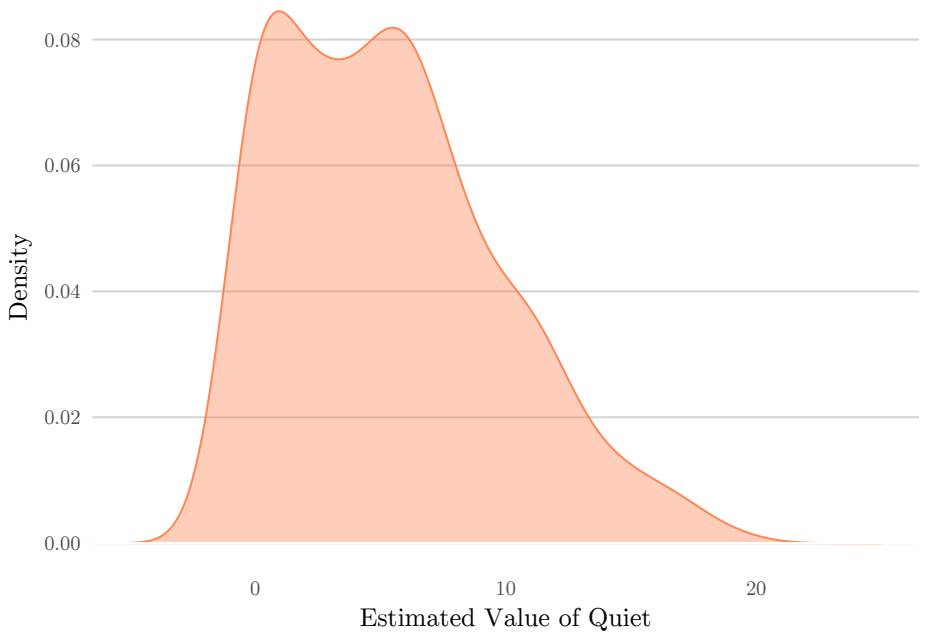


Figure A11: Average Willingness to Pay by Compensation

Note: The figure shows the distribution of willingness to pay in order to work in the quiet room by whether the respondent was facing a piece rate or a flat rate. The first panel shows the results for the first experiment, while the second shows the results for the second. The results show that willingness to pay for quiet is generally quite low.

(a) Experiment One



(b) Experiment Two

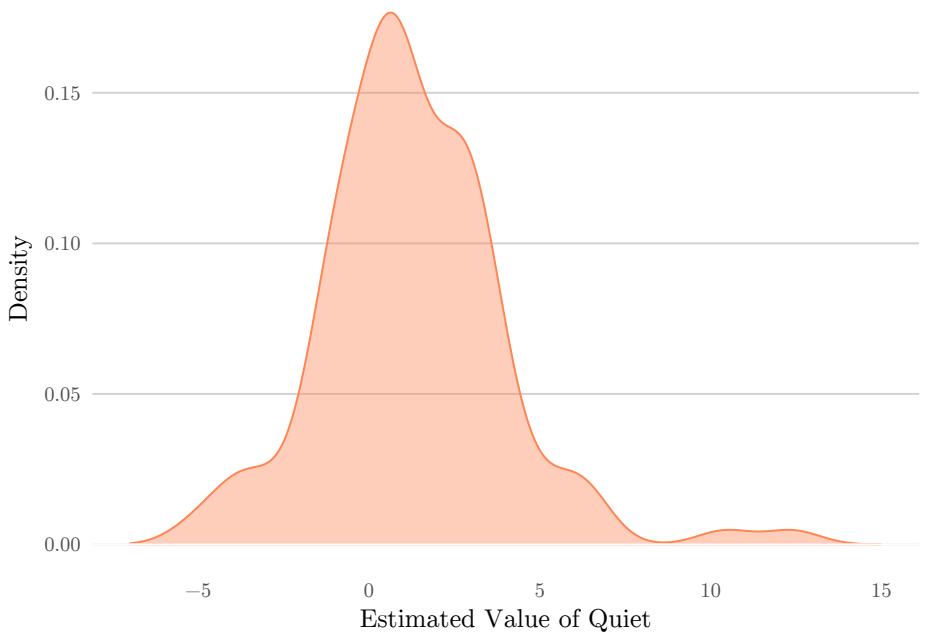


Figure A12: Productive Value of Quiet

Note: The figure shows the densities of the hierarchical linear models' predicted income gains from working in the quiet room. The first panel shows the density from the first experiment and the second shows the density from the second. The model was used to obtain better predictions of the within-person treatment effect than would be obtained from simply taking the difference between treatment and control performance within person.

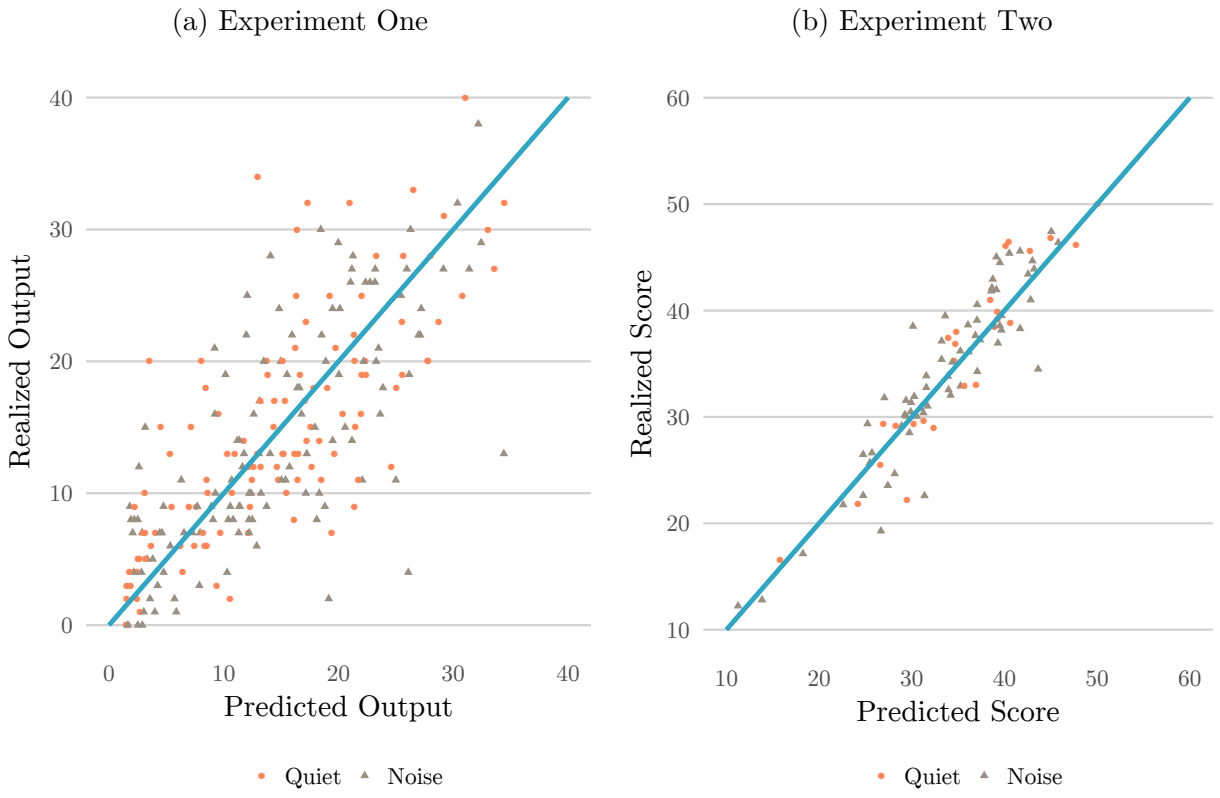
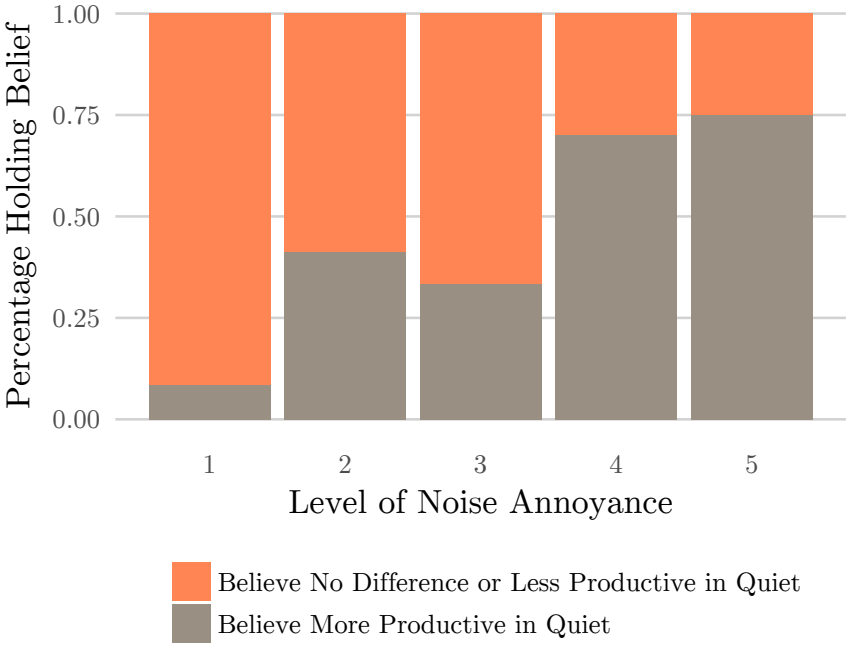


Figure A13: Model Fit

Note: The figure plots the hierarchical linear model's predictions of the respondents' output and scores in the willingness to pay sessions on the x-axis against the respondents' realized output and scores on the y-axis. Values are plotted separately depending on whether the individual ended up in quiet or in noise based on their willingness to pay. The solid line shows the 45 degree line or perfect prediction.

(a) Experiment 1



(b) Experiment 2

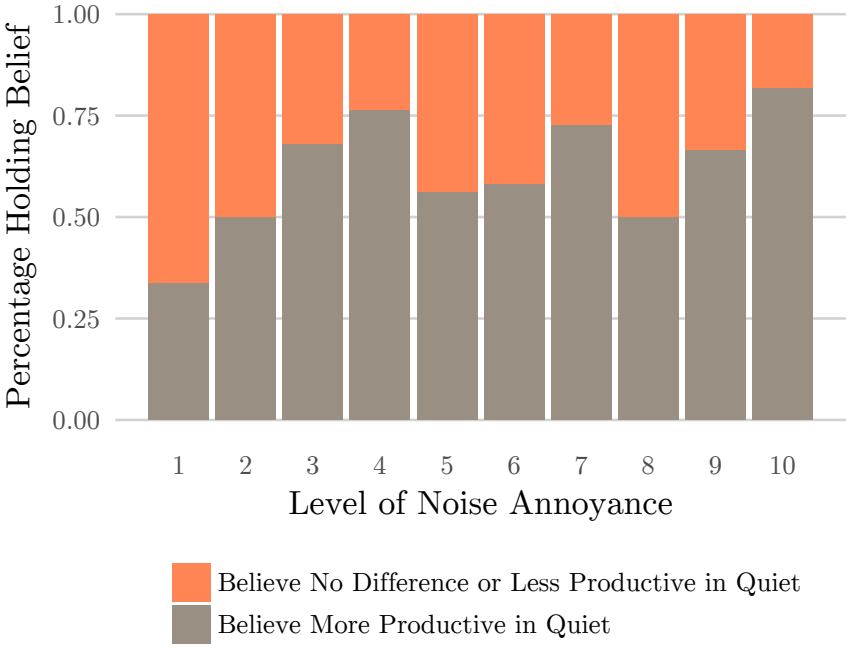


Figure A14: Beliefs and Annoyance

Note: This figure shows the proportion of individuals who believe they are more productive in quiet for each level of stated annoyance with the noise level. The high level of correlation provides suggestive evidence that individuals do not actually understand the impact of noise on their productivity and are instead substituting in their annoyance level.

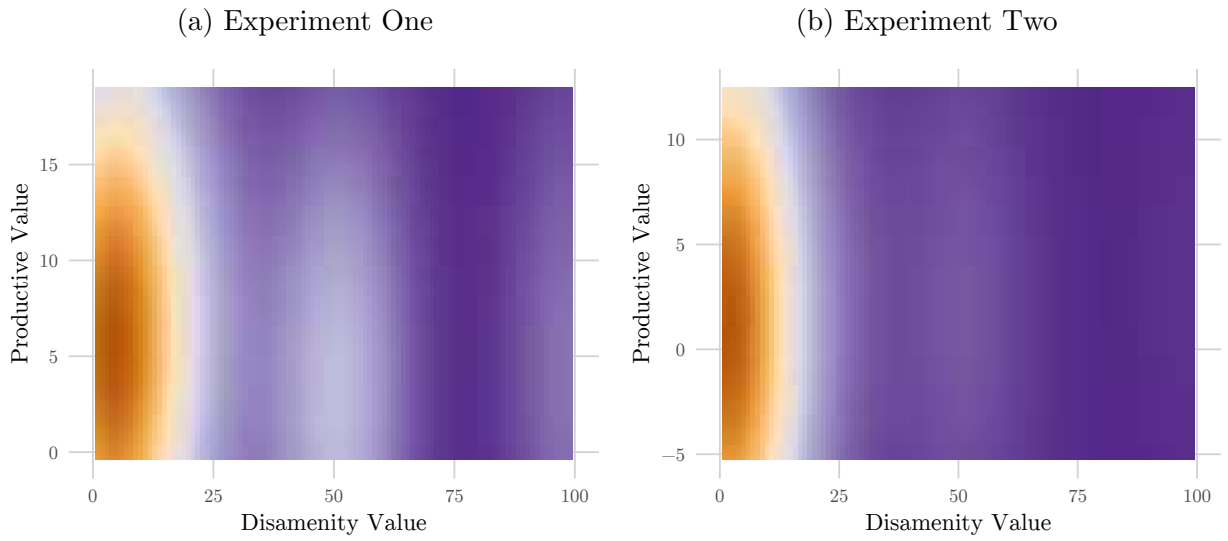


Figure A15: Correlation Between Amenity and Productive Value of Quiet

Note: This figure plots the joint density of each respondent's willingness to pay for quiet when facing a flat rate compensation scheme and what the model predicts is their productive value of quiet. The results show that the two are essentially uncorrelated. This suggests that if respondents neglect the productive impact and sort simply on annoyance, this will change the composition of workers sorting into working in noise.

B Supplementary Tables For Online Publication

Table B1: Sample Summary Statistics

	Experiment 1	Experiment 2	Total
Female	0.641	0.521	0.566
	(0.482)	(0.501)	(0.496)
Age	28.84	26.07	27.11
	(6.791)	(6.748)	(6.885)
High School or More	0.516	0.690	0.625
	(0.502)	(0.464)	(0.485)
Typical Daily Wage	677.2	548.6	597.0
	(725.8)	(633.4)	(671.5)
Days Worked Last Week	2.188	1.235	1.592
	(2.528)	(2.130)	(2.330)
More Annoyed by Noise than Others	0.258	0.305	0.287
	(0.439)	(0.462)	(0.453)

Note: This table presents summary statistics for each experiment sample. The main entries are the means of the variable in each row. Standard deviations are in parentheses below. The samples are relatively similar on demographic terms.

Table B2: Experiment One Balance

	(1) Female	(2) Age	(3) High School or More	(4) Typical Daily Wage	(5) Days Worked Last Week	(6) More Annoyed by Noise than Others
Treatment Mean	0.641	28.812	0.518	684.163	2.192	0.257
Control Mean	0.640	28.861	0.513	670.259	2.183	0.259
Two-Sided P-Value	0.962	0.889	0.846	0.673	0.915	0.936
Normalized Difference	0.006	−0.007	0.016	0.021	−0.006	−0.006

Note: This table assesses the balance of sample characteristics between treatment and control sessions. The first two rows display the average of the variable indicated in the column for individuals observed in treatment and control sessions, respectively. Row three shows the p-value from a regression of the variable on a treatment indicator with standard errors clustered at the room by session level. The normalized difference is the difference between the treatment and control means divided by the square root of the average of the treatment and control variances as defined by Imbens and Rubin (2015). The sample observed in treatment and control are almost identical. This is a result of the within-person randomization. The only reason balance does not hold exactly is due to small levels of attrition.

Table B3: Experiment One Poisson Regressions

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
				Marginal Effects				
Treatment	−0.3094**	−1.7523**	−0.2961**	−0.3124***	−0.3496***	−0.3392**	−0.3000**	−0.1671
	(0.1210)	(0.7287)	(0.1212)	(0.1206)	(0.1290)	(0.1343)	(0.1381)	(0.1309)
				Poisson Coefficients				
Treatment	−0.0269**	−0.0284**	−0.0258**	−0.0274***	−0.0320***	−0.0326**	−0.0306**	−0.0216
	(0.0105)	(0.0118)	(0.0106)	(0.0106)	(0.0118)	(0.0129)	(0.0141)	(0.0169)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	11.527	61.849	11.493	11.421	10.965	10.446	9.832	7.692
Control Median	10	54	10	10	10	9	9	6
Observations	2447	2447	2447	2447	2447	2447	2447	2447

Note: This table shows the marginal effects and coefficients from poisson regressions of productivity outcome variables on a treatment indicator, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. Respondents in treated rooms (those working with the background noise of a vacuum instead of a dishwasher) made approximately 3% fewer pockets.

Table B4: Experiment One Fisher P-Values

	Total Pockets	Total Points Earned	Pockets Meeting 1 Criterion	Pockets Meeting 2 Criteria	Pockets Meeting 3 Criteria	Pockets Meeting 4 Criteria	Pockets Meeting 5 Criteria	Pockets Meeting 6 Criteria
IHS Transformed	0.008	0.008	0.013	0.004	0.003	0.006	0.053	0.597
Levels	0.081	0.13	0.098	0.08	0.066	0.081	0.148	0.754

Note: This table shows the p-values from randomization inference. Treatment was randomly reassigned 1000 times using the original randomization code. Each outcome variable was then regressed on the reassigned treatment indicator, individual, session, room, and wage fixed effects. The true coefficient was then compared to the distribution of coefficients induced by reassignment in order to generate p-values. The inferences are similar to those reported in the main regressions.

Table B5: Effect of Treatment in Week Two

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
				Inverse Hyperbolic Sine Transformation				
Treatment	−0.0212	−0.0289	−0.0203	−0.0187	−0.0256	−0.0506**	−0.0450*	−0.0279
	(0.0149)	(0.0174)	(0.0149)	(0.0146)	(0.0188)	(0.0244)	(0.0251)	(0.0271)
				Levels				
Treatment	−0.1162	−0.6172	−0.1071	−0.0826	−0.0920	−0.1544	−0.1569	−0.0242
	(0.1956)	(1.1361)	(0.1954)	(0.1928)	(0.1911)	(0.1966)	(0.2027)	(0.2111)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean-IHS	3.241	4.909	3.240	3.233	3.177	3.111	3.023	2.687
Control Median-Levels	14	75	14	14	13	13	12	9
Observations	1190	1190	1190	1190	1190	1190	1190	1190

Note: This table shows ordinary least squares regressions of productivity outcome variables on a treatment indicator, wage, session, person, and room fixed effects with standard errors clustered at the room by session level for the second week of the first experiment. The first panel shows the results for the inverse hyperbolic sine-transformed outcomes, while the second panel shows the results for the untransformed outcomes. The results demonstrate that during the second week the effect size is as large on the perfect pockets as it is on the total number of pockets even though there is no longer power to detect whether the coefficients are significantly different from zero.

Table B6: Intensity Level Balance

	Experiment 1				Experiment 2			
	(1) Temperature	(2) CO_2	(3) Humidity	(4) Second Half	(5) Temperature	(6) CO_2	(7) Humidity	(8) Second Half
Intensity 1	27.17	642.67	39.24	0.50	25.10	894.75	45.87	0.40
	(0.67)	(44.03)	(2.13)	(0.11)	(0.77)	(91.41)	(2.05)	(0.14)
Intensity 2	25.94	635.52	44.76	0.88	25.19	848.38	45.77	0.25
	(0.65)	(42.63)	(2.06)	(0.11)	(0.88)	(103.64)	(2.32)	(0.16)
Intensity 3	27.78	636.00	39.05	0.38	22.19	872.54	52.26	0.80
	(0.67)	(44.03)	(2.13)	(0.11)	(0.77)	(91.41)	(2.05)	(0.14)
Intensity 4	26.51	648.78	41.51	1.00	23.28	853.90	49.24	0.25
	(0.70)	(45.58)	(2.20)	(0.12)	(0.88)	(103.64)	(2.32)	(0.16)
Intensity 5	26.16	653.34	44.17	0.62	23.54	909.17	48.13	1.00
	(0.65)	(42.63)	(2.06)	(0.11)	(0.82)	(96.95)	(2.17)	(0.16)
Intensity 6	27.59	624.70	41.68	0.38	24.02	1003.74	50.90	0.60
	(0.67)	(44.03)	(2.13)	(0.11)	(0.73)	(86.72)	(1.94)	(0.14)
Intensity 7	26.35	565.96	44.00	0.14	23.30	847.84	50.98	0.75
	(0.70)	(45.58)	(2.20)	(0.12)	(0.82)	(96.95)	(2.17)	(0.16)
Intensity 8	26.96	617.94	42.52	0.75	26.37	897.77	38.83	0.40
	(0.70)	(45.58)	(2.20)	(0.11)	(0.73)	(86.72)	(1.94)	(0.14)
Intensity 9	26.11	654.69	43.67	0.62	26.74	1033.98	40.79	0.00
	(0.65)	(42.63)	(2.06)	(0.11)	(0.82)	(96.95)	(2.17)	(0.16)
Intensity 10	25.93	647.63	43.30	0.43	24.75	849.89	47.85	0.50
	(0.70)	(45.58)	(2.20)	(0.12)	(0.82)	(96.95)	(2.17)	(0.16)
Observations	149	149	149	154	84	84	84	88

Note: This table shows the observable differences in sessions by treatment intensity. The main entries in each row show the means of the variables listed at the top for sessions of a given decile of intensity. The standard errors of the means are in parentheses and are clustered at the session level. The results show no clear relationship between treatment intensity and any observable characteristic.

Table B7: First Stages

	Experiment 1		Experiment 2	
	(1) Noise Level	(2) Noise Level	(3) Noise Level	(4) Noise Level
Treatment	0.6745***		0.9403***	
	(0.0247)		(0.0368)	
Treated with Intensity 1		0.1529***		0.3419***
		(0.0294)		(0.0363)
Treated with Intensity 2		0.3146***		0.5649***
		(0.0057)		(0.0102)
Treated with Intensity 3		0.4171***		0.7394***
		(0.0113)		(0.0150)
Treated with Intensity 4		0.4942***		0.8635***
		(0.0041)		(0.0127)
Treated with Intensity 5		0.5725***		0.9210***
		(0.0067)		(0.0075)
Treated with Intensity 6		0.6841***		1.0675***
		(0.0071)		(0.0087)
Treated with Intensity 7		0.7620***		1.1137***
		(0.0056)		(0.0052)
Treated with Intensity 8		0.8572***		1.1803***
		(0.0117)		(0.0077)
Treated with Intensity 9		1.0970***		1.2953***
		(0.0194)		(0.0239)
Treated with Intensity 10		1.4459***		1.3966***
		(0.0460)		(0.0091)
F-Statistic	745	6699	651	23347
Observations	2512	2512	762	762

Note: This table reports coefficients of a regression of the noise level on the excluded instruments with standard errors clustered at the room by session level. Columns 1 and 3 use a single indicator for being in a treatment session. Columns 2 and 4 use separate indicators for each level of treatment intensity. F-statistics are for a joint test that the coefficients are zero. The results show that all instruments generate a strong first stage.

Table B8: IV Effect of Noise on Productivity – Treatment Intensity Instruments

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
				Inverse Hyperbolic Sine Transformation				
Noise Level	−0.0646***	−0.0751***	−0.0651***	−0.0661***	−0.0905***	−0.0975***	−0.0861***	−0.0549**
	(0.0152)	(0.0180)	(0.0151)	(0.0150)	(0.0198)	(0.0240)	(0.0247)	(0.0252)
				Levels				
Noise Level	−0.5253***	−2.9572***	−0.5192***	−0.5187***	−0.5466***	−0.5671***	−0.5205***	−0.2851*
	(0.1696)	(0.9632)	(0.1695)	(0.1691)	(0.1718)	(0.1723)	(0.1653)	(0.1492)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean-IHS	2.924	4.487	2.918	2.901	2.775	2.645	2.529	2.163
Control Median-Levels	10	54	10	10	10	9	9	6
Observations	2400	2400	2400	2400	2400	2400	2400	2400

Note: This table shows estimates from two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by a set of treatment indicators interacted with the session in order to capture variation in treatment intensity. The first panel shows the results for the inverse hyperbolic sine-transformed outcomes, while the second panel shows the results for the untransformed outcomes.

Table B9: Quality Response

	(1) Proportion Meeting 1 Criterion	(2) Proportion Meeting 2 Criteria	(3) Proportion Meeting 3 Criteria	(4) Proportion Meeting 4 Criteria	(5) Proportion Meeting 5 Criteria	(6) Proportion Meeting 6 Criteria
			Reduced Form Effect of Treatment			
Treatment	0.0000	−0.0025	−0.0113*	−0.0133*	−0.0063	0.0054
	(0.0019)	(0.0035)	(0.0058)	(0.0073)	(0.0075)	(0.0074)
			2SLS Effect of Noise - Treatment Indicator Instrument			
Noise Level	−0.0009	−0.0018	−0.0117	−0.0134	−0.0030	0.0131
	(0.0024)	(0.0047)	(0.0079)	(0.0101)	(0.0105)	(0.0107)
			2SLS Effect of Noise - Treatment Intensity Instruments			
Noise Level	−0.0009	0.0002	−0.0137*	−0.0174*	−0.0100	0.0022
	(0.0021)	(0.0044)	(0.0078)	(0.0097)	(0.0104)	(0.0099)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean-IHS	0.995	0.980	0.904	0.833	0.765	0.574
Control Median-Levels	2389	2389	2389	2389	2389	2389

Note: This table shows the impact of treatment on the proportion of pockets meeting or exceeding each quality threshold. The first panel shows the estimates from a regression of the proportions on a treatment indicator, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The second panel shows the estimates from a two-stage least squares regression of the proportions on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level and the noise level instrumented with a treatment indicator. The third panel shows the estimates from a two-stage least squares regression of the proportions on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level and the noise level instrumented by a set of treatment intensity indicators in order to capture variation in treatment intensity. The results show that there does not appear to have been a quality response to treatment.

Table B10: Comparison with Other Environmental Effects

Source	Setting	Stimulus	Stimulus Change	Productivity Effect
This Paper	Textile Production	Noise	Perceived Doubling	5%
Adhvaryu et al. (2016)	Textile Production	Temperature	0.81σ	1.3%
Zivin and Neidell (2012)	Agricultural Labor	Ozone Pollution	0.76σ	5.5%
Chang et al. (2016)	Call Center	Air Pollution	15%	0.35%
Chang et al. (2016)	Factory	Air Pollution	1σ	8%
He et al. (2019)	Manufacturing	Air Pollution	0.2σ	0%

Note: This table compares the effects of noise on productivity estimated in this experiment with the effects of other environmental factors on productivity estimated in the literature. While we should be cautious in interpreting results from different experiments with different kinds of environmental changes on different types of tasks, it appears the effects estimated in this paper are similarly sized to other environmental factors.

Table B11: Lagged Treatment Results

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
Treatment	−0.0163	−0.0305	−0.0168	−0.0302*	−0.0649***	−0.0554*	−0.0289	0.0011
	(0.0172)	(0.0208)	(0.0171)	(0.0159)	(0.0221)	(0.0282)	(0.0284)	(0.0291)
Lagged Treatment	0.0000	−0.0198	−0.0043	−0.0125	−0.0406	−0.0077	0.0149	0.0194
	(0.0213)	(0.0250)	(0.0214)	(0.0201)	(0.0291)	(0.0384)	(0.0390)	(0.0428)
Treatment × Lagged Treatment	−0.0504	−0.0356	−0.0515	−0.0344	0.0101	−0.0033	−0.0297	−0.0023
	(0.0354)	(0.0473)	(0.0366)	(0.0353)	(0.0447)	(0.0571)	(0.0598)	(0.0637)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean-IHS	2.924	4.487	2.918	2.901	2.775	2.645	2.529	2.163
Observations	2209	2209	2209	2209	2209	2209	2209	2209

Note: This table shows estimates from an ordinary least squares regression of the inverse hyperbolic sine-transformed productivity outcome variables on a treatment indicator, a lagged treatment indicator, an interaction of the treatment indicator and the lagged treatment indicator, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The results are imprecise, but do not suggest that cumulative effects of noise exposure are important.

Table B12: Decision Task Results

	(1) Net Savings	(2) Bought Bulk	(3) Worked Extra Hour
Treated 1st Session	0.3483	0.0358	−0.0241
	(39.9039)	(0.0723)	(0.0942)
Treated 2nd Session	20.1870	−0.0504	0.0457
	(41.6946)	(0.0715)	(0.0945)
Treated 3rd Session	10.7555	−0.0782	0.0013
	(33.9952)	(0.0717)	(0.0930)
Day FE	Yes	No	No
Person FE	Yes	No	No
Outcome Mean	8.204	0.190	0.525
Outcome SD	694.611	0.394	0.501
Observations	733	126	120

Note: This table shows regressions of the outcome variables from three decision tasks conducted at the end of selected days on indicators for whether the respondent was treated in the first, second, or third session on those days. Standard errors are clustered at the individual level. The first column shows the net amount saved (deposits less withdrawals) by respondents in an account with an interest rate of 1% per working day. The second column shows whether an individual chose to buy a 5 kg bag of maize flour when they had the opportunity to buy five 1 kg bags of flour at a lower cost. The final column shows whether the respondents elected to stay for an extra hour and work for a piece rate when offered the chance. All results show that noise exposure during the day does not seem to affect decisions taken later in quiet.

Table B13: Effect of Piece Rate on Productivity

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criterion	(4) Pockets Meeting 2 Criteria	(5) Pockets Meeting 3 Criteria	(6) Pockets Meeting 4 Criteria	(7) Pockets Meeting 5 Criteria	(8) Pockets Meeting 6 Criteria
10 Ksh Piece Rate	0.0270*	0.0336	0.0245	0.0267	0.0238	0.0290	0.0513*	0.0407
	(0.0158)	(0.0207)	(0.0162)	(0.0171)	(0.0233)	(0.0283)	(0.0299)	(0.0329)
15 Ksh Piece Rate	−0.0180	−0.0239	−0.0223	−0.0104	−0.0040	−0.0028	−0.0139	−0.0120
	(0.0166)	(0.0233)	(0.0173)	(0.0179)	(0.0250)	(0.0296)	(0.0310)	(0.0341)
Noise Condition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5 Ksh Mean	2.898	4.450	2.894	2.869	2.728	2.590	2.476	2.129
5 Ksh Median	10	51	10	10	9	9	8	6
Observations	2447	2447	2447	2447	2447	2447	2447	2447

Note: This table shows ordinary least squares regressions of inverse hyperbolic sine-transformed productivity outcome variables on piece rate indicators, treatment indicators, session, person, and room fixed effects with robust standard errors. The results demonstrate that increasing the piece rate from 5 to 10 Ksh increased productivity by approximately 3%, but that there was no effect of the 15 Ksh piece rate condition, possibly due to income effects.

Table B14: Measures of Cognitive Function

Domain	Task name	Ability task measures	Why ability is needed to sew
Attention	Psychomotor Vigilance	Ability to sustain focus	To avoid sewing off the edge or going past where the turn is supposed to be
	d2	Ability to ignore distractions	To focus on task while other things are going on around you
Working Memory	Reverse Corsi Block	Ability to store and manipulate information in your mind	To be able to keep in mind how elements will ultimately fit together
	N-Back	Ability to continuously update information	To be able to keep track of where you are in the task
Inhibitory Control	Hearts and Flowers	Ability to resist tempting impulses	To maintain control of sewing speed when surprised by something
Cognitive Flexibility	Wisconsin Card Sort	Ability to maintain multiple rules in memory and select which is most appropriate	To be able to switch from one element of the task to another (e.g. hemming to sewing the sides)
Higher-Level Reasoning	Raven's	Ability to recognize patterns and extrapolate	To identify potentially better methods for accomplishing the task

Note: This table contains descriptions of the cognitive tests used in the second experiment. The first column shows the domain of cognitive function that the test is designed to assess. The second column shows the name of each test. The third column shows the specific cognitive ability the test is designed to assess. The final column shows how this ability is potentially important in sewing.

Table B15: Experiment Two Balance and Summary Stats

	(1) Female	(2) Age	(3) High School or More	(4) Typical Daily Wage	(5) Days Worked Last Week	(6) More Annoyed by Noise than Others
Treatment Mean	0.523	25.846	0.696	528.916	1.208	0.296
Control Mean	0.509	25.940	0.706	550.188	1.203	0.302
Two-Sided P-Value	0.716	0.868	0.768	0.670	0.973	0.852
Normalized Difference	0.028	−0.014	−0.021	−0.033	0.003	−0.014

Note: This table assesses balance of sample characteristics between treatment and control sessions. The first two rows display the average of the variable indicated in the column for individuals observed in treatment and control sessions, respectively. Row three shows the p-value from a regression of the variable on a treatment indicator with standard errors clustered at the room by session level. The normalized difference is the difference between the treatment and control means divided by the square root of the average of the treatment and control variances as defined by Imbens and Rubin (2015). The results show that those observed in treatment and control are well balanced on observable characteristics. This is due to the within-person design. The only lack of perfect balance comes from a small amount of attrition.

Table B16: Experiment Two Reduced-Form Effect of Treatment

	Cognitive Function Tests				Placebo Effort Task	
	(1)	(2)	(3)	(4)	(5)	(6)
	Normalized Sum of Scores	Average of Normalized Scores	PCA of Percent Correct and Reaction Time	CFA of Percentage Correct and Reaction Time	Key Presses	Normalized Score
Treatment	-0.0304^{**}	-0.0239^{**}	-0.0589^{***}	-0.0635^{***}	1.8234	0.0039
	(0.0128)	(0.0092)	(0.0165)	(0.0194)	(19.0984)	(0.0408)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	762	762	762	762	762	762

Note: This table shows estimates from an ordinary least squares regression of cognitive outcome variables on an indicator for treatment, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The first outcome is the normalized sum of points that participants earned on tests during a session. The second column normalizes first at the test-score level and averages across normalized scores within a session. The third outcome is the first component of a principal component analysis of percentage correct and reaction time estimated on each individual's first control session. The fourth column is my preferred outcome: the first factor of a common factor analysis of percentage correct and reaction time estimated on each individual's first control session. The last two columns show that there was no effect of the same noise change on the placebo effort task.

Table B17: Experiment Two IV Effect of Noise – Treatment Intensity Instruments

	Cognitive Function Tests				Placebo Effort Task	
	(1)	(2)	(3)	(4)	(5)	(6)
	Normalized Sum of Scores	Average of Normalized Scores	PCA of Percent Correct and Reaction Time	CFA of Percentage Correct and Reaction Time	Key Presses	Normalized Score
Noise Level	-0.0233^{**}	-0.0168^{**}	-0.0478^{***}	-0.0529^{***}	-2.8033	-0.0060
	(0.0110)	(0.0082)	(0.0154)	(0.0182)	(15.8894)	(0.0339)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	762	762	762	762	762	762

Note: This table shows estimates from a two-stage least squares regression of cognitive outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by a set of treatment intensity indicators. The first outcome is the normalized sum of points that participants earned on tests during a session. The second column normalizes first at the test-score level and averages across normalized scores within a session. The third outcome is the first component of a principal component analysis of percentage correct and reaction time estimated on each individual's first control session. The fourth column is my preferred outcome: the first factor of a common factor analysis of percentage correct and reaction time estimated on each individual's first control session. The last two columns show that there was no effect of the same noise change on the placebo effort task.

Table B18: Experiment Two Fisher P-Values

Normalized Sum of Scores	Average of Normalized Scores	PCA of Percentage Correct and Reaction Time	CFA of Percentage Correct and Reaction Time	Key Presses	Normalized Score
0.165	0.115	0.022	0.035	0.906	0.906

Table B19: Impacts of Noise on Normalized Scores by Metric

	Attention		Working Memory		Inhibitory Control	Cognitive Flexibility	Higher Reasoning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PVT	D2	Corsi	NBack	Hearts and Flowers	Wisconsin	Ravens
Noise Level	−0.0210	−0.0011	−0.0308	−0.0253	−0.0380	−0.0509*	−0.0106
	(0.0266)	(0.0192)	(0.0303)	(0.0193)	(0.0232)	(0.0266)	(0.0204)
Wage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	762	762	762	762	762	762	762

Note: This table shows estimates from a two-stage least squares regression of the normalized score on each test on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by an indicator for being in a treated room. The results show that the effects of noise do not appear to be concentrated in any particular domain.

Table B20: Effects of Beliefs in Experiment One

	(1) WTP	(2) WTP Any	(3) WTP COP
Piece Rate	−0.2584	0.0169	−1.5658
	(1.5306)	(0.0203)	(2.5481)
Believe More Productive in Quiet	6.2208	0.2614***	−3.0795
	(5.7762)	(0.0760)	(7.9450)
Believe More Productive × Piece Rate	2.6918	−0.0669	7.1020
	(3.8755)	(0.0480)	(5.4276)
Day FE	Yes	Yes	Yes
Outcome Mean	17.697	0.538	32.906
Observations	476	476	256

Note: This table shows the results of a regression of willingness to pay and an indicator for being willing to pay a positive amount on an indicator for whether an individual was facing a piece rate, whether they stated they were more productive in quiet and their interaction. Because willingness to pay was elicited over two days in experiment one, day fixed effects are also included. Standard errors are clustered at the individual level. The results are consistent with the more detailed belief data from experiment two.

C Cognitive Task Descriptions For Online Publication

This appendix describes how the cognitive tasks were implemented and scored. All tasks were programmed on the python-based, open-source platform OpenSesame developed by Mathôt et al. (2012). During each trial session, respondents were seated at a desk and worked autonomously for approximately two hours. Tasks were presented in a random order on Windows touch-screen tablets with external keyboards attached at a resolution of 1280x768. During practice sessions, participants were instructed on the rules of each task, shown demonstrations, and given the opportunity to ask clarifying questions.

C.1 Attention

C.1.1 Psychomotor Vigilance

The Psychomotor Vigilance Task is implemented following Basner and Dinges (2011). Respondents stare at a blank white screen while resting a finger on the spacebar. At random intervals between 2 and 10 seconds, a red counter appears (see Figure C16). When the counter appears, the respondent's job is to tap the spacebar as quickly as possible. In each session respondents completed 100 trials scored as follows:

- Pressing the spacebar while no counter is present results in an incorrect response, the screen flashes "FALSE START" and earns zero points.
- Responses faster than 100 ms are considered as anticipatory responses, counted as incorrect, and earn zero points.
- Responses slower than 500 ms are considered attentional lapses, counted as incorrect, and earn zero points.
- Following Basner and Dinges (2011), for each correct response participants earn points depending on their inverse response time according to the following scoring rule: $5000 \times$ Inverse RT $- 10$.

The total score is then the average of the trial scores. For consistency with the other tests, in the common factor and principal component analyses response times are used rather than inverse response times.

C.1.2 d2

The d2 task follows the general instructions outlined in Brickenkamp and Zillmer (1998) and Bates and Lemay Jr. (2004), but is modified for computer presentation. For each trial, eleven

Figure C16: PVT Stimulus

Note: The figure shows a snapshot of a counter that appears in the PVT test displaying a time of 320 ms. The test is designed to assess attention. When the counter appears, respondents must press the space bar to stop it from counting up. The faster they press the space bar, the more points they earn.

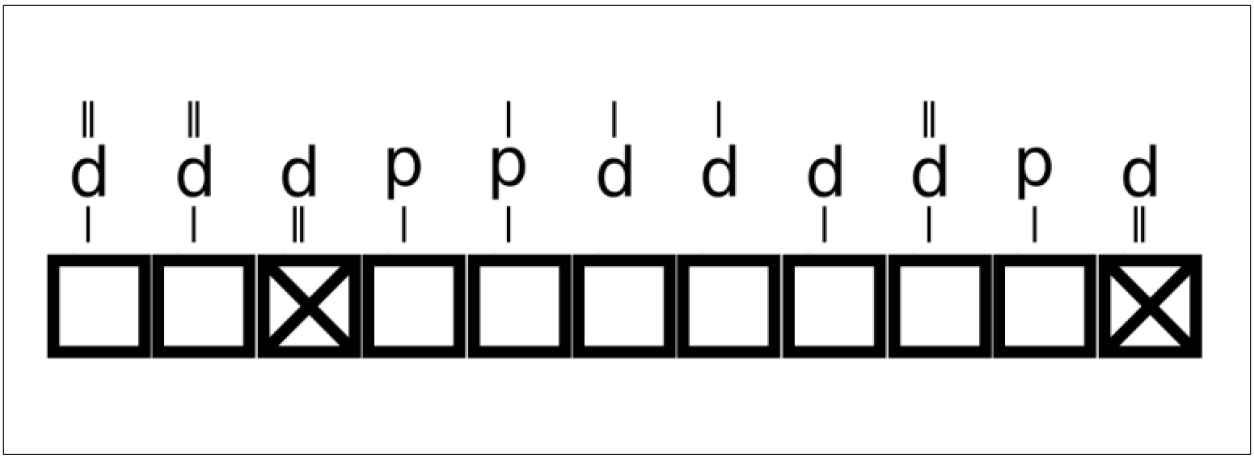


Figure C17: d2 Stimuli

Note: The figure shows an example of a trial from the d2 test. The test is designed to assess attention. Respondents see a series of d's and p's with up to two lines below and above. They must tap the boxes below all d's with a total of two dashes before the trial ends.

letters (either p or d) appear on the screen with between zero and two dashes above and zero and two dashes below for a total number of dashes between zero and four (see Figure C17). The respondent's job is to mark all of the d's with a total of two dashes by tapping the box below the letter. After 5106 ms, the trial ends. Until that time has elapsed, respondents can un-mark and re-mark letters as they please. Another set of eleven letters appears after 500 ms. Respondents complete 100 trials. For every d with two dashes correctly marked, respondents earn one point. Respondents lose one point for marking anything else. Their score is total number of points earned divided by number of possible points.

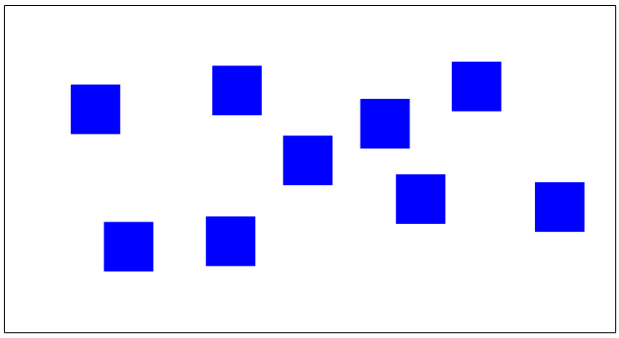
C.2 Working Memory

C.2.1 Reverse Corsi Block

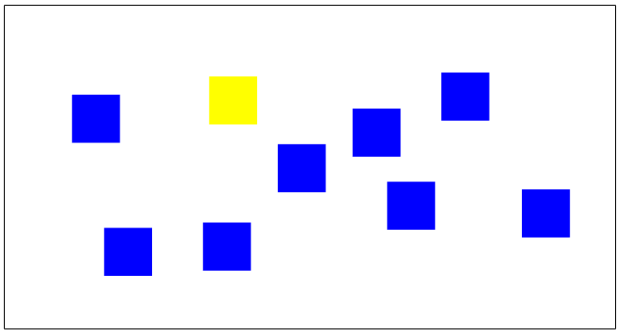
Implementation of the Reverse Corsi Block task follows Brunetti et al. (2014). For each trial, nine blue blocks appear in random locations on the screen. They take turns lighting up for 500 ms with 1000 ms between each flash. Respondents are then asked to tap the blocks in reverse order of how they lit up (see Figure C18). For each element in the sequence, if the respondent taps on the correct block, it turns green for 500 ms and the respondent can proceed to tap the next block in the sequence. If the respondent taps any other block, it flashes red and the respondent moves to the next trial. The first trial sequence contains two elements. For each sequence the respondent gets completely correct, the sequence length increases by one. For every sequence incorrect, the length decreases by one up to a minimum sequence length of two. Respondents complete 50 trials. The score is the average length of

the sequences that respondents complete.

(a) Blocks appear in random positions



(b) Blocks light up yellow randomly



(c) Respondents tap blocks in reverse order

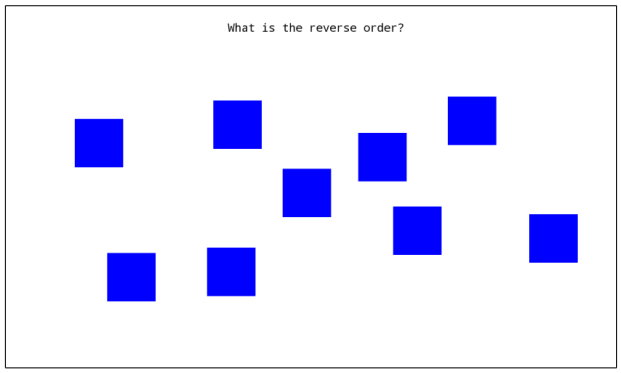


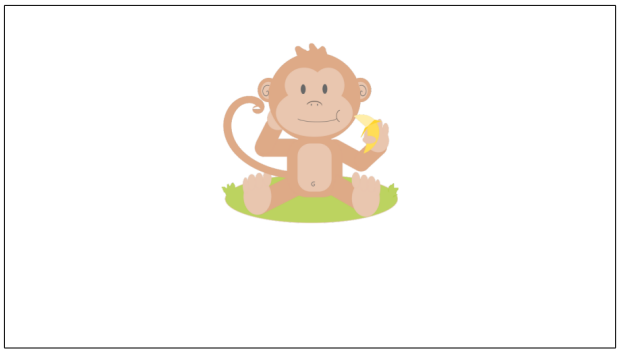
Figure C18: Corsi Stimuli

Note: This figure shows the three stages of the reverse corsi blocks test. The test is designed to measure working memory. First nine blocks appear in random positions. They then light up in a random sequence. Respondents must then tap the blocks in the reverse order of how they lit up. After each correct trial, the length of the sequence increases by one, and after every incorrect trial, the length of the sequence decreases by one down to a minimum of two elements.

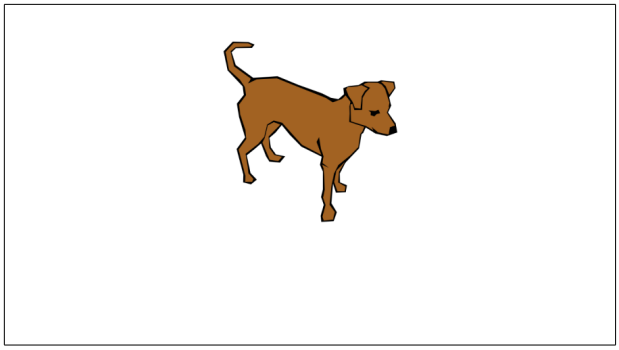
C.2.2 N-Back

Implementation of the N-Back task follows Wilhelm et al. (2013) with an "N" of two. For each trial, respondents see a sequence of twelve animal pictures. For each picture following the second, the respondents are required to tap either "MATCH" or "NO MATCH" depending on whether the image currently on screen matches the image shown two animals ago (see Figure C19). Each image is presented with a 2500 ms maximum response time and a 500 ms interstimulus interval. Each sequence is randomly determined by randomly drawing elements from a pool of ten images such that for each trial there is a 50% chance of the draw being a match. At the start of every session, respondents complete one practice trial sequence and then another 40 scored sequences. A respondent's score is the percentage of responses correctly marked times 10.

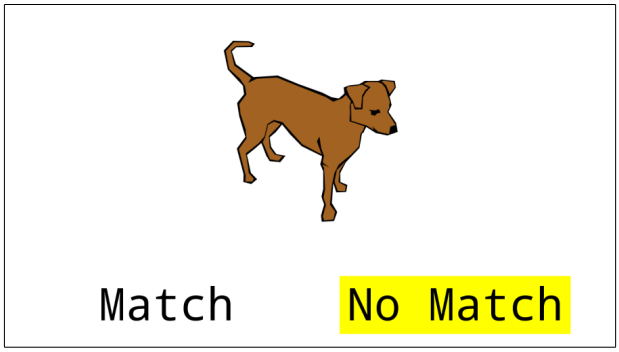
(a) First element



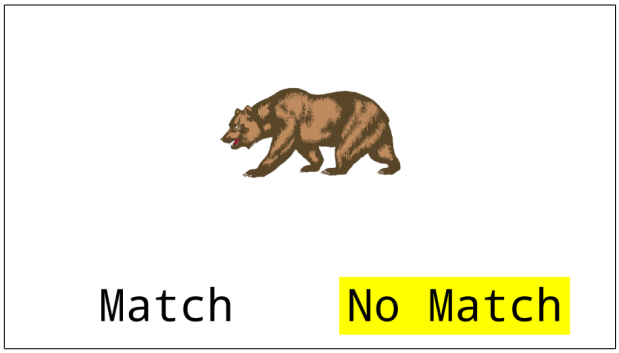
(b) Second element



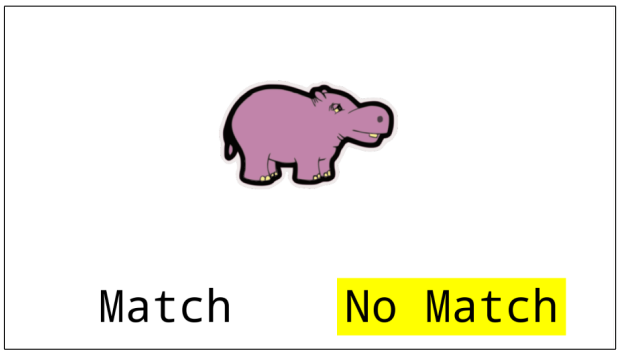
(c) Third element does not match first



(d) Fourth element does not match second



(e) Fifth element does not match third



(f) Sixth element does match fourth

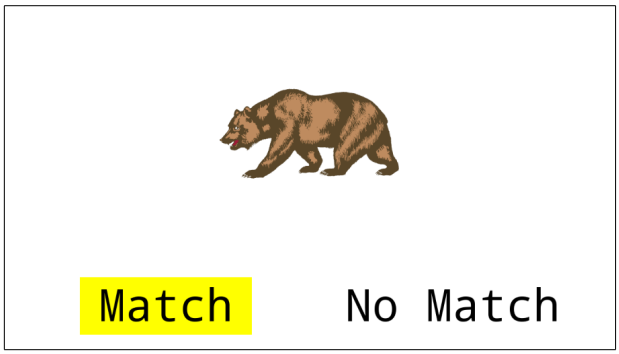


Figure C19: N-Back Stimuli and Responses

Note: This figure shows an example of six elements from an N-back sequence. The test is designed to assess working memory. Respondents see a series of animals and must indicate whether the animal currently displayed matches the animal seen two elements previously.

C.3 Inhibitory Control

C.3.1 Hearts and Flowers

Implementation of the Hearts and Flowers task follows the "dots" task outlined by Davidson et al. (2006). Respondents see a fixation dot in the center of their screen with blue boxes on the left and right. Respondents then see a sequence of hearts and flowers appear on the boxes. For each trial, respondents must press either the "Q" or "P" key. When a heart appears, respondents must press the key on the same side as the heart. While when a flower appears, respondents must press the key on the opposite side (see Figure C20). During each session respondents complete the following:

1. 6 practice trials with only hearts.
2. 126 scored trials with only hearts.
3. 6 practice trials with only flowers.
4. 126 scored trials with only flowers.
5. 492 scored trials with both hearts and flowers.

Each stimulus times out after 750 ms and there is a 500 ms interstimulus interval. Trials are scored as follows:

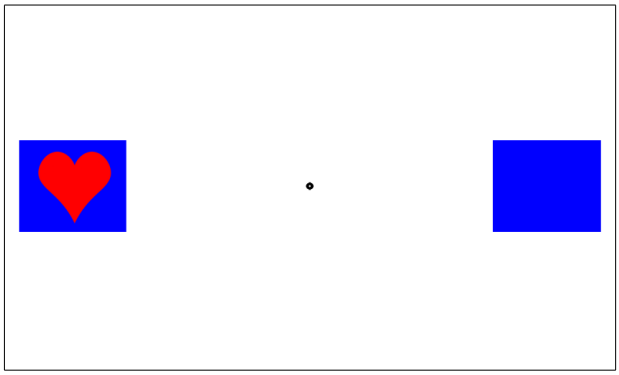
- Responses faster than 100 ms are scored as incorrect, anticipatory responses and earn zero points.
- Trials where the incorrect key or no key is pressed are scored as incorrect and earn zero points.
- For each trial with a correct response, respondents earn points according to the following scoring rule that is linear in their response time: $10 \times \frac{\text{RT} - 750}{200 - 750}$

C.4 Cognitive Flexibility

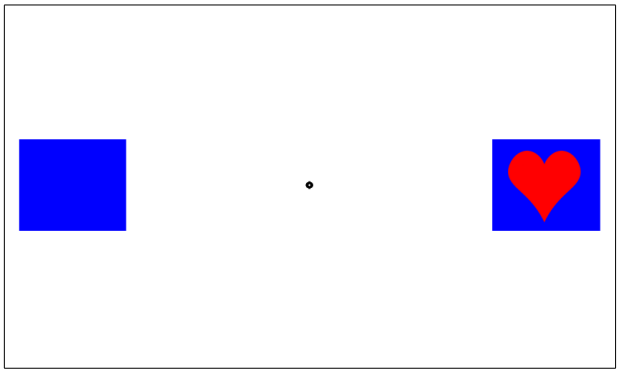
C.4.1 Wisconsin Card Sort

The Wisconsin Card Sort task follows the procedure originally outlined by Grant and Berg (1946) as modified for computer display by PsyToolkit (Stoet 2010, 2017). The respondent sees four response cards at the top of the screen and one question card (see Figure C21). Their job is to tap the response card that "matches" the question card. There are three possible matching rules:

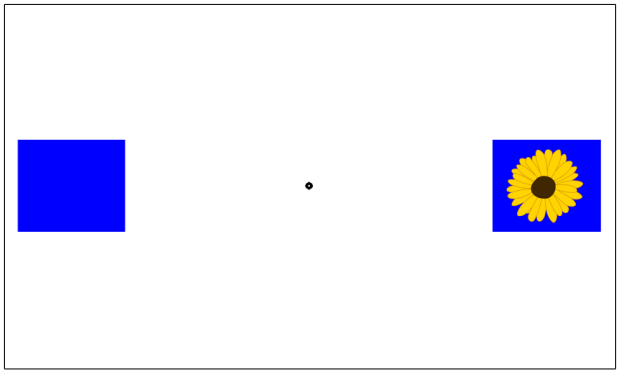
(a) Press ‘Q’ Key



(b) Press ‘P’ Key



(c) Press ‘Q’ key



(d) Press ‘P’ key

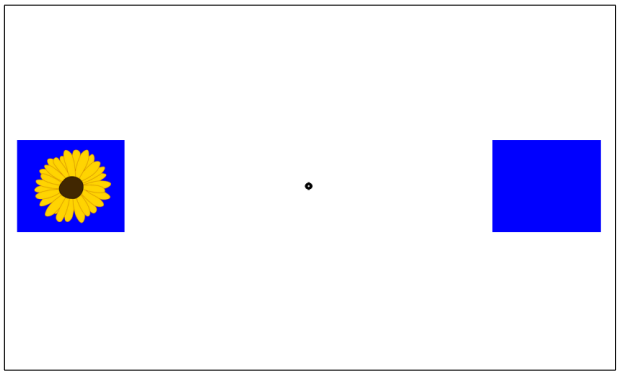


Figure C20: Hearts and Flowers Possible Stimuli and Responses

Note: The figure shows the four possible stimuli and responses for the hearts and flowers test. The test is designed to assess inhibitory control. Respondents see a series of hearts and flowers appear on the blocks. When a flower appears, the respondent must press the key on the opposite side of the keyboard. When a heart appears, the respondent must press the key on the same side of the keyboard.

1. Shape – In the example, the correct answer would be the fourth response card (four gold stars).

2. Color – In the example, the correct answer would be the third response card (three blue crosses).

3. Number – In the example, the correct answer would be the second response card (two green triangles).

Every ten trials a sorting rule is chosen at random. Respondents must figure out the sorting rule through trial and error. If the respondent taps the correct response card, the screen flashes "Correct!". If the response card they tap is incorrect, the screen flashes "Wrong!". Respondents complete 100 trials. Every incorrect trial earns zero points. Every correct trial is scored according to the following scoring rule linear in reaction time[34]: $10 + 200 \times \frac{10}{30000 - 200} - \text{RT} \times \frac{10}{30000 - 200}$.

C.5 Higher-Level Reasoning

C.5.1 Raven's

The Raven's task follows the classic task described by Raven (2000) with supplemental matrices graciously provided by Heather Schofield based on Schofield (2014). Respondents see a matrix with a missing piece and a set of possible pieces (see Figure C22), and their job is to tap the piece that completes the pattern in the matrix. In each session, respondents completed ten original Raven's progressive matrices alternating with ten supplemental matrices increasing in difficulty. For each incorrect response, respondents earned zero points. For each correct response, respondents earned points in a scoring rule linear in their reaction time[35]: $10.0 + 200 \times \frac{10}{60000 - 200.0} - \text{RT} \times \frac{10}{60000 - 200}$.

C.6 Effort

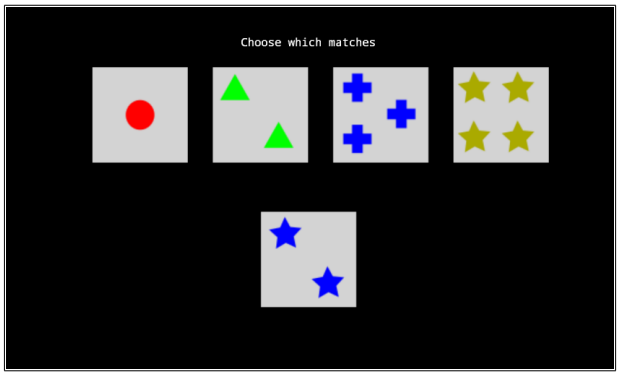
C.6.1 Effort Task

The effort task is implemented following DellaVigna and Pope (2018). Respondents have 10 minutes to alternate pressing the 'a' and 'b' keys. For each complete alternation, a progress

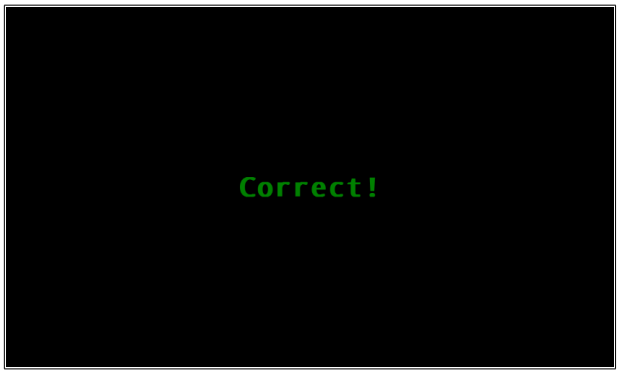
[34]Note that it is not traditional to score reaction time on this task because the task is typically presented with physical cards by an enumerator. I took advantage of the computer-based administration to collect reaction time and improve the measure's sensitivity.

[35]Reaction time is not traditionally collected on this test; however, I decided to take advantage of computer-based implementation and maximize the sensitivity of the test.

(a) Question



(b) If correct



(c) If incorrect

Figure C21: Wisconsin Stimuli

Note: The figure shows the three key screens from the Wisconsin card sort test. The test is designed to assess cognitive flexibility. Respondents are shown a card at the bottom of the screen and are asked to choose which of four cards at the top of the screen it matches according to one of three possible sorting rules. Respondents are not told which of the rules is being used and must figure it out by trial and error. Every ten trials the sorting rule changes.

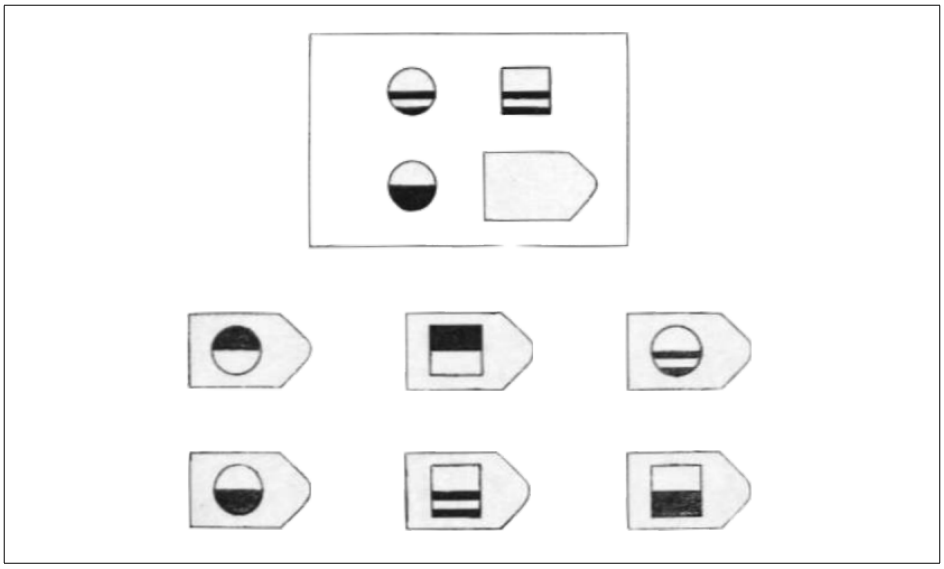
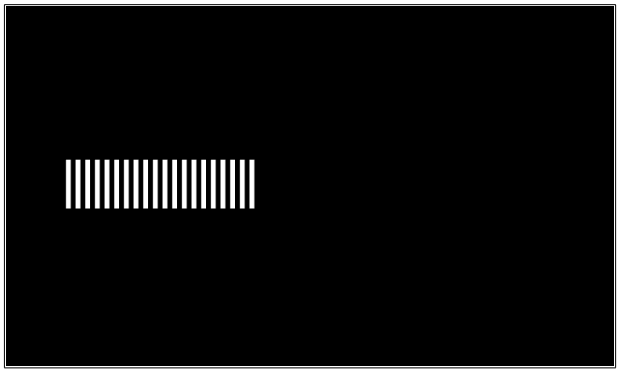


Figure C22: Raven's Stimulus

Note: This figure shows an example of a trial from the Raven's matrices test. The test is designed to assess higher-reasoning skills. The respondent sees a pattern of shapes with one missing. They must choose which of the possible answers completes the pattern.

bar on the screen increases by one hash mark. At increments of 50, the bar resets and respondents are reminded of their total score (see Figure C23). Respondents earn one point for every 300 alternations.

(a) Press ‘a’ and ‘b’ until progress bar fills



(b) See total score every 50 presses

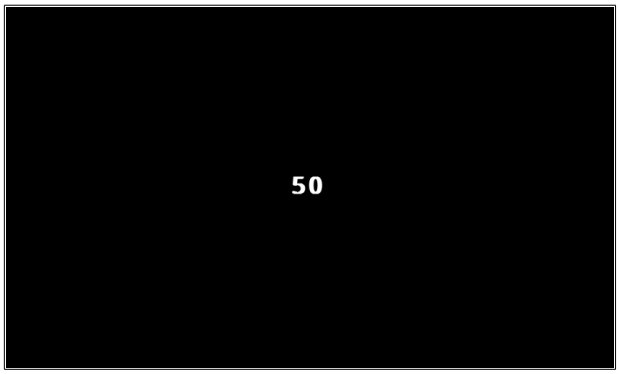


Figure C23: Effort Stimuli

Note: The figure shows the two key screens from the effort task. The respondent must alternate pressing the ‘a’ and ‘b’ keys. As they do, a progress bar (shown on the left) begins to fill up. After every 50 completed alternations the respondent sees his/her score (shown on the right), and the progress bar resets to zero.

D Willingness to Pay Script For Online Publication

“I’m sure you’ve noticed these two weeks that sometimes a noisy engine is outside of the rooms. For each of the first two practice sessions tomorrow, we are going to give you the chance to pay in order to work in a room without the engine outside. However, the price for working in the quieter room has not yet been decided. It will be determined for each session by a game of chance. You will not have to pay anything more than you want to, and you might even get it for less! Here’s how this will work:

For each session, you and I will figure out the highest price that you are willing to pay to work in the quieter room. Then tonight our computer will randomly decide the price. If the price is higher than you said you are willing to pay, when you come tomorrow you will be in the room with the engine outside. If the price is lower than what you said you were willing to pay, the randomly chosen price will be deducted from your pay for that session, and you will work in the quieter room.

Since this is complicated, we will first make a plan for which prices you would like to pay to work in the quieter room. I will ask you whether you would be willing to pay several prices in order to be in the quieter room and you will tell me yes or no. After we are done, you will not be able to change your plan. Do you understand?”