Noise, Cognitive Function, and Worker Productivity

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Abstract

Noise is ubiquitous in the developing world, yet its impacts on economic outcomes are poorly understood. I investigate whether noise lowers worker productivity. First, I estimate the reduced-form impact of noise pollution by randomly exposing workers in a textile training course to engine noise. An increase of 10 dB (from the noise level of a dishwasher to a vacuum cleaner) decreases worker productivity by approximately 5%. The primary channel proposed in the psychology literature for noise to affect human performance is by impeding cognitive functions such as attention and working memory. I explore this mechanism by conducting a second experiment where I randomly expose individuals from the same population to engine noise while they complete cognitive tests. The same noise change decreases cognitive function by 0.05 standard deviations but does not affect performance on an effort task. This suggests the returns to improving cognitive function are large. Finally, I assess whether individuals understand these effects by allowing participants in both experiments to pay for quiet working conditions under different performance incentive schemes. Individuals' willingness to pay is not affected by the wage structure, suggesting participants neglect the productivity effects of noise. I conclude by using a compensating differentials model to consider the efficiency implications of this neglect.

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1 Introduction

Noise is ubiquitous in the developing world. Car horns are used so incessantly in India that manufacturers had to develop louder and more durable versions to cut through the din (Sen Gupta 2014). Factory workers are exposed to eight or more hours of noise as loud as a jet engine (Nandi and Dhatrak 2008; Kimani 2011). In addition to hearing loss and annoyance, cognitive science research suggests these noise levels might reduce worker productivity by impairing the basic cognitive functions, such as attention and working memory, needed to manage deliberate activity (Szalma and Hancock 2011; Matthews et al. 2000b; Jones and Broadbent 1991). However, unlike other worker attributes that are important to productivity (e.g. human capital) there are no causal estimates of the economic return to cognitive function. Without this link, understanding the economic importance of excessive noise exposure is difficult.

This paper investigates the impact of noise on productivity via impediments to cognitive function with two randomized experiments in Kenya. 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. This mechanism is of particular interest because a recent literature in economics considers how conditions of poverty might affect cognitive function, but no work has yet estimated a causal relationship between cognitive function and economic activity (Lichand and Mani 2016; Mani et al. 2013; Schilbach et al. 2016). 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 their performance incentives. Finally, I use a compensating differentials model to consider the efficiency implications of my results.

I demonstrate that noise can meaningfully reduce productivity in a real-work setting. While a significant literature considers the impact noise can have 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 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 minimized participants' familiarity with their neighbors by randomly assigning work stations. I estimate that increasing the noise level by 10 dB (from the noise level of a dishwasher to the noise level of a vacuum cleaner) decreased output by approximately 5%. For comparison, Bloom et al. (2013) find that an intensive, nine-month management intervention increased output by 9%.

Given that the task did not involve communication, the most plausible channel for this impact is through the effect noise has on cognitive function. Cognitive function (also called executive function) encompasses all of the general-purpose abilities involved in task management such as the ability to direct one's attention or to manipulate information in memory (Diamond 2013). These skills appear critical for many types of work. For example, a foreman in a factory requires a broad range of attention in order to ensure that none of the workers under his/her supervision are making mistakes. An auto-rickshaw driver must simultaneously manage all of the tasks of driving while taking directions from his/her passenger. Cognitive science research has shown stronger cognitive function is correlated with better job market outcomes, better physical health, and success in school (Bailey 2007; Borella et al. 2010; Crescioni et al. 2011; Duncan et al. 2007; Gathercole et al. 2004). Yet, we do not have any causal estimates of the impact of these task management abilities on real-world economic outcomes.

Decades of cognitive science research has highlighted the damaging effect excessive noise exposure has on cognitive function (Evans and Hygge 2007; Hockey 1970; Jones and

Broadbent 1991; Matthews et al. 2000b; Smith 1989; Szalma and Hancock 2011). Noise has been shown to inhibit performance on tasks that require broad attention, management of several component sub-tasks, and memory recall – especially the loud and variable types of noise common in developing contexts (Hygge et al. 2003; Irgens-Hansen et al. 2015; Jahncke et al. 2011; Kjellberg et al. 2008). This large literature suggests noise pollution provides a promising context in which to study the importance of cognitive function for real-work tasks. It both provides assurance that cognitive function is likely an important mechanism and provides guidance on what alternative channels to examine – namely decreased motivation and physical distress from a sufficiently large stress increase.

In order to assess cognitive function, I randomly exposed individuals from the same population to noise while they completed a wide variety of cognitive tests. The same engine noise reduced performance on a common factor index of test outcomes by 0.05 standard deviations. In order to assess alternative mechanisms, I also recorded respondents' blood pressure and had respondents complete an effort task (DellaVigna and Pope 2016). I find the increased noise led to a small increase in blood pressure suggesting that respondents did experience more stress, but the effect is too small to have had physical effects. Moreover, I find no change in performance on the effort task. Combined, this evidence suggests physical distress or diminished motivation are unlikely to be important mechanisms. Of course, there could be alternative channels not considered in the literature, but if we are willing to assume cognitive function is the primary mechanism, the combined results of these two experiments imply cognitive function is an important input to worker productivity.

I then demonstrate that individuals neglect the productive impact of noise. 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, almost no work exists on whether individuals take actions to protect their productivity from detrimental environments or stimuli.[1] In order to

[1] One exception is Schofield (2014) which demonstrates that individuals fail to make food purchases that would improve their productivity.

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. Using my within-person variation, I then compare the effect noise had on each individual's output with that individual's willingness to pay for quiet to 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 when asked, but their stated beliefs about the productive impact of noise were incorrect. Moreover, individuals appeared to realize that they did not understand the productive value of quiet and were unwilling to stake any money on their stated beliefs.

Finally, I use a compensating differentials model to consider the efficiency implications of this neglect and argue distortions are likely to persist even with government intervention. In both experiments, I estimate that the productive effects of noise are heterogeneous across workers. Thus, in the model workers vary in both their disutility from noise and the impact noise has on their productivity. I assume firms are unable to observe these attributes directly. This means that if firms pay fixed wages, even without neglect, efficiency losses are likely due to the standard contracting problems associated with private information. The typical solution to these problems is to make workers the residual claimants of their own productivity; however, if workers neglect the productivity effects, this fails to solve the problem. The intuition is that to the extent that the disutility and productivity effects of noise are not perfectly correlated, neglect undoes the screening effect of the piece rate, changing the composition of workers willing to work in noise. Thus, without information about each worker's type neither firm action nor government intervention will be able to restore the first-best composition of workers in the noisy sector.

The remainder of this paper is organized as follows: Section 2 discusses the prevalence

of noise pollution in developing cities and its effects on cognitive function, 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 Section 6 concludes.

2 Background

2.1 Noise Pollution in Developing Contexts

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 of 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 not surprising 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 1 out of 4 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 citizens of poorer cities have substantially more age-adjusted hearing loss. In particular, the average citizen of Delhi or Mumbai has hearing loss equivalent to their counterparts in New York or Tokyo who are eight years older.

2.2 Noise and Productivity

In spite of 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 hard to interpret this result. Broadbent and Little (1960) studied the effects of a noise-abatement treatment in one room of a Kodak factory and found that the noise decrease of 10 dB was associated with fewer worker errors; although, there was significant improvement in the non-abated rooms as well. Finally, Levy-Leboyer (1989) cross-randomized 52 workers into assembling either carburetors or air conditioners in either their typical noisy conditions or in a separate quiet room. Workers assigned to assemble air conditioners in quiet were 14% faster than those in normal conditions, but those assigned to assemble carburetors in quiet were 10% slower than their counterparts in noise. Together, this work suggests noise might impact real-work outcomes, but none provides large-sample evidence that distinguishes the effects of noise exposure from other location-specific features.[2]

[2]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 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, a 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 can affect productivity directly. This includes recent work in economics on how temperature, alcohol, air pollution, and hunger can affect productivity (Adhvaryu et al. 2016; Chang et al. 2016b, 2016a; Park 2017; Schilbach 2017; Schofield 2014; Zivin and Neidell 2012). While these studies provide invaluable evidence on the potential for environments to affect productivity, they are unable to speak directly to the importance of a cognitive mechanism because the factors they study generally affect productivity through multiple channels.

To my knowledge, no work bridges the gap between these two groups and studies how a single stimulus affects productivity through cognitive function. Without tracing this entire path, interpreting the importance of environmental stimuli where we only have evidence on cognitive effects is difficult. In particular, in order to evaluate the importance of the cognitive impediments associated with poverty, we need an estimate that translates these effects into economic outcomes (Schilbach et al. 2016). As noted above, the large literature on the cognitive effects of noise exposure makes an exploration of this cognitive channel possible.

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 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 vocational training facility located in an industrial development zone outside of Nairobi. 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 indicates 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).

3.1.2 Generating Noise

There are three ways to manipulate noise exposure: ambient-level abatement, individual-level protection and generating additional noise. Ambient-level abatement is undesirable from an experimental perspective because it involves significant, location-specific investments that 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 mate-

rial. While effective at reducing noise, this means 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 doesn't 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 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. For these reasons, I chose to manipulate noise by adding a new noise source to the preexisting noise generated by the sewing machines.

In order to create noise representative in both level and quality of that faced by residents of developing countries, I chose to generate noise with a car engine the TDC uses for auto-mechanic training classes (see Figure A2). This type of engine noise is representative of both noise pollution generated by 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). The representative nature of the noise is thus important for external validity. 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; while in the treatment condition, workers experienced noise equivalent to listening to a home vacuum cleaner.

One might be concerned that, in addition to creating noise, engine exposure could alter other environmental conditions. For example, engine exhaust might decrease the 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 increased noise exposure was the only effect of treatment, enumerators were instructed

to keep the windows and doors unchanged and to 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.[3]

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 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. 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 with the criteria marked). In the analysis below, I use these grading data to construct three

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

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 4 criteria and another meeting 3 criteria, the total number of points earned would be 7. 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 2 criteria, the number of pockets meeting 3 criteria, and so on. The distribution of these outcomes is skewed, but has zeros (see Figure A4). Thus, to improve power I use inverse hyperbolic sine transformations as my preferred outcomes following Burbidge et al. (1988).[4] For robustness I also present the results in levels. All of the outcomes 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 they created. On the last two days, respondents had the opportunity to pay to work in quiet. On all days, participants worked for 3 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. This, combined with the lack of knowledge

[4] 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 coefficients can be interpreted in a similar manner to a standard log transformation.

about future treatment status, isolated 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 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. 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 either by raising the contemporaneous marginal utility of consumption or by narrowing attention to the present.

2. On the fifth day participants decided whether to buy maize flower in 5 kg bags or in 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. To do so I generated random schedules for each round that satisfied both of the following constraints:

- Each worker spent half of the time in noise and half in quiet.

- In each session an equal number of participants worked in quiet and in noise.

I then randomly assigned each participant to one of the schedules. In order to avoid any location-specific confounds, participants worked in two similar rooms, and I randomized which room was noisy for each session[5] (see Table B2 for balance tests). This generalization of stratification was necessary because my piloting demonstrated significant heterogeneity in 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. Following this randomization method, I include worker, room and session fixed effects in my regressions which significantly improves my power.

3.2.4 Compensation

For each production session, I randomized workers to one of three wage conditions. Each wage was a combination of a piece rate paid based on the number of perfect pockets produced and a flat payment for participation. All three conditions were calibrated to yield approximately 200 Ksh per session (or 600 Ksh per day), but differed in the relative importance of the piece rate and flat payment.[6] This allows me to benchmark the observed effect of noise against the effect of traditional incentives.

[5]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.

[6]On training days all respondents received 600 Ksh (approximately $6.00) for participating. The production day piece rates were one of 15, 10 or 5 Ksh per perfect pocket. In the first round, the corresponding flat rates were 140, 160 and 180 respectively. After participants in the first round were more productive than anticipated, the flat rates were decreased to 95, 130, and 165 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

Treatment increased the noise level by approximately 7 dB (Figure A3 and Table 1).[7] 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 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 (1). The regression includes individual, time, room, and wage fixed effects and has standard errors clustered at the level of randomization (room $\times$ session).

$$y_{ijtw} = \tau \cdot \text{Treatment}_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijtw} \tag{1}$$

$$y_{ijtw} = \nu \cdot \text{Noise Level}_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijtw} \tag{2}$$

To improve interpretability I also estimate an instrumental-variables specification shown in equation (2) with two sets of instruments. First I use the treatment indicator as an instrument as shown in equation (3) below; however, this 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, I estimate a second specification shown in equation (4) that takes advantage of this variation. To do so, I generate 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.

[7] For interpretability all noise levels 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.

There are no clear relationships between session intensity and any observable characteristics besides noise (Table B6).

$$\text{Noise Level}_{jt} = \eta \cdot \text{Treatment}_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijt} \tag{3}$$

$$\text{Noise Level}_{jt} = \sum_{p=1}^{10} \lambda_p \cdot \text{Treatment}_{jpt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijt} \tag{4}$$

One might worry that the second set of instruments is weak, but a regression of the noise level on the excluded instruments yields an F-statistic over 80 (see Table B3). For robustness I also present results estimated using limited information maximum likelihood (LIML) in Appendix B.

3.3.3 Main Results

Workers sewing in treated rooms produced approximately 3% fewer pockets (Table 2). 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). Interestingly, in these specifications, there appears to be no effect of the noise on the number of perfect pockets. This is likely because for the first days of work most participants were unable to make any perfect pockets and so there was no variation for treatment to alter.[8] Fisher p-values shown in Table B4 yield similar inferences.

However, as noted above, these estimates do not take full advantage of the variation in treatment intensity. Thus my preferred specification uses the full set of intensity instruments and the transformed outcomes. Using this full amount of variation, the coefficients are larger and a 10 dB increase in the noise level decreases the number of perfect pockets by approximately 5% (Table 4).

[8] 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 B8 shows this is not the case. Additionally, estimations 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, as 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 selling water on the side of the road. On the other hand, many factory employees are required to work in teams assembling complex objects, and noise would likely both impede 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. More research is needed to understand the effects of other common sources, such as your child overhearing your neighbor's television while trying to study.

3.3.4 Treatment Effect Heterogeneity

One might wonder if 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.[9] I then estimate the treatment effect separately for each group using the treatment intensity instruments in a stacked regression with common fixed effects.[10] The treatment effects are just as large among better workers (Figure A5).

Another question is whether these results are specific to the context where individuals are learning how to perform a task or where they have not yet had the chance to adjust fully

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

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

to their surroundings. I assess this possibility by estimating the treatment effect separately for each week in the following specification:

$$y_{ijt} = \nu_1 \cdot \text{Noise Week } 1_{jt} + \nu_2 \cdot \text{Noise Week } 2_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijt} \tag{5}$$

In order to have a strong first stage against both endogenous variables, I re-group the sessions by treatment intensity within each week and generate new treatment intensity indicators. The effect on perfect output, total points and total output is constant across the two weeks (Figure A6).

Finally, in terms of generalizing these effects, one might wonder whether distractions are substitutable. That is, once an individual is distracted by something (say financial concerns) the effect of an additional distraction is negligible. I assess this possibility by estimating the treatment effect in the presence of another distractor studied in the literature – temperature (Adhvaryu et al. 2016; Park 2017). I first split the sessions by the median temperature and then estimate the treatment effect separately for each sample in the following specification:

$$y_{ijt} = \nu_1 \cdot \text{Noise Low Temp}_{jt} + \nu_2 \cdot \text{Noise High Temp}_{jt} + \alpha_i + \gamma_t + \phi_j + \kappa_w + \epsilon_{ijt} \tag{6}$$

Similar to the estimation strategy across weeks, in order to maintain a strong first stage, I re-group the sessions by treatment intensity within each temperature group and generate new treatment indicators. The treatment effect of noise appears either to remain constant or grow as other distractions increase (Figure A7).

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.[11] The results are imprecise but do not suggest that lagged exposure is important (Table B10). Additionally, treatment did not affect any of the decision tasks (Table B11). Taken together, all this suggests that while the effects of short-term noise exposure can be important contemporaneously, the effects do not persist into later periods of quiet.

3.5 Conclusions from Experiment One

These results suggest that noise pollution has the potential to have a significant impact on productivity. In their noise survey of central Nairobi, Wawa and Mulaku (2015) found that noise levels ranged between approximately 55 dB (the level of a background conversation) and 85 dB (the level of a lawn mower). If we can believe the effect of noise remains linear outside of the range considered in this experiment, this implies that workers in the quieter areas of Nairobi are 15% more productive than those in the more noisy areas.

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 4%.[12] Kaur et al. (2015) found that offering commitment contracts increased output by 2.3%. Finally Bloom et al. (2013) found 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

[11] The lagged treatment indicator is set to zero for the first session of each day assuming that respondents did not have significant noise exposure in the time between waking up and arriving at the training center.

[12] 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 the flat rates were calibrated to compensate on average, income effects began to mitigate the piece rate's effectiveness as an incentive.

and the production processes (Hansen and Goelzer 2001). Nevertheless, one can consider whether this effect is large enough 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 translated 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 $12.50 an hour. 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 B9). 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.

4 Experiment Two: Noise and Cognitive Function

While the evidence from experiment one described above demonstrates the potential importance of noise pollution, it does not speak to the underlying cognitive mechanisms. These mechanisms are of particular interest because recent work argues that conditions of poverty may trap participants by impeding their cognitive function (Schilbach et al. 2016). Yet, without causal evidence on the importance of these cognitive functions for economic activity it is difficult to evaluate the plausibility of this claim.

The extensive psychology literature on the effects of noise provides an opportunity to assess the importance of this cognitive mechanism. In particular, I can estimate the effect that the same noise change has on cognitive function and other mechanisms through which the literature suggests noise might affect productivity (namely changing the technology of

the task, decreasing motivation and causing physical distress). If the other possible channels were not affected, I can use noise exposure as an instrument to obtain an estimate of the importance of cognitive function for productivity.

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 as before (see Table B1 for a comparison of sample demographics). The experiment was conducted in similar rooms less than a mile away from the TDC (see Figure A1 for a map of the locations). The timing was a condensed version of experiment one (see Figure 4). Participants came for two-day rounds. They first spent two hours learning how to complete the cognitive tests. They then spent the remaining sessions working autonomously on the assessments in two-hour increments. I randomized each participant to work in quiet and noise for two sessions each (see Table B13 for balance tests). Noise was generated by a similar engine as the one in the first experiment.

4.2 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 B12 (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.

For analysis, I aggregate these individual test results into an index. Because the literature does not thus far provide guidance on which aspects of cognitive function are most

important for 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:

$$m_{ij} = b_j \psi_i + \Sigma_{ij} \tag{7}$$

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' 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 normalized total number of points earned by a participant, the average of the normalized test scores 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 5). Moreover the differences in average noise level between treatment and control were also quite similar to those in experiment one (Figure 5). 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 same IV with treatment-intensity instruments as described above. The first stage is strong with

an F-statistic of 33 (Table B3). For robustness I also present the results of the reduced-form effect of treatment, the just-identified IV, and the LIML estimation of the IV with treatment intensity instruments in Table B14, Table B15 and Table B16 respectively. All specifications yield similar results. Fisher p-values presented in Table B17 yield similar inferences.

I estimate that the doubling of the perceived level of noise reduces performance on my preferred index by approximately 0.05σ (Table 6). This change does not appear to be driven by any particular domain (Table B18).[13] While this effect may seem small, it is important to recognize that the size of the standard deviation is driven primarily 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.

These effects are 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 Estimating the Effect of Cognitive Function on Productivity

While these effects are of independent interest, they also provide the opportunity to shed light on the relationship between cognitive function and productivity. In particular if we believe that noise affects productivity only through cognitive function, we can use noise exposure as an instrument in a split-sample IV to obtain an estimate of the impact of cognitive function on productivity (Angrist and Krueger 1992). However, we must first consider whether there are other channels through which noise could have affected workers' productivity. In particular,

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

based on the literature we should assess whether noise affected the technology of the task directly, decreased motivation, or caused physical distress (Matthews et al. 2000b).

The first concern one might have is that the noise level affects the technology of the task. For example, if the task depended heavily on communication, the increased noise level would likely reduce productivity by making it harder to hear. As mentioned above, the task in experiment one was chosen precisely because it does not require any kind of listening or communication in order 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 to not talk to each other, and I randomized seat assignments to avoid participants becoming friendly with their neighbors.

Another concern one might have is that the noise level reduces a respondent's motivation.[14] To assess this possibility, participants in experiment two complete an effort task used by DellaVigna and Pope (2016) where respondents must alternate between pressing the "a" and "b" keys on a keyboard for 10 minutes. The results presented in Table B19 show that effort did not change in response to the increase in noise. The point estimate suggests that a doubling of the noise level decreases the number of key presses by 2.8 relative to a control mean of 2192, and a decrease in effort larger than 1.6% is outside of the 95% confidence interval. This is consistent with the results of the first experiment where being in noise did not decrease respondents' willingness to stay and work for another hour for a piece rate (see Table B11).

A final concern is whether the noise caused physical distress through increased stress. A significant psychology literature has demonstrated that one of the ways an increase in the noise level can impair cognitive function is by increasing stress levels (Szalma and Hancock 2011). This might cause one to worry that a sufficiently large increase in stress could have a direct effect on task performance by impairing normal body functions like breathing and the

[14]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.

ability to sit still. I find that stress, as measured by blood pressure, increases as expected among individuals in the treatment condition, but that the effect is too small to manifest as physical impairment (see Table B20). To put the magnitudes in perspective, the variation is one twentieth the size that I observe in the cross-section and one twentieth the size Madden et al. (2017) find as residual variation after controlling for individual-specific trends. Moreover, any physical impairment should have affected performance on the effort task.

If cognitive function is indeed the only channel through which noise affects productivity, the estimate of the effect on productivity from the first experiment provides a reduced-form, and the estimate of the effect on cognitive function provides a first stage, for a split-sample IV (Angrist and Krueger 1992). Specifically, I take the ratio of the noise level coefficients from the treatment intensity specifications and use the delta method to calculate standard errors. The estimates imply a substantial return to temporary shifts in cognitive function (Table 7). In particular, for perfect pockets, I estimate a return of 103% for every one standard deviation change in cognitive function, and the estimates for the other outcomes are larger.

Equipped with this estimate we can use back-of-the-envelope calculations to consider how other cognitive impediments from the literature might impact productivity. Table 8 reports the results of several studies that examine how other stimuli can affect cognitive function. In the last column I combine these findings with my estimate for the impact of cognitive function on perfect output to show what they imply for productivity. For example, Ebenstein et al. (2016) find a 10 unit increase in fine particulate matter on the day of a high-stakes exam reduces performance by 0.017 standard deviations. Assuming this change in performance is driven by diminished cognitive function, my estimate implies the same change should reduce productivity by approximately 2%. Reassuringly Chang et al. (2016b) study the productivity effect of this pollution change directly and find it reduces factory-worker output by 8%. This suggests that after accounting for the physical effects of pollution, an effect of approximately 2% through diminished cognitive function is reasonable.

Because the impacts on cognitive function observed by Mani et al. (2013) are an order of magnitude larger than those observed in this study, we should be cautious in applying this estimate to their context. However, this estimate does imply that the changes that they report are likely to have significant economic impacts. This suggests that when setting priorities policy makers should seriously consider how environments of poverty might reduce productivity by impeding 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. To understand whether noise has meaningful, real-world consequences, it is vital to understand whether individuals and firms will employ strategies to mitigate these effects. For example, the most obvious mitigation strategy for this type of distractor is paying a compensating differential to be able to work in quiet. If the effects observed in the experiment are driven by a subsample who are willing to accept lower wages in order to have higher productivity, then in equilibrium the effect might be significantly attenuated by sorting. More generally, with the exception of Schofield (2014) which demonstrates that individuals fail to make food purchases that would more than pay for themselves through increased productivity, no work so far has assessed whether, or to what degree, individuals take actions to protect their cognitive function from potential impediments.

In order to consider the potential for adaptation, I first assess whether individuals are aware of the impact noise has on their productivity. At the end of each round of both experiments, I offer participants the chance to pay for quiet working conditions and randomly

vary whether they face a piece rate or a flat rate wage.[15] This allows me to assess both individuals' disutility from noise and the degree to which they are attuned to its impact on their productivity. In particular, workers' willingness to pay while they are facing a flat rate is a measure of the pure disutility value of working in noise. Any additional amount they are willing to pay when facing a piece rate is a measure of their understanding of the impact noise has on their productivity. This is because workers who understand that noise lowers their productivity will be more willing to pay for quiet when their pay depends on their performance. For example, the median worker in my study who produces 9 pockets should be willing to pay an extra 7 Ksh to work in quiet when they are facing a piece rate of 15 Ksh rather than a pure flat rate. I then combine these results on neglect and disutility with estimates of the true productivity effects from my experiments in a simple compensating differentials framework to discuss implications for efficiency.

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 they are willing to pay for a good. Then a random price is drawn. If the price is below the respondent's willingness to pay, he or 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.

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?".[16] This procedure makes the task as concrete as possible and narrows to a final

[15] 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 and a flat rate. They are told that one of their choices will be randomly implemented.

[16] 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

number in only eight questions. In order to ensure understanding, after finalizing a maximum willingness to pay, respondents must correctly answer verification questions, and before doing the task for quiet working conditions, 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 also has the benefit of approximating a labor-market situation where individuals deciding where to work must choose whether to forgo higher potential wages for the sake of future quiet.

5.3 Willingness to Pay Results

The histograms presented in Figure A10 demonstrate that willingness to pay for quiet is extremely low, even before trying to distinguish willingness to pay due to increased productivity from willingness to pay due to disutility of noise. The median willingness to pay in the first experiment is only 2 Ksh ($0.02) and 0 Ksh in the second experiment. Thus it appears that most individuals are not willing to forgo any significant amount of earnings for more comfortable working conditions.

Still, 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 for those willing to pay a positive amount[17] on an indicator for whether the respondent was offered a piece rate or a flat rate with standard errors clustered at the individual level. 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 9).

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.

[17]This is a potentially problematic outcome because it involves selecting the sample on the dependent variable; however, in this case, the specification serves to show the subsample does not behave differently than the complete sample.

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 using the following hierarchical linear model to estimate a within-person treatment effect:

$$y_{it} = \rho_i + \tau_i \text{treatment}_{it} + \phi_i \text{session}_t + \beta \text{session}_t^2 + \epsilon_{it} \tag{8}$$

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

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. This is especially concerning in this context because the hypothesis of interest is whether the coefficient is zero and including an imprecisely-estimated, right-hand-side variable would create attenuation bias. The hierarchical model reduces this bias in the individual estimates by engaging in partial-pooling. This is analogous to the approach used by Chetty et al. (2014) and Kane and Staiger (2008) to evaluate a teacher's value added. The model appears to fit the data well and strongly predicts the out-of-sample, realized scores in the willingness to pay sessions (Figure A12). The distribution of estimated productive values of quiet shown in Figure A11 has significant mass beyond the 95% confidence interval of the response to the piece rate estimated above.

To test for differential responses among those for whom quiet is most valuable, I re-estimate the willingness to pay regressions while interacting the model's estimate of the value of quiet with the 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. This is not the case (Table 10). In particular, consider the benchmark case of perfectly rational individuals who understand how noise affects their productivity. For these individuals, the interaction term should be one as they increase their maximum

willingness to pay when facing a piece rate one-for-one with the additional amount they will earn through increased productivity.[18] I can reject this benchmark for both experiment one and experiment two at the 10% and 5% confidence levels respectively.

Another potential explanation for this lack of response is that individuals are inattentive to the possible productive gains from quiet and that once their attention is drawn to their relative productivities they will be willing to pay more. 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. 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 response is due to simple 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 11 show this is not the case. I 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 noise will have on their productivity. I test for this possibility using the belief data collected in experiment two. The results are presented in Table 12. Columns 1 and 2 test whether beliefs are at least correct on average by comparing the predictive power of the respondents' beliefs to the predictive power of the model. While individuals' beliefs are reasonably predictive, they are significantly outperformed by the model. In column 3, I then compare what the model predicts an individual's income gain from working in quiet would be to what the participant predicted and find that they are essentially unrelated. 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 and 5 by interacting respondents' predictions of their income gain from quiet with the piece-rate indicator. I

[18] Note that in the case where 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, but it is still a useful benchmark for comparison.

find that even those who stated that they believe they are more productive in quiet do not respond to the piece rate.[19] 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 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. Then at the lower level, individuals form beliefs about the productive impact of the variables 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 noise has on their productivity and will be unwilling to stake any money on their stated beliefs. This is consistent with the pattern of effects described above.[20]

5.4 Efficiency Implications

This neglect creates the potential for efficiency losses. Because the productivity losses that I estimate are heterogeneous, and because firms' costs of noise abatement are known to be heterogeneous, an efficient allocation would match the workers whose productivity is least affected by noisy working conditions with the firms that have the highest cost of noise abate-

[19] Experiment one's belief data is not as detailed but is consistent with these findings (Table B21).

[20] Additionally, respondents' stated beliefs are suspiciously similar to their stated levels of annoyance (see Figure A13). This is what we would expect in a world where respondent's do not understand the impact noise has on their productivity, and instead provide something they do understand – how annoying they find noise.

ment. However, this is complicated by the fact that working in noise is also unpleasant and firms will have to pay a wage premium in order to attract workers. This creates a screening problem as the firm wants to separate those workers whose productivity is minimally affected by noise from those who simply want to take advantage of the higher wages. The traditional solution to these screening problems is to pay workers based on their performance; however, if workers neglect the impact noise has on their productivity, this screening mechanism no longer works, and simple policy interventions will be unable to restore the efficient allocation.

To illustrate, 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. Workers can produce according to $Y(\eta_i, S_i) = \theta - S_i\eta_i$ where $S_i = 1$ if the worker is in the noisy sector and η_i represents each worker's heterogeneous productivity loss due to working in noise. So that workers never destroy value, this loss is assumed to be less than θ. Firms pay workers sector-specific wages W_N and W_Q which are allowed to depend on observed output but not on η_i directly. Each worker tries to maximize their utility given by $U(S_i) = (1 - S_i)W_Q + S_i(W_N - \psi_i)$ where ψ_i is each worker's heterogeneous disutility from working in noisy conditions. Finally assume the workers have free entry and an outside option of zero. In this economy, a worker chooses the noisy sector if and only if

$$W_N - \psi_i > W_Q \tag{9}$$

Free entry and the worker's outside option imply $W_Q = 0$. Thus a worker chooses the noisy sector if $W_N > \psi_i$. The firm then chooses not to abate if and only if

$$\mathbb{E}[Y_N|W_N > \psi] - W_N > \mathbb{E}[Y_Q|W_N \leq \psi] - \gamma_i \tag{10}$$

$$\mathbb{E}[\eta|W_N > \psi] + W_N < \gamma_i \tag{11}$$

That is if the expected productivity losses and the wage premium are lower than the cost of

abatement. Setting the supply of workers in the noisy sector equal to the noisy sector labor demand gives the equilibrium condition

$$1 - G\left(\mathbb{E}[\eta | W_N > \psi] + W_N\right) = M(W_N) \tag{12}$$

where $G(\cdot)$ and $M(\cdot)$ are the CDFs of γ and ψ respectively.

Efficiency then depends on how the wages are structured and whether the worker neglects the productive effects of noise. First, consider the case where the firm pays a fixed-wage contract and workers fully attend to noise's impact. Even without neglect, the fact that the productive impact of noise is the worker's private information creates inefficient allocations through standard contracting problems. Specifically, firms in the noisy sector would like to hire the workers whose productivity is least affected by noise, but will be unable to identify these workers. Because the wages are fixed, workers will not internalize the productive impacts of noise and instead will sort solely based on whether the wage premium exceeds their disutility. This leads to an inefficient composition of workers in the noisy sector. Worker neglect does not have efficiency implications under this wage structure because the fixed wage means that workers already do not base their decisions on their productivity.

As usual, these contracting problems can be solved by paying the worker based on their performance. Specifically, consider the case where the worker is paid a sector-specific piece rate w_s and workers attend to the impact of noise. The worker chooses the noisy sector if and only if

$$w_N > \frac{\psi_i}{\theta - \eta_i} \tag{13}$$

It follows that the supply curve of workers in the noisy sector is given by $F(w_N)$ where $F(\cdot)$ is the CDF of the random variable $\chi = \frac{\psi_i}{\theta - \eta_i}$. The firm then chooses to be in the noisy sector

if and only if

$$(1 - w_N)\mathbb{E}[Y_N|w_N > \chi] > \mathbb{E}[Y_Q|w_N \leq \chi] - \gamma_j \tag{14}$$

$$(1 - w_N)\mathbb{E}[\eta|w_N > \chi] + w_N\theta < \gamma_j \tag{15}$$

This achieves the first best equilibrium where $1 - G((1 - w_N)\mathbb{E}[\eta|w_N > \chi] + w_N\theta) = F(w_N)$.

However, if workers neglect the impact that noise has on their productivity, this solution to the private information problem no longer works. Specifically, suppose that workers do not realize that their ability depends on noise and instead think they have constant ability θ. The worker's decision rule changes to:

$$w_N > \frac{\psi_i}{\theta} \tag{16}$$

By changing the composition of workers sorting into the noisy sector, this in turn changes the firm's decision rule to the following:

$$(1 - w_N)\mathbb{E}\left[\eta \middle| w_N > \frac{\psi_i}{\theta}\right] + w_N\theta < \gamma_j \tag{17}$$

Thus inattention when the worker is the residual claimant affects efficiency in two ways. First, neglecting the productive effects of noise makes workers more willing to work in the noisy sector for a given wage. Second, neglect changes the composition of the workers in the noisy sector, which in turn changes the expected productivity penalty that the firm faces. In essence, this neglect undoes the screening effect of the piece rate and restores the situation where the firm is paying a fixed-wage contract and faces a private information problem.

This implies that the efficiency implications of worker neglect depend critically on the joint distribution of the productive effect of noise and the disutility of noise. If they are perfectly, positively correlated, then worker neglect or being paid a fixed-wage contract

does not change each worker's propensity to work in the noisy sector.[21] In this case, a properly-calibrated wage (as set by the firm or as modified by a tax) can restore the first-best composition of workers in each sector. However, the further the joint distribution moves away from perfect correlation, the more each worker's propensity for working in the noisy sector will be changed by neglect or fixed-wage contracts. This means that with neglect, in most realistic scenarios, simply manipulating wages or quantities will not be able to restore the first-best allocation.

To illustrate, consider the instinctive response of a corrective tax when the worker is being paid a piece rate. If policy makers were omniscient they could restore the first-best by simply taxing each individual's noisy sector wages at rate $\tau_i = \frac{\theta - \eta_i}{\theta}$.

$$\frac{\theta - \eta_i}{\theta} w_N > \frac{\psi_i}{\theta} \implies w_N > \frac{\psi_i}{\theta - \eta_i} \tag{18}$$

But this is unlikely to be feasible. Suppose, instead, the planners try to use a constant *ad valorem* tax. This will cause the labor supply curve to shift back towards the optimum by making the noisy sector less attractive. But because firms also care about the composition of the workers in the noisy sector, the effect on the labor demand curve will depend on how closely the disutility and productive impacts of noise are related.

The data from these experiments provide the opportunity to examine this joint distribution for noise. In particular, the amount that individuals are willing to pay for quiet when facing a flat rate captures the amenity value of quiet, and the within-person treatment effects I previously estimated provide the productive value of quiet for each person. In my data these two features are essentially uncorrelated (Figure A14). This suggests neglect will significantly modify the composition of workers choosing to work in the noisy sector and that efficiency losses relative to the fully-informed case are likely to persist even with government intervention.

[21] This follows from the fact that $\eta_i < \theta$. This condition means that in the optimal sorting case each successively larger ψ_i is divided by a smaller number and thus the ordering is preserved when neglect changes the denominator to a constant.

To illustrate, I can compare how the average productivity penalty faced by a firm choosing not to abate depends on whether workers in my sample choose to sort based on the sum of the productivity and the amenity gains, or on the amenity values alone. In my sample, because the two attributes are essentially uncorrelated, neglect and fixed rate contracts increase the expected productive penalty the firm faces for almost all allocations (Figure A15).

More generally, many of the cognitive impediments studied in the literature have both productivity and disutility components. For example, it is both unpleasant to be hot and high termperatures lower 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, cognitive impediments and how workers attend to each aspect.

6 Conclusion

As the developing world continues to become more urban and industrial, 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 policy problem worth both further research and policy makers' attention. Noise levels can meaningfully decrease productivity, and market forces appear unlikely to attenuate this effect.

While eliminating noise pollution is likely an unrealistic goal, there are steps 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 to 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; 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. For example, if the effect of cognitive function on productivity is as large as it seems to be, it suggests that governments may be able to offset the costs of improving living conditions for the poor via subsequent productivity gains. Additionally, the results here suggest that policies that tax the poor's cognitive resources may have serious costs through decreased productivity. Future research should provide estimates of these costs and how policies can be designed that account for these cognitive constraints.

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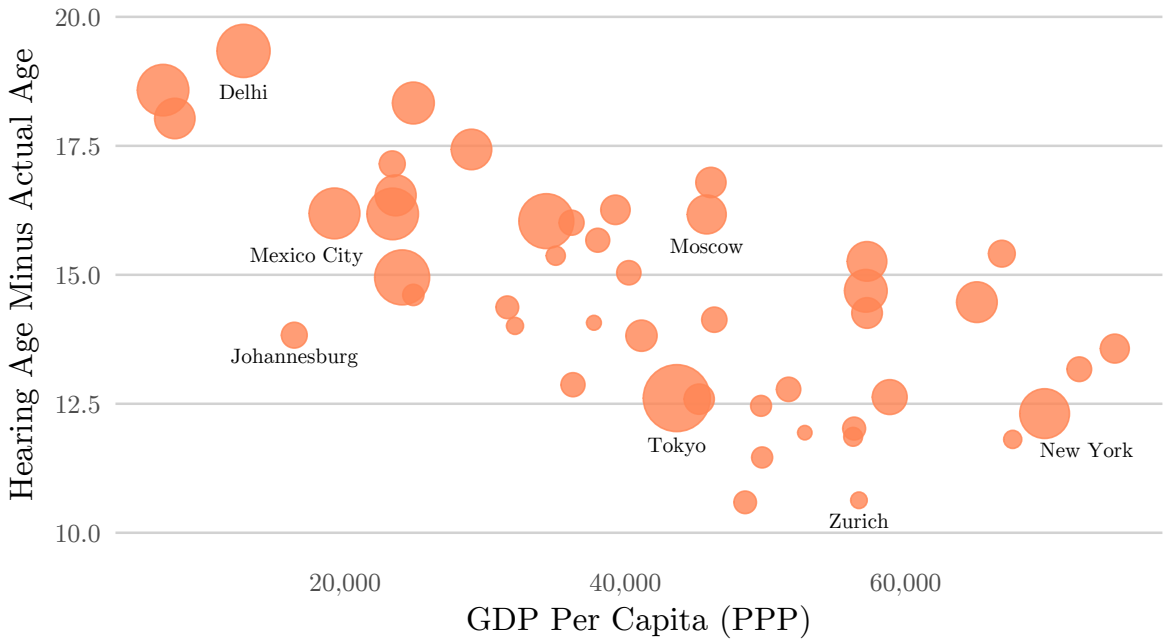
Figures

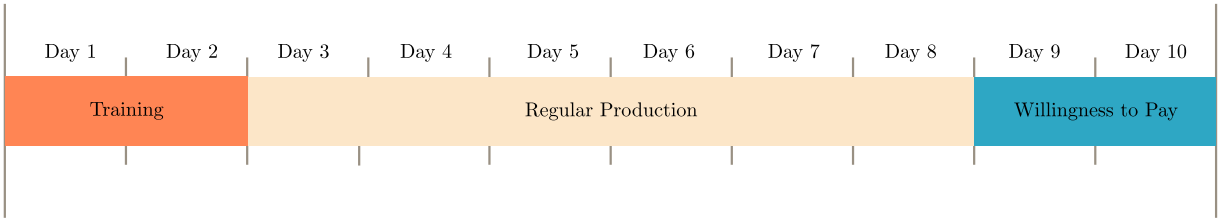
Figure 1: Average Hearing Loss in Cities by Income



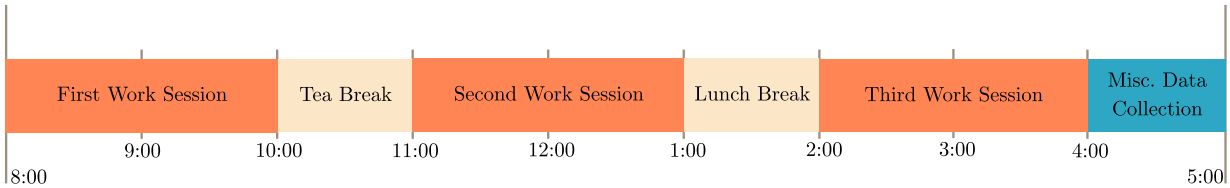
This figure shows the relationship between hearing loss and income at a city level. The y-axis plots years of hearing loss in excess of what would be expected based solely on age as measured by the firm Mimi (2017). The x-axis plots the city's income per capita as estimated by Berube et al. (2014). The size of each circle is proportional to the population of each city. In 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

(a) Course Overview

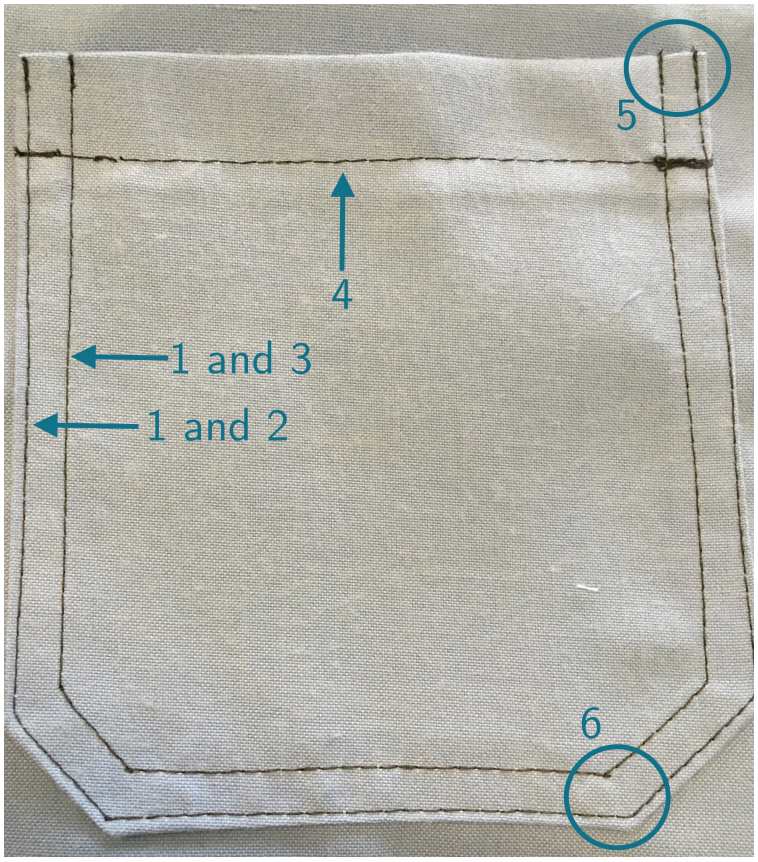


(b) Day Overview



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 in order to isolate the contemporaneous effects of noise.

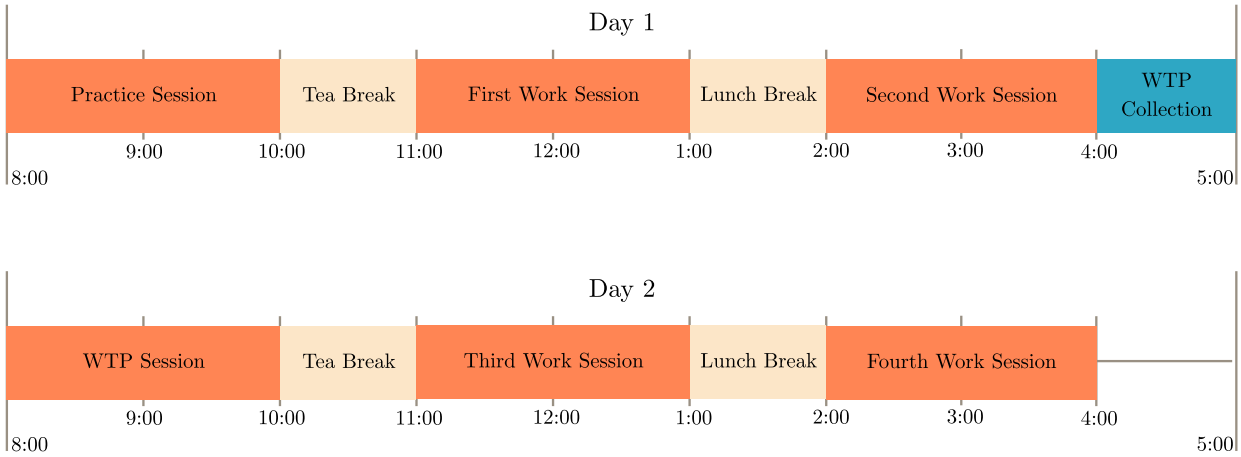
Figure 3: Example Pocket with Marked Grading Criteria



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:

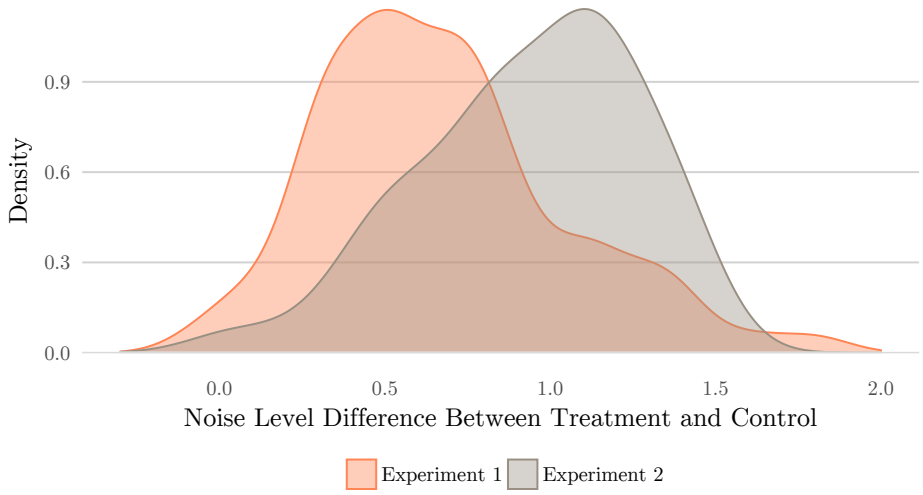
1. Are there double stitches around the pocket?
2. Is the outer stitch uniformly 1 mm from the edge?
3. Is the inner stitch uniformly 6 mm from the edge?
4. Is the top of the pocket correctly hemmed?
5. Are the ends of the seams reversed?
6. Are the corners even and continuous?

Figure 4: Experiment Two Timing



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



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) CO_2	(3) Humidity	(4) Temperature
Treatment	0.6737***	4.7650	0.0379	0.0477
	(0.0360)	(24.6781)	(0.4496)	(0.1747)
Session FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Control Mean	6.8921	624.6771	42.4738	26.5473
Normalized Difference	2.4625	0.0716	0.0037	0.0085
Observations	157	153	153	153

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). 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 Criteria	(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

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 decreased 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 Criteria	(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	-0.0523^{***}	-0.0605^{***}	-0.0525^{***}	-0.0568^{***}	-0.0797^{***}	-0.0810^{***}	-0.0630^{**}	-0.0184
	(0.0161)	(0.0188)	(0.0161)	(0.0161)	(0.0203)	(0.0250)	(0.0257)	(0.0272)
				Levels				
Noise Level	-0.3903^{**}	-1.9446^{*}	-0.3806^{**}	-0.3781^{**}	-0.3900^{**}	-0.3939^{**}	-0.3267^{*}	-0.0754
	(0.1796)	(1.0233)	(0.1795)	(0.1788)	(0.1823)	(0.1797)	(0.1787)	(0.1735)
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	2354	2354	2354	2354	2354	2354	2354	2354

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 treatment 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) decreases productivity by approximately 5%.

Table 4: IV Effect of Noise on Productivity – Treatment Intensity Instruments

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criteria	(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	-0.0639^{***}	-0.0741^{***}	-0.0642^{***}	-0.0653^{***}	-0.0900^{***}	-0.0963^{***}	-0.0850^{***}	-0.0544^{**}
	(0.0152)	(0.0181)	(0.0151)	(0.0151)	(0.0198)	(0.0240)	(0.0248)	(0.0254)
				Levels				
Noise Level	-0.5204^{***}	-2.9339^{***}	-0.5140^{***}	-0.5137^{***}	-0.5436^{***}	-0.5629^{***}	-0.5171^{***}	-0.2826^{*}
	(0.1703)	(0.9676)	(0.1703)	(0.1701)	(0.1727)	(0.1732)	(0.1659)	(0.1495)
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	2354	2354	2354	2354	2354	2354	2354	2354

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 by a set of treatment intensity indicators in order to take advantage of all of the variation. 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) decreases productivity by approximately 5%.

Table 5: Environmental Effects of Treatment in Experiment Two

	(1) Noise Level	(2) CO_2	(3) Humidity	(4) Temperature
Treatment	0.9379***	−47.9563	−0.5516	−0.0405
	(0.0494)	(46.6334)	(0.2954)	(0.1131)
Session FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Control Mean	7.2059	924.4597	47.4469	24.4332
Normalized Difference	3.1546	−0.1538	−0.1269	0.0290
Observations	88	84	84	84

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). 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 6: IV Effect of Noise on Cognitive Function – Treatment Intensity Instruments

	(1) Sum of Scores	(2) Average of Normalized Scores	(3) PCA of Percent Correct and Reaction Time	(4) CFA of Percentage Correct and Reaction Time
Noise Level	−0.0233**	−0.0168**	−0.0478***	−0.0529***
	(0.0110)	(0.0082)	(0.0154)	(0.0182)
Wage FE	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Observations	762	762	762	762

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 final 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) decreases performance on my preferred index by 0.05 standard deviations.

Table 7: Split-Sample IV of Productivity on Cognitive Function

	(1) IHS Total Pockets	(2) IHS Pocket Points	(3) IHS Perfect Pockets
CFA Index	1.2093**	1.4011**	1.0299*
	(0.5063)	(0.5916)	(0.5967)

This table shows the ratio of the noise level coefficients from the two-stage least squares regressions of productivity and cognitive function on the noise level, wage, session, person, and room fixed effects. The noise level is instrumented by a set of treatment intensity indicators in order to capture variation in treatment intensity. Standard errors are first clustered in each regression and then computed for the ratio using the delta method. The results show that a one standard deviation change in cognitive function increases productivity by approximately 100%.

Table 8: 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	1.75%
Park (2017)	Temperature	1σ	0.052σ	5.4%
Lichand and Mani (2016)	Low Rainfall	$< 30^{th}$ percentile	0.041σ	4.2%
Mani et al. (2013)	Harvest		0.67σ	69%

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, in 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 9: 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

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 experiment one 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 10: 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	−1.5896	−0.0226	−1.4583	0.7110	0.0431*	−2.5101
	(2.5194)	(0.0311)	(3.7061)	(1.6572)	(0.0235)	(5.1276)
Model Predicted Income Gain	−0.5646	−0.0080	−0.7278	1.6734**	0.0189*	2.9648*
	(0.6162)	(0.0091)	(1.0299)	(0.7200)	(0.0111)	(1.7303)
Model Predicted Income Gain × Piece Rate	0.3988	0.0045	0.4804	−0.3504	−0.0047	−0.5879
	(0.3808)	(0.0038)	(0.6849)	(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

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 experiment one 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 11: Testing for Inattention

	(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

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 any simple inattention story like bounded rationality. Standard errors are clustered at the individual level.

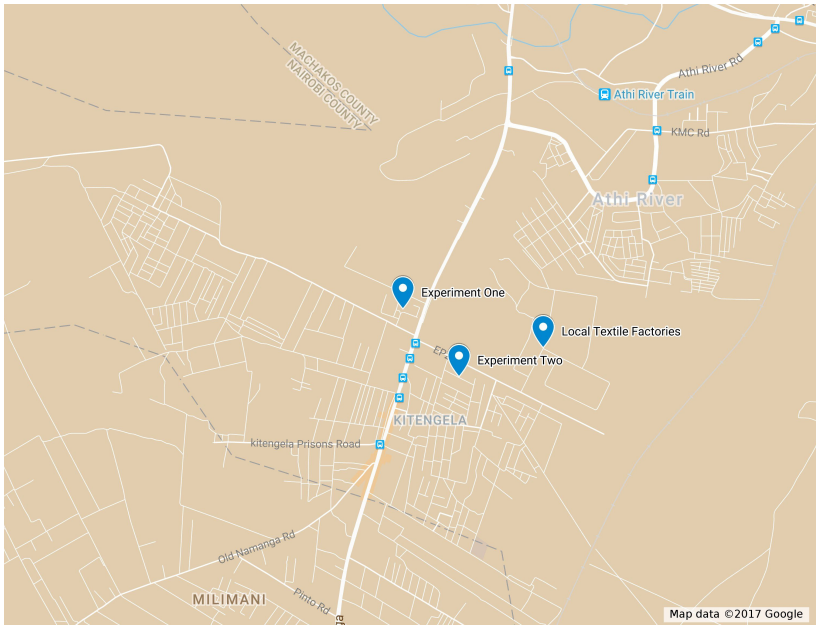
Table 12: Testing for Incorrect Beliefs

	(1) Realized Score	(2) Realized Score	(3) Model Predicted Income Gain	(4) WTP	(5) WTP Any	(6) WTP COP
Model Predicted Score	0.9986***					
	(0.0286)					
Participant Predicted Score		0.1535***				
		(0.0408)				
Participant Predicted Income Gain			−0.0031	0.0558*	0.0011**	0.0381
			(0.0036)	(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	33.967	33.967	1.078	13.392	0.316	42.373
Observations	187	187	210	424	424	142

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. 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 steak 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

Figure A1: Experiment Locations and Surrounding Area

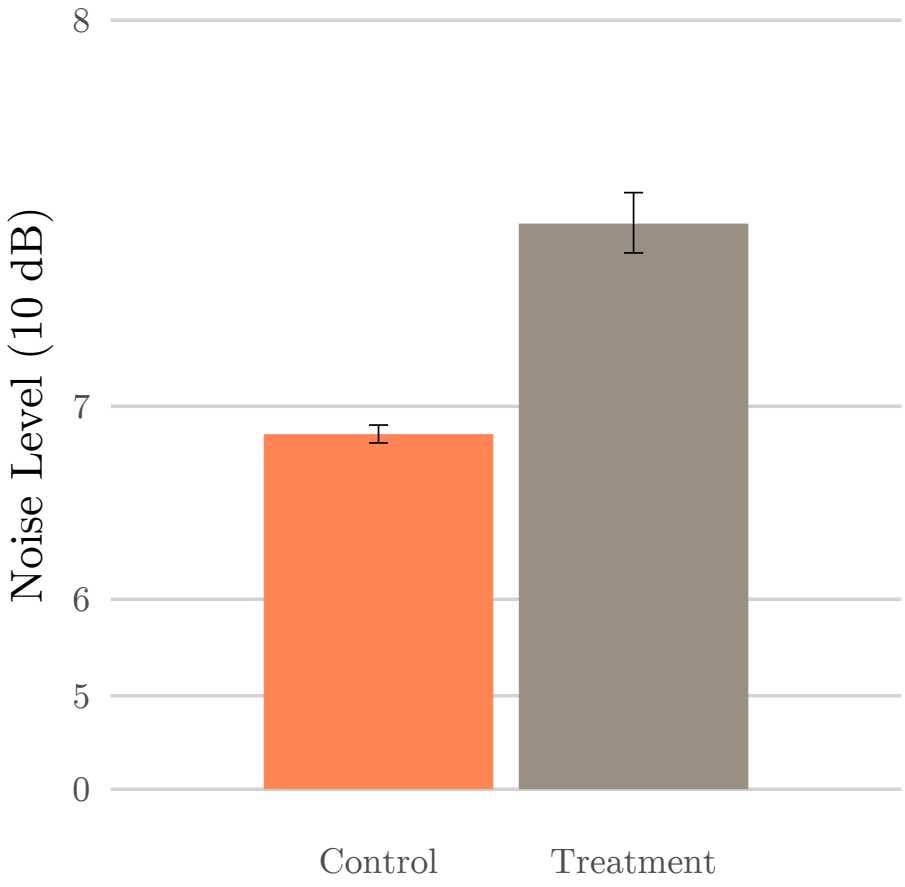


This figure shows a map of the experiment locations and recruitment location in Kitengela, Kenya just outside of Nairobi. The experiment sites are less than a mile apart and close to the recruitment site at the gates of the local textile factories.

Figure A2: Noise Generating Engine

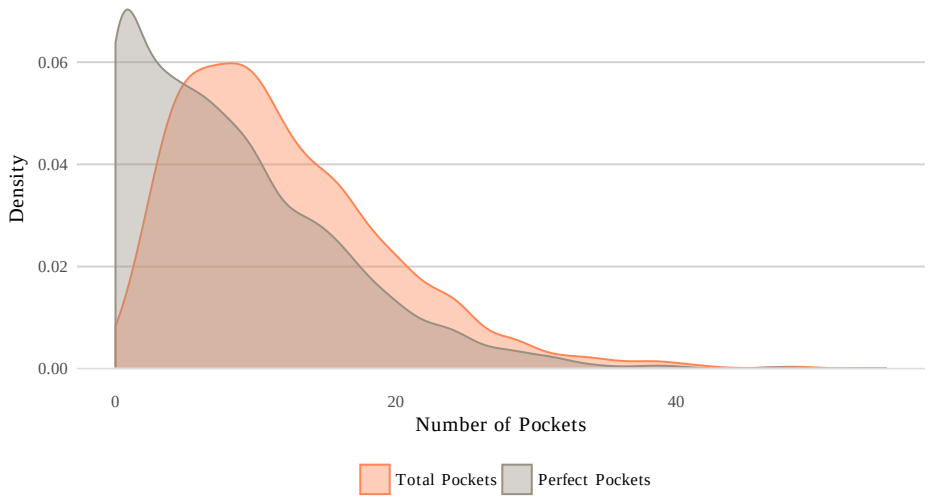
This figure shows a picture of the car engine used to generate noise in experiment one. The engine was borrowed from an automotive mechanic training facility at the TDC. A car engine was chosen as the noise source because it is representative of important sources of noise pollution – traffic noise and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

Figure A3: Noise Level By Treatment Status



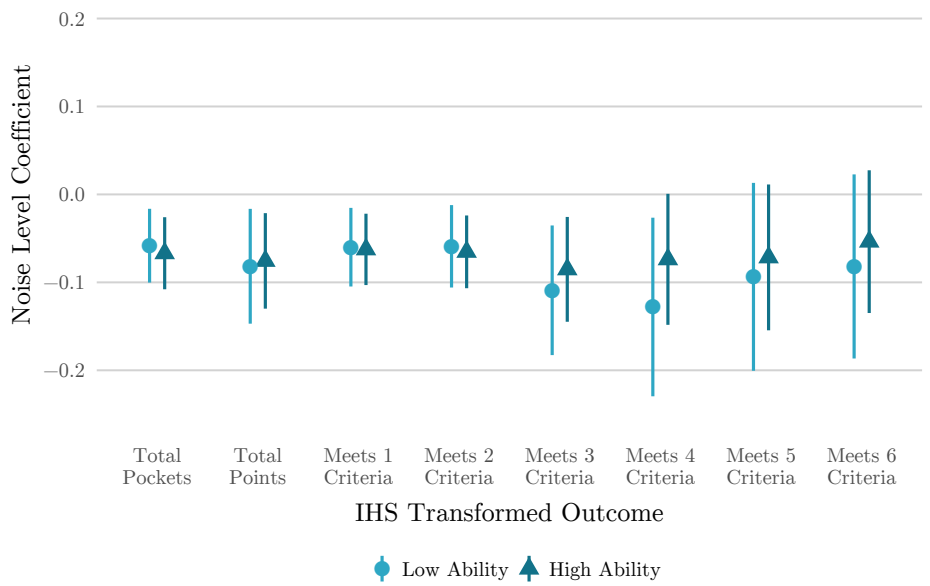
This figure shows the average noise level in treatment and control with the y-axis on a log scale. A noise increase of 10 dB is perceived as twice as loud by the human year. Thus for interpretability, all noise levels are reported as 10s of decibels. Treatment increased the noise level by the same amount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

Figure A4: Output Density



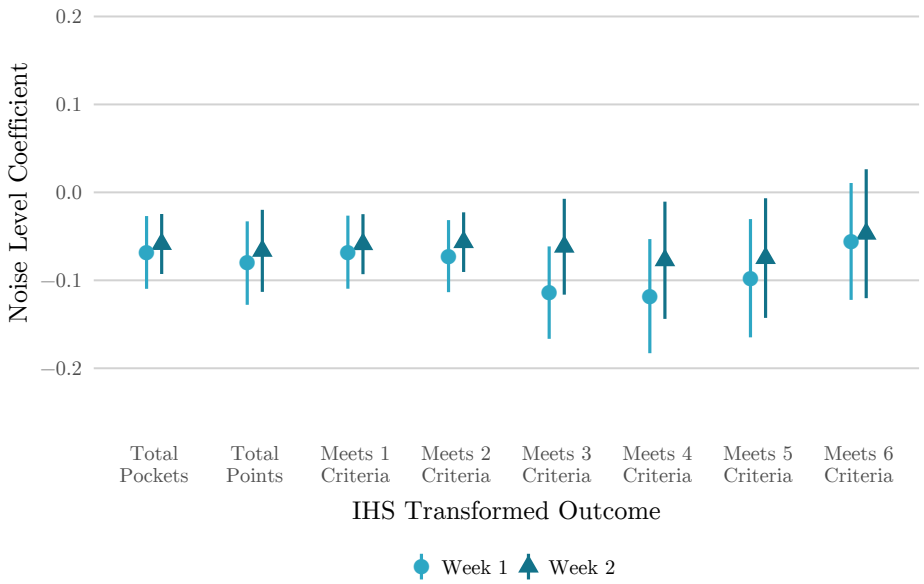
This figure shows the density of the number of total and perfect pockets created in experiment one. The distribution is significantly skewed, but has zeros. Thus to increase power I present the inverse hyperbolic sine-transformed versions of the outcome variables.

Figure A5: Treatment Effects by Ability



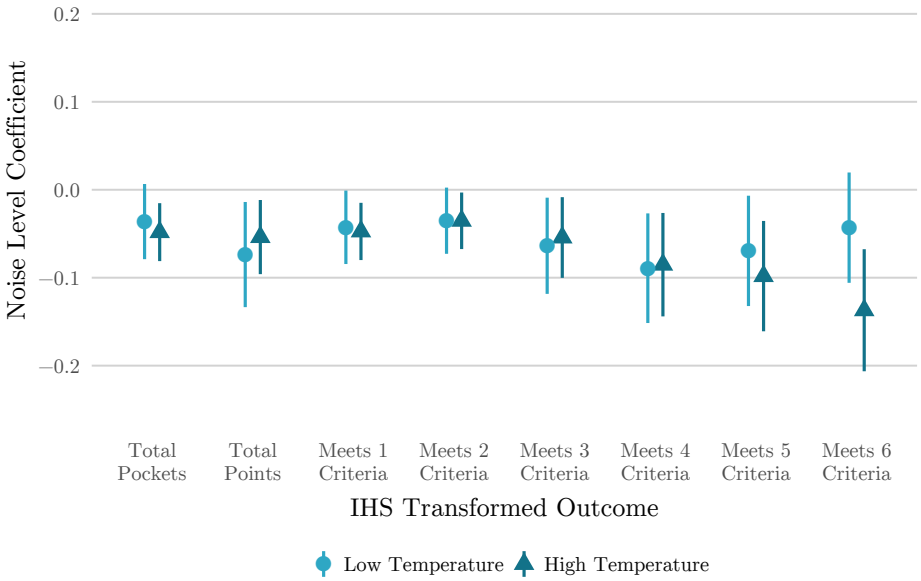
This figure shows coefficient estimates and their 95% confidence intervals from a two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by a set of treatment intensity indicators in order to capture variation in treatment intensity. 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: Treatment Effects Over Time



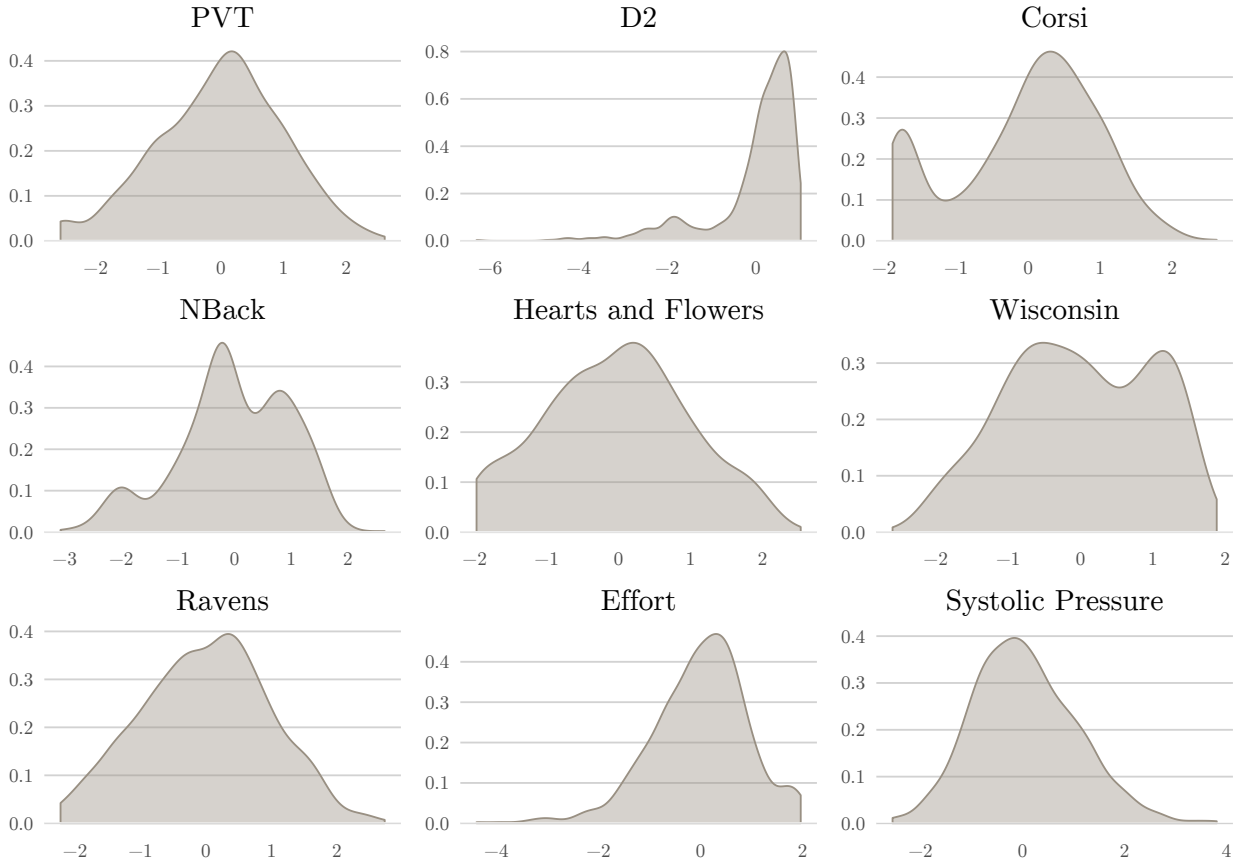
This figure shows coefficient estimates and their 95% confidence intervals from a two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by a set of treatment intensity indicators in order to capture variation in treatment intensity. 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: Treatment Effects by Temperature



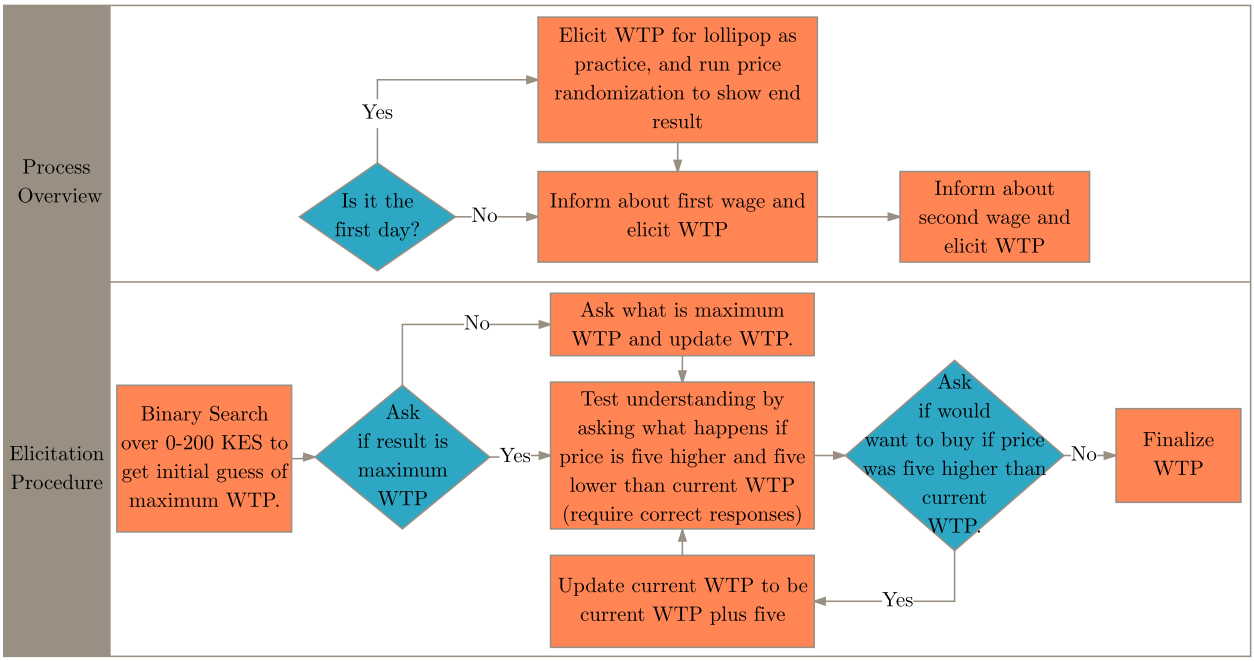
This figure shows coefficient estimates and their 95% confidence intervals from a two-stage least squares regression of productivity outcome variables on the noise level, wage, session, person, and room fixed effects with standard errors clustered at the room by session level. The noise level is instrumented by a set of treatment intensity indicators in order to capture variation in treatment intensity. Before estimation the sample was split into two groups by whether the temperature was above or below the median. Treatment effects were estimated separately for the two groups in a stacked regression. The results show that effects are either similar or possibly larger in the presence of other environmental distractions.

Figure A8: Normalized Test Score Variation



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 don't appear susceptible to ceiling or floor effects.

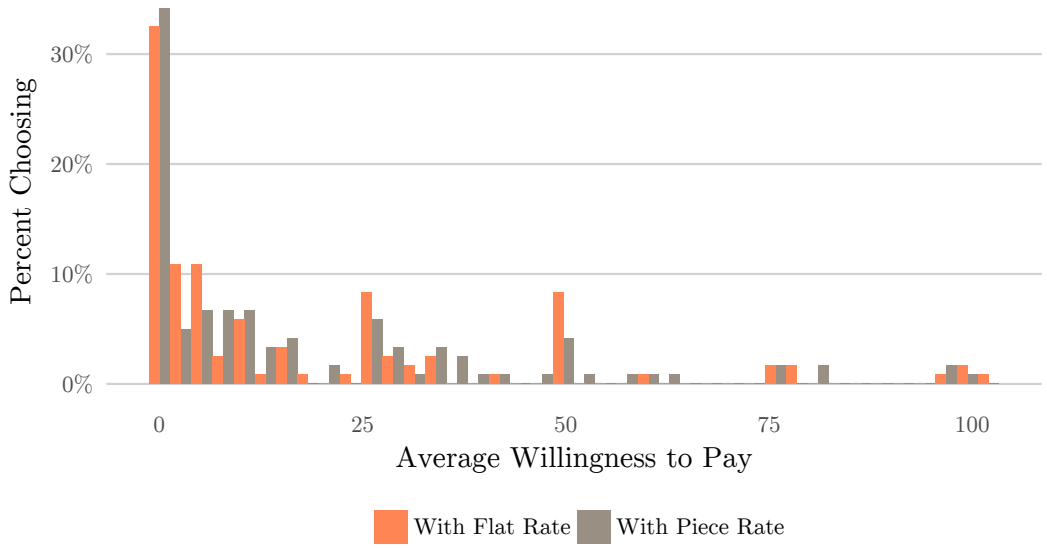
Figure A9: Willingness to Pay Overview and Elicitation Procedure



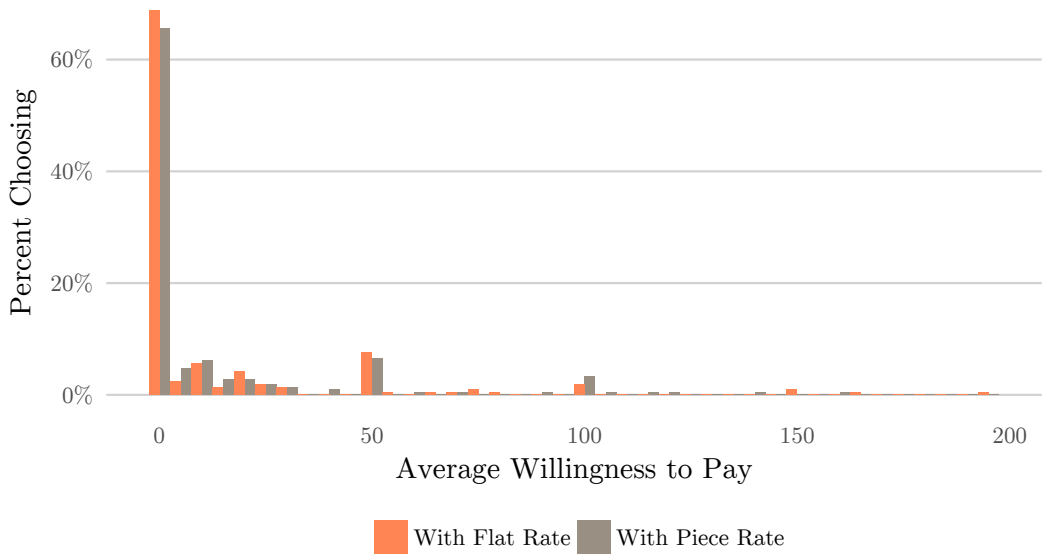
The first panel of this figure shows the overview of the process of eliciting willingness to pay including when practices were conducted, and how information was timed with the elicitation. The second panel is a detailed view of how willingness to pay was elicited using a modified version of the procedure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

Figure A10: Average Willingness to Pay by Compensation

(a) Experiment One



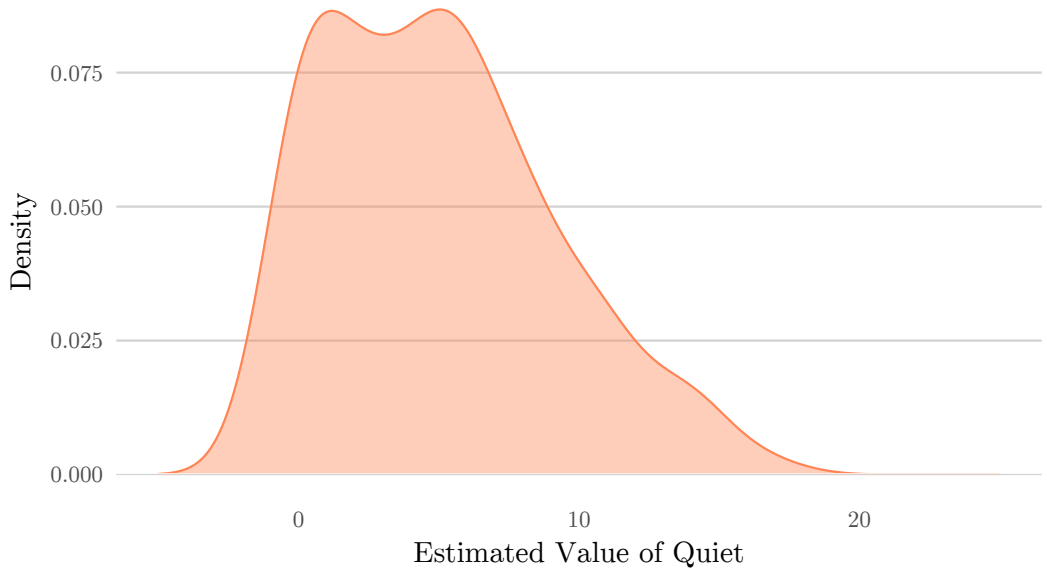
(b) Experiment Two



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.

Figure A11: Productive Value of Quiet

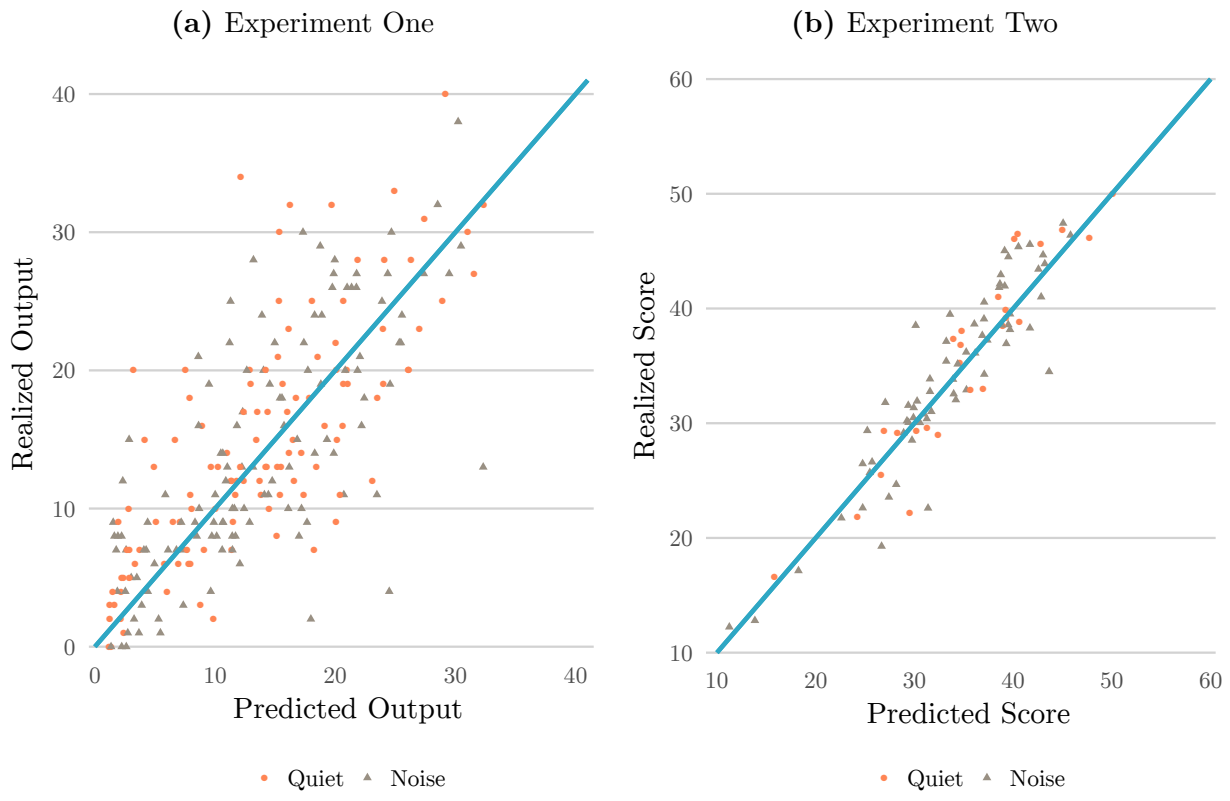
(a) Experiment One



(b) Experiment Two

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 if we simply took the difference between treatment and control performance within person.

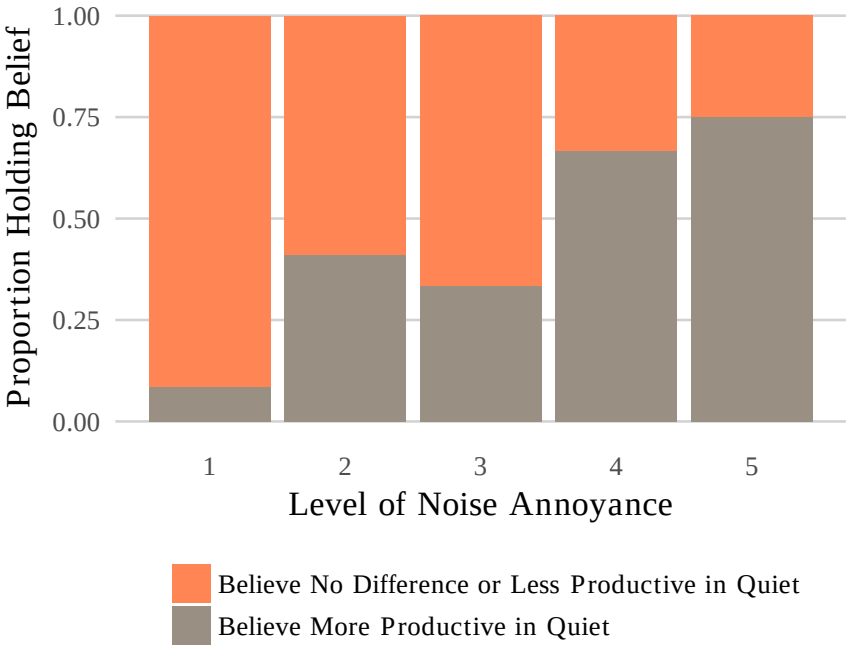
Figure A12: Model Fit



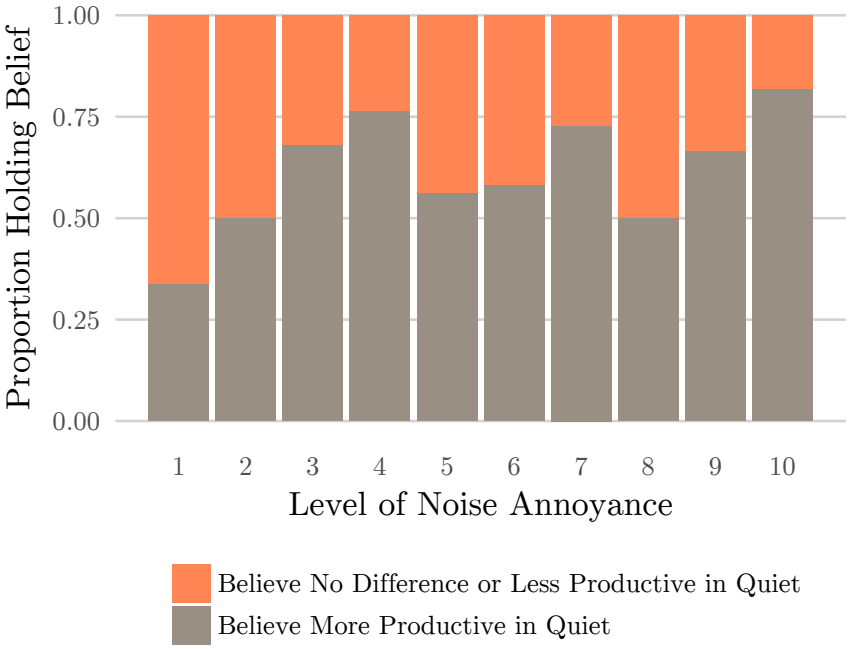
The figure plots the hierarchical linear model's predictions of the respondents' output and scores in the willingness to pay sessions on the x-axis against the respondents' realized output and scores on the y-axis. Values are plotted separately depending on whether the individual ended up in quiet or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

Figure A13: Beliefs and Annoyance

(a) Experiment 1



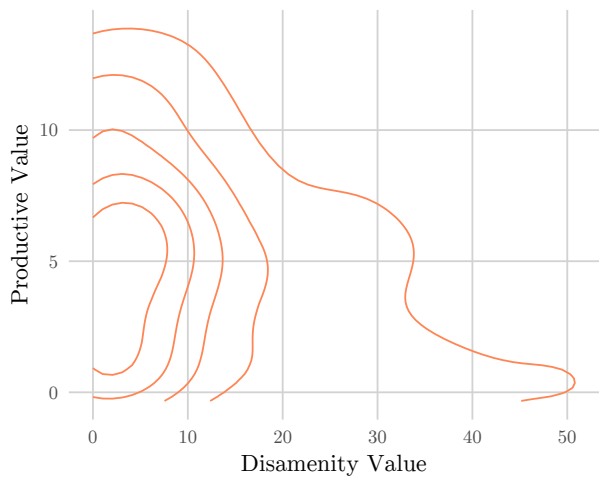
(b) Experiment 2



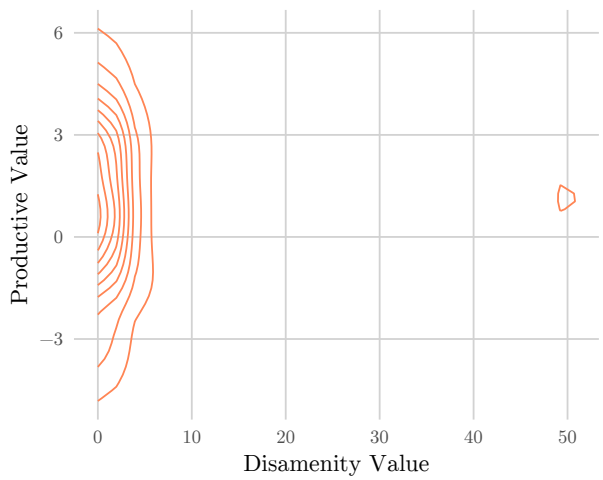
This figure shows the proportion of individuals who believe they are more productive in quiet for each level of stated annoyance with the noise level. The high level of correlation provides suggestive evidence that individuals do not actually understand the impact of noise on their productivity and are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

Figure A14: Correlation Between Amenity and Productive Value of Quiet

(a) Experiment One



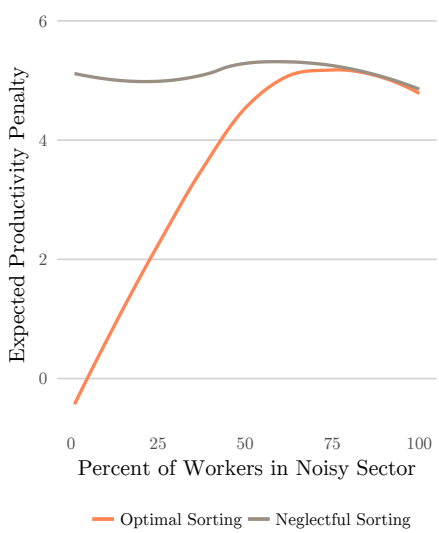
(b) Experiment Two



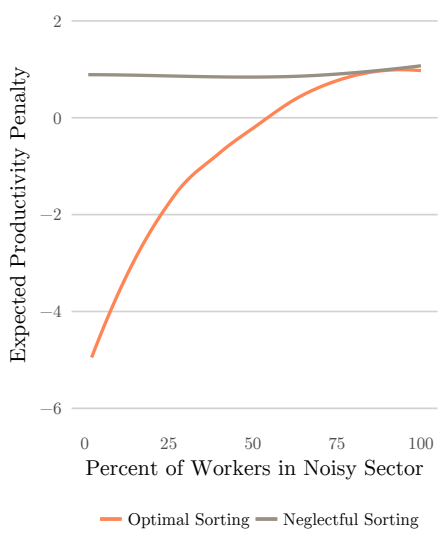
This figure plots the joint density of each respondent's willingness to pay for quiet when facing a flat rate and what the model predicts is their productive value of quiet. The results show that the two are essentially uncorrelated. This suggests that if respondents neglect the productive impact and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

Figure A15: Dependence of Productive Losses on Sorting Rules

(a) Experiment One



(b) Experiment Two



This figure plots the average treatment effect of workers who choose to work in noise based on whether they incorporate the productive value of quiet into their sorting decision or simply sort based on their willingness to pay for quiet when facing a flat rate. Because the annoyance and productive factors are essentially uncorrelated, the expected treatment effect (and thus penalty faced by a firm) is significantly changed when the worker neglects the productive effect when making their sorting decision.

B Supplementary Tables

Table B1: Sample Summary Statistics

	Experiment One	Experiment Two	Combined
Female	0.641	0.513	0.564
	(0.482)	(0.501)	(0.497)
Age	28.84	26.47	27.41
	(6.791)	(6.891)	(6.938)
HS Degree	0.516	0.712	0.638
	(0.502)	(0.454)	(0.481)
Typical Wage	677.2	574.9	615.8
	(725.8)	(654.9)	(684.9)
Days Worked Per Week	2.188	1.280	1.642
	(2.528)	(2.161)	(2.353)
More Annoyed by Noise	0.258	0.377	0.332
	(0.439)	(0.486)	(0.472)

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

	Treatment Mean	Control Mean	Two-Sided P-Value	Normalized Difference
Female	0.633	0.630	0.934	0.006
Age	28.79	28.84	0.903	-0.007
High School or More	0.520	0.512	0.743	0.016
Has Experience Sewing	0.232	0.232	0.992	-0.000
Typical Daily Wage	684.9	669.8	0.652	0.021
Days Worked Last Week	2.175	2.190	0.863	-0.006
More Annoyed by Noise than Others	0.251	0.253	0.888	-0.006

This table assesses the balance of sample characteristics between treatment and control sessions. The first two columns display the average of the variable indicated in the row for individuals observed in treatment and control sessions respectively. Column 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 they do not hold exactly is because of small levels of attrition.

Table B3: First Stages

	Experiment 1		Experiment 2	
	(1) Noise Level	(2) Noise Level	(3) Noise Level	(4) Noise Level
Treatment	0.6720***		0.9434***	
	(0.0437)		(0.0616)	
Treated with Intensity 1		0.2892***		0.7436***
		(0.0559)		(0.1388)
Treated with Intensity 2		0.4503***		0.8571***
		(0.0488)		(0.1635)
Treated with Intensity 3		0.3661***		0.9132***
		(0.0410)		(0.0867)
Treated with Intensity 4		0.5814***		1.1475***
		(0.0576)		(0.2475)
Treated with Intensity 5		0.5404***		0.8949***
		(0.0371)		(0.0942)
Treated with Intensity 6		0.6327***		0.9486***
		(0.0482)		(0.0776)
Treated with Intensity 7		0.6674***		1.0407***
		(0.0798)		(0.0830)
Treated with Intensity 8		0.7903***		0.9683***
		(0.0386)		(0.0752)
Treated with Intensity 9		1.0685***		0.9641***
		(0.0661)		(0.0608)
Treated with Intensity 10		1.3775***		1.0500***
		(0.0972)		(0.0713)
Constant	6.8950***	6.8950***	7.2016***	7.2016***
	(0.0183)	(0.0184)	(0.0500)	(0.0503)
F-Stat	236.9608	88.9311	234.7527	33.1020
Observations	2354	2354	762	762

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 B4: Experiment One Fisher P-Values

	(1) Total Pockets	(2) Total Points Earned	(3) Pockets Meeting 1 Criteria	(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
IHS Transformed	0.012	0.012	0.014	0.006	0.003	0.008	0.054	0.603
Levels	0.087	0.137	0.109	0.084	0.073	0.090	0.178	0.762

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 Criteria	(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

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	27.23	645.50	39.05	0.49	25.13	880.57	45.79	0.38
	(0.95)	(41.08)	(2.73)	(0.18)	(1.44)	(34.46)	(3.48)	(0.22)
Intensity 2	25.89	630.81	44.89	0.74	25.28	848.82	45.54	0.27
	(0.83)	(34.63)	(2.79)	(0.16)	(1.15)	(52.00)	(2.77)	(0.23)
Intensity 3	27.82	637.83	38.86	0.36	22.18	863.61	52.34	0.77
	(0.55)	(38.31)	(1.66)	(0.17)	(0.13)	(35.56)	(1.05)	(0.20)
Intensity 4	26.48	644.40	41.58	1.00	23.64	855.64	48.72	0.20
	(0.76)	(33.00)	(2.55)	(0.00)	(0.86)	(37.34)	(1.99)	(0.19)
Intensity 5	26.11	652.64	44.35	0.61	23.62	915.63	47.97	1.00
	(0.90)	(31.87)	(2.88)	(0.18)	(1.46)	(57.00)	(4.16)	(0.00)
Intensity 6	27.60	622.09	41.69	0.37	24.11	1022.96	50.72	0.58
	(0.52)	(35.63)	(2.37)	(0.17)	(0.96)	(94.04)	(2.15)	(0.23)
Intensity 7	26.34	565.77	43.99	0.14	23.94	865.37	49.44	0.84
	(0.97)	(37.44)	(2.65)	(0.13)	(1.33)	(28.04)	(2.32)	(0.16)
Intensity 8	26.96	615.75	42.50	0.62	26.38	915.12	38.93	0.38
	(1.00)	(37.26)	(2.72)	(0.17)	(0.53)	(39.97)	(1.14)	(0.22)
Intensity 9	26.07	650.78	43.80	0.49	26.76	1020.56	40.47	0.00
	(0.92)	(29.79)	(2.41)	(0.18)	(0.70)	(143.60)	(3.06)	(0.00)
Intensity 10	25.87	644.52	43.54	0.28	24.77	858.47	47.77	0.52
	(1.07)	(33.12)	(4.38)	(0.17)	(1.25)	(36.56)	(4.07)	(0.25)
Observations	2274	2274	2274	2354	734	734	734	762

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: LIML Estimated IV – Treatment Intensity Instruments

	(1) IHS Total Pockets	(2) IHS Total Points Earned	(3) IHS Pockets Meeting 1 Criteria	(4) IHS Pockets Meeting 2 Criteria	(5) IHS Pockets Meeting 3 Criteria	(6) IHS Pockets Meeting 4 Criteria	(7) IHS Pockets Meeting 5 Criteria	(8) IHS Pockets Meeting 6 Criteria
				Inverse Hyperbolic Sine Transformation				
Noise Level	-0.0639^{***}	-0.0741^{***}	-0.0642^{***}	-0.0653^{***}	-0.0900^{***}	-0.0963^{***}	-0.0850^{***}	-0.0544^{**}
	(0.0152)	(0.0181)	(0.0151)	(0.0151)	(0.0198)	(0.0240)	(0.0248)	(0.0254)
				Levels				
Noise Level	-0.5205^{***}	-2.9341^{***}	-0.5140^{***}	-0.5137^{***}	-0.5436^{***}	-0.5628^{***}	-0.5171^{***}	-0.2827^{*}
	(0.1703)	(0.9676)	(0.1703)	(0.1701)	(0.1727)	(0.1732)	(0.1660)	(0.1496)
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	2354	2354	2354	2354	2354	2354	2354	2354

This table shows estimates from limited information maximum likelihood 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 intensity indicators 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. The results show there's no weak instrument problem as the coefficients are almost identical to those reported in the two-stage least squares regressions.

Table B8: Quality Response

	(1) Proportion Meeting 1 Criteria	(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	−0.0017	−0.0120	−0.0133	−0.0027	0.0133
	(0.0024)	(0.0047)	(0.0078)	(0.0100)	(0.0105)	(0.0108)
			2SLS Effect of Noise - Treatment-Session Interaction Instrument			
Noise Level	−0.0008	0.0003	−0.0138*	−0.0171*	−0.0097	0.0023
	(0.0021)	(0.0043)	(0.0077)	(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	0.995	0.980	0.904	0.833	0.765	0.574

This table shows the impact of treatment on the proportion of pockets meeting 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 B9: Comparison with Other Environmental Effects

Source	Task	Stimulus	Stimulus Change	Implied 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. (2016)	Manufacturing	Air Pollution	0.2σ	0%

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 B10: Lagged Treatment Results

	(1) IHS Total Pockets	(2) IHS Total Points Earned	(3) IHS Pockets Meeting 1 Criteria	(4) IHS Pockets Meeting 2 Criteria	(5) IHS Pockets Meeting 3 Criteria	(6) IHS Pockets Meeting 4 Criteria	(7) IHS Pockets Meeting 5 Criteria	(8) IHS 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
Control Median-Levels	10	54	10	10	10	9	9	6
Observations	2209	2209	2209	2209	2209	2209	2209	2209

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 B11: 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	8.2042	0.1905	0.5250
Observations	733	126	120

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 B12: 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

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 B13: Experiment Two Balance and Summary Stats

	Treatment Mean	Control Mean	Two-Sided P-Value	Normalized Difference
Female	0.516	0.503	0.751	0.026
Age	26.28	26.29	0.978	-0.002
High School or More	0.711	0.720	0.791	-0.022
Typical Daily Wage	667.1	684.4	0.894	-0.010
Days Worked Last Week	1.238	1.238	0.998	-0.000
More Annoyed by Noise than Others	0.362	0.369	0.887	-0.016

This table assesses balance of sample characteristics between treatment and control sessions. The first two columns display the average of the variable indicated in the row for individuals observed in treatment and control sessions respectively. Column 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 B14: Experiment Two Reduced-Form Effect of Treatment

	(1) Normalized Sum of Scores	(2) Average of Normalized Scores	(3) PCA of Percent Correct and Reaction Time	(4) CFA of Percentage Correct and Reaction Time
Treatment	-0.0304^{**}	-0.0239^{**}	-0.0589^{***}	-0.0635^{***}
	(0.0128)	(0.0092)	(0.0165)	(0.0194)
Wage FE	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Observations	762	762	762	762

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 final 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 performance was 0.06 standard deviations lower in treatment conditions.

Table B15: Experiment Two IV Effect of Noise – Treatment Indicator Instrument

	(1) Normalized Sum of Scores	(2) Average of Normalized Scores	(3) PCA of Percent Correct and Reaction Time	(4) CFA of Percentage Correct and Reaction Time
Noise Level	-0.0323^{***}	-0.0254^{***}	-0.0626^{***}	-0.0676^{***}
	(0.0113)	(0.0083)	(0.0150)	(0.0175)
Wage FE	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Observations	762	762	762	762

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 treatment indicator. 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 final 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 a 10 dB increase decreases performance on my preferred index by 0.07 standard deviations.

Table B16: Experiment Two LIML Estimated IV – Treatment Intensity Instruments

	(1) Sum of Scores	(2) Average of Normalized Scores	(3) PCA of Percent Correct and Reaction Time	(4) CFA of Percentage Correct and Reaction Time
Noise Level	-0.0233^{**}	-0.0168^{**}	-0.0478^{***}	-0.0529^{***}
	(0.0110)	(0.0082)	(0.0154)	(0.0182)
Wage FE	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes
Person FE	Yes	Yes	Yes	Yes
Room FE	Yes	Yes	Yes	Yes
Observations	762	762	762	762

This table shows estimates from a limited information maximum likelihood 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 in order to capture variation in treatment intensity. 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. The final 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 there is no weak instruments problem as the estimates match the two-stage least squares estimates from the main tables.

Table B17: Experiment Two Fisher P-Values

(1) Sum of Scores	(2) Average of Normalized Scores	(3) PCA of Percent Correct and Reaction Time	(4) PFA of Percent Correct and Reaction Time
0.154	0.112	0.022	0.035

This table presents p-values computed using 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 results yield similar inferences to those presented in the main regression tables.

Table B18: 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	−0.0137	−0.0013	0.0027	−0.0243	−0.0113	−0.0577**	−0.0120
	(0.0297)	(0.0180)	(0.0299)	(0.0199)	(0.0229)	(0.0262)	(0.0205)
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

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 a set of treatment intensity indicators in order to capture variation in treatment intensity. The results show that the effects of noise do not appear to be concentrated in any particular domain.

Table B19: Effort Task Results

	(1) Key Presses	(2) Normalized Score
Noise Level	−2.8033	−0.0060
	(15.8894)	(0.0339)
Wage FE	Yes	Yes
Session FE	Yes	Yes
Person FE	Yes	Yes
Room FE	Yes	Yes
Control Mean	2192.013	0.000
Observations	762	762

This table shows estimates from a two-stage least squares regression of the number of alterations in an effort task also used by DellaVigna and Pope (2016) 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 in order to capture variation in treatment intensity. The results show that there was no change in performance suggesting that physical impediments or decreased motivation are unlikely to explain the effects of noise on productivity.

Table B20: Effects on Stress

	(1) Systolic Pressure	(2) Diastolic Pressure
Noise Level	0.7234**	0.3950
	(0.2973)	(0.2642)
Wage FE	Yes	Yes
Session FE	Yes	Yes
Person FE	Yes	Yes
Room FE	Yes	Yes
Control Mean	115.719	73.719
Observations	762	762

This table shows estimates from a two-stage least squares regression of blood pressure on 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 in order to capture variation in treatment intensity. The results show that while noise exposure increased stress, the stress increase is likely too small to have physical effects.

Table B21: 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 in Quiet × 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

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

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, were shown demonstrations, and were 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, are incorrect and earn zero points.
- Responses slower than 500 ms are considered attentional lapses, are 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 $- 10$.

Figure C16: PVT Stimulus

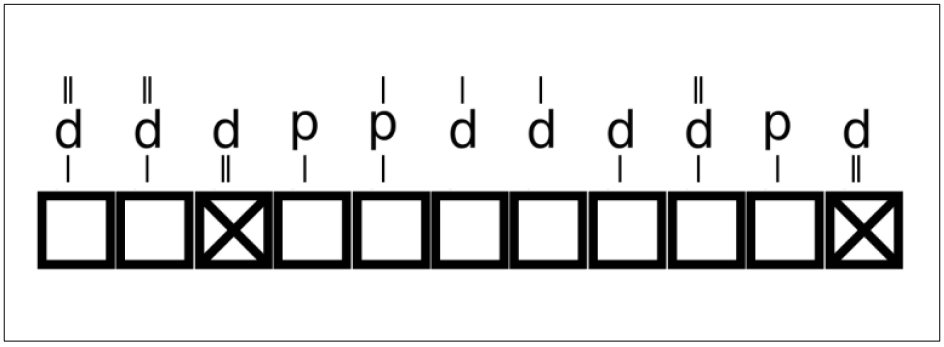
The figure shows a snapshot of a counter that appears in the PVT test displaying a time of 320 ms. The test is designed to assess attention. When the counter appears, respondents must press the space bar in order to stop it from counting up. The faster they press the space bar, the more points they earn.

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 time.

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, 11 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 11 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.

Figure C17: d2 Stimuli



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.

C.2 Working Memory

C.2.1 Reverse Corsi Block

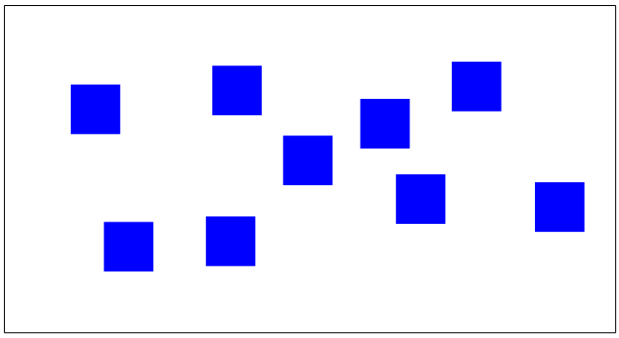
Implementation of the Reverse Corsi Block task follows Brunetti et al. (2014). For each trial, nine blue blocks appear in random locations on the screen. They take turns lighting up for 500 ms with 1000 ms between each flash. Respondents are then asked to tap the blocks in reverse order of how they lit 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.

C.2.2 N-Back

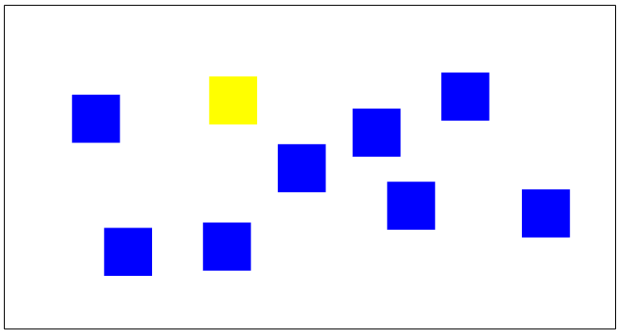
Implementation of the N-Back task follows Wilhelm et al. (2013) with an "N" of two. For each trial, respondents see a sequence of 12 animal pictures. For each picture following the second, the respondents are required to tap either "MATCH" or "NO MATCH" depending on

Figure C18: Corsi Stimuli

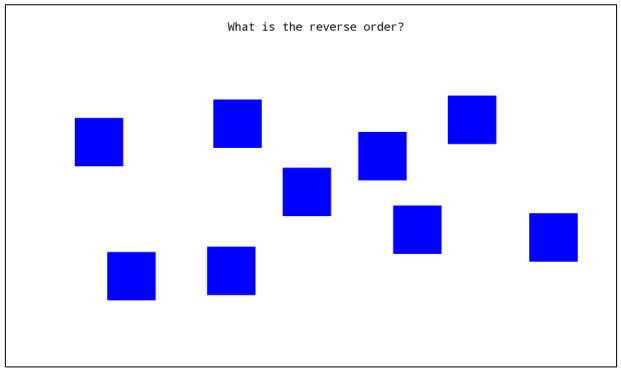
(a) Blocks appear in random positions



(b) Blocks light up yellow randomly



(c) Respondents tap blocks in reverse order



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.

if 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 10 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.

C.3 Inhibitory Control

C.3.1 Hearts and Flowers

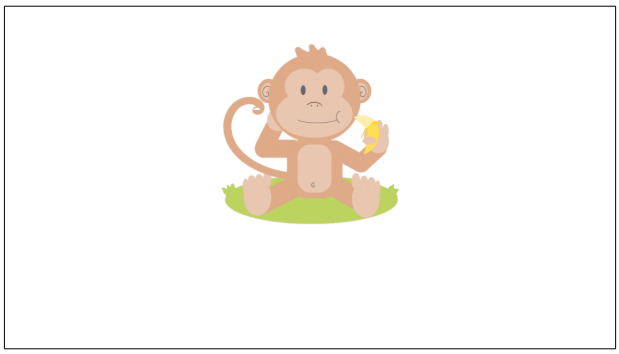
Implementation of the Hearts and Flowers task follows the "dots" task outlined by Davidson et al. (2006). Respondents see a fixation dot in the center of their screen with blue boxes on the left and right. Respondents then see a sequence of hearts and flowers appear on the boxes. For each trial respondents 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.

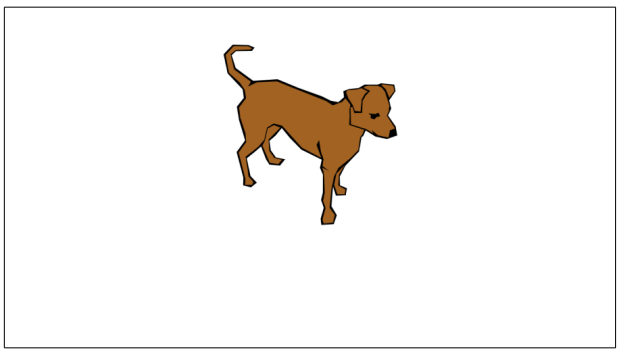
Each stimulus times out after 750 ms and there is a 500 ms interstimulus interval. Trials are scored as follows:

Figure C19: N-Back Stimuli and Responses

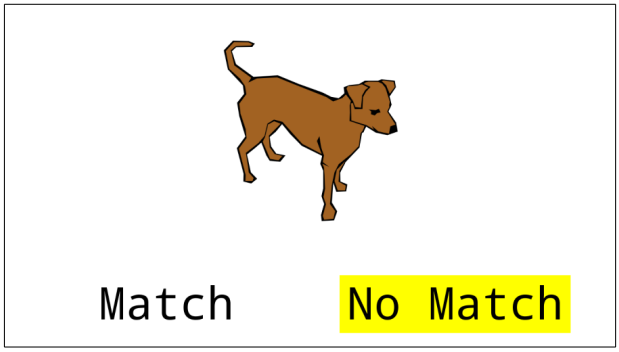
(a) First element



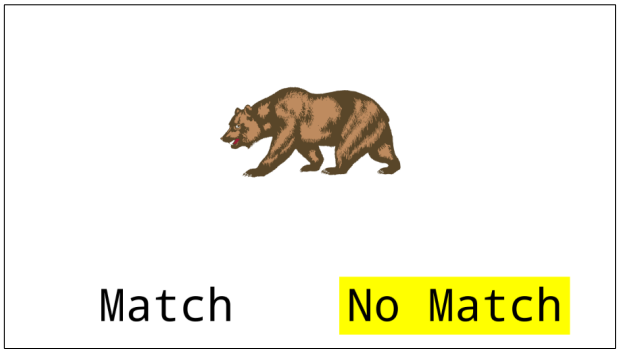
(b) Second element



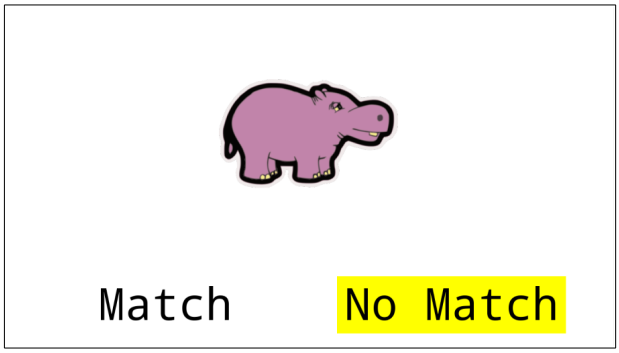
(c) Third element does not match first



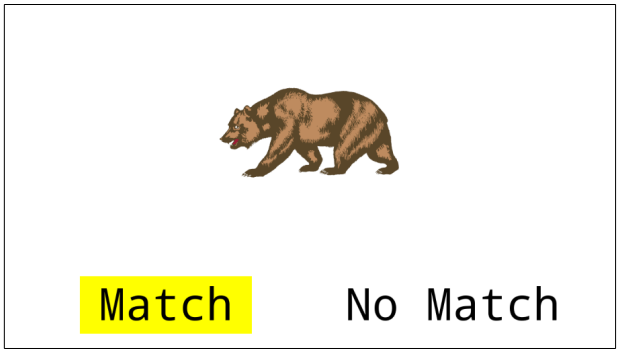
(d) Fourth element does not match second



(e) Fifth element does not match third



(f) Sixth element does match fourth



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.

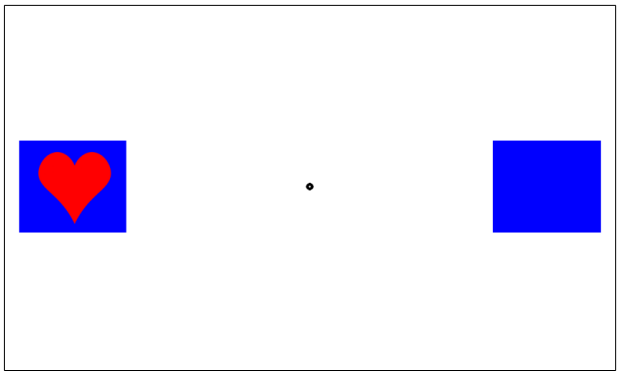
- Responses faster than 100 ms are scored as incorrect, anticipatory responses and earn zero points.

- Trials where the incorrect key or no key is pressed are scored as incorrect and earn zero points.

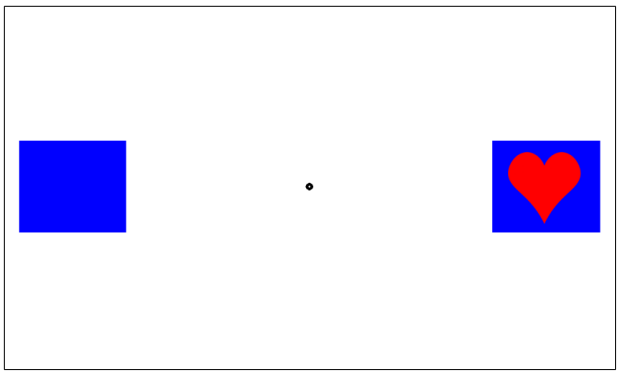
- For each trial with a correct response, respondents earn points according to the following scoring rule that is linear in their response time: $10 \times \frac{\text{RT} - 750}{200 - 750}$

Figure C20: Hearts and Flowers Possible Stimuli and Responses

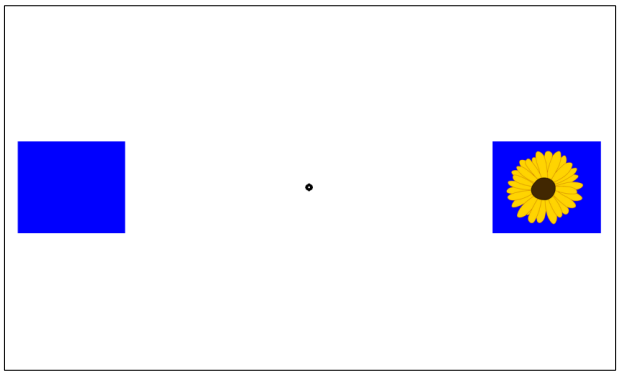
(a) Press 'Q' Key



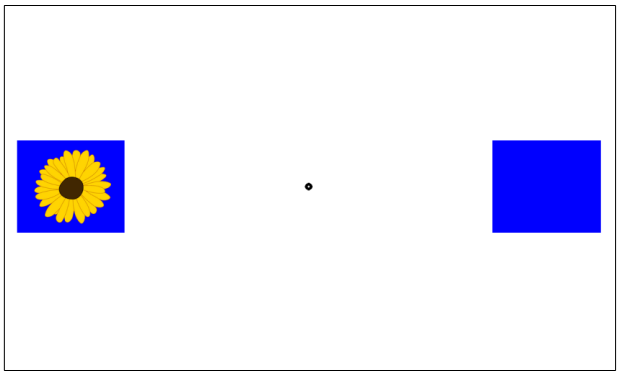
(b) Press 'P' Key



(c) Press 'Q' key



(d) Press 'P' key



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.

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:

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).

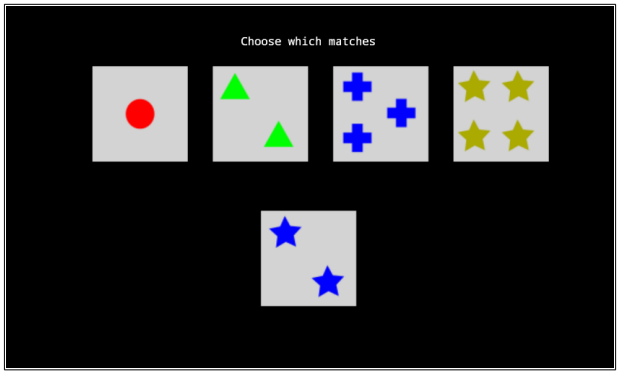
3. Number – In the example the correct answer would be the second response card (two green triangles).

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[22]: $10 + 200 \times \frac{10}{30000 - 200} - \text{RT} \times \frac{10}{30000 - 200}$.

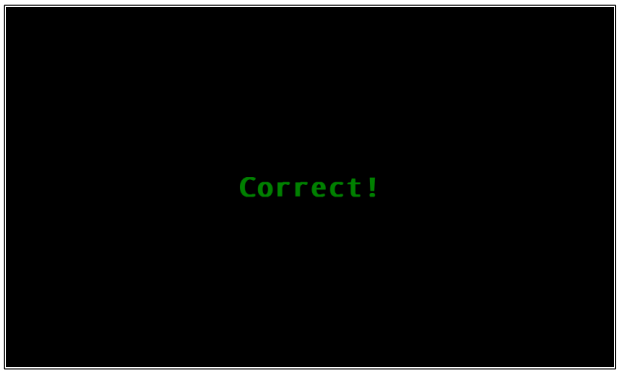
[22]Note that it is not traditional to score reaction time on this task because the task is typically presented with physical cards by an enumerator. I took advantage of the computer-based administration to collect reaction time and improve the measure's sensitivity.

Figure C21: Wisconsin Stimuli

(a) Question



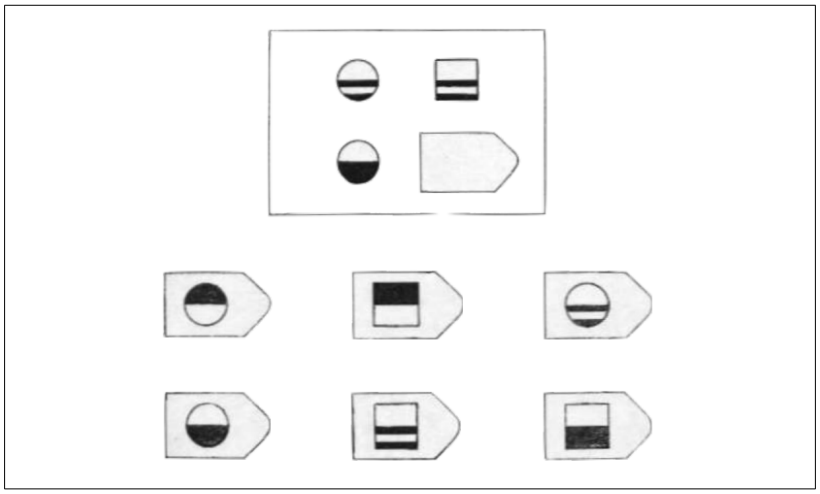
(b) If correct



(c) If incorrect

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



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.

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[23]: $10.0 + 200 \times \frac{10}{60000 - 200.0} - \text{RT} \times \frac{10}{60000 - 200}$.

[23]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.

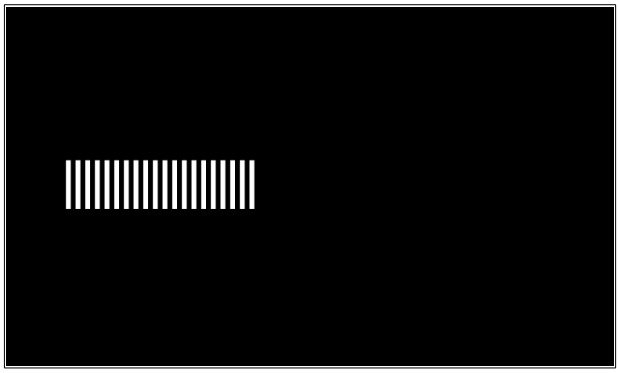
C.6 Effort

C.6.1 Effort Task

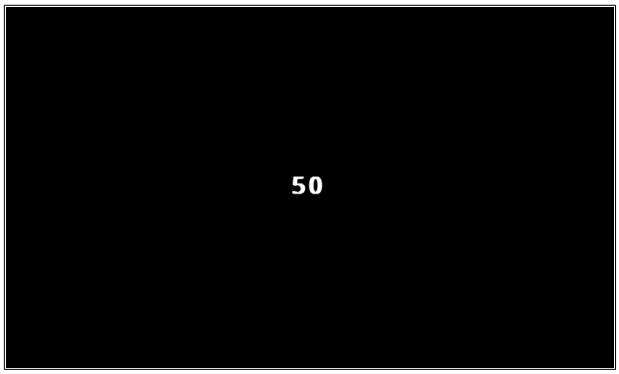
The effort task is implemented following DellaVigna and Pope (2016). Respondents have 10 minutes to alternate pressing the 'a' and 'b' keys. For each complete alternation, a progress bar on the screen increases by one hash mark. At increments of 50 the bar resets and respondents are reminded of their total score (see Figure C23). Respondents earn one point for every 300 alternations.

Figure C23: Effort Stimuli

(a) Press 'a' and 'b' until progress bar fills up



(b) See total score every 50 presses



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

"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?"