“Shhh! It’s Decision Time”: Effect of Traffic Noise on Intertemporal Decision-Making

by

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Abstract

Many economic decisions, such as choosing between spending and saving, or deciding whether to pursue education or enter the labor force, are driven by time preferences. It has been well-documented in behavioral research that people's intertemporal choices are malleable and can be easily influenced by various factors. Despite the growing issue of noise pollution in modern society and frequent exposure to noise in daily life, little research has been done to investigate the effect of noise on intertemporal decision-making. To address this research gap, I conduct laboratory experiments using a between-subject design, where participants completed the Convex Time Budget tasks while being exposed to different levels of pre-recorded traffic noise. Structural estimation results indicate that exposure to traffic noise significantly reduces present bias (larger β), but has no effect on discounting (δ). These findings suggest that ambient noise can play an important role in shaping intertemporal decisions. I also discuss the potential explanations for the observed effects, policy implications, and future research directions.

Key Words: *Time preferences, Environmental pollution, Decision-making, Convex time budget, Lab experiment*

Preface

My undergraduate coursework in experimental and behavioral economics has led me to develop a deep interest in economic decision-making and the impact of environmental factors on human behavior. It was this fascination that sparked some initial ideas for my thesis, which was further refined with the guidance and suggestions of my advisors. Specifically, I am interested in investigating intertemporal decision-making, as it plays a crucial role in fostering long-term economic growth through investment decisions and is also linked to various health issues like smoking, exercise, and healthy eating. As I delved deeper into the topic, I was surprised to find a lack of research on how environmental noise affects intertemporal decision-making. Thus, I designed and conducted a series of lab experiments to explore this area further. Through this research, I hope to contribute to a better understanding of the factors that influence intertemporal decision-making, offer potential insights for environmental policy, and inspire further research on this topic.

1 Introduction

In modern society, noise pollution is a ubiquitous environmental stressor that has been found to have adverse impacts on public health. Researchers estimated that approximately 104 million individuals in 2013 were at risk of noise-induced hearing loss as a result of their annual $L_{EQ(24)}$ levels surpassing 70 dBA (Hammer et al., 2014). The World Health Organization has also ranked acoustic pollution among the greatest stressors affecting public health (Organization et al., 2011). Traffic noise is a major contributor to this issue, especially in urban areas, and its detrimental effects on health and well-being, such as sleep disturbance, stress, and cardiovascular disease, have also been widely documented in the existing literature (Babisch et al., 2000; Basner et al., 2014; Fyhri & Aasvang, 2010; Recio et al., 2016).

Over the course of several decades, researchers in the fields of psychology and environmental sciences have extensively investigated the effects of noise on human behavior. Studies dating back to the last century demonstrate that exposure to high levels of white noise can reduce helping behavior in laboratory settings (Mathews & Canon, 1975). Furthermore, noise has been associated with reduced frustration tolerance and decreased performance efficiency, even after the noise has stopped (Glass et al., 1969). Until recently, there has been limited research into the impact of noise on economic decision-making, with a primary focus on its effects on risk-taking. For example, recent research suggests that exposure to noise stressors containing speech can lead to greater risk aversion, particularly among female participants (Syndicus et al., 2018). Noise has also been studied in the field of public economics, with research indicating that background noise is associated with higher rates of violent crime (Hener, 2022).

Despite the growing body of literature on the effects of noise on behavior, there remains a gap in research regarding the influence of traffic noise on intertemporal decision-making. Although intertemporal preferences are generally considered stable in economic literature, studies have shown that they can be influenced by various factors and contextual manipulations, which can be categorized into framing effects and incidental affective effects (Lempert & Phelps, 2016). Recent research has shown that when evaluating alternatives, reference points can have a significant impact on intertemporal choices. This phenomenon is known as the framing effect (Loewenstein, 1988). According to Kahneman and Tversky's Prospect Theory (Kahneman & Tversky, 2013), many of these framing effects can be explained by shifts in the points of reference used to evaluate prospects. Incidental affective effects, on the other hand, can also influence intertemporal choices and typically include exposure to affective stimuli, mood, and stress (Lempert & Phelps, 2016). Noise can be broadly classified into the second category because it can induce a range of emotional responses, such as frustration, anxiety, and annoyance, potentially affecting intertemporal decision-making.

Studying the effect of noise on intertemporal decision-making is critical for several reasons. Firstly, as highlighted by Becker and Mulligan (1997), investment in patience is a key driver of long-term economic growth. Therefore, if traffic noise does impact how individuals make intertemporal choices, policymakers can leverage this knowledge to develop effective environmental policies that promote sustainable long-term economic growth. Secondly, intertemporal decision-making can have significant implications for individual life quality, affecting health, financial situations, and education choices. For instance, intertemporal decisions related to saving, investment, and retirement planning can result in long-term financial consequences (Bernheim et al., 2001; Finke & Huston, 2013), and intertemporal decisions related to health, such as exercise and smoking habits, can significantly affect long-term health outcomes (Chao et al., 2009; Herberholz, 2020; Lawless et al., 2013). Moreover, choices related to education, such as whether to pursue higher education or directly enter the labor force, can have lasting impacts on an individual's career and earning potential (Card, 1999; Tamborini et al., 2015). Studying the factors that influence intertemporal choices can therefore help policymakers and researchers design interventions or nudges that encourage individuals to make better choices, leading to improved long-term outcomes and ultimately enhancing their overall quality of life.

This study, therefore, aims to bridge the aforementioned research gap by conducting laboratory experiments. To the best of my knowledge, this is the first study that attempts to establish a link between exposure to noise and intertemporal decision-making. The paper is structured as follows: Section 2 provides a brief summary of the existing literature and hypothesis development. Section 3 outlines the experimental design. The model specification and parameter estimation approach are introduced in Section 4. The results of the study are presented in Section 5. The paper concludes with a summary of the findings, limitations, and future directions in Section 6.

2 Literature Review and Hypothesis Development

In this section, I will present a summary of previous research on how environmental change and stimuli influence behavior and decision-making, with a specific focus on time preferences. I will also discuss possible mechanisms through which environmental noise can influence intertemporal choices.

In terms of significant environmental changes, previous studies have investigated how encountering drastic environmental harm, such as natural disasters, affects time preferences. However, the existing literature does not provide a consistent conclusion on the effects. In a study by Akesaka (2019), panel survey data revealed that there is an increase in present bias after the Great East Japan Earthquake but no effect on discounting, and the increase continued to persist even five years after the earthquake. However, in another study, it was found that people who experienced the 2004 tsunami in Thailand discount the future approximately 22% more than those who did not experience it (Cassar et al., 2017). While these studies generally suggest that exposure to severe disasters leads to decreased patience, Callen (2015) found that exposure to the Indian Ocean Earthquake increases patience in a sample of Sri Lankan wage workers.

Although the exact mechanism through which life-threatening events can have a long-lasting effect on individual preferences is not yet fully understood, research suggests that in the short term, when confronted with imminent physical danger or stimuli, the activation of the human body's sympathetic nervous system biologically induces the "fight-or-flight" response (Cannon, 1925). In this process, the sympathetic nervous system can facilitate the release of certain hormones, including catecholamines (e.g., adrenaline and noradrenaline) and glucocorticoids (e.g., cortisol), which activate the body's stress response, leading to various physiological changes, such as increased heart rate, elevated blood pressure, and narrowed blood vessels.

Studies in the fields of environmental science and psychology found that such activation of the sympathetic nervous system is not exclusive to life-threatening situations, but can also be triggered by everyday environmental stimuli, such as traffic noise. This is supported by the findings of Babisch et al. (2000), who found that individuals who sleep in bedrooms facing busy streets have significantly higher levels of noradrenaline in their urine compared to those who sleep in quieter areas. Similarly, a study by Maschke et al. (2002) showed that nocturnal electroacoustically simulated aircraft noise in apartments resulted in higher levels of cortisol in men. These studies all suggest that noise exposure can prompt the secretion of stress hormones and activate the sympathetic nervous system, which is immediate and transient in nature (Miki et al., 1998). The increased level of stress is found to be associated with aggressive behaviors, reduced self-control, and violence. Using the fMRI scans, Maier et al. (2015) found that stress reduced connectivity between the ventromedial prefrontal cortex and dorsolateral prefrontal cortex, regions known to be involved in self-control. This suggests that stress could result in impatience, causing individuals to favor immediate rewards over delayed ones. Based on these findings, it is reasonable to suggest that exposure to traffic noise, an acute stressor, may stimulate stress and physiological responses in individuals, inducing greater impatience and a more intuitive decision-making style.

Another potential mechanism for the contradictory hypothesis that people tend to be more patient when exposed to noise stems from research that suggests that exposure to noise increases the mental effort required to complete a task (Choi et al., 2014; Szalma & Hancock, 2011; Tafalla & Evans, 1997). This increased cognitive load prompts individuals to exert more mental and cognitive effort to deal with their surroundings, resulting in greater attentional control, which could enable individuals to resist the temptation of immediate rewards in favor of delayed ones (Keren et al., 1977; Kujala & Brattico, 2009). In this process, the increased cognitive load could possibly lead to cognitive overshooting, where individuals overestimate the effort required to perform a task. Consequently, individuals may exhibit an excessively patient decision-making pattern and tend to choose delayed over immediate gratification. Therefore, it is also plausible to hypothesize that individuals' levels of patience could increase when exposed to traffic noise. Therefore, the direction of the hypothesis regarding the effects of noise on time preferences is thus unclear and may depend on the intensity and characteristics of the noise. Given the relatively low intensity of the pre-recorded traffic noise to which participants are exposed in the laboratory settings, it is reasonable to expect that the increased cognitive load and excessive mental effort resulting from noise exposure would lead to greater patience and a more deliberate decision-making style.

3 Experimental Design and Procedure

IRB approval is obtained for this study.[1]. The oTree platform is used to implement the experimental interface, which allows dynamic text adjustments and volume visualization through the use of Javascript. The Heroku server is utilized to present the interfaces to participants. Instructions are converted to audio format using Microsoft Azure, and all participants use Sennheiser headphones of the same model (HD650) during the experiment. Each session lasts for around 30 minutes. The study employs a between-subject design and includes four different treatments:

Treatment A (Quiet): Reduced Traffic Noise

Treatment B (Noisy): Traffic Noise

Treatment C (Adaptation): Adaptation + Traffic Noise

Treatment D (Baseline): Reduced Traffic Noise + No WTP section

Treatments A, B, C, and D differ only in the following ways:

- Only participants in treatment C are exposed to the Adaptation Phase at the beginning of the experimental session.

- Participants in Treatments A and Treatment D are exposed to a lower level of noise (around 30 to 35 dB) when completing the Convex Time Budget, and participants in Treatment B and Treatment C are both exposed to the same level of noise (around 70 to 75 dB), which is higher than that in treatment A.

[1]NYU Shanghai IRB approval number: 2022-052.

- Participants undergo an identical process as Treatment B, with the exception that they are not asked to indicate their Willingness to Pay. During the count zero tasks, they are therefore exposed to the minimal level of noise.

- Participants experience the same procedure as those in Treatment B, except that they are not asked to complete the Willingness to Pay section. In the count zero tasks, they are therefore exposed to the minimal level of noise.

Treatment D was conducted as a follow-up treatment after treatments A, B, and C. In addition, throughout the experiment, task compensation is referred to as "experimental coins", and upon completion of the experiment, these coins are converted into RMB at a currency ratio of 1:100. In other words, for every 100 coins earned by participants, they will receive a payment of ¥1. Figure 1 displays the flowchart that illustrates the process, and the following sections provide a more detailed description of the various stages of the experimental session.

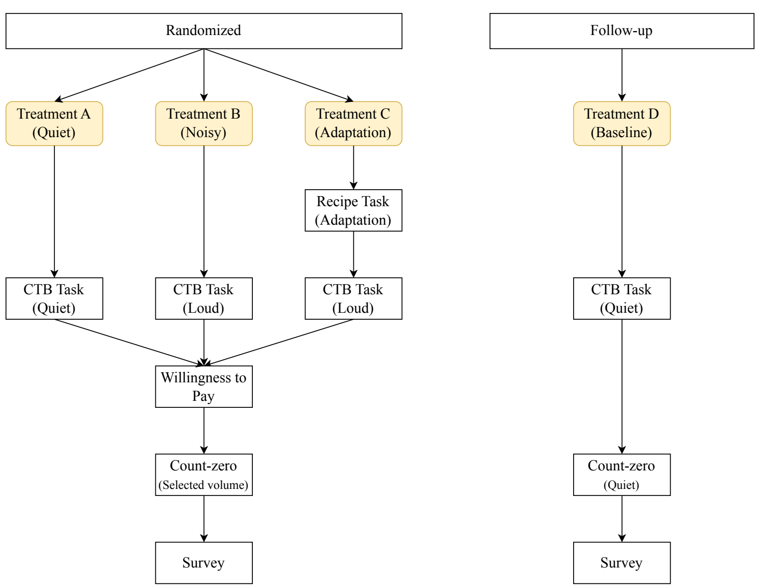

Figure 1: Experimental Procedure

3.1 Tasks

3.1.1 Adaptation Phase

Participants who are in treatment C are first presented with an audio clip detailing a recipe. To incentivize participants to keep their headphones on, upon listening to the audio clip, participants are asked to identify what dish the clip refers to and rewarded ¥5 for answering correctly. The design of this section is intended to serve as an adaptation phase for participants prior to being exposed to traffic noise during the primary task. The aim is to investigate whether the adaption of noise will influence subsequent intertemporal choices.

3.1.2 Convex Time Budget

Then I elicit the time preferences of participants in all treatments. To measure time preferences, I use the Convex Time Budget (CTB) choice sets developed by Andreoni and Sprenger (Andreoni & Sprenger, 2012). Unlike other methods that estimate discounting, utility curvature, and present bias separately, CTB allows for simultaneous estimation of all three variables. This makes it a widely used and suitable measure for this study, as it has been found to improve out-of-sample predictive accuracy and prevent unrealistically high discounting estimates (Andreoni et al., 2015; Andreoni & Sprenger, 2012).

In the CTB tasks, participants allocate payments between two time periods: (i) today versus 5 weeks later, (ii) today versus 9 weeks later, (iii) 5 weeks later versus 10 weeks later, and (iv) 5 weeks later versus 14 weeks later. Participants face a budget constraint when allocating payments across the two periods t and $t+k$: $(1+r)c_t + c_{t+k} = Y$, where the budget is fixed at $Y = ¥50$. In addition, five price ratios are implemented in each choice set, summarized by $P \in \{1.05, 1.11, 1.18, 1.25, 1.43, 1.82\}$

Choice set	First payment (t)	Delay (k)	t+k	Price ratio (P)
(i)	0	35	35	1.05, 1.11, 1.18, 1.25, 1.43, 1.82
(ii)	0	63	63	1.00, 1.05, 1.18, 1.33, 1.67, 2.22
(iii)	35	35	70	1.05, 1.11, 1.18, 1.25, 1.43, 1.82
(iv)	35	63	98	1.00, 1.05, 1.18, 1.33, 1.67, 2.22

Table 1: Parameters Used in the Convex Time Budget Tasks

for set (i) and set(iii), and $P \in \{1.00, 1.05, 1.18, 1.33, 1.67, 2.22\}$ for set (ii) and set (iv). These values were selected to be consistent with prior literature (e.g. Aycinena & Rentschler, 2018; Lindner & Rose, 2017). Therefore, each participant makes 24 choices in total, and Table 1 is a summary of the first payment dates (t), delay (k), and price ratios (P) that are used in the experiment. Figure 2 presents a screenshot of a sample CTB choice set (where $t = 0$ and $k = 35$).

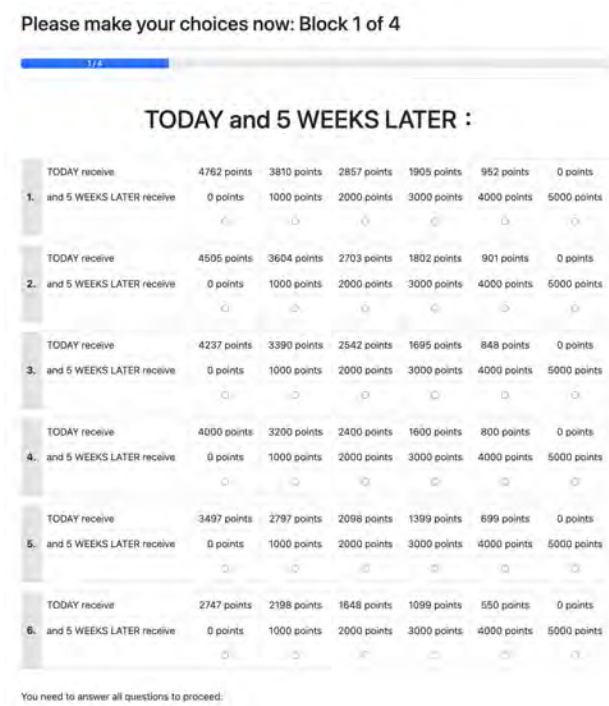

Figure 2: Sample CTB Choice Set

3.1.3 Willingness To Pay

In this part, I measure participants' willingness to pay for reducing noise. A slider tool is provided to the participants, allowing them to indicate the amount of a fixed budget (¥10) they are willing to allocate towards reducing the noise levels in their headphones. Each position of the slider corresponds to a predetermined noise level, with a negative association between the noise level and the amount of money required for reduction. Moreover, the slider positions exhibit decreasing marginal returns, which means that it would cost more to reduce a relatively smaller level of noise compared to a larger one. This is designed to align with the real-world relationship between reducing noise levels and the associated engineering costs (Bowes et al., 2006). The experimental interface is displayed in Figure 3. It is noteworthy that as participants slide the slider, the volume in their headphones, the points needed to pay shown on the screen, and the volume circle displayed all dynamically adjust accordingly.

Figure 3: Willingness to Pay Task

3.1.4 Real Effort Task

Following the WTP task, participants proceed to complete a real-effort task while wearing headphones with the noise level set to their chosen level. Specifically, they are instructed to count the number of 0s in matrices that contained both 0s and 1s. Their earnings in this section are based on their performance in the counting task, whereby they received a payment of ¥1 for each matrix that is counted correctly. Figure 4 is a screenshot of the task interface.

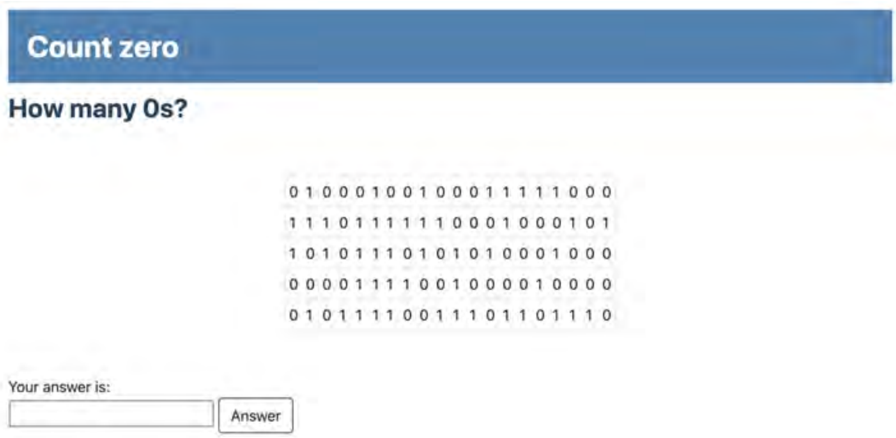

Figure 4: Real Effort Task

3.1.5 Survey

At the end of the experiment, participants are asked to voluntarily report some of their demographic information, including gender, age, nationality, major, birthplace, and location of high school.

3.2 Recruitment and Sample

Participants are recruited through posters put up on public bulletin boards on the NYU Shanghai campus, messages sent to previous participants in the SONA system, as well as electronic ads posted on social media. Experimental sessions are conducted in the NYU Shanghai Behavior & Experimental Economics Laboratory. A total of 125 students participated in this study. Since the participants were asked to provide demographic information voluntarily, it should be noted that the total number of responses for each category may not necessarily sum up to 125.

The age of the participants ranges from 18 to 24, with an average age of 19.4876. Out of the participants who provided their demographic information, 47 were male and 75 were female. Furthermore, 77 of the students were Chinese and 42 were international students. Regarding the treatment assignments, 37 participants were assigned to Treatment A, 36 to Treatment B, 26 to Treatment C, and 26 to Treatment D.

4 Model Specification and Estimation Strategy

To obtain estimates of participants' time preferences, in the upcoming analysis, I follow the parametric assumptions by Andreoni and Sprenger (2012). Specifically, I assume that subjects' per-period preferences are stationary and do not change over time. Furthermore, participants' preferences are also characterized by Constant Relative Risk Aversion (CRRA), where $u(x_t) = x_t^\alpha$ and the coefficient of relative risk aversion is given by $R(x) = -\frac{xu''(x)}{u'(x)} = 1 - \alpha$, which is a constant. To account for the commonly observed dynamic inconsistencies in discounting behavior, the utility function follows the quasi-hyperbolic form by incorporating a parameter β that stands for present bias (Laibson, 1997; O'Donoghue & Rabin, 1999). Thus, preferences are defined as follows:

$$U(c_t, c_{t+k}) = c_t^\alpha + \beta^{t_0}\delta^k c_{t+k}^\alpha \tag{1}$$

where c_t and c_{t+k} are amounts received at the earlier and later date, respectively. t_0 is a time indicator with $t_0 = 1$ if the sooner payment is received at present, and 0 otherwise. Y stands for future value budget. k is the delay length of the later payment. α is the curvature of the utility curve function. δ is the discount factor, and β captures present bias.

In the experiment, subjects face the following budget constraint:

$$(1 + r)c_t + c_{t+k} = Y \tag{2}$$

A participant maximizes utility (1) subject to the budget constraint (2). In this framework, the Marginal Rate of Substitution (MRS) is given by:

$$MRS = \frac{\partial U / \partial c_t}{\partial U / \partial c_{t+k}} = \frac{\alpha c_t^{\alpha-1}}{\beta^{t_0} \delta^k \alpha c_{t+k}^{\alpha-1}} = \frac{c_t^{\alpha-1}}{\beta^{t_0} \delta^k c_{t+k}^{\alpha-1}} \tag{3}$$

The price ratio can be represented by $P = 1 + r$, and the standard Euler equation can then be derived since:

$$MRS = \frac{c_t^{\alpha-1}}{\beta^{t_0} \delta^k c_{t+k}^{\alpha-1}} = P \tag{4}$$

Solving for c_{t+k} in the budget constraint (2):

$$c_{t+k} = Y - (1 + r)c_t = Y - Pc_t \tag{5}$$

and substituting into equation (4), we get:

$$P(\beta^{t_0} \delta^k)(Y - Pc_t)^{\alpha-1} = {c_t}^{\alpha-1} \tag{6}$$

Rearranging and simplifying gives:

$$c_t = \frac{Y(\beta^{t_0}\delta^k P)^{(\frac{1}{\alpha-1})}}{1 + P(\beta^{t_0}\delta^k P)^{(\frac{1}{\alpha-1})}} \tag{7}$$

Expression (7) serves as the foundation of the Nonlinear Least Squares estimation, without adding the effect of noise or demographic features. Specifically, in the experimental design, Y is fixed at 50, and Ps are predetermined for each scenario as well. Participants' choices provide the values of c_t, and the three parameters α, β, and δ are to be estimated.

To account for the potential impact of noise and demographic characteristics on time preferences, I specify the preference parameters α, β, and δ in the linear forms below:

$$\alpha = \alpha_0 + \alpha_1 * noise + \alpha_2 * gender + \alpha_3 * Chinese + \alpha_4 * age \tag{8}$$

$$\beta = \beta_0 + \beta_1 * noise + \beta_2 * gender + \beta_3 * Chinese + \beta_4 * age \tag{9}$$

$$\delta = \delta_0 + \delta_1 * noise + \delta_2 * gender + \delta_3 * Chinese + \delta_4 * age \tag{10}$$

Here, α_0, β_0, and δ_0 represent the baseline values of the preference parameters, and α_1, α_2, α_3, β_1, β_2, β_3, β_4, δ_1, δ_2, δ_3, δ_4 are coefficients that capture the potential effects of noise and demographic characteristics on the preference parameters. Furthermore, *noisy*, *gender*, and *Chinese* are three dummy variables, where $noise = 1$ indicates that the participant is assigned to the noisy treatment, $gender = 1$ indicates that the participant is female, and $Chinese = 1$ indicates that the participant is Chinese. Additionally, we have a numerical variable *age*. By incorporating equations (8), (9), and (10) into equation (7), c_t becomes a composite function of the preference parameters and noise and demographic characteristics. The estimation procedure focuses on simultaneously estimating the different αs, βs, and δs using Nonlinear Least Squares estimation.

5 Results

5.1 Choice Overview

Figure 5 presents the overview of the aggregate data from the CTB tasks. It reports the mean budget allocation towards earlier payment dates, at various values of $P = (1 + r)$ from the equation $Pc_t + c_{t+k} = Y$, for the recruited sample of 125 subjects in all treatments. The left section of the graph shows two sets of data for payments that are delayed by five weeks, whereas the right section demonstrates the data sets for payments delayed by nine weeks.

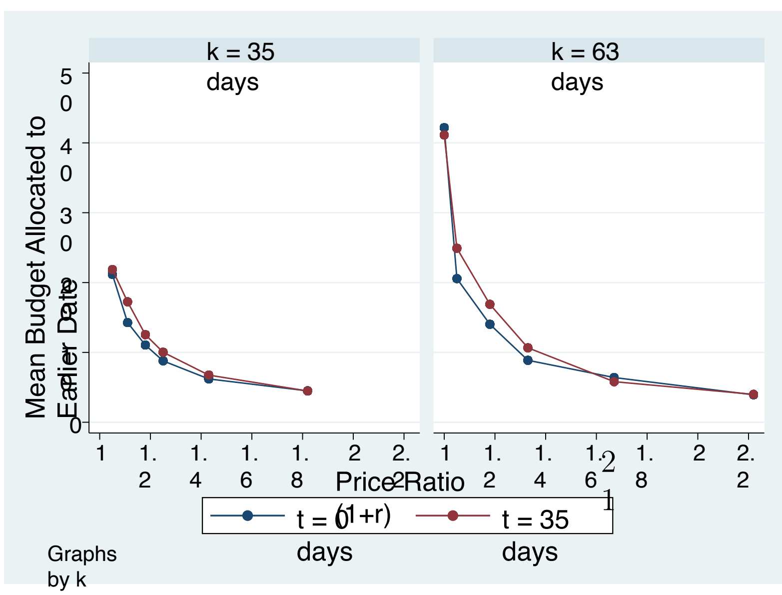

Figure 5: Comparison of Mean Budget Allocated to Earlier Date Across Scenarios

It is worth noting as shown in Figure 5, as the price ratio (1+r) increases, there is a decreasing tendency in the average allocation to the sooner payment, in accordance with the law of demand. This suggests that the participants generally understand the intertemporal trade-offs involved in the CTB tasks. This pattern is in line with previous studies (Andreoni & Sprenger, 2012; Augenblick et al., 2015; Lindner & Rose, 2017).

I then conducted individual-level Non-linear least squares estimation using expression (7) without including any controls. The distributions of the estimated betas and deltas are illustrated in Figure 6. Since six data points fail to converge during the estimation process and two participants' responses do not show enough variation to be estimated, they are excluded from this part of the analysis.

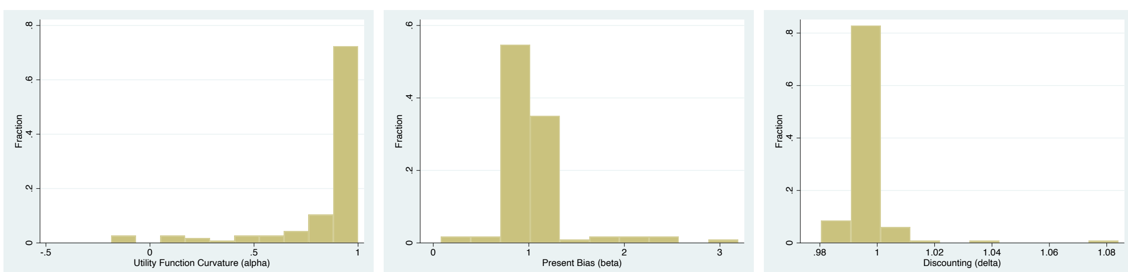

Figure 6: Distributions of estimated parameters

Out of the 117 data points that converged, 35 participants (29.9%) display present-biased behavior, which I define as having an estimated β value strictly less than 0.99 (as in Augenblick et al., 2015).

5.2 Results

5.2.1 Main Analysis: Noise on Intertemporal Decision-making

Next, I turn to the main analysis of how exposure to noise affects intertemporal decision-making. For this part of the analysis, I exclude the data from Treatment C since participants went through an adaptation phase before completing the CTB tasks, which could potentially confound the pure treatment effect. Additionally, I consider Treatment D, the baseline follow-up treatment group, as a quiet group too since participants were also exposed to reduced traffic noise prior to completing the CTB tasks. To ensure the validity of this grouping, I conducted statistical tests, which revealed no significant differences in the distributions of the estimated values of α (t-test,p-value $= 0.3272$), β (t-test, p-value $= 0.8928$), and δ (t-test, p-value $=$ 0.6751) between Treatment A and Treatment D. Consequently, I group Treatment A and D as the quiet group, while Treatment B is the noisy group. Figure 7 illustrates the comparison of mean budget allocation towards earlier payment dates across treatments.

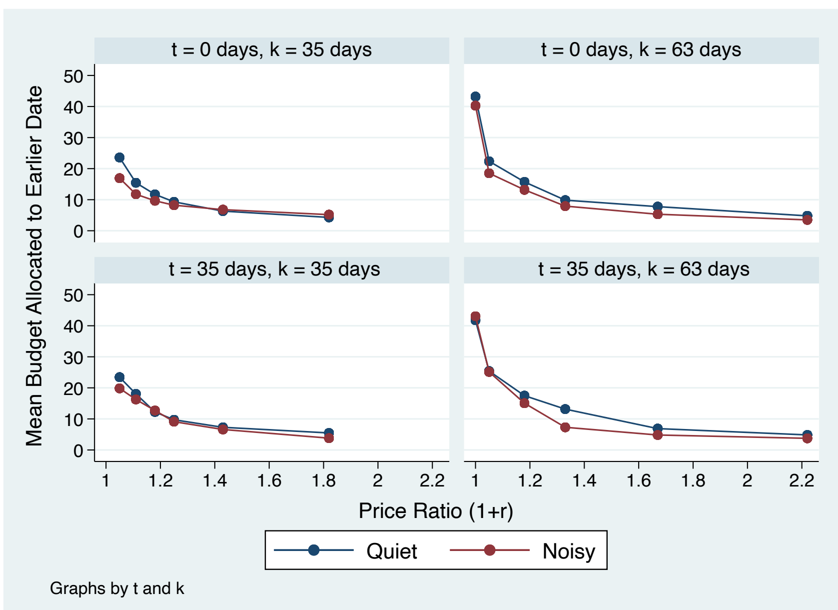

Figure 7: Comparison of Mean Budget Allocated to Earlier Date Across Treatments

Table 2 reports the estimation results based on equations (7), (8), (9), and (10). The columns below present results obtained by considering preferences alone, by incorporating the effect of noise into the parameters, and by incorporating both the noise and different demographic variables into the parameters. Robust standard errors are reported in parentheses. The standard errors are clustered at the individual level. Columns (3), (4), and (5) have 6 clusters and 144 observations fewer than Columns (1) and (2) because 6 participants didn't provide their demographic information.

I first compare the performance of different models. According to Spiess and Neumeyer (2010), using R^2 obtained from a nonlinear fit is not an ideal measure because, even in cases with very poor models, it is hardly affected beyond the third or fourth decimal place. Instead, both Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) perform significantly better. From the result table, estimations in Columns (4) and (5) have the lowest BIC and AIC, respectively, which indicates that they provide the best fit for the model. The results from these two columns imply that after controlling for demographic variables, the coefficient of $Noise\_on\_\beta$ is positive and significant, suggesting that exposure to noise leads to a 0.054 increase in β, when compared to the baseline parameter $\hat{\beta}_0$. However, noise has no significant effect on the utility curvature α or discounting δ in all of the specification checks. However, it should be noted that this effect is not very robust as it only remains significant in Columns (4) and (5), when controlling for both gender and nationality. This could potentially be attributed to the relatively small size of the sample used in the study.

In summary, the findings suggest that exposure to noise leads to a significant reduction in present bias, with an average increase of approximately 0.054 in β, holding other factors constant. These outcomes remain relatively robust after including control variables in several econometric specification checks.

5.2.2 Mechanism: Noise, WTP, and Performance

The observed decrease in present bias due to exposure to noise is in line with the excessive mental effort hypothesis mentioned in Section 2. That is, participants might

	(1)	(2)	(3)	(4)	(5)
$\hat{\alpha}_0$	0.874***	0.865**	0.839***	0.817***	0.534***
	(0.012)	(0.017)	(0.025)	(0.031)	(0.147)
$\hat{\beta}_0$	1.032***	1.025***	1.026***	1.074***	1.220***
	(0.012)	(0.015)	(0.019)	(0.031)	(0.153)
$\hat{\delta}_0$	0.998***	0.998***	0.999***	0.998***	0.996***
	(0.012)	(0.000)	(0.000)	(0.001)	(0.004)
Noise_on_α	–	0.025	0.002	-0.038	-0.030
		(0.023)	(0.025)	(0.024)	(0.027)
Noise_on_β	–	0.018	0.033	0.054**	0.054**
		(0.024)	(0.027)	(0.026)	(0.025)
Noise_on_δ	–	0.000	0.000	-0.002	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Gender	No	No	Yes	Yes	Yes
Chinese	No	No	No	Yes	Yes
Age	No	No	No	No	Yes
R^2	0.579	0.582	0.590	0.598	0.600
Adjusted R^2	0.575	0.578	0.585	0.593	0.596
AIC	41392.24	41385.04	38865.91	38824.93	38821.3
BIC	41409.56	41419.68	38917.31	38893.45	38906.96
Observations	2,376	2,376	2,232	2,232	2,232
Clusters	99	99	93	93	93

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses.

Table 2: Estimation Results

overestimate the cognitive effort required to deal with their environment and resist traffic noise in their headphones. The validity of this hypothesis can be supported if the level of noise is shown to have only a moderate impact on cognitive performance, leading to cognitive overshoot. Below are several data patterns from the experiment that support this, indicating that the recorded noise used in this study is relatively mild and does not significantly affect cognitive performance.

Noise and Performance: First, I examine how the level of noise affects participants' performance in the count-zero tasks. 41 participants' performances were not properly recorded due to a programming error, and therefore, they are excluded from the analysis. Moreover, two participants used a keyboard shortcut to search for the number of zeros during the experiment, resulting in an unexpectedly high number of correct matrices, which are also excluded from the analysis. After excluding these data points, there are 22 remaining data points for Treatment A, 17 for Treatment B, 17 for Treatment C, and 18 for Treatment D.

First, I pool the data from all treatments to conduct the analysis. The noise volume was standardized and ranges from 0.03 to 1. The lowest level of 0.03 corresponded to the level of noise in the CTB section of the Quiet Treatment. After controlling for demographic characteristics, the analysis showed that the effect of volume on the number of correctly counted matrices was not statistically significant, despite the reasonable direction of the sign (coefficient = 0.288, p-value = 0.872).

Pooling the data from all treatments may have the issue of endogeneity since participants self-selected the level of noise in Treatment A, B, and C, and they might inherently possess different abilities to resist noise. To address the issue, I specifically compared participants' cognitive performance in Treatment D (Baseline) and the non-baseline treatments. When performing the count-zero tasks, participants in Treatment D (Baseline) were automatically placed in the environment where volume

$= 0.03$, which is the lowest level. The statistical test yields broadly similar results (t-test, p-value=0.175), indicating that the increase in the level of noise used in this experiment has no significant effect on participants' cognitive performance.

Adaptation Phase and Intertemporal Choices: Next, I examine whether an adaptation phase can mitigate the impact of noise on participants' intertemporal decision-making. If no such effect is observed, it may also suggest that the volume level in this experiment used is too mild to elicit an observable adaptation effect. To test this, I compare the distributions of β and δ in Treatment C (Adaptation) with those in Treatment A + D (Quiet). As expected, the results show that there is no statistically significant effect of the adaptation phase on participants' estimated β (t-test, p-value = 0.373) or δ (t-test, p-value = 0.327). Comparison between Treatment C (Adaptation) and Treatment B (Noisy) provides similar results; there is no statistically significant effect of the adaptation phase on participants' estimated β (t-test, p-value = 0.611) or δ (t-test, p-value = 0.660). These results support the hypothesis that the audio used in this experiment is too mild to trigger an observable adaptation effect.

Willingness to Pay and Performance: Lastly, I explored the relationship between the amount participants paid for noise reduction and their performance in the count-zero task. For data in Treatments A, B, and C, controlling for characteristics, there is no significant effect of the number of coins paid on the number of correct matrices solved (coefficient = 0.001, p-value = 0.706). This suggests that the participants in the experiment may not have a clear understanding of how much noise affects their performance in the real-effort task, which supports the hypothesized cognitive overshoot. The non-significant result could be attributed to the possibility that participants who perceived themselves as more susceptible to noise may have offered to pay a higher amount, leading to this observed data pattern. Thus, the conclusion cannot be considered definitive.

To summarize, the results mentioned above provide some evidence to support the conjecture that the level of noise utilized in the experiment is mild and has little impact on participants' cognitive performance. However, participants may not have a thorough understanding of the effect of noise. This lack of understanding may lead to cognitive overshoot, potentially resulting in an overestimation of mental effort and a decision-making style that is overly patient.

6 Conclusion

This study employs laboratory experiments to address the novel research question of how exposure to traffic noise affects intertemporal decision-making. Results suggest that exposure to traffic noise significantly reduces present bias (larger β), but has no effect on utility curvature α or discounting δ. This finding holds important policy implications as it provides a simple and low-cost intervention for improving intertemporal decision-making and reducing impulsive behavior. For instance, noise exposure interventions could be used in financial education programs to encourage long-term savings. Additionally, policymakers could consider utilizing noise exposure in public spaces where impulsive behavior is a significant issue, such as preventing smoking or violent behavior, to encourage individuals to make more informed and rational decisions.

While this study sheds light on the potential effects of noise exposure on intertemporal decision-making, I have also identified some limitations of this study that might guide future research. First, the results of this study may not be very robust, and increasing the sample size could provide more reliable findings. Second, the noise level used in the study was only mild and close to the borderline of safe decibel levels, which may limit the generalizability of our results. Future research could consider using more extreme levels of noise to explore the effects further and whether participants' behaviors alter the direction when exposed to different levels of traffic noise. Third, the hypothesis of cognitive overshoot is rather conjectural, and future research could measure the precise mental effort exerted to validate this hypothesis. Finally, while our study only focuses on the CTB measure of time preferences, other measures could be utilized in future research to check the robustness of the current findings. Taken together, these limitations imply that it is important to exercise caution when attempting to generalize the findings of this study, and further research is necessary before drawing more comprehensive conclusions on the mechanism through which traffic noise impacts intertemporal decision-making.

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