# Complexity and Time*

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**Abstract**

We provide experimental evidence that core intertemporal choice anomalies – including extreme short-run impatience, econometrically estimated present bias, hyperbolicity and transitivity violations – reflect responses to complexity rather than time or risk preferences. First, these anomalies also arise in structurally similar atemporal decision problems involving valuation of recursively discounted but immediately-paid rewards. These computational errors are strongly predictive of intertemporal decisions. Second, in intertemporal choice, anomalies are highly correlated with indices of complexity responses including cognitive uncertainty and choice inconsistency. Multiple streams of evidence suggest that the complexity of intertemporal choice is driven by the difficulty of recursive reasoning.

**Keywords:** Complexity, hyperbolic discounting, present bias, bounded rationality, noise, cognitive uncertainty
**JEL codes:** C91, D91, G0

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# 1 Introduction

In this paper we provide evidence that some of the core empirical anomalies in intertemporal choice documented by behavioral economists – extreme short-run impatience, hyperbolic discounting, subadditivity and econometric estimates of present bias – are an outgrowth of the complexity of intertemporal choice rather than non-standard preferences.

The canonical model of intertemporal choice in economics is the exponential discounted utility model, which uniquely produces time-consistent behavior. As summarized by Cohen et al. (2020) and Ericson and Laibson (2019), decision makers typically depart from the predictions of exponential discounting in a number of systematic ways when asked to value time-dated monetary rewards. The most influential of these anomalies concern how people evaluate time delays of varying lengths. First, people tend to show evidence of extreme short-run impatience, discounting relatively short delays at a very high rate. In model estimations, such extremely high short-run impatience is often attributed to a present bias parameter, as in $\beta - \delta$ models (Laibson, 1997; O'Donoghue and Rabin, 1999). Second, people's revealed preferences are non-stationary, with measured per-period impatience strongly decreasing as evaluated delays increase. That is, choices tend to show characteristics of hyperbolicity rather than exponentiality. Third, decision makers' valuations exhibit subadditivity, with subjects violating transitivity by making less patient choices when a single time interval is decomposed into two separate intervals. Finally, decision makers show evidence of a front-end delay effect, decreasing their impatience when earlier and later dates are both delayed to the same degree. The main theme that characterizes all of these anomalies – except for front-end delay effects – is that they reflect an *inelasticity* of empirically observed discounting with respect to the length of the delay.

What produces these systematic anomalies? The most influential explanations in the literature are *motivational* in nature, rooted in non-standard preferences or internal conflicts that appear because of temporal delay in the choice problem. For instance, the literature has proposed that the anomalies are driven by non-standard discounting functions such as hyperbolic or quasi-hyperbolic preferences (e.g., Loewenstein and Prelec, 1992; Laibson, 1997), short-term temptation (Gul and Pesendorfer, 2001), or self-control problems formalized as multiple selves (Fudenberg and Levine, 2006). Other motivational explanations emphasize that the passage of time produces transaction costs or risks that the rewards being valued will not be paid out (Halevy, 2008; Andreoni and Sprenger, 2012; Halevy, 2015; Chakraborty et al., 2020).

Importantly, however, intertemporal choice is not only temporal (and therefore shaped by motivational factors like preferences) – it is also *complex*, requiring decision makers to engage in non-trivial cognitive information processing to translate the inputs of a problem (e.g., payment amounts and time delays) into an output (e.g., a valuation or choice). In particular, rational theories of intertemporal choice posit that decision makers "recursively attenuate" future utilities: they evaluate utilities paid with a one-period delay by shrinking it at some rate, repeating successively for each additional period of delay. This is likely to be a cognitively difficult procedure. If precisely engaging in this cognitive process is difficult and costly, decision makers may elect to (or be forced to) pursue less careful approaches to valuation instead. We will refer to such substitutions from complex, optimal valuation procedures to simpler alternatives as "complexity responses."

The theoretical literature has proposed a number of models that characterize such simpler-than-optimal procedures, ranging from heuristics (e.g., Rubinstein, 2003; Ericson et al., 2015), to noisy introspection about one's discount factor (Regenwetter et al., 2018; Lu and Saito, 2018; He et al., 2019), to Bayesian cognitive noise models that posit that decision makers combine imprecise mental representations with a prior (Vieider, 2021; Gabaix and Laibson, 2022; Gershman and Bhui, 2020). What these simplified evaluation procedures have in common is that they tend to produce insensitivity to variation in the parameters of the problem (e.g., the magnitude of temporal delay). As a result, these models are often capable of generating classical intertemporal choice anomalies. For instance, insensitivity to variation in the delay can produce exaggerations in short-term discounting and, simultaneously, attenuated discounting of longer-term delays, generating classical phenomena like hyperbolicity and econometric estimates of present bias.

While there is some evidence that bounded rationality may influence intertemporal decisions,[1] we still lack a solid understanding of which of the two broad classes of mechanisms (motivational vs. complexity-based) drives the famous anomalies. Developing such an understanding is important for at least two reasons. First, if anomalies are rooted in complexity, there are clear welfare advantages to taking steps to reduce the severity of these anomalies rather than accommodate them. Second, to whatever degree anomalies are complexity-driven, we should expect their severity to be sensitive to aspects of the choice environment that we are otherwise likely to ignore when making forecasts, designing choice architectures and developing policies.

To identify the role of complexity in intertemporal choice, we pursue two complementary strategies. First, we experimentally remove scope for temporal motivations

[1]For example, there are known linkages between patience and cognitive skills (e.g., Dohmen et al., 2010; Benjamin et al., 2013) and systematic effects of cognitive load, time pressure and framing (e.g., Ebert and Prelec, 2007; Imas et al., 2021; Dertwinkel-Kalt et al., 2021). Moreover, model-fitting exercises of, e.g. random-utility models provide indirect evidence that noisiness affects choice, see Regenwetter et al. (2018) for a review.

while holding complexity constant and study which anomalies remain. Second, we directly measure fingerprints of complexity responses (i.e., the use of noisy or heuristic procedures) in intertemporal decisions and study which anomalies they predict. These two strategies produce strikingly similar answers to our motivating question.

***Removing scope for motivational explanations.*** A key idea in our paper is that we can identify the role complexity plays in intertemporal choice anomalies by entirely removing scope for motivational explanations while retaining much of what makes intertemporal choice complex. We do this by removing actual time delay from standard elicitations and inducing an exponential reward function instead. Applying the design idea of Oprea (2022) to intertemporal choice, we ask experimental subjects to value not only intertemporal payments but also "atemporal mirrors" of the same payments – immediate, deterministic payoffs that are deliberately described in such a way as to require the same kind of recursive reasoning and a similar degree of information processing as the original intertemporal choice problem. Thus, in addition to asking subjects to value a dollar amount $x$ paid in $t$ periods,[2] we also ask subjects to value an *immediate* payment of $x$, recursively attenuated ("shrunk") $t$ times, each time by a fixed factor $\delta$. Here, the number of recursions $t$ is a direct analog to the length of the delay. An atemporal mirror is, hence, simply a standard intertemporal choice in which we *experimentally induce* an exponential time preference, so that anomalous deviations from exponential discounting cannot be rationalized by non-standard time preferences, temptation, self-control or risk. However, doing this retains much of the complexity of recursively attenuating future rewards present in the original choice problem.

By comparing the way people value delayed payments to the way they value similarly complexly-described immediate payments, we can gauge to what degree complexity alone is capable of producing intertemporal choice anomalies. We do not expect subjects to precisely calculate discounted values in these atemporal mirrors any more than we expect them to pull out a calculator to inform decisions in actual intertemporal choice. Rather, our interest is in what heuristic or noisy procedures people substitute to instead of precise evaluation, and whether these substitutions produce classical anomalies.

We find that almost all of the intertemporal choice anomalies arise also in the valuation of atemporal mirrors, both qualitatively and with a similar magnitude. The basic pattern is that subjects treat different numbers of steps of recursion too similarly, producing "discounting" that is insufficiently sensitive to the number of recursions. As a result, our

[2] As summarized by Cohen et al. (2020), a key discussion is whether the fungibility of money prevents the elicitation of true time preferences. This discussion is less relevant to our paper because we are not attempting to measure *preferences*. Rather, our interest is in explaining classical anomalies, which are defined over *behaviors*. Indeed, one of the important takeaways from our paper is that intertemporal choice experiments do not directly measure preferences, but instead, to a great extent, complexity responses.

atemporal mirrors reveal the direct analogues of extreme short-run impatience and decreasing impatience (hyperbolic discounting): subjects severely under-value payments attenuated only one or two times, discounting more than the experimentally induced discount factor $\delta$ specifies. At the same time, subjects discount payments attenuated a large number of times considerably less strongly than they should. Thus, even though we experimentally induce a fixed discount factor, subjects' revealed per-period "impatience" strongly decreases in the number of recursions, replicating the hyperbolicity widely observed in intertemporal choice experiments.

We further find pronounced evidence of subadditivity: subjects discount summed subsequences of recursions more than the longer sequence they compose, violating transitivity in a way that is directly analogous to transitivity violations in intertemporal decisions. The only intertemporal choice anomaly that is present in intertemporal choice but not in the atemporal mirrors are front-end delay effects, a canonical behavioral signature of present bias. We return to this observation below.

Importantly, because we measure each subject's behavior in both atemporal mirrors and true intertemporal choice, we can show that behavior in the former *predicts* behavior in the latter. We find correlations across the two choice problems as high as 0.5, producing one of the strongest predictors of intertemporal choice in the literature. This provides evidence that behaviors in the two settings are likely to a great extent driven by a common behavioral mechanism, which cannot be motivational in nature.

***Measuring and manipulating complexity responses.*** The fact that anomalies arise in atemporal mirrors and predict their appearance in intertemporal choices, suggests that these anomalies are likely driven by complexity. We complement the approach of experimentally inducing exponential preferences by directly identifying complexity responses *within* classical intertemporal choice: we examine whether behavioral fingerprints of complexity responses (i.e., substitutions to simpler-than-optimal procedures) predict the severity of anomalies.

Complexity-inspired theories are generally descriptions of noisy and / or heuristic decision procedures. These complexity responses often produce auxiliary fingerprints that are identifiable in the data. Our strategy is to measure some of these fingerprints and study how strongly they link to the strength of the anomalies.

First, to the degree decision makers are aware that they have substituted to a simpler-than-optimal procedure, we expect them to express less confidence in the quality of their choices. Thus, adapting the methodology of Enke and Graeber (2022) to an intertemporal choice context, we elicit subjects' cognitive uncertainty about each decision, asking them how certain they are (in percentage terms) that their stated range of valuations for a delayed payment actually contains their true valuation for that payment. Second, many recent complexity-inspired explanations root intertemporal choice anomalies in decision or cognitive noise. To the degree decision makers use such noisy decision procedures, we expect them to make inconsistent, noisy decisions. To measure this, we gather data on choice inconsistencies in repeated instances of the same decision problems.

We find that both cognitive uncertainty and choice inconsistency are strongly correlated with the exact same anomalies that survive in atemporal mirrors: (i) extreme short-run impatience; (ii) hyperbolicity of discounting; and (iii) subadditivity. For example, while subjects who are more inconsistent or more cognitively uncertain are less patient over short horizons, they are more patient over long horizons – which precisely mirrors the results from the atemporal experiments in which decisions are too "impatient" over few recursions but too "patient" over many ones. These fingerprints of complexity responses even predict the strength of anomalies within-subject: a given subject exhibits more pronounced decreasing impatience in precisely those decisions where s/he articulates high cognitive uncertainty. Overall, our data suggest that 85% of decreasing impatience and 100% of subadditivity are driven by complexity responses.

To provide causal evidence that our empirical measures of complexity responses (cognitive uncertainty and choice inconsistency) as well as the anomalies indeed reflect complexity, we present a series of experimental treatments that increase the cognitive costs of evaluating rewards and delays. We find that increasing complexity consistently leads to a joint increase in cognitive uncertainty, choice inconsistency and anomalies, hence again confirming the link between complexity, the use of imperfect decision procedures and anomalies.

***Estimating present bias.*** A natural question is how complexity relates to present bias. A standard experimental tool to identify present bias is front-end delay designs, in which people appear more patient when both earlier and later payments are moved into the future to the same degree. In all of our experiments, we never find any indication that complexity increases front-end delay effects: (i) cognitive uncertainty is uncorrelated with these effects; (ii) the complexity manipulation does not amplify them; and (iii) there are no front-end delay effects present in the atemporal mirrors. However, while *causal* estimates of present bias do not appear to be confounded by complexity, *non-experimental, econometric* estimates may be severely biased, and inflate the degree of true present bias. The reason is that cross-sectional model-fitting exercises of models of present bias are often identified off variation in behavior as a function of time delays – a variation that can be confounded because it partly reflects complexity-driven short-run impatience.

To confirm this intuition, we estimate a standard $\beta - \delta$ model in each of our experiments. In the atemporal mirrors experiment, where there is no true passage of time and exponential discounting is experimentally induced, we estimate $\hat{\beta} = 0.85$ – an estimate that would conventionally be interpreted as strong evidence of present bias. Consistent with this, in true intertemporal decisions, estimated present bias is substantially more pronounced (i) for subjects with high cognitive uncertainty; (ii) for subjects with choice inconsistencies; and (iii) for subjects in the more complex experimental treatments. This body of evidence suggests that non-experimental estimates of present bias that do not account for complexity are biased, though we also highlight that our data show clear evidence of present bias that cannot be explained by complexity.

***The complexity of recursive reasoning.*** In a final step, we investigate what it is about intertemporal choice that creates complexity (and, as a result, induces subjects to use noisy or heuristic decision procedures). We present multiple pieces of evidence suggesting that the complexity of intertemporal choice is largely an outgrowth of the difficulty of recursive reasoning as opposed to, e.g., the difficulty of assessing one's own discount rate. To this effect, we document that subjects' noisiness strongly increases in the number of required recursive reasoning steps. First, in both true intertemporal choice and our atemporal mirrors, the variance of subjects' decisions strongly increases in the delay / the number of recursions required to discount. Second, subjects' cognitive uncertainty also strongly increases in the length of the time delay. This evidence of strong heteroscedasticity suggests that reasoning recursively is cognitively costly, producing noise that increases in the number of recursions required to discount a reward.

***Takeaways.*** Taken together, over a number of distinct empirical approaches – including atemporal mirrors, objective measures of decision noise, self-reported cognitive uncertainty and a set of experimental complexity manipulations – we document the same story. The most important intertemporal choice anomalies occur because people respond to the complexity of intertemporal choice by using imperfect decision procedures that are excessively *insensitive* to variation in the time delay. This inelasticity, in turn, manifests in extreme short-run impatience, hyperbolicity, subadditivity, and econometrically estimated present bias.

Our findings have several implications. First, they have welfare and policy implications: to the degree anomalies are complexity-driven mistakes rather than expressions of underlying motivations, some models of non-standard discounting behavior, though no less descriptively valuable, lose their normative bite. Second, our results suggest that we can likely improve prediction and design better policy by modeling intertemporal choice as dependent upon the complexity of the decision environment, rather than as context-independent discount functions. For instance, our results illuminate how complexity responses confound the econometric estimation of present bias, one of the central objects measured in behavioral economics. This suggests that in some of those field contexts in which present bias has been identified through model estimations, there may be scope for "improving" behavior by reducing complexity. Third, results like ours suggest that traditional methods of recovering preferences, which often rely heavily on the idea that preferences are transparently revealed in choice, may produce misleading results because choice often primarily reflects a complexity response rather than a clean revelation of preferences. This speaks to a widely-known puzzle in lab-to-field studies, in which correlations between lab measures of time preferences and ecological behaviors such as savings behavior are typically much smaller than any reasonable discounting model would predict.

Our paper is organized as follows. In Section 2 we review common anomalies in intertemporal choice, explanations offered by the literature and discuss our empirical strategies for separating them. Section 3 presents our experimental design. Sections 4 and 5 discuss the main results. Section 6 presents findings on the role of recursion as a mechanism driving complexity, and Section 7 discusses related literature and concludes.

# 2 Conceptual Background and Empirical Approaches

## 2.1 Anomalies in Intertemporal Choice

Consider a simple intertemporal choice problem $D = (x_1, t_1; x_2, t_2)$ in which a decision maker must decide what $x_1$ paid at $t_1$ (e.g., now) makes her indifferent to earning $x_2$ paid at $t_2 > t_1$ (e.g., in two months). Define $\Delta t \equiv t_2 - t_1$ (all time units are in months). Following standard procedures in the literature (e.g., Cohen et al., 2020), suppose that the decision maker discounts rewards exponentially at a rate $\delta = 1 - \gamma$, where $\gamma$ is an approximation of the discount rate that is implicit in choice. Throughout the paper we treat $\gamma$ not as a preference parameter but rather as a descriptive empirical measurement of the per-period discounting rate that is implicit in choice.[3] We can then analyze the discounting implied by choices in decision problem $D$ as follows:

$$(1-\gamma)^{t_1/12} x_1 = (1-\gamma)^{t_2/12} x_2 \qquad \Leftrightarrow \qquad \gamma = 1 - \left(\frac{x_1}{x_2}\right)^{12/\Delta t} = 1 - e^{-RRR/\Delta t}, \qquad (1)$$

where $RRR/\Delta t = ln(x_2/x_1)/\Delta t$ is the "delay-adjusted required rate of return" that the decision maker reveals through her choices. In the exponential discounting model, the delay-adjusted RRR – and, hence, also $\gamma$ – are constant, absent confounding factors. In what follows, we refer to the empirical measurement of $\gamma$ as "implied annual discount-

[3] In other words, throughout, we follow Frederick et al. (2002) in making a distinction between "time discounting" (discounting for *any* reason) and "time preference" (discounting because of tastes for utilities in the present versus future) and unless otherwise specified, we always make statements about the former.

ing," with the understanding that it is a conventional approximation of the discount rate.

Since Thaler (1981), behavioral economists have gathered significant evidence that decision makers behave in ways that are incompatible with the exponential discounting model when valuing financial flows (see Cohen et al. (2020) and Ericson and Laibson (2019) for reviews). Many of the core anomalies boil down to the observation that per-period discounting varies systematically as a function of features of the delay.

***Extreme short-run impatience.*** Many studies famously show that decision makers tend to discount a relatively short delay from the present at an extremely steep rate. This tendency has often been confused with "present bias" in part because many early studies exclusively featured problems in which the sooner payoff date was immediate (i.e. $t_1 = 0$). More recent evidence (e.g., Kable and Glimcher, 2010) shows that, even when $t_1 > 0$, decision makers exhibit short-run impatience that is so pronounced that a constant discount factor would imply implausible and empirically counterfactual medium-run discounting behavior.

***Decreasing impatience / hyperbolicity.*** Extreme short-run impatience is a component of a more general tendency for decision makers' revealed per-period impatience to decrease as the delay $\Delta t$ becomes longer. That is, discounting of monetary rewards tends to be *hyperbolic* rather than *exponential*.

***Subadditivity.*** There is robust evidence that decision makers tend to violate transitivity in intertemporal choice because discounting over a composite time interval $(t_1, t_3)$ tends to be smaller than the total discounting implied by the joint decisions over intervals $(t_1, t_2)$ and $(t_2, t_3)$, with $t_1 < t_2 < t_3$.[4]

***Front-end delay effects.*** Pushing the date of both the earlier and the later payment forward by a fixed delay $d$ often causes a decrease in impatience. This is in violation of exponential discounting because exponentiality prescribes that only the delay as such $(\Delta t)$ rather than its starting date $(t_1)$ matters for $\gamma$. Front-end delay effects are a direct way of measuring "present bias" – people's inclination to put a premium on immediately paid rewards when discounting.

***Sub-unitary estimates of $\beta$.*** Present bias can be estimated *causally* using front-end delays (or revising-earlier-choices designs as in Augenblick et al. (2015)). However, present bias is often *indirectly* gauged by econometrically estimating $\beta - \delta$ models (Laibson, 1997) that are identified off choices without variation in front-end delays. This approach

[4] Formally, denote by $a_{i,j}$ the indifference point for the tradeoff over delay $(t_i, t_j)$. Then, subadditivity means that there is less discounting (more patient indifference values) over the single long interval: $a_{1,3} > a_{1,2}a_{2,3}$, or, equivalently, $\gamma(a_{1,3}) > \gamma(a_{1,2}a_{2,3})$.

relies on the hyperbolicity of discounting per se, leveraging variation in observed decisions across different time delays. The resulting structural estimates of $\beta < 1$ are often (though, as we will argue, inappropriately) interpreted as direct evidence of present bias.

These anomalies are often overlapping and not independent. For instance, short-run impatience is a component of decreasing impatience / hyperbolicity. Likewise, subadditivity and front-end delay are two possible proximal foundations for decreasing impatience. In addition, these anomalies are sometimes confused with one another. For instance, extreme short-run impatience, front-end delay effects and sub-unitary estimates of $\beta$ have often all been treated as evidence of "present bias," though among these only front-end delay effects represent direct estimates.

All of these anomalies describe patterns in the way decision makers respond to *time delays*. There are other choice anomalies that relate not to dates, but instead to payoffs – most notably magnitude effects and asymmetries between gains and losses. Our experiments relate only to the classic anomalies related to time; we refer the reader to Cohen et al. (2020) for discussion of the class of anomalies related to payoffs.

## 2.2 Time and Complexity

A number of explanations have been offered for these deviations from the exponential model. We group these explanations into two broad classes: *motivational* explanations that are rooted in the actual passage of time, and *complexity* explanations that are instead about the costs and difficulties of reasoning about relative intertemporal rewards.

By far the dominant class of explanations offered by the literature are *motivational* explanations: explanations rooted in preferences or internal conflicts that arise due to the fact that intertemporal choices involves the elapse of time. One category is *preference-based* explanations which argue that people simply do not have exponential, dynamically consistent time preferences. This includes, for instance, hyperbolic and quasi-hyperbolic models (e.g., Loewenstein and Prelec, 1992; Laibson, 1997; O'Donoghue and Rabin, 1999). Other authors have proposed that people have, in effect, "multiple selves" with divergent preferences at different dates, or that two selves strategically vie for control (Fudenberg and Levine, 2006). Another set of models posits temptation effects (Gul and Pesendorfer, 2001). A final class of motivational explanations is offered by the literature that emphasizes how transaction costs (of collecting delayed payments) and / or the inherent riskiness of the future induce decision makers to behave in such a way as to produce present bias and decreasing impatience (e.g., Halevy, 2008; Andreoni and Sprenger, 2012; Chakraborty et al., 2020).

An alternative class of explanations argues that anomalies arise because intertemporal decision making is inherently *complex*: it requires potentially costly cognitive operations. In order to properly discount a delayed payment in the process of valuing it, an exponential decision maker must (consciously or unconsciously) (i) introspect or calculate her discount factor, $\delta$, and then (ii) reason recursively, attenuating value by $\delta$ at each step of recursion. Both processes require potentially significant information processing, which is likely to be costly for decision makers (such procedural costs are what the term "complexity" means, e.g., in computer science).

If the procedural costs of precise evaluation are sufficiently large relative to available cognitive resources, decision makers may substitute to less costly, imprecise or heuristic methods of valuation instead. Throughout the paper, we will refer to this causal sequence as a "complexity response": rational choice is complex and therefore costly, creating an incentive for the decision maker to use a simpler-than-rational noisy or heuristic procedure to guide her choices instead.

A small-but-growing theoretical literature has shown that many plausibly simpler-than-rational evaluation procedures are capable of generating classical intertemporal choice anomalies. Each of these complexity-inspired accounts effectively describes a different imperfect or imprecise valuation procedure that decision makers might substitute to in lieu of precise, recursive evaluation. For instance, Rubinstein (2003), Ericson et al. (2015) and Read et al. (2013) present heuristic accounts of decision making that fit experimental data better than commonly-studied discounted-utility models. Other recent complexity-inspired papers postulate that people *do* engage in recursive reasoning, but reduce the costs of doing so by reasoning imprecisely (Gabaix and Laibson, 2022; Vieider, 2021; Gershman and Bhui, 2020), by injecting noise into their behavior (e.g., Regenwetter et al., 2018; Lu and Saito, 2018), or by systematically misperceiving quantities (Brocas et al., 2018; Zauberman et al., 2009). This literature shows that noise (and responses to noise) can generate some or all of the anomalies discussed in the previous section. What most of these accounts have in common is that they describe decision-making procedures that are less sensitive to the parameters of the decision problem (e.g., the magnitude of the time delay) than standard rational choice. This insensitivity generates phenoma like excessive short term discounting and very low long term discounting and can therefore produce many of the classical anomalies documented in the literature.

Our goal is to empirically separate these two broad classes of explanations for intertemporal choice anomalies: motivational explanations rooted in the elapse of time and complexity explanations rooted in boundedly rational responses to the costs and difficulties of making intertemporal choices. We propose two strategies for doing this.

### 2.2.1 Removing Temporal Motivations

A key observation motivating our study is that (unlike the motivational explanations described above) the complexity-based explanations do not rely in any special way on the actual elapse of time. They instead rely on the idea that intertemporal choice problems require decision makers to conduct intensive information processing. Because they do not depend on time, these sorts of explanations may also generate anomalies in decision problems that involve no actual temporal delay, but that require a structurally similar and similarly complex type of reasoning.

Building on this observation, we propose a method for separating the two classes of explanations that has the virtue that it doesn't require us to articulate any specific model of complexity response. For any intertemporal choice problem $D = (x_1, t_1; x_2, t_2)$, we can construct an immediately paid "atemporal mirror" $M_D$ of that same problem that replaces payment dates with steps of recursive payoff attenuation. In each step of attenuation, decision makers know that the payoff from the previous step will be multiplied by an exogenously provided and known fixed factor $\delta < 1$. Thus, an atemporal mirror of $D$ pays a deterministic amount $\delta^{t_1} x_1$ or $\delta^{t_2} x_2$ immediately. Instead of, e.g., valuing a payoff "\$50 in two months," a decision maker evaluating a mirror is asked to value a payoff "\$50 shrunk by $\delta$ two times." An atemporal mirror is therefore nothing more or less than an immediate dollar payment that has been deliberately described in such a way as to require a similar kind of information processing as is required in intertemporal choice.[5]

Because atemporal mirrors involve no actual time delay, anomalies in their evaluation cannot be driven by any of the motivational explanations reviewed above. For instance, they cannot be driven by non-exponential time preferences: an atemporal mirror *induces* exponential preferences. Similarly, there is no scope for multiple selves, temptation effects or "implicit risk" to generate anomalies. However, atemporal mirrors do maintain much of the *complexity* of intertemporal choice: under exponential discounted utility theory, the cognitive act required to properly value a mirror is formally highly similar to the cognitive act required to precisely discount a future payment. As such, the suite of simpler-than-optimal decision procedures – ranging from non-recursive heuristics to behavioral or cognitive noise – remain available to distort choice.[6]

[5]This empirical strategy is similar to that used in Oprea (2022), which compares valuations of lotteries to valuations of "deterministic mirrors" of lotteries which contain no risk.

[6]If anything, the information processing required to value atemporal mirrors might be lower than in true intertemporal choice, such that our estimates of the role of complexity would constitute a lower bound. First, people might have non-linear utility, which matters for choosing between time-dated payments but not for a choice between two atemporal mirrors. Second, in intertemporal decisions people may not have access to their own discount factor. Because the atemporal mirrors transparently provide the discount factor, this may reduce complexity.

Based on this logic, we first compare the way decision makers evaluate a set of intertemporal choice problems to the way they evaluate atemporal mirrors. To whatever extent the same anomalies arise in the evaluation of mirrors as in the evaluation of intertemporal choice, we have evidence against motivational explanations and evidence in favor of complexity explanations. Second, we correlate the magnitude of anomalies in the two types of problems across subjects to verify that anomalies in the two cases are driven by a related behavioral mechanism.

### 2.2.2 Linking Anomalies to Signatures of Complexity Responses

A second, and complementary approach to removing temporal motivations is to directly measure the presence of complexity responses in traditional intertemporal choice, and to study whether they predict the severity of anomalies. Our strategy relies on the observation that complexity-inspired intertemporal choice theories typically invoke noisy and / or heuristic decision procedures as proximate mechanisms behind classical anomalies. These complexity responses often produce auxiliary fingerprints that are identifiable in the data. We measure these fingerprints and link them to the anomalies.

The literature has proposed two empirical indicators that a decision was made using a heuristic or noisy procedure: self-reported cognitive uncertainty and choice inconsistencies. First, we ask subjects how likely it is (in percentage terms) that their choice actually complies with their true tastes and preferences. This type of simple, unincentivized self-report about the optimality of choice has been shown to be highly predictive of anomalous behaviors in several other choice settings (Enke and Graeber, 2022; Arts et al., 2020), in no small part because people often appear to have some awareness to what degree they use heuristic and / or noisy decision procedures. Second, we complement this *subjective* measurement with an *objective* measure of noisy decision-making. As proposed in various contributions (e.g. Agranov and Ortoleva, 2017, 2020; Agranov et al., 2020; Khaw et al., 2021), we can classify a decision as reflecting a noisy procedure if it is *inconsistent* with other choices made in repeated elicitations of an identical decision problem.[7]

An attractive feature of our multi-pronged research design is that it relies on two essentially orthogonal approaches with different strengths and weaknesses: (i) stripping away time and inducing exponential preferences while maintaining a very similar degree of complexity and (ii) directly measuring signatures of complexity responses in standard intertemporal problems. To the degree that the approaches identify the same anomalies

[7]As with atemporal mirrors, this general research strategy likely identifies a *lower bound* for the role complexity in intertemporal choice. The reason is that cognitive uncertainty can only identify complexity responses that subjects themselves are actually somewhat aware of. Likewise, choice inconsistency can only identify those complexity responses that produce noisy behavior rather than stable heuristics.

as being complexity-driven, we will have encouraging converging evidence.

# 3 Experimental Design

## 3.1 Basic Setup

Table 1 provides an overview of the experimental design. Following standard methods used in the literature, the core tasks in our experiments are *multiple price lists* that ask subjects to evaluate a payment of $x_2$ at a time $t_2$ in terms of dollars paid at an earlier date $t_1 < t_2$. An example of the subject's decision screen is shown in Appendix Figure 9. In each list, Option A is kept identical in every row, paying $x_2$ at date $t_2$. By contrast, Option B pays an amount $x_1$ that declines montonotically by \$2 in each row (ranging between $x_2$ and \$2), at date $t_1$. Non-negative discounting entails that subjects choose A in early rows of the list (or, with extreme preferences, never) and switch to B at some later row.[8] This switching point between earlier and later payment yields a direct measure of implied per-period discounting, $\gamma$.[9]

We refer to these true intertemporal choice problems as "delays" (the *Delay* treatment). In most cases we randomize (at the subject-list level) the delayed payment $x_2 \in \{\$40, \$42, \ldots \$52\}$. The experimental design includes three main types of price lists. First, "Now Lists," in which $t_1 = 0$ and $t_2$ varies across 1/4, 1, 2, 12, 24, 36, 48 and 84 months. Second, "Later Lists," which are identical to Now Lists except that the earlier payment is slightly delayed: $t_1 = 1$ or $t_1 = 1/4$ months. Finally, "Subadditivity/Front-End Delay (SA/FED) Lists", in which for some horizon $T$ we assign subjects lists ($t_1$=0, $t_2 = T/2$), ($t_1$=T/2, $t_2 = T$) and ($t_1$=0, $t_2 = T$), maintaining a consistent $x_2$ across the three lists. We randomly assign $T$ across subjects to be either 8 or 12. Dates $t_1, t_2$ represent months. Lists from each of these categories are included in every treatment, for every subject and randomly ordered at the subject level. Now and Later lists are used primarily to study the anomalies of extreme short-run discounting, decreasing impatience / hyperbolicity and sub-unitary $\beta$. SA/FED Lists are used to measure the anomalies of subadditivity and front-end delay effects.

## 3.2 Removing Temporal Motivations

Our first variation on this standard choice setting is to study companion problems in which we pay subjects a recursively attenuated version of the stated payoff immediately.

[8]We enforce this "single switching" property by automatically choosing (highlighting in yellow) A choices above and B choices below any choice the subject makes.

[9]Recall, our goal is *not* to recover a true preference parameter, but rather to measure the discounting implied by behavior.

| Sessions | Description | Subjects |
|---|---|---|
| *Delay & Mirror* | 18 tasks under *Mirror* & exactly repeated under *Delay* (order of treatments randomized) | 500 |
| *Delay Noise* | 12 delay tasks with elicitations of cognitive uncertainty and choice inconsistencies | 645 |
| *Voucher Noise* | 12 delay tasks with UberEats vouchers and elicitations of cognitive uncertainty and choice inconsistencies | 500 |

Table 1: Overview of main experiments.

In these tasks, attenuation occurs though a known, exogenous discount factor, transforming A and B into "atemporal mirrors" of standard intertemporal choice tasks. This is framed to subjects as "shrinking" a payment $t$ times. Each time a payment is "shrunk," it falls to $\delta < 1$ of its previous value, but a subject must reason through the consequence of this attenuation in order to properly value it. The fact that atemporal mirrors are paid immediately is repeatedly emphasized to subjects in the instructions.

A choice list from treatment *Mirror* is displayed in Appendix Figure 9. Each list asks subjects an exactly analogous sequence of binary choice questions as in the *Delay* treatment. Option A (kept identical in each row of the list) is a dollar payment, paid out immediately but recursively attenuated some number of times. Option B is a dollar payment that involves strictly fewer recursions, and often none, which mimics an immediate earlier payment. For example, in one row of a list, subjects are asked to choose between "Option A: $42 shrunk 12 times" and "Option B: $2". The value of Option B increases monotonically over the rows of the list, and we again elicit a standard switching interval to calculate the implied per-period discounting.

The mirrors we implement include a single step of attenuation for each month of discounting in the delay problem it mirrors. Throughout the experiment, we set the per-period $\delta = 0.96$ (based on actual estimates of the discount factor $\delta$ from the intertemporal choices made in other sessions of the design, discussed below).

Every subject participated in both *Delay* and *Mirror* in a random order. The upside of this within-subjects design is that it allows us to correlate behavior in the two types of problems across subjects. When we are not interested in correlating behavior across treatments, we take care to rule out contamination effects by only analyzing decisions from the treatment that a subject encountered first (though we verify in Appendix Table 6 that the results are very similar when we also include the data from the second-assigned treatment).

Because the treatments were designed to be compared to one another, we took great pains to use an identical interface and identical numbers. However, we were careful to strongly differentiate the two treatments from one another using clear instructions. Importantly, to minimize cross-treatment contagion, subjects first assigned to *Mirror* did not know they would later be making intertemporal choices, and vice versa.

The *Mirror* treatment is incentivized using real payments, but the *Delay* treatment is a purely hypothetical preference elicitation. This was unavoidable because our motivating questions in *Delay* require us to study choices regarding multi-year delays, which are infeasible to implement using real incentive schemes. We expect this design choice to have little effect on our *Delay* results, as we discuss in Section 3.4 below. Still, to whatever degree hypothetical payments lead to, e.g., less careful decision making in *Delay* than in *Mirror*, we should expect this to work *against* the complexity hypothesis we are testing when we contrast the two treatments – exaggerating anomalies in unincentivized *Delay* observations relative to *Mirror* observations. We view this, therefore, as a conservative feature of our design.

## 3.3 Measuring Evidence of Noisy / Heuristic Behavior

As motivated in Section 2.2, in other treatments we gather auxiliary evidence that subjects are responding to the complexity of intertemporal choice by using noisy or heuristic decision procedures. To do this, we implement treatments *Delay Noise* and *Voucher Noise*. In both of these treatments, we measure the following objects.

***Cognitive Uncertainty.*** Adapting the methodology from Enke and Graeber (2022), after each choice list, we measure cognitive uncertainty (CU) as the subject's subjective probabilistic belief that their true valuation of the later payment is actually contained in their stated switching interval:

> *Your choices on the previous screen indicate that you value \$$y_2$ in $t_2$ somewhere between \$a and \$b in $t_1$. How certain are you that you actually value \$$y_2$ in $t_2$ somewhere between \$a and \$b in $t_1$?*

Participants answer this question by selecting a radio button between 0% and 100%, in steps of 5%. Appendix Figure 10 provides a screenshot.[10] We interpret this question as measuring the participant's awareness that their decision procedure is noisy or heuristic

[10]This elicitation is closely related to work on "decision confidence," in which subjects indicate on Likert scales how confident they are in their decision (e.g., Yeung and Summerfield, 2012; De Martino et al., 2013, 2017; Polania et al., 2019; Bulley et al., 2021; Xiang et al., 2021; Butler and Loomes, 2007).

rather than perfectly rational.[11] We are agnostic about what exact sources of complexity in the decision problem cause subjects to doubt their decisions; our interest is purely in using this doubt as an empirical marker of subjects' use of noisy or heuristic procedures.[12] The measure is not incentivized. We view this as a conservative feature of our design: if subjects expend mental effort in the intertemporal choices but not in the CU question, then our results will make the links between CU and intertemporal choice anomalies look smaller than they actually are.

***Choice inconsistencies.*** A standard way of measuring the noisiness of subjects' decision mode is choice inconsistency in repetitions of the same choice problem (e.g., Agranov and Ortoleva, 2017, 2020; Agranov et al., 2020; Khaw et al., 2021; Oprea, 2022). In our study, each subject completes two randomly selected choice lists twice. We generate a binary indicator that equals one if the subject's decisions on the two repeated trials are different from each other. We verify that our results continue to hold if we instead compute the absolute difference between the two decisions as our measure of inconsistency.

We collected these two pieces of data in two different treatments. In *Delay Noise* we again use hypothetical monetary payments, which allows us to study multi-year delays. However, we pair this with a second incentivized treatment to show that our main findings are robust to the inclusion of incentives. The *Voucher Noise* treatment is identical to the *Delay* treatments in most respects, except (i) that we actually pay subjects for their choices using UberEats food delivery vouchers and (ii) we do not study delays of more than one year (for feasibility reasons). In *Voucher Noise*, payments are denominated in UberEats vouchers usable starting at date $t_1$ or $t_2 \leq 12$, respectively; these vouchers are valid for a period of only seven days from the starting date, which minimizes fungibility concerns. Subjects again complete multiple price lists. In each list, the left-hand side Option A is a fixed delayed UberEats voucher with value $x_2 \in \{40, 42, \ldots, 50\}$. The later payout date $t_2$ varies between one week and one year. The right-hand side Option B is an UberEats voucher the value of which increases as one goes down the list, from \$2 to \$$y_2$, in steps of \$2 each.[13]

[11] We ensure that subjects properly understand the question as referring to their *internal* uncertainty about how to value a delayed payment rather than their beliefs about the *external* uncertainty that they may not actually receive the reward. To this effect, our experiments include a comprehension check question that directly asks participants to indicate whether the CU elicitation question asks about (i) the subject's subjective probability of actually receiving the money or (ii) their certainty about their own valuation, given that they know they will receive the money with certainty.

[12] For instance, for our purposes, it is irrelevant whether subjects struggle with computing (or accessing) their discount function $D(t)$ or with integrating $D(t)$ and the payments / vouchers.

[13] UberEats is the largest online food ordering and delivery service in the world. The service can be used to order food for takeout or delivery from a wide array of restaurants and is widely available throughout the United States (Curry, 2021).

Participants' vouchers were directly credited to their personal UberEats accounts within 10 hours of completion of the study, such that subjects did not have to actively claim the voucher. The vouchers were always visible in their accounts, they could just not be used before the validity period. Because participants could always view vouchers in their account within a few hours of the study regardless of the precise validity period, there is no differential payment risk across vouchers with different time delays. Participants received automatic reminders 24 hours before a voucher became valid and 24 hours before it expired.

## 3.4 Discussion of Implementation

Our experimental design includes two characteristics that merit comment in light of common discussions in the literature. First, our *Delay* and *Delay Noise* treatments both feature hypothetical payments – a design choice that allows us to elicit choices over multi-year delays that would be difficult to assess using an incentivized design. There are strong reasons based on the prior literature to believe that this is a benign design choice. Reviewing the literature, Cohen et al. (2020) conclude "there is little evidence of systematic differences between RRR in incentivized and unincentivized experiments." Nonetheless, we use the *Delay Voucher* treatment to verify this for our design and subject pool and indeed the data show no systematic differences in our results between hypothetical and incentivized elicitations.

Second, our experiments (like much of the literature motivating the anomalies) involve delays in monetary payments rather than in consumption. A common concern about intertemporal choice experiments is that they may not elicit true time preferences because money (unlike consumption) is fungible.[14] This concern is less relevant for our purposes than in much of the literature because we are not attempting to measure true time *preferences* – we are only interested in measuring and explaining the kind of discounting *behavior* that is often documented even in money experiments. Indeed, a central conclusion of ours is that even putting fungibility concerns aside, intertemporal choice experiments to a great extent fail to recover preferences due to the confounding influence of complexity.

## 3.5 Procedures

All experiments were conducted on Prolific. Online Appendix C contains details on experimental instructions, visual display and screening questions used. All sessions include

[14]This view is not universal in the literature. An alternative line of argument holds that experimental participants narrowly bracket their choices and treat monetary amounts in experiments as proxies for utils (Halevy, 2014; Sprenger, 2015; Andreoni et al., 2018; Epper et al., 2020).

three risk aversion elicitations after all intertemporal choice problems to allow for the separate measurement of risk aversion.

Subjects in the *Mirror & Delay* sessions were paid a \$6 base payment and had a 20% chance of being paid a bonus based on their choice from a randomly selected list and row of Mirror or Risk Elicitation. In *Delay Noise*, subjects earned a flat \$4.50 payment. In *Voucher Noise*, subjects received a \$4 base payment and voucher payments from a randomly selected list and row with 25% chance.

# 4 Results from Atemporal Mirrors

We begin by examining whether intertemporal choice anomalies appear in atemporal mirrors (the *Mirror* treatment), and comparing and correlating them with anomalies that appear in true intertemporal delays (*Delay*). In analyzing this data, it is important to emphasize that there are at best weak reasons to expect similar "patience" *levels* in the *Delay* and *Mirror* treatments. In *Mirror*, subjects face an induced discount factor of 0.96; in *Delay*, subjects bring in their own discount factors, which may differ from 0.96. Our focus will therefore be on comparing the *severity of anomalies*, which are derived by comparing behavior across different decision problems, rather than comparing the levels of revealed discount factors.

## 4.1 Evidence of Anomalies in Mirrors

Figure 1 provides a raw overview of the data by plotting, for both the *Delay* and *Mirror* treatment, the average switching point (expressed as a percentage of the "later" payment, $x_2$) as a function of the time delay or the number of recursions.[15] Recall that in an exponential discounting framework with linear utility, these normalized switching points correspond to $\delta^{\Delta t}$. For the *Mirror* treatment, we overlay the indifference point that a payoff-maximizing subject would choose given the induced "monthly discount factor" ($\delta = 0.96$). The left panels plot data from "Now Lists" (the earlier date is immediate in *Delay* and paid with no recursive attenuations in *Mirror*); the right panels are from "Later Lists" (the earlier date is in one month or after one step of recursive attenuation). The top panels plot data from *Delay* and the bottom panels data from *Mirror*.

Figure 2 transforms this data in a straightforward way by computing implied annual discounting, $\hat{\gamma} = 1-(x_1/x_2)^{12/\Delta t} = 1-e^{-RRR\cdot 12/\Delta t}$, see eq. (1).[16] For ease of illustration, we combine "Now tasks" and "Later tasks"; the figures look very similar if separated.

[15]We approximate switching points by computing the midpoint of the switching interval.

[16]A significant practical advantage to expressing decisions in terms of implied discounting $\gamma$ rather than the delay-adjusted RRR is that the latter by construction produces large outliers that render visualizations and econometric analyses challenging.

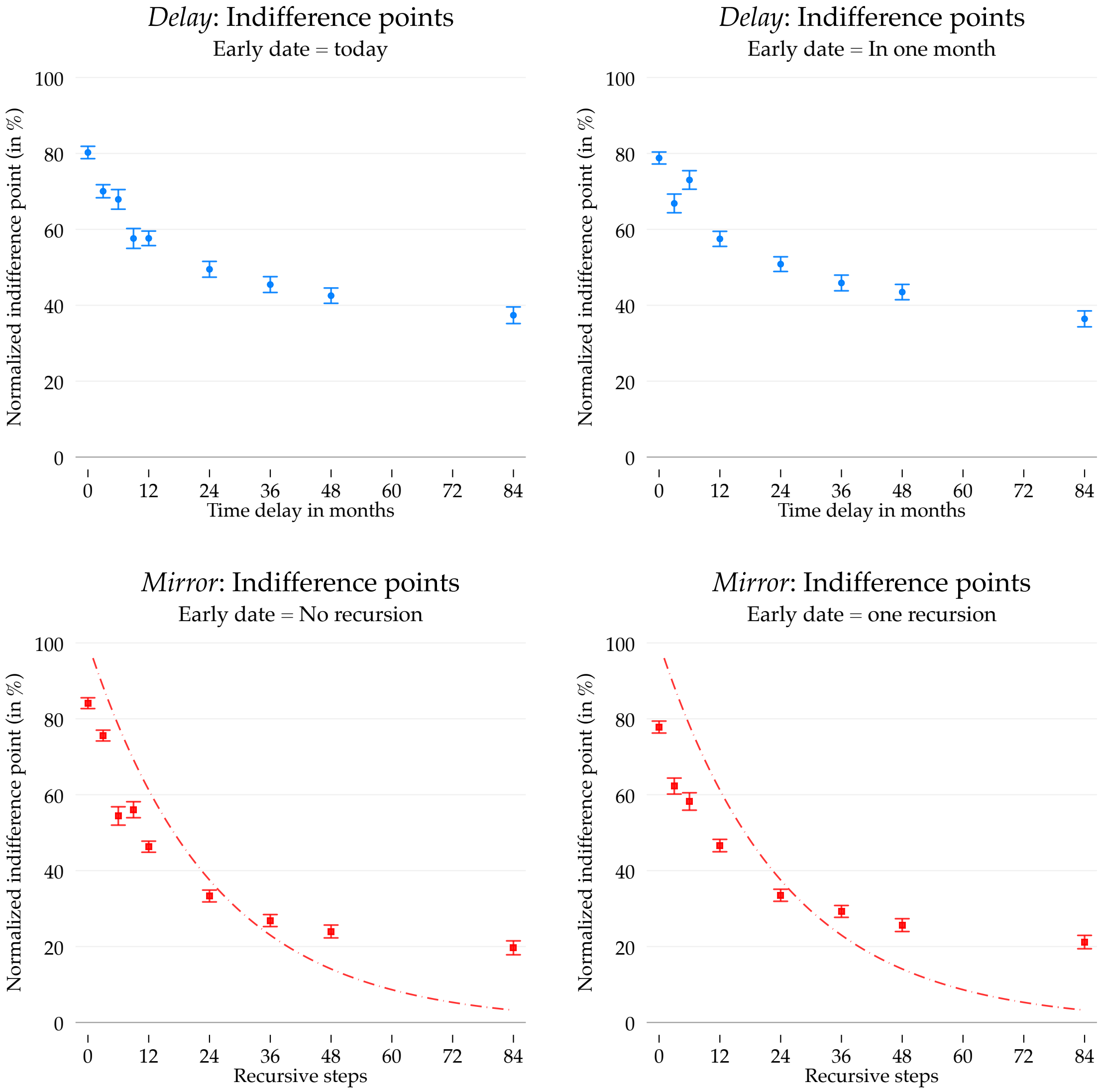


Figure 1: Average normalized indifference points by time delay (*Delay*) or number of recursions (*Mirror*). The top panels show data for the *Delay* treatment with choices involving actual delays (4,572 decisions from 254 participants), the bottom panels show the *Mirror* treatment data from atemporal mirrors (4,428 decisions from 246 participants). In the *Mirror* panels, the dashed line represents payoff-maximizing decisions. Between the left and right panels we split the sample according to whether or not the smaller payment occurs today/requires no recursion. The figure includes data from the first-assigned treatment only. The time delay in months and the number of recursions are rounded to the nearest multiple of three. Whiskers show standard error bars, computed based on clustering at the subject level.

***Short-run impatience.*** It is clear from these figures that subjects in *Delay* show extremely high impatience over short horizons, both when the earlier payoff is immediate and when it is delayed by one month. Figure 2 shows that subjects discount very short horizons such as one month at an annualized rate of about 0.6.

Our first main finding is that subjects also show extreme discounting over the first few steps of attenuation in *Mirror*, even though there is no delay in these problems –

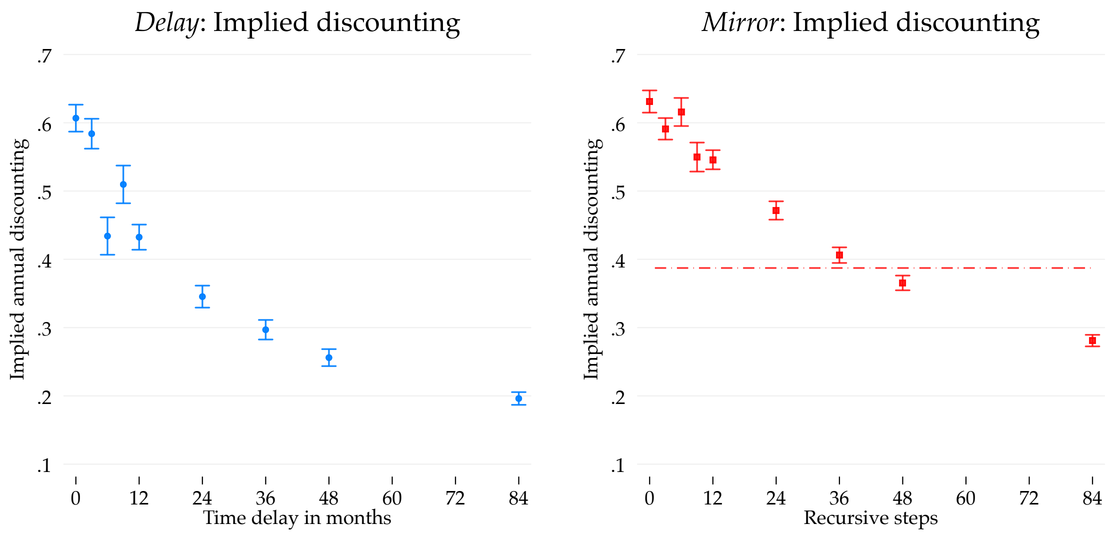


Figure 2: Average implied annual discounting $\hat{\gamma}$ by time delay (treatment *Delay*; 4,572 decisions from 254 participants) or number of recursions (treatment *Mirror*; 4,428 decisions from 246 participants). In the *Mirror* panel, the dashed line represents payoff-maximizing decisions. The time delay in months and the number of recursions are rounded to the nearest multiple of three. Whiskers show standard error bars, computed based on clustering at the subject level.

and even though subjects are incentivized to maximize an exponential discount function. Importantly, in *Mirror* (unlike in *Delay*) we can identify this behavior as a mistake: subjects discount payments made in $\Delta t = 1$ or $\Delta t = 2$ to a far greater degree than their true (experimentally induced) discount rate warrants.

***Decreasing impatience.*** A second classical pattern visible in Figure 1 is that although indifference payments in *Delay* consistently fall as payments are delayed further into the future, they fall at a decreasing rate. Figure 2 shows that this implies that revealed annual discounting is sharply and generally monotonically decreasing in the length of the delay. This pattern of decreasing impatience is a primary motivation for models of non-geometric time preferences like hyperbolic or quasi-hyperbolic discounting.

Our second main finding is that in the atemporal mirrors we similarly observe a strong decrease in implied "annual discounting" as the number of recursive steps increases, see Figure 2. Once again the figure highlights that this reflects financially suboptimal behavior: subjects' average switch points in Figure 1 are located above the normative benchmark for few recursions but below it for many recursions.

***Subadditivity.*** In our SA/FED lists, we asked subjects to complete tasks that have the subadditivity structure explained above, where we varied $(t_1, t_2, t_3)$ randomly to be $(0, 4, 8)$ or $(0, 6, 12)$. Table 2 shows regression analyses on how implied annual discounting differs between the choice over interval $(t_1, t_3)$ and the combined choices over

Table 2: Anomalies in *Delay* and *Mirror*

| | *Dependent variable:* Implied annual discounting (in %) | | | | | |
|---|---|---|---|---|---|---|
| Phenomenon: | Decreasing impatience | | Subadditivity | | Front-end delay | |
| Treatment: | *Delay* | *Mirror* | *Delay* | *Mirror* | *Delay* | *Mirror* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Delay / number of recursions (in years) | -5.76$^{***}$ (0.25) | -5.14$^{***}$ (0.26) | | | | |
| 1 if one long interval | | | -7.57$^{***}$ (1.38) | -9.93$^{***}$ (1.16) | | |
| 1 if front end delay | | | | | -4.24$^{**}$ (1.85) | 3.79$^{**}$ (1.69) |
| Payment amount FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subadditivity set FE | No | No | Yes | Yes | Yes | Yes |
| Observations | 4572 | 4428 | 508 | 492 | 508 | 492 |
| $R^2$ | 0.17 | 0.19 | 0.09 | 0.06 | 0.07 | 0.02 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. In columns (1) and (2), the sample consists of all decisions in the respective treatment. In columns (3) and (4), the sample consists of two observations per subject: their implied annual discounting over the long (composite) interval and their implied discounting over the two shorter intervals that have a subadditivity structure. In columns (5) and (6), the sample includes those two decisions per subject that have a front-end delay structure. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

$(t_1, t_2)$ and $(t_2, t_3)$ for *Delay* in column (3) and *Mirror* in column (4) (see fn. 4). We find strong evidence for subadditivity in both *Delay* and *Mirror*. In both conditions people are roughly 10 percentage points less "patient" when a composite interval is broken up into two sub-intervals. Thus, once again, these results suggest that an anomaly occurs in a setting in which preferences are unavailable to rationalize the anomaly.

***Front-end delay effects.*** A fourth regularity observable in our design is the "front-end delay effect:" subjects often reveal lower discounting in evaluating $(t_1 + d, t_2 + d)$ than in $(t_1, t_2)$, for $d > 0$. Some of our tasks feature such a front-end delay structure (with $d$ randomized between 4 and 6 months across subjects). Columns (5) and (6) of Table 2 show that we find a statistically significant front-end delay effect in the *Delay* treatment but the *opposite* effect in the *Mirror* treatment. Thus, in contrast to the preceding anomalies, our data provides no evidence that the front-end delay effect is an outgrowth of complexity. If anything, our results suggest that complexity might work against the identification of these effects.

***Sub-unitary estimates of $\beta$.*** A fifth, and final, empirical regularity is econometric evidence of present bias in estimations of $\beta - \delta$ models. Notably, as explained above, in econometric estimations, $\beta$ my not only be identified causally from front-end delay effects, but also from variation in behavior across different time delays and the hyperbolic shape of discounting per se. Because this hyperbolic shape can occur due to complexity effects, as we've just shown, we examine whether there is evidence for $\beta < 1$ in our *Mirror* treatment.

Recall that in our price lists, a subject is asked to state an amount $x_1$ in $t_1$ that makes her indifferent to $x_2$ in $t_2$. In a $\beta - \delta$ model with linear utility, we therefore have:

$$\delta^{t_1} \cdot x_1 = \beta_{t_1=0} \cdot \delta^{t_2} \cdot x_2 \tag{2}$$

We estimate this model, amended by a mean-zero error term. In *Mirror*, we estimate $\hat{\beta} = 0.85$ ($s.e. = 0.009$) and $\hat{\delta} = 0.96$ ($s.e. = 0.009$).[17] Complexity alone, therefore, induces behavior that *looks like* present bias under the lens of standard estimation approaches. Intuitively, the reason for this result is that decisions in the *Mirror* treatment have a hyperbolic shape with high short-run "impatience", which gets attributed to $\beta$ in estimations of $\beta - \delta$ models.

***Magnitudes.*** To compare magnitudes across treatments, Table 2 presents regression evidence on decreasing impatience, subadditivity and front-end delay effects. Note that we cannot directly compare magnitudes for short-run impatience because the induced discount factor in Mirror need not equal naturally occurring ones in Delay, even under the hypothesis that anomalies are largely complexity effects. Columns (1) and (2) quantify decreasing impatience by documenting how much implied annual discounting decreases as the time delay gets longer. In *Delay*, for each year of additional delay, implied discounting decreases by 5.6 percentage points (pp). In *Mirror*, that effect is 4.8 pp, meaning that decreasing impatience in *Mirror* is 86% as strong as in *Delay*. Similar calculations show that subadditivity is slightly *stronger* in *Mirror* than in *Delay*.

With respect to econometrically estimated present bias, we find $\hat{\beta} = 0.76$ ($s.e. = 0.009$) in *Delay*. This implies that the estimated deviation from a $\beta$ of one is 63% as strong in *Mirror* as in *Delay*.

**Result 1.** *Subjects exhibit extreme short-run impatience, decreasing impatience, subadditivity and sub-unitary estimates of $\beta$ when evaluating atemporal mirrors just as they do when evaluating delays. For mirrors, these are clear misvaluations. In contrast, there is a front-end delay effect in evaluating delays but not atemporal mirrors.*

[17]Estimates at the individual level corroborate this result. As shown in Appendix Figure 12, for the majority (62%) of subjects we estimate $\beta < 1$.

## 4.2 Linkage between Atemporal and Intertemporal Anomalies

Finally, we show that the appearance of similar anomalies in *Mirror* and *Delay* are not coincidental but are tightly linked at the individual level and, hence, likely driven by a common behavioral mechanism. To do this, we leverage our within-subjects design to examine the relationship between behaviors across the two treatments. If there is a common behavioral mechanism behind the anomalies across treatments (common heuristic or noisy responses to complexity), they should be correlated with each other. Thus, unlike in the analyses above, we now analyze both treatments a subject participated in, rather than only the first-assigned one.

We first link subjects' decisions in those choice problems that are direct mirror images of each other, such as "$40 in 6 months" vs. "$40 shrunk 6 times". Thus, we compute a correlation coefficient for (500 subjects * 18 unique problems * 2 treatments =) 18,000 observations. In doing so, we take care to net out that component of the correlation that is mechanically driven by the fact that for longer delays / a higher number of recursions subjects should be expected to state lower valuations. Thus, we compute the partial correlation between decisions, netting out fixed effects for each unique problem type / price list. As a result, the correlation captures how similar subjects' behavior is across the two treatments, holding fixed the nature of the choice problem.

We find a partial correlation of $r = 0.48$ ($p < 0.01$), see Figure 3. This is remarkably high given the absence of time preference-based variation in the *Mirror* treatment, which should produce correlations close to zero for rational decision makers. Indeed, comparing this to predictors reviewed in a recent overview of this literature (Cohen et al., 2020), behavior in *Mirror* is among the strongest predictors of intertemporal choice ever documented in the literature.[18]

A second approach to studying linkages across treatments is to focus not on each separate decision but, instead, on the magnitude of decreasing impatience: whether those subjects whose impatience strongly decreases in the length of the delay in treatment *Delay* are also those whose implied per-period "impatience" strongly decreases in the number of recursions in treatment *Mirror*.[19] To compute this, for each subject and treatment, we regress the annual discounting implied by a decision on the length of the time delay, akin to columns (1) and (2) of Table 2. Under exponential discounting, the

[18]To put this correlation into context, the correlation between valuations of recursions and delays is *higher* than the 0.44 correlation documented between identical intertemporal (i.e. delay) list choices made by the same subjects in elicitations delivered several months apart (Meier and Sprenger, 2015). Most predictors of intertemporal choice behavior discussed in Cohen et al. (2020) (e.g. demographics, personality metrics, cognitive measures) are smaller, rarely rising above 0.3 and generally far below that.

[19]We focus on decreasing impatience because we can estimate it relatively precisely (having access to 18 observations per subject per treatment), while for subadditivity effects we effectively only have one observation per subject (three decisions that jointly constitute one subadditivity set).

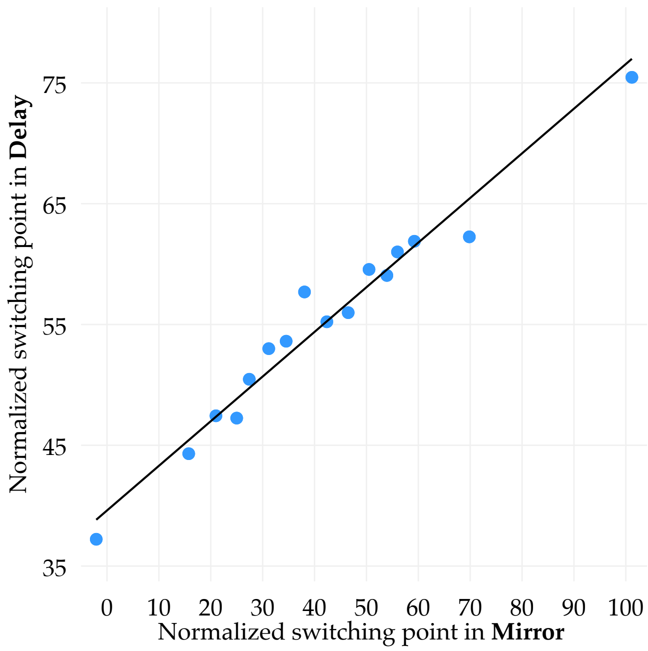


Figure 3: Binned scatter plot of normalized indifference points in structurally identical choice problems in *Delay* and *Mirror*. Partial correlation plot, controlling for fixed effects for each choice list type. Based on 18,000 decisions by 500 subjects. The correlation coefficient is $r = 0.48$.

regression coefficient should be zero for each subject. The magnitude of the coefficient thus serves as a measure of the degree to which impatience decreases as the delay gets longer. We find that, across subjects, the magnitudes of decreasing impatience exhibit a correlation of $r = 0.34$, $p < 0.01$.

**Result 2.** *Across subjects, valuation of intertemporal delays is strongly correlated with valuation of atemporal mirrors. This suggests they are driven by a common behavioral mechanism, which cannot be temporal motivations.*

# 5 Results from Measures of Complexity Responses

## 5.1 Anomalies and Measures of Noisy/Heuristic Behavior

***Prevalence of choice inconsistencies and cognitive uncertainty.*** Our data from the *Delay Noise* and *Voucher Noise* treatments show strong *prima facie* evidence that subjects' decisions are noisy and / or heuristic in nature. In *Delay Noise*, 75% of all decisions are associated with strictly positive cognitive uncertainty and 60% of all repeated decisions show strictly positive inconsistency. In the *Voucher Noise* experiments, the corresponding frequencies are 83% and 60%.[20] We now investigate how variation in these measures predicts the strength of anomalies.

***Short-run impatience and decreasing impatience.*** The left panels of Figure 4 illustrate the raw data for the *Delay Noise* treatment: the relationship between normalized indifference points (in percent) and time delays. Each panel shows a different split that links discounting behavior to our measures of CU (top panel) and choice inconsistency (bottom panel). The corresponding right-hand panels transform these data (as in the previous section), by computing the implied annual discounting $\hat{\gamma}$. All panels pool the data for Now and Later lists (the results are very similar looking at each of them separately). Figure 5 shows analogous results for the incentivized voucher experiments.

The top panels illustrate that decisions associated with CU are considerably less sensitive to variation in the delay, making them look considerably more hyperbolic. This has two direct implications. First, CU is strongly predictive of short-run impatience. For instance, in *Delay Noise*, the raw correlation between normalized indifference points for one-week delays and CU is $\rho = -0.45$ both when $t_1 = 0$ and when $t_1 > 0$. In *Voucher Noise*, the same correlations are $\rho = -0.39$ and $\rho = -0.45$.

The second implication of the inelasticity of cognitively uncertain decisions is that implied discounting decreases much more rapidly in the time delay for uncertain than certain subjects. For instance, going from $\Delta t \approx 1$ to $\Delta t \approx 84$ months, the implied annual discounting drops by a factor of 4.5 for $CU > 0$, but only by a factor of 2 for $CU = 0$.

Notably, in treatment *Delay Noise*, this pattern implies that cognitively uncertain participants act as if they are *less* patient over relatively short horizons, yet *more* patient over relatively long horizons, with a crossover point at around one year. This suggests that the main behavioral response to complexity (as measured by tendency to make noisy or heuristic decisions) in intertemporal choice is insensitivity to time delays, rather than universally higher impatience. This matches exactly what we find in *Mirror*, where complexity drives subjects to make choices that are significantly less sensitive to variation in dates than their induced discount rate demands.

The bottom panels of Figures 4 and 5 show analogous results for choice inconsistency. We find that inconsistent decisions are associated with lower sensitivity to the time delay and, as a result, more strongly decreasing impatience. Again, this pattern implies that inconsistent decisions appear more impatient over short horizons but less impatient over long ones.

The main takeaway from these figures is that both of our measures of noisy or heuris-

[20] In both the *Delay Noise* and *Voucher Noise* sessions, cognitive uncertainty and choice inconsistency are significantly but modestly correlated with one another ($r = 0.16$ and $r = 0.23$). Note that choice inconsistency is likely noisily measured, potentially attenuating these correlations significantly.

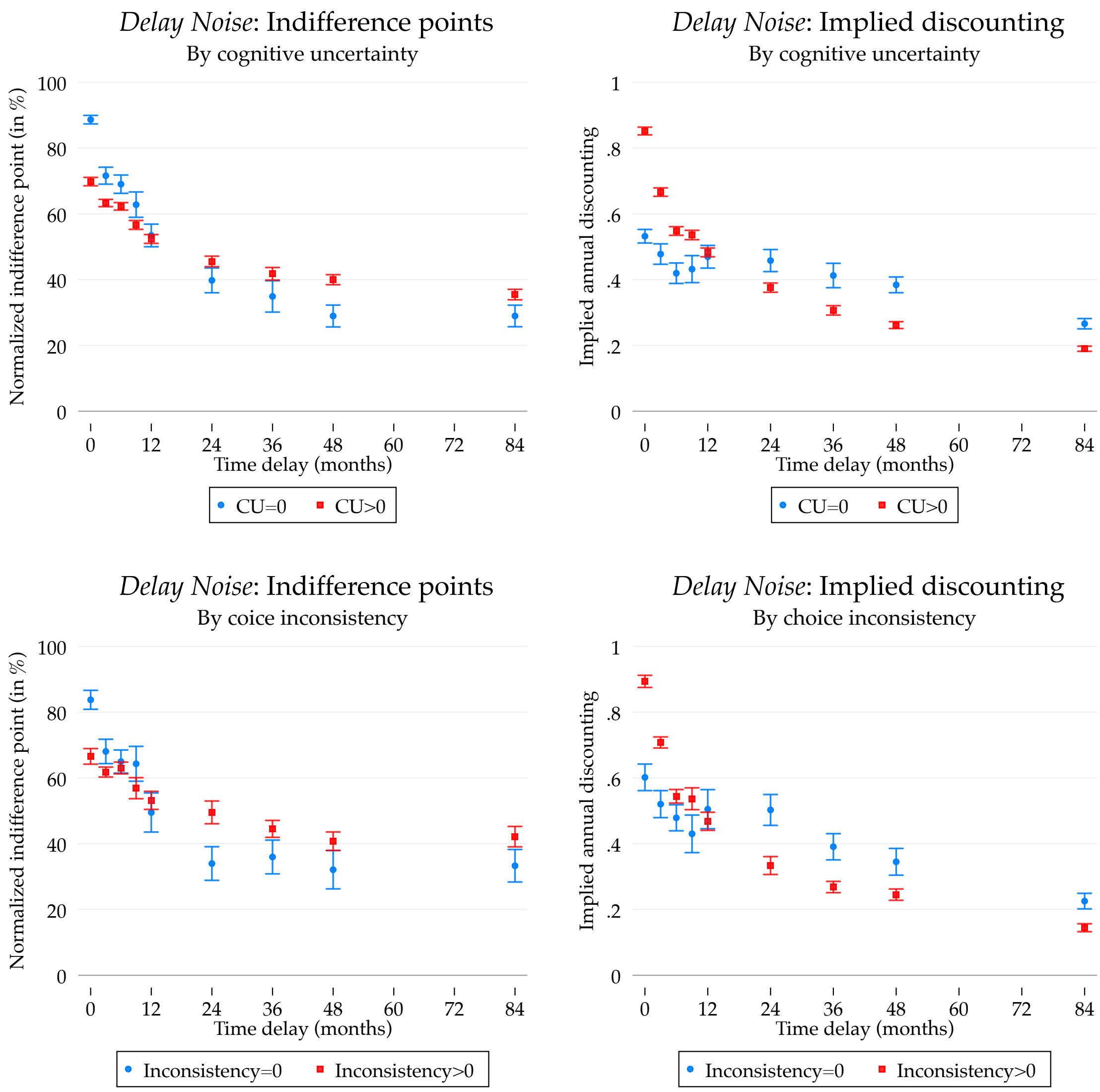


Figure 4: Normalized indifference points (left panels) and implied annual discounting (right panels) as a function of the time delay. The top panels include all decisions from *Delay Noise*, and we split the sample according to whether or not a choice is associated with strictly positive CU (7,740 decisions by 645 subjects). The bottom panels include data from all decisions in *Delay Noise* that were elicited twice (two repeated problems per subject for a total of 2,580 decisions from 645 subjects), and we split the sample according to whether or not decisions differed in a set of repeated choices. Time delays are rounded to nearest multiple of three months. Whiskers show standard error bars, computed based on clustering at the subject level.

tic complexity responses predict the same pattern: an inelasticity of decisions with respect to the delay, which generates short-run impatience and decreasing impatience.

Table 3 investigates these patterns econometrically. Across specifications and datasets, we see that (i) both CU and choice inconsistency are strongly correlated with short-run impatience (columns (1) and (4)) and (ii) decreasing impatience is subantially stronger in the presence of either CU or choice inconsistencies (columns (3) and (6)).

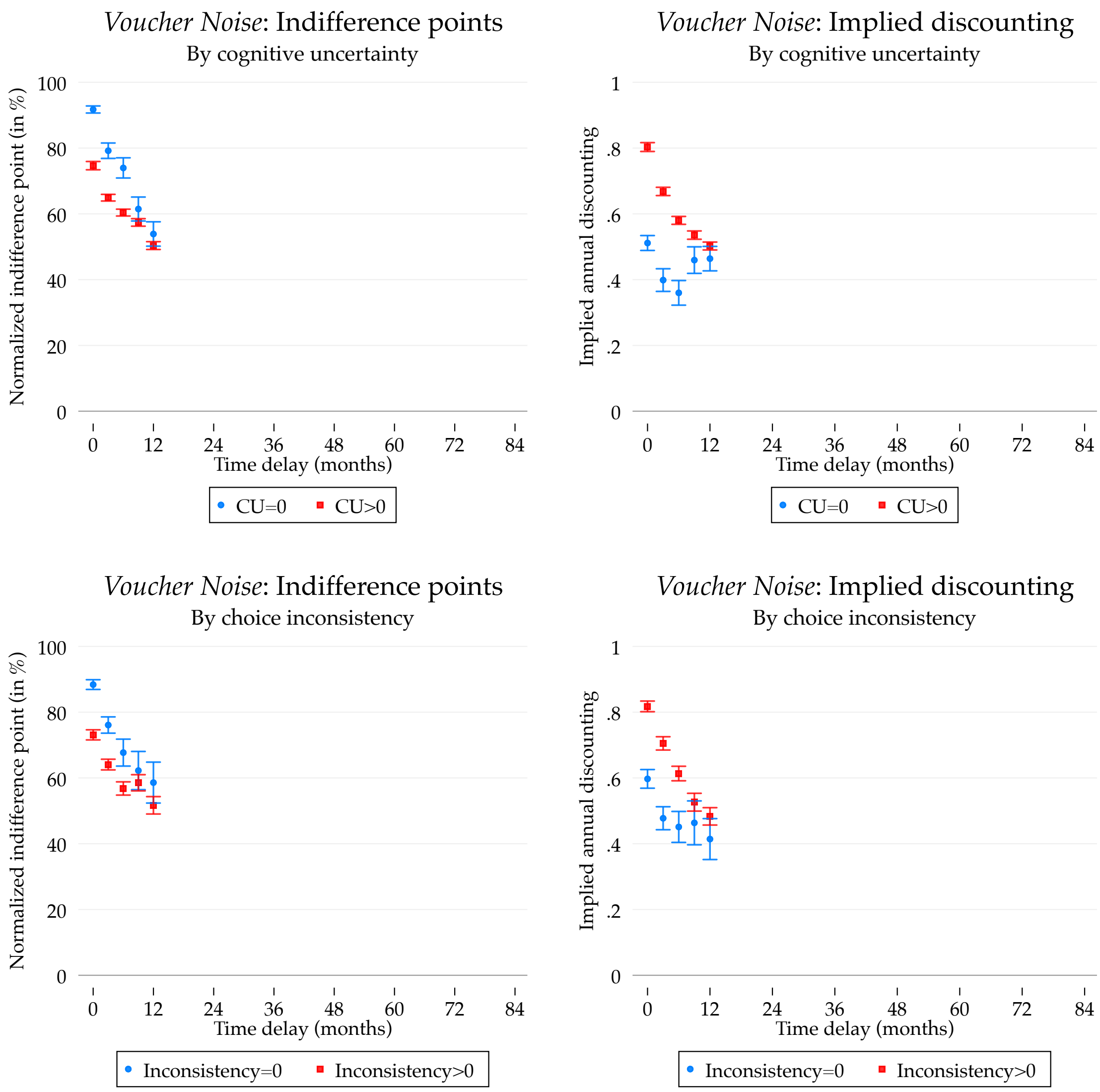


Figure 5: Normalized indifference points (left panels) and implied annual discounting (right panels) as a function of the time delay in *Delay Voucher Noise*. The top panels include all decisions, and we split the sample according to whether or not subjects indicate strictly positive CU (6,000 decisions from 500 subjects). The bottom panels include data from all decisions that were elicited twice (two repeated problems per subject, for a total of 2,000 decisions from 500 subjects), and we split the sample according to whether or not decisions differed in a set of repeated choices. Time delays are rounded to nearest multiple of three months. Whiskers show standard error bars, computed based on clustering at the subject level.

What fraction of decreasing impatience is driven by noise / heuristics? To quantify this, we compare the magnitudes in two sub-samples: (i) decisions that are associated with no CU and no choice inconsistency vs. (ii) decisions that reflect either strictly positive CU or choice inconsistency. We examine how strongly implied annual discounting increases in the delay, akin to the regressions in Table 3. We find that in the sample with no CU and no choice inconsistencies, the magnitude of decreasing impatience is

Table 3: Short-run and decreasing impatience as functions of CU and choice inconsistency

| | *Dependent variable:* Implied annual discounting (in %) | | | | | |
|---|---|---|---|---|---|---|
| Dataset: | *Delay Noise* | | | *Voucher Noise* | | |
| Phenomenon: | SR imp. ($\leq$ 1m) | Decreasing impat. | | SR imp. ($\leq$ 1m) | Decreasing impat. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Time delay | | -6.87*** | -3.56*** | | -25.3*** | -20.6*** |
| | | (0.18) | (0.54) | | (1.50) | (6.12) |
| Cognitive uncertainty | 0.42*** | | 0.24*** | 0.61*** | | 0.57*** |
| | (0.11) | | (0.05) | (0.10) | | (0.08) |
| Inconsistent decision | 25.2*** | | 11.9*** | 16.7*** | | 19.6*** |
| | (4.59) | | (2.38) | (3.30) | | (2.94) |
| Time delay × Cognitive uncertainty | | | -0.061*** | | | -0.47*** |
| | | | (0.01) | | | (0.13) |
| Time delay × Inconsistent decision | | | -4.95*** | | | -13.0** |
| | | | (0.61) | | | (6.44) |
| Payment amount FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 344 | 7740 | 2580 | 766 | 6000 | 2000 |
| $R^2$ | 0.24 | 0.16 | 0.24 | 0.17 | 0.06 | 0.19 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. In columns (1) and (4), the sample is restricted to time delays of at most one month. All other columns include all data. Time delay is in years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

only 10% of that in the comparison sample. This suggests that at least 90% of decreasing impatience is driven by noisy or heuristic complexity responses, rather than preferences. This conclusion is strikingly close, quantitatively, to the decomposition computed by comparing decreasing impatience in atemporal mirrors and intertemporal delays in Section 4.

***Subadditivity.*** Recall that we elicited only two randomly selected decisions per subject repeatedly. Given that these repeated decisions do not always occur for the choices in the SA/FED lists designed to measure subadditivity effects, we do not have access to a task-level measure of choice inconsistency that could be used to shed light on subadditivity or front-end delay effects. By contrast, the CU measure is available for each decision a subject makes.

Columns (1)–(4) of Table 4 shows the results. In both *Delay Noise* and *Voucher Noise*, we find strong evidence of subadditivity: the discounting implied by a decision over one "long" interval $(t_1, t_3)$ is about 9 pp. smaller than the combined discounting over $(t_1, t_2)$ and $(t_2, t_3)$, see columns (1) and (3) of Table 4. More importantly from the perspective of our research question, we find that CU is consistently linked to stronger subadditivity effects. Moreover, we find that subjects with $CU = 0$ exhibit no subadditivity at all. In other words, our findings suggest that 100% of subadditivity is driven by noisy/heuristic complexity responses. Again, this decomposition exactly matches what we found in the

Table 4: Subadditivity, front-end delay effects and cognitive uncertainty

| | *Dependent variable:* Implied annual discounting (in %) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Phenomenon: | Subadditivity | | | | Front-end delay effects | | | |
| Dataset: | *Delay Noise* | | *Voucher Noise* | | *Delay Noise* | | *Voucher Noise* | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 1 if one long interval | -8.58*** | -3.55*** | -9.39*** | -1.14 | | | | |
| | (0.63) | (1.34) | (0.60) | (1.60) | | | | |
| 1 if one long interval × Cognitive uncertainty | | -0.24*** | | -0.33*** | | | | |
| | | (0.06) | | (0.06) | | | | |
| 1 if front-end delay | | | | | -3.07*** | -2.51 | -4.11*** | -7.23*** |
| | | | | | (0.99) | (1.53) | (1.09) | (2.12) |
| 1 if front-end delay × Cognitive uncertainty | | | | | | -0.058 | | 0.070 |
| | | | | | | (0.05) | | (0.07) |
| Payment amount FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Subadditivity set FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1948 | 1948 | 2000 | 2000 | 2393 | 2393 | 2337 | 2337 |
| $R^2$ | 0.03 | 0.08 | 0.04 | 0.08 | 0.02 | 0.07 | 0.02 | 0.08 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. Each specification also includes the relevant interaction variable as regressor. For example, column (2) also includes the raw CU measure. In columns (1)–(4), the sample consists of two observations per subadditivity set for each subject: their implied annual discounting over the long (composite) interval and their implied discounting over the two shorter intervals. In columns (5)–(8), the sample includes those decisions for each subject that have a front-end delay structure. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

previous section in our decomposition of subadditivity in atemporal mirrors and intertertemporal delays.

***Front-end delay effects.*** Columns (5)–(8) of Table 4 summarize the results on front-end delay effects. We see that there is robust evidence for the presence of front-end delay effects in both *Delay Noise* and *Voucher Noise*: discounting over $(t_1, t_2)$ is 3–4 pp. larger than over $(t_1 + d, t_2 + d)$, see columns (5) and (7). Importantly for our purposes, however, these effects are entirely uncorrelated with CU, suggesting that they have little to do with complexity. Yet, again, this exactly matches what we found in the previous section, using a different methodology: front-end delays occured in *Delay* (where temporal/ motivational explanations are available) but not in *Mirror* (where only complexity explanations are available).

***Sub-unitary estimates of $\beta$.*** Finally, as in the previous section, we estimate present bias under the lens of the $\beta - \delta$ model (equation 2). Again we do this both at the population level (to facilitate comparison with previous estimates in the literature) and at the individual level (to avoid aggregation problems, see Weitzman, 2001; Jackson and Yariv, 2014). At the population level, we estimate $\hat{\beta} = 0.76$ in *Delay Noise*. However, this estimate is far smaller in cognitively uncertain vs. certain decisions ($\hat{\beta} = 0.72$ vs.

$\hat{\beta} = 0.87$) and in inconsistent vs. consistent ones ($\hat{\beta} = 0.75$ vs. $\hat{\beta} = 0.82$).[21]

Estimating eq. (2) instead at the individual level, we find similar results. Figure 6 shows empirical cumulative distribution functions of the estimated $\beta$ parameters in treatment *Delay Noise*, separately for subjects who only show minimal evidence for noisy/heuristic responses[22] and subjects who show stronger evidence of such responses. The $\beta$ estimates for the former group first-order stochastically dominate estimates for the latter, meaning that subjects with low CU and low choice inconsistency exhibit substantially less estimated present bias, a finding that is highly statistically significant ($p < 0.001$, Kolmogorov-Smirnov test).

Note that we find this strong evidence of a link between estimated present bias and noise / heuristics *even though* there is no difference in present bias as causally identified using a front-end delay design. Rather, our results show that in model estimations one spuriously estimates present bias that largely reflects complexity responses. This again matches our conclusion from the atemporal mirrors, where we likewise showed how even in the absence of true delays complexity can spuriously generate estimates of $\beta < 1$.

***Robustness 1: Sample splits.*** The results reported above do not hinge on splitting the sample into decisions with zero or strictly positive CU. To show this, we split the sample into CU quartiles. We find that the effect of the time delay on decisions continuously decreases (in absolute terms) as CU increases, see Appendix Figure 11. This shows that the results are not just driven by the particular sample splits employed above, and that variation in CU strongly predicts decisions also conditional on $CU > 0$.

***Robustness 2: Within-subject variation.*** A potential issue is that subjects interpret the CU question in heterogeneous ways. To show that this does not drive the results, we restrict attention to within-subject variation in CU. To this effect, we normalize the CU data to have mean zero and standard deviation one for each subject, and then look at whether this pure within-subject measure of CU still predicts choices. Appendix Table 7 shows that the decrease of implied annual discounting with respect to the delay is more pronounced precisely in those tasks in which the subject exhibits higher CU.

***Choice inconsistency in atemporal mirrors.*** In our *Mirror* treatment, we also repeated one randomly-selected choice list, allowing us to investigate whether choice in-

[21]In *Voucher Noise*, the results are very similar. We estimate $\hat{\beta} = 0.85$ in cognitively uncertain and $\hat{\beta} = 0.87$ inconsistent decisions, compared to $\hat{\beta} = 0.95$ in cognitively certain and $\hat{\beta} = 0.96$ in consistent ones.

[22]Only 2% of subjects state zero cognitive uncertainty in *all* tasks and show no inconsistency in all sets of repeated decisions. We therefore classify subjects with minimal evidence for noisy/heuristic behavior as those with average stated cognitive uncertainty below 5% and average inconsistencies of less than 15 percentage points. This group comprises 17.2% of all subjects.

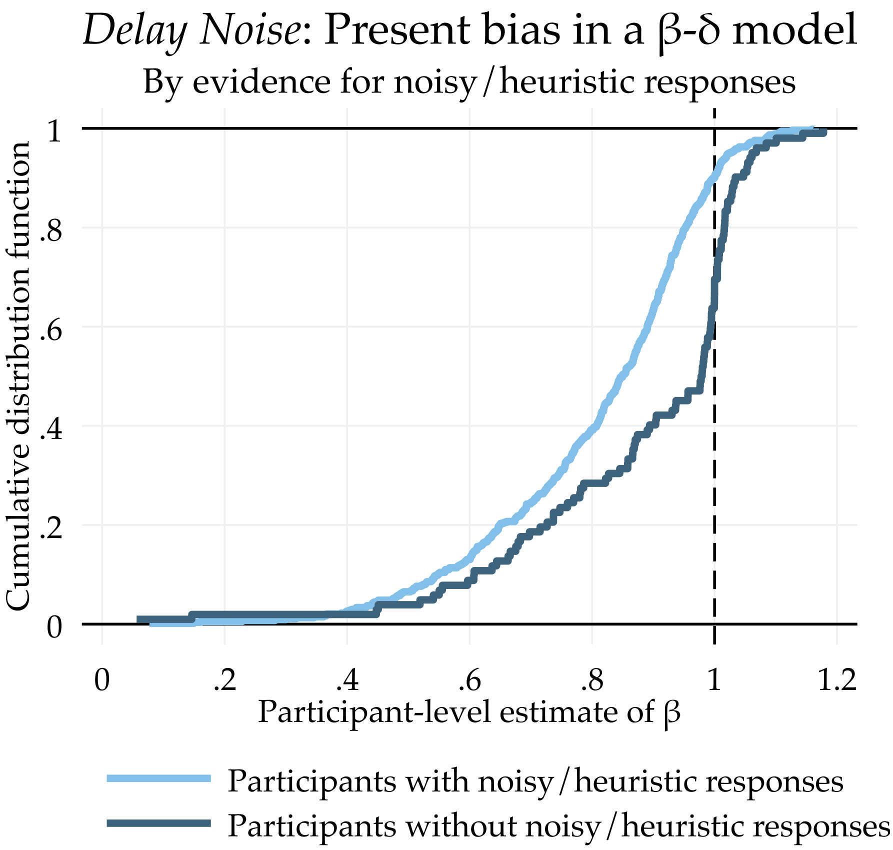


Figure 6: Empirical CDFs of individual-level estimates of a $\beta - \delta$ model (eq. (2)) in *Delay Noise*. The figure includes data from 645 subjects. A two-sample Kolmogorov-Smirnov test on equality of distributions gives $p < 0.001$. We classify participants as "without noisy/heuristic responses" if their average stated cognitive uncertainty is below 5% and their average choice inconsistencies in repeated problems is less than 15 percentage points. This group comprises 17.2% of all subjects.

consistencies are also linked to the anomalies in the evaluation of atemporal mirrors.[23] As shown in Appendix Table 10, we find that in atemporal mirrors the choice inconsistencies are strongly predictive of "short-run impatience" and "decreasing impatience," the same way they are in true intertemporal decisions. This further supports our interpretation that complexity leads to noisy and heuristic decision procedures, which then generate the anomalies.

**Result 3.** *Short-run impatience, decreasing impatience, subadditivity and sub-unitary estimates of $\beta$ are all strongly correlated with auxiliary evidence of noisy or heuristic decision-making. For front-end delay effects, we find no such links.*

[23]In *Mirror*, the frequency of choice inconsistencies is almost exactly the same as in *Delay* (13% and 15%). This suggests that inconsistencies largely capture a response to complexity (rather than, e.g., random utility).

## 5.2 Manipulation of Task Difficulty

Our interpretation of the correlations between anomalies and CU / choice inconcistency is that they reflect the influence complexity has on intertemporal choice. That is, we interpret the noisy/heuristic behavior we measure as a direct *response* to the fact that intertemporal choice is complex. To provide direct evidence for this linkage, we ran an additional experiment that exogenously increases the cognitive difficulty of intertemporal choice. To the degree this manipulation jointly intensifies (i) our measures of noisy/heuristic behavior and (ii) intertemporal choice anomalies, we have complementary causal evidence supporting our interpretation.

In treatment *Opaque Payments/Delays*, for a subset of subjects, ($N = 153$), we express all of the payoffs in the price list as an algebraic expression (e.g., $40 is described as "$(4*8/2)+(8*9/2)-12"). For another subset ($N = 149$), we express all dates in the price list as algebraic expressions (e.g., 1 year is described as "in (6*2/3-3) years AND (3*6/2-9) months AND (5*4/2-10) days"). These interventions are always paired with time constraints of 25 seconds to make the relevant information processing constraints more likely to bind. Both of these interventions are designed to increase the information processing required to evaluate intertemporal tradeoffs, thereby increasing complexity.

We find that this intervention significantly increases both of our measures of boundedly rational choice. Average CU rises from 21.7% in *Delay Noise* to 35.2% for *Opaque Payments/Delays*; choice inconsistency rises from 60.4% in *Delay Noise* to 67.2% in *Opaque Payments/Delays* (both comparisons are statistically significant at least at the 5% level, see Appendix Table 8). These results suggest that both of our measures of noisy/heuristic response are sensitive to the complexity of the choice environment.

Next, we find that this manipulation simultaneously intensifies intertemporal choice anomalies. As Figure 7 shows, the decisions of subjects in *Opaque Payments/Delays* are significantly less sensitive to time delays, evincing stronger short-run impatience and flatter long-run impatience than subjects in *Delay Noise*. Indeed, as we document in Appendix Tablew 8 and 9, we find that this exogenous manipulation of task difficulty has the same effects as the patterns we observed correlationally for choice inconsistency and CU: higher task difficulty leads to (i) more pronounced short-run impatience; (ii) more pronounced decreasing impatience; (iii) stronger subadditivity; (iv) larger estimated present bias $\beta$; but (v) no changes in, or even weakened, front-end delay effects. This pattern not only matches our correlational results, but also our findings from *Mirror*, identifying the exact same anomalies as being complexity driven.

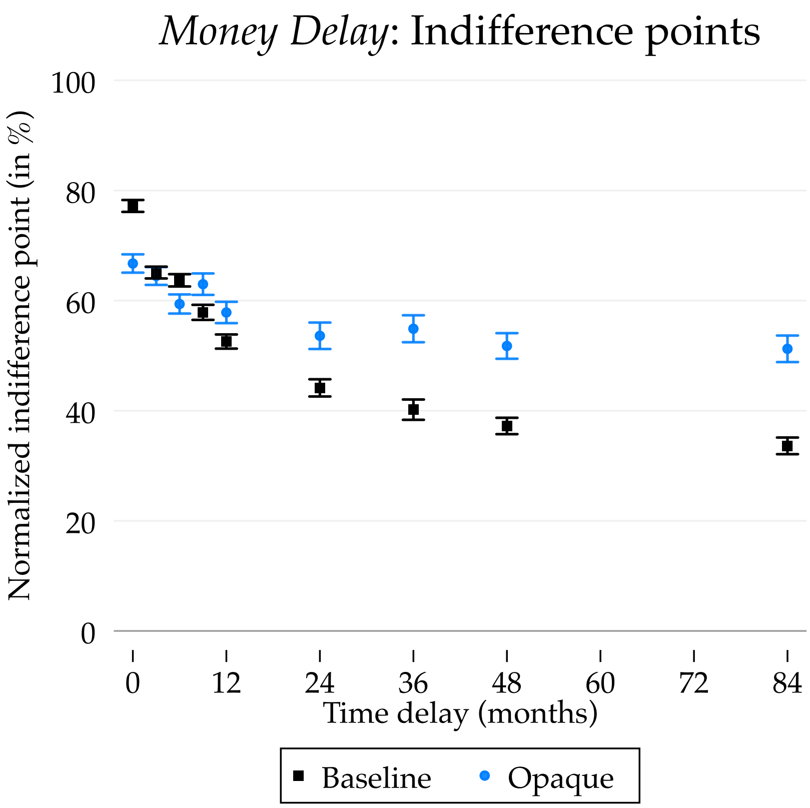


Figure 7: Normalized indifference points as a function of the time delay (rounded to nearest multiple of three months) in *Delay Noise* and the two *Opaque* manipulations, pooled for ease of readability (11,364 decisions from 947 subjects). Whiskers show standard error bars, computed based on clustering at the subject level.

## 6 The Complexity of Recursions

Finally, we investigate *what* it is about intertemporal choice that makes it complex, and therefore vulnerable to noisy or heuristic procedures. One possibility, ex ante, is that complexity is a consequence of the fact that it is difficult to introspectively evaluate or calculate one's own time preferences (e.g., one's discount factor). Similarly, another ex ante possibility is that complexity is an outgrowth of the difficulty of integrating one's risk and time preferences to inform choice.

Results from our *Mirror* treatment (in which time preferences are clearly induced and risk and time preferences needn't be integrated), suggest an alternative possibility: that the complexity of intertemporal choice is instead a direct outgrowth of the costs and difficulties of recursively attenuating / discounting rewards. If true, we would expect indices of complexity responses to vary with the intensity of the recursive task. For instance, we would expect a larger number of required attenuations / a longer time delay to be associated with more pronounced complexity responses.[24]

To examine this, re-reconsider equation (2). Rearranging, taking logs and adding a mean-zero noise term yields that a subject's observed indifference point in our experiments can be expressed as

$$ln\left(\frac{x_1}{x_2}\right) = ln(\beta_{t_1=0}) + \Delta t \cdot ln(\delta) + \varepsilon. \tag{3}$$

where the first term on the right-hand side collapses to zero if $\beta = 1$. Importantly, our hypothesis of complexity responses (noisy or heuristic procedures) that increase in the delay implies that $Var(\varepsilon)$ should not be constant but, instead, heteroscedastic and increasing in the delay. Because in equation (3) a subject's log normalized indifference point is a linear function of the delay, the equation can be estimated using simple OLS. We run this regression and then inspect the variance of the regression residuals.

The top left panel of Figure 8 shows the results for treatment *Delay*.[25] We find that the variance of the regression residuals indeed strongly increases in the length of the delay. A different way of saying this is that the variance of subjects' normalized indifference points strongly increases in the delay.

The top right panel shows an analogous plot for treatment *Mirror*, where the x-axis now represents the required number of recursions. Again, we see strong evidence of heteroscedasticity, in line with the hypothesis that complexity responses become more pronounced as the number of reasoning steps required to attenuate rewards increases.

Notice that in a standard exponential discounting model the regression residuals or the variance of log indifference points *should* increase in the delay if there is strictly positive preference heterogeneity.[26] However, in treatment *Mirror*, where the increase is almost equally strong, there is no preference heterogeneity available to rationalize the pattern because we experimentally induced the same discount factor for all subjects. In *Mirror*, this pattern must be driven by increasingly idiosyncratic responses to complexity as the number of steps of recursion increases. The fact that that the pattern (including magnitudes) is almost identical in *Delay* suggests the same complexity-based explanation applies there as well.

The bottom panels of Figure 8 provide additional evidence in suport of this claim. We plot subjects' cognitive uncertainty as a function of the delay in treatments *Delay Noise* and *Voucher Noise*.[27] In both treatments, people report being much more uncertain

[24]Some models of complexity and intertemporal discounting directly consider this possibility: Gabaix and Laibson (2022) model a decision maker whose degree of cognitive noisiness increases in the delay.

[25]The results are identical in *Delay Noise* and *Voucher Noise*.

[26]With exponential discounting and linear utility, $Var[ln(x_1/x_2)] = (\Delta t)^2 Var[ln(\delta)] + Var(\epsilon)$.

[27]Analyzing how choice inconsistencies vary with the delay is confounded by the relationship between choice inconsistency and the "extremity" of the intertemporal decision problem. In all treatments, we find that subjects exhibit less inconsistency when the delay is either very short or very long, in large part

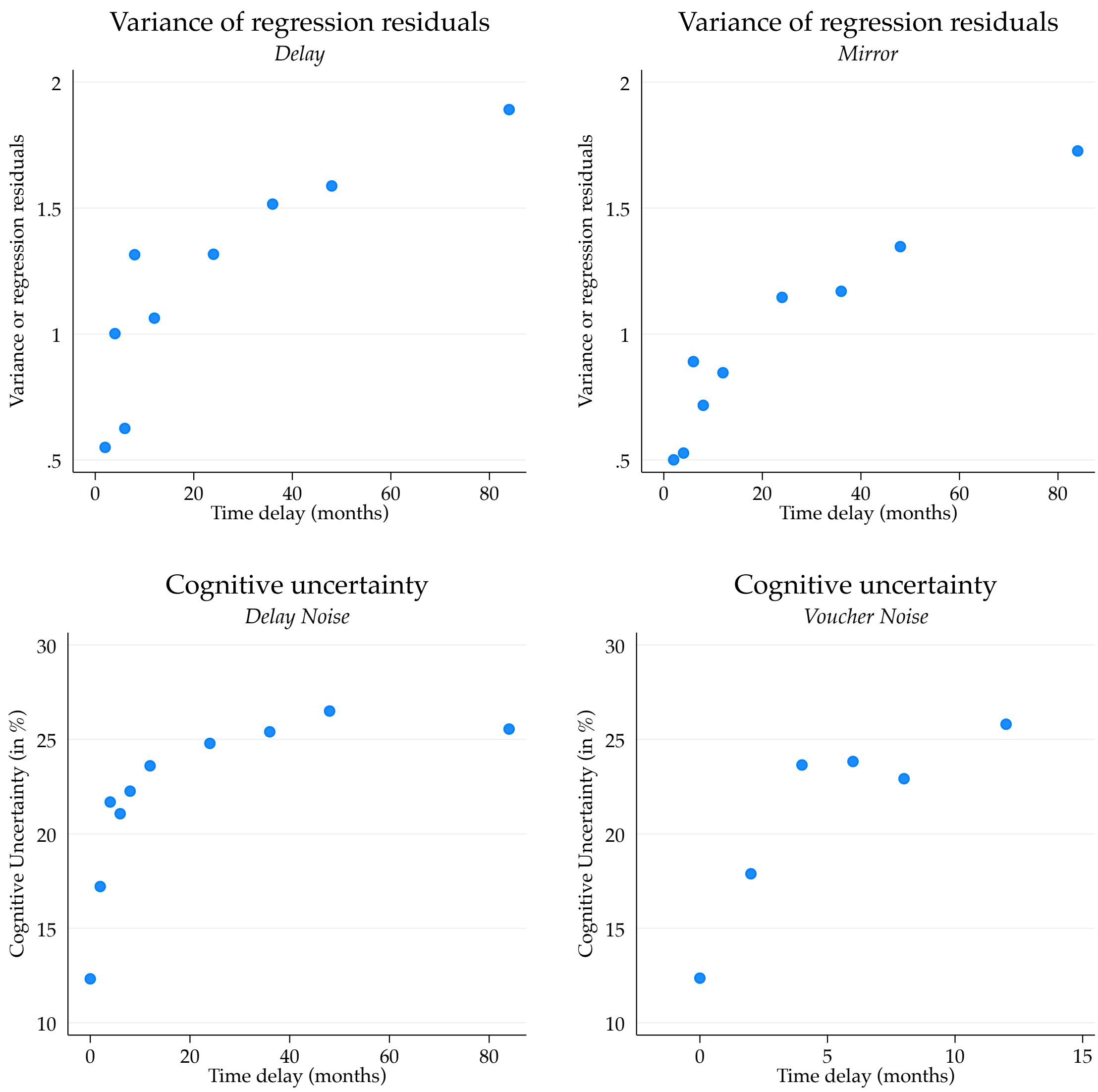


Figure 8: Noisiness as a function of the delay. Top panels show the variance of the regression residuals of eq. (3) in *Delay* and *Mirror*. Bottom panels show average cognitive uncertainty in *Delay Noise* and *Voucher Noise*. In all panels, delays are rounded to the nearest multiple of two.

about which decision to take as the delay gets longer. Going from very short delays of less than one month to delays of seven years, CU more than doubles. This increase is strongly concave, with CU barely increasing for delays longer than 1–2 years (recall that in *Voucher Noise* the longest delay is one year).

Taken together, multiple streams of evidence suggest that the difficulty of decision-making increases in the length of the delay / the number of cognitive recursions required. This, when combined with the appearance of anomalies in the atemporal mirrors (where there is little to drive complexity except the difficulty of recursive reasoning), strongly

because in these decision problems a large share of subjects make boundary choices that artifically make them look perfectly consistent.

suggests that the most important source of complexity in intertemporal decision-making is the cognitive act of recursively attenuating future rewards.

# 7 Discussion

Table 5 summarizes the results from this paper across all treatments. The main takeaway is that even though we deployed various different types of research strategies, we find highly consistent results. Regardless of how we measure complexity and complexity responses (through atemporal mirrors, choice inconsistency, cognitive uncertainty and exogenous treatment interventions), we consistently find that complexity is strongly associated with short-run impatience, decreasing impatience, subadditivity and econometric estimates of present bias, but not with front-end delay effects.

We interpret this as evidence that many of the core empirical anomalies in intertemporal choice that behavioral economists have documented are driven by noisy or heuristic responses to complexity rather than preferences or self-control problems. Intertemporal decisions appear to generate behavioral distortions because intertemporal tradeoffs require intensive recursive reasoning on the part of decision makers, generating a great deal of costly information processing. Subjects respond to this complexity by substituting from costly rational procedures for evaluating tradeoffs to less costly noisy or heuristic alternatives that are relatively inelastic to time delays, generating systematic departures from time consistency.

***Understanding present bias.*** Perhaps the most surprising result from this paper is that the noisy / heuristic procedures that complexity triggers, produce systematic confounds in the econometric estimation of one of the central objects of interest in behavioral economics: $\beta$. As we have shown, even though complexity has no impact on front-end delay effects (a *causal* estimate of present bias), model estimations that rely on cross-sectional variation in time delays will generally wrongly attribute the hyperbolic shape of discounting to present-biased preferences rather than complexity. This suggests that in some of the field contexts in which $\beta < 1$ has been estimated, there may be normative scope for "correcting" time-inconsistent behavior by reducing complexity and / or increasing comprehension.

Taken together, our results suggest that there are two different classes of intertemporal choice anomalies that are related to time delays. A first is causal evidence of front-end delay effects and dynamic inconsistency that are generally interpreted as direct evidence of temptation or present bias. Our experiments provide support for this body of work because we find no evidence that measures of front-end delay effects (i.e. direct, causal measurements of present bias) are confounded by complexity. A second, and larger, class

Table 5: Summary of results across experiments

| | Short-run impatience | Diminishing impatience | Sub-additivity | Front-end delay effect | Sub-Unitary $\beta$ |
|---|---|---|---|---|---|
| Present in atemporal mirrors? | ✓ | ✓ | ✓ | – | ✓ |
| More pronounced with cognitive uncertainty? | ✓ | ✓ | ✓ | x | ✓ |
| More pronounced with choice inconsistency? | ✓ | ✓ | n/a | n/a | ✓ |
| More pronounced in difficult problems? | ✓ | ✓ | ✓ | – | ✓ |

*Notes.* "✓" means that an anomaly is present / more pronounced, "x" that it is not present / not more pronounced and "–" that the opposite is present / the anomaly is less pronounced. "n/a" means that data limitations do not allow us to assess a relationship.

of anomalies is that intertemporal decisions are insufficiently sensitive to variations in time delay, which generates extreme impatience, hyperbolicity and transitivity violations. A classic approach in the literature has been to develop models that capture both classes of phenomena. However, our evidence suggests that the two sets of regularities are driven by different principles: the second is largely generated by complexity, while the first one is not.

***Related literature.*** Our work connects to several literatures. First, a long literature documents anomalies in time discounting, initiated by Thaler (1981) and reviewed by Frederick et al. (2002), Cohen et al. (2020) and Ericson and Laibson (2019). Second, there is a literature proposing explanations for these anomalies (reviewed earlier in detail in Section 2). Third, a recent strand of work attempts to operationalize, measure and make use of complexity as a tool for understanding economic behavior (e.g., Oprea, 2020; Banovetz and Oprea, 2022; Camara, 2021). This includes work on the link between noisiness and behavioral anomalies (Agranov and Ortoleva, 2017, 2020; Agranov et al., 2020; Khaw et al., 2021; Enke and Graeber, 2022). Fourth are experimental literatures showing that people have difficulty with exponential reasoning, suffering an "exponential growth bias" (Stango and Zinman, 2009). We too find errors in exponential reasoning, though unlike this literature we show that these errors generate (and predict) classic intertemporal choice anomalies.

Finally, our work relates to the literature that studies "cognitive effects" in intertemporal choice. Most closely related are documentations of the role of noise: Carrera et al. (2022) identify noise as a driver of commitment demand, while Chakraborty et al. (2017) argue that noise or confusion spuriously drives estimates of present bias in convex budget experiments. More generally, there is a literature documenting that intertemporal choice anomalies tend to be correlated with measures of cognitive ability (e.g., Dohmen et al., 2010; Benjamin et al., 2013) and are sensitive to cognitive load and time pressure (Ebert and Prelec, 2007; Imas et al., 2021), which resonates well with our findings. Regenwetter et al. (2018) provide an overview of the psychology literature, which argues through model-fitting exercises that noise contributes to the hyperbolicity of hyperbolic discounting (e.g., He et al., 2019). One of our contributions is to provide substantially more direct evidence on the role of noise / heuristics in generating the famous anomalies than can be achieved through model-fitting exercises.

***Broader takeaways and connection to decision making in other domains.*** An important takeaway from all of the experiments reported in this paper is that complexity (and the heuristic / noisy responses that it induces) produces a *particular type of behavioral response*: an insufficient elasticity of decisions to variation in the main parameter of the problem, the time delay.[28] This observation may suggest deep connections between intertemporal choice anomalies and other anomalies that have similarly been identified as growing out of complexity. In two related papers, Oprea (2022) and Enke and Graeber (2022), we use similar methods to show that some of the core anomalies behavioral economists have observed in the domain of risk (such as probability weighting) are similarly rooted in complexity and the heuristic and / or noisy procedures it induces. In particular, an overarching message that emerges from the three papers is that, when decisions are complex, observed behavior is insufficiently sensitive with respect to variation in objective problem parameters, including probabilities, deterministic frequencies, time delays, and atemporal recursions. Together, these papers thus suggest the possibility that many apparently distinct phenomena in behavioral economics might in fact be outgrowths of closely related forces, and that they might be parsimoniously united by models built to describe the way humans manage and respond to complexity.

[28]See Ebert and Prelec (2007) for a related discussion.

# References


**Agranov, Marina and Pietro Ortoleva**, "Stochastic choice and preferences for randomization," *Journal of Political Economy*, 2017, *125* (1), 40–68.

**_ and _** , "Ranges of Preferences and Randomization," *Working Paper*, 2020.

**_ , Paul J Healy, and Kirby Nielsen**, "Non-Random Randomization," *Available at SSRN*, 2020.

**Andreoni, James and Charles Sprenger**, "Risk preferences are not time preferences," *American Economic Review*, 2012, *102* (7), 3357–76.

**_ , Christina Gravert, Michael A Kuhn, Silvia Saccardo, and Yang Yang**, "Arbitrage or narrow bracketing? On using money to measure intertemporal preferences," Technical Report, National Bureau of Economic Research 2018.

**Arts, Sara, Qiyan Ong, and Jianying Qiu**, "Measuring subjective decision confidence," *Working Paper*, 2020.

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

**Banovetz, James and Ryan Oprea**, "Complexity and Procedural Choice," *Unpublished Manuscript*, 2022.

**Benjamin, Daniel J, Sebastian A Brown, and Jesse M Shapiro**, "Who is 'behavioral'? Cognitive ability and anomalous preferences," *Journal of the European Economic Association*, 2013, *11* (6), 1231–1255.

**Brocas, Isabelle, Juan D Carrillo, and Jorge Tarrasó**, "How long is a minute?," *Games and Economic Behavior*, 2018, *111*, 305–322.

**Bulley, Adam, Karolina Lempert, Colin Conwell, and Muireann Irish**, "Intertemporal choice reflects value comparison rather than self-control: insights from confidence judgments," *PsyArXiv*, 2021.

**Butler, David J and Graham C Loomes**, "Imprecision as an account of the preference reversal phenomenon," *American Economic Review*, 2007, *97* (1), 277–297.

**Camara, Modibo**, "Computationally Tractable Choice," *Unpublished Manuscript*, 2021.

**Carrera, Mariana, Heather Royer, Mark Stehr, Justin Sydnor, and Dmitry Taubinsky**, "Who chooses commitment? Evidence and welfare implications," *The Review of Economic Studies*, 2022, *89* (3), 1205–1244.

**Chakraborty, Anujit, Evan M Calford, Guidon Fenig, and Yoram Halevy**, "External and internal consistency of choices made in convex time budgets," *Experimental economics*, 2017, *20* (3), 687–706.

**_ , Yoram Halevy, and Kota Saito**, "The relation between behavior under risk and over time," *American Economic Review: Insights*, 2020, *2* (1), 1–16.

**Cohen, Jonathan, Keith Marzilli Ericson, David Laibson, and John Myles White**, "Measuring time preferences," *Journal of Economic Literature*, 2020, *58* (2), 299–347.

**Curry, David**, "Uber Eats Revenue and Usage Statistics (2021)," 2021.

**Dertwinkel-Kalt, Markus, Holger Gerhardt, Gerhard Riener, Frederik Schwerter, and Louis Strang**, "Concentration bias in intertemporal choice," *Review of Economic Studies*, 2021.

**Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde**, "Are risk aversion and impatience related to cognitive ability?," *American Economic Review*, 2010, *100* (3), 1238–60.

**Ebert, Jane EJ and Drazen Prelec**, "The fragility of time: Time-insensitivity and valuation of the near and far future," *Management science*, 2007, *53* (9), 1423–1438.

**Enke, Benjamin and Thomas Graeber**, "Cognitive uncertainty," Technical Report, National Bureau of Economic Research 2022.

**Epper, Thomas, Ernst Fehr, Helga Fehr-Duda, Claus Thustrup Kreiner, David Dreyer Lassen, Søren Leth-Petersen, and Gregers Nytoft Rasmussen**, "Time discounting and wealth inequality," *American Economic Review*, 2020, *110* (4), 1177–1205.

**Ericson, Keith Marzilli and David Laibson**, "Intertemporal choice," in "Handbook of Behavioral Economics: Applications and Foundations 1," Vol. 2, Elsevier, 2019, pp. 1–67.

**_ , John Myles White, David Laibson, and Jonathan D Cohen**, "Money earlier or later? Simple heuristics explain intertemporal choices better than delay discounting does," *Psychological science*, 2015, *26* (6), 826–833.

**Frederick, Shane, George Loewenstein, and Ted O'donoghue**, "Time discounting and time preference: A critical review," *Journal of economic literature*, 2002, *40* (2), 351–401.

**Fudenberg, Drew and David K Levine**, "A dual-self model of impulse control," *American economic review*, 2006, *96* (5), 1449–1476.

**Gabaix, Xavier and David Laibson**, "Myopia and discounting," Technical Report, National bureau of economic research 2022.

**Gershman, Samuel J and Rahul Bhui**, "Rationally inattentive intertemporal choice," *Nature Communications*, 2020, *11.*

**Gul, Faruk and Wolfgang Pesendorfer**, "Temptation and self-control," *Econometrica*, 2001, *69* (6), 1403–1435.

**Halevy, Yoram**, "Strotz meets Allais: Diminishing impatience and the certainty effect," *American Economic Review*, 2008, *98* (3), 1145–62.

_ , "Some comments on the use of monetary and primary rewards in the measurement of time preferences," *Unpublished manuscript*, 2014.

_ , "Time consistency: Stationarity and time invariance," *Econometrica*, 2015, *83* (1), 335–352.

**He, Lisheng, Russell Golman, and Sudeep Bhatia**, "Variable time preference," *Cognitive psychology*, 2019, *111*, 53–79.

**Imas, Alex, Michael Kuhn, and Vera Mironova**, "Waiting to choose: The Role of Deliberation in Intertemporal Choice," *American Economic Journal: Microeconomics*, 2021.

**Jackson, Matthew O and Leeat Yariv**, "Present bias and collective dynamic choice in the lab," *American Economic Review*, 2014, *104* (12), 4184–4204.

**Kable, Joseph W and Paul W Glimcher**, "An "as soon as possible" effect in human intertemporal decision making: behavioral evidence and neural mechanisms," *Journal of neurophysiology*, 2010, *103* (5), 2513–2531.

**Khaw, Mel Win, Ziang Li, and Michael Woodford**, "Cognitive imprecision and small-stakes risk aversion," *The review of economic studies*, 2021, *88* (4), 1979–2013.

**Laibson, David**, "Golden eggs and hyperbolic discounting," *The Quarterly Journal of Economics*, 1997, *112* (2), 443–478.

**Loewenstein, George and Drazen Prelec**, "Anomalies in intertemporal choice: Evidence and an interpretation," *The Quarterly Journal of Economics*, 1992, *107* (2), 573–597.

**Lu, Jay and Kota Saito**, "Random intertemporal choice," *Journal of Economic Theory*, 2018, *177*, 780–815.

**Martino, Benedetto De, Sebastian Bobadilla-Suarez, Takao Nouguchi, Tali Sharot, and Bradley C Love**, "Social information is integrated into value and confidence judgments according to its reliability," *Journal of Neuroscience*, 2017, *37* (25), 6066–6074.

_ , **Stephen M Fleming, Neil Garrett, and Raymond J Dolan**, "Confidence in value-based choice," *Nature neuroscience*, 2013, *16* (1), 105–110.

**Meier, Stephan and Charles D Sprenger**, "Temporal stability of time preferences," *Review of Economics and Statistics*, 2015, *97* (2), 273–286.

**O'Donoghue, Ted and Matthew Rabin**, "Doing it now or later," *American Economic Review*, 1999, *89* (1), 103–124.

**Oprea, Ryan**, "What Makes a Rule Complex?," *American Economic Review*, 2020, *110* (12), 3913–3951.

_ , "Simplicity Equivalents," *Working Paper*, 2022.

**Polania, Rafael, Michael Woodford, and Christian C Ruff**, "Efficient coding of subjective value," *Nature neuroscience*, 2019, *22* (1), 134–142.

**Read, Daniel, Shane Frederick, and Marc Scholten**, "DRIFT: an analysis of outcome framing in intertemporal choice.," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 2013, *39* (2), 573.

**Regenwetter, Michel, Daniel R Cavagnaro, Anna Popova, Ying Guo, Chris Zwilling, Shiau Hong Lim, and Jeffrey R Stevens**, "Heterogeneity and parsimony in intertemporal choice.," *Decision*, 2018, *5* (2), 63.

**Rubinstein, Ariel**, ""Economics and psychology"? The case of hyperbolic discounting," *International Economic Review*, 2003, *44* (4), 1207–1216.

**Sprenger, Charles**, "Judging experimental evidence on dynamic inconsistency," *American Economic Review*, 2015, *105* (5), 280–85.

**Stango, Victor and Jonathan Zinman**, "Exponential growth bias and household finance," *The Journal of Finance*, 2009, *64* (6), 2807–2849.

**Thaler, Richard**, "Some empirical evidence on dynamic inconsistency," *Economics letters*, 1981, *8* (3), 201–207.

**Vieider, Ferdinand M**, "Noisy coding of time and reward discounting," Technical Report, Ghent University, Faculty of Economics and Business Administration 2021.

**Weitzman, Martin L**, "Gamma discounting," *American Economic Review*, 2001, *91* (1), 260–271.

**Xiang, Yang, Thomas Graeber, Benjamin Enke, and Samuel Gershman**, "Confidence and Central Tendency in Perceptual Judgment," *Attention, Perception and Psychophysics*, 2021.

**Yeung, Nick and Christopher Summerfield**, "Metacognition in human decision-making: confidence and error monitoring," *Philosophical Transactions of the Royal Society B: Biological Sciences*, 2012, *367* (1594), 1310–1321.

**Zauberman, Gal, B Kyu Kim, Selin A Malkoc, and James R Bettman**, "Discounting time and time discounting: Subjective time perception and intertemporal preferences," *Journal of Marketing Research*, 2009, *46* (4), 543–556.

# Online Appendix

# A Additional Figures

| | Option A | Option B |
|---|---|---|
| 1 | $42.00 in 12 months | $2.00 now |
| 2 | $42.00 in 12 months | $4.00 now |
| 3 | $42.00 in 12 months | $6.00 now |
| 4 | $42.00 in 12 months | $8.00 now |
| 5 | $42.00 in 12 months | $10.00 now |
| 6 | $42.00 in 12 months | $12.00 now |
| 7 | $42.00 in 12 months | $14.00 now |
| 8 | $42.00 in 12 months | $16.00 now |
| 9 | $42.00 in 12 months | $18.00 now |
| 10 | $42.00 in 12 months | $20.00 now |
| 11 | $42.00 in 12 months | $22.00 now |
| 12 | $42.00 in 12 months | $24.00 now |
| 13 | $42.00 in 12 months | $26.00 now |
| 14 | $42.00 in 12 months | $28.00 now |
| 15 | $42.00 in 12 months | $30.00 now |
| 16 | $42.00 in 12 months | $32.00 now |
| 17 | $42.00 in 12 months | $34.00 now |
| 18 | $42.00 in 12 months | $36.00 now |
| 19 | $42.00 in 12 months | $38.00 now |
| 20 | $42.00 in 12 months | $40.00 now |
| 21 | $42.00 in 12 months | $42.00 now |

**a)** Delay treatment

| | Option A | Option B |
|---|---|---|
| 1 | $42.00 shrunk 12 times | $2.00 |
| 2 | $42.00 shrunk 12 times | $4.00 |
| 3 | $42.00 shrunk 12 times | $6.00 |
| 4 | $42.00 shrunk 12 times | $8.00 |
| 5 | $42.00 shrunk 12 times | $10.00 |
| 6 | $42.00 shrunk 12 times | $12.00 |
| 7 | $42.00 shrunk 12 times | $14.00 |
| 8 | $42.00 shrunk 12 times | $16.00 |
| 9 | $42.00 shrunk 12 times | $18.00 |
| 10 | $42.00 shrunk 12 times | $20.00 |
| 11 | $42.00 shrunk 12 times | $22.00 |
| 12 | $42.00 shrunk 12 times | $24.00 |
| 13 | $42.00 shrunk 12 times | $26.00 |
| 14 | $42.00 shrunk 12 times | $28.00 |
| 15 | $42.00 shrunk 12 times | $30.00 |
| 16 | $42.00 shrunk 12 times | $32.00 |
| 17 | $42.00 shrunk 12 times | $34.00 |
| 18 | $42.00 shrunk 12 times | $36.00 |
| 19 | $42.00 shrunk 12 times | $38.00 |
| 20 | $42.00 shrunk 12 times | $40.00 |
| 21 | $42.00 shrunk 12 times | $42.00 |

**b)** Mirror treatment

Figure 9: Screenshots from the experimental software.

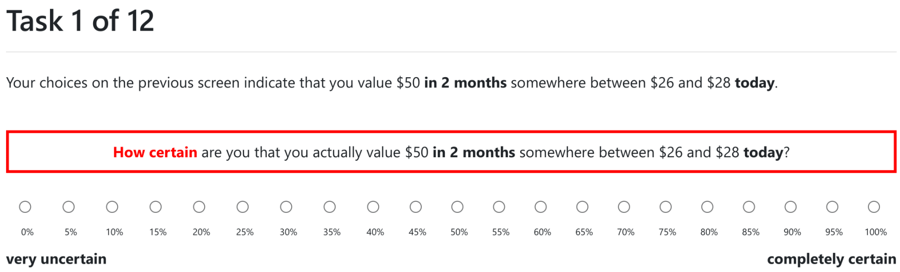


Figure 10: Screenshot of an example cognitive uncertainty elicitation screen in *Delay Noise*

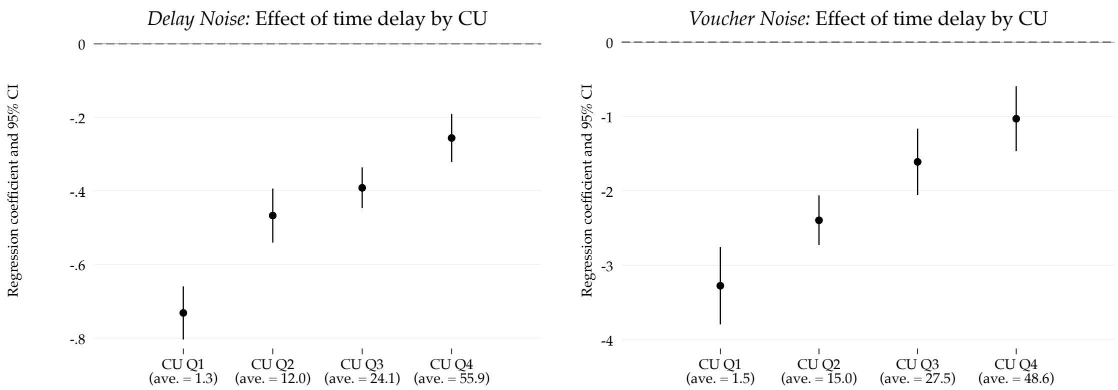


Figure 11: Coefficients from regressions of normalized indifference points on time delay for $t_1 = 0$, split by CU quartiles; left: *Delay Noise*; right: *Voucher Noise*.

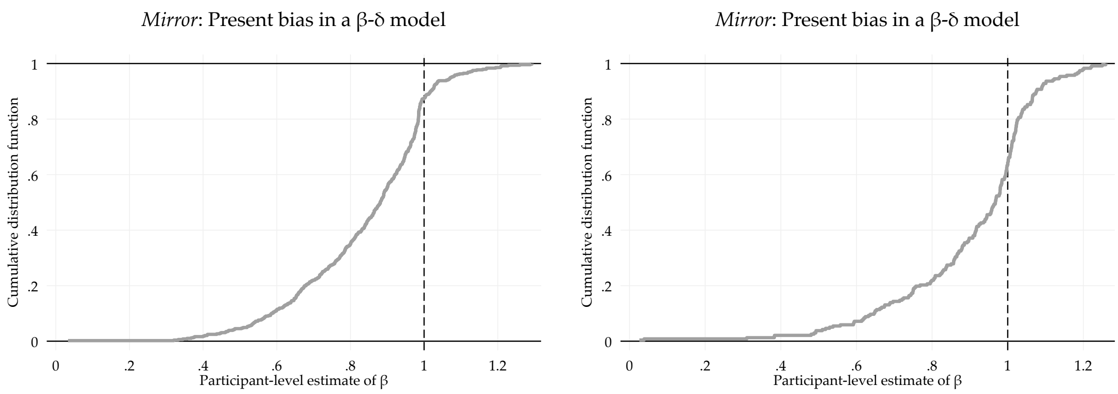


Figure 12: Empirical CDFs of individual-level estimates of a $\beta - \delta$ model (eq. (2)) in *Delay* ($N = 254$) and *Mirror* ($N = 246$), using first-assigned treatment only. Non-linear least squares estimation based on 18 decisions from each individual.

# B Additional Tables

Table 6: Anomalies in *Delay* and *Mirror*, pooling first-assigned and second-assigned treamtents

| | *Dependent variable:* Implied annual discounting (in %) | | | | | |
|---|---|---|---|---|---|---|
| Phenomenon: | Decreasing impatience | | Subadditivity | | Front-end delay | |
| Treatment: | *Delay* | *Mirror* | *Delay* | *Mirror* | *Delay* | *Mirror* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Time delay (years) | -5.76$^{***}$ | -5.14$^{***}$ | | | | |
| | (0.25) | (0.26) | | | | |
| 1 if one long interval | | | -7.57$^{***}$ | -9.93$^{***}$ | | |
| | | | (1.38) | (1.16) | | |
| 1 if front end delay | | | | | -4.24$^{**}$ | 3.79$^{**}$ |
| | | | | | (1.85) | (1.69) |
| Payment amount FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Subadditivity set FE | No | No | Yes | Yes | Yes | Yes |
| Observations | 4572 | 4428 | 508 | 492 | 508 | 492 |
| $R^2$ | 0.17 | 0.19 | 0.09 | 0.06 | 0.07 | 0.02 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. In columns (1) and (2), the sample consists of all decisions in the respective treatment. In columns (3) and (4), the sample consists of two observations per subject: their implied annual discounting over the long (composite) interval and their implied discounting over the two shorter intervals. In columns (5) and (6), the sample includes those two decisions per subject that have a front-end delay structure. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 7: Decreasing impatience in *Delay Noise* and within-subject variation of cognitive uncertainty

| | *Dependent variable:* Implied annual discounting (in %) | |
|---|---|---|
| Dataset: | *Delay Noise* | |
| Phenomenon: | Decreasing impatience | |
| | (1) | (2) |
| Time delay | -6.87*** | -5.46*** |
| | (0.18) | (0.26) |
| Cognitive uncertainty (standard. within subject) | | 0.28*** |
| | | (0.04) |
| Time delay × Cognitive uncertainty (standard. within subject) | | -0.068*** |
| | | (0.01) |
| Payment amount FE | Yes | Yes |
| Observations | 7740 | 7740 |
| $R^2$ | 0.16 | 0.18 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. In these regressions, the measure of cognitive uncertainty was standardized at the subject level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 8: Anomalies in the *Delay Noise* vs. the *Opaque* treatments

| Phenomenon: | Manipulation check | | Decr. imp. | Subadd. | Front-end |
|---|---|---|---|---|---|
| | *Dependent variable:* | | | | |
| | CU | Inconsistent | Implied annual discounting (in %) | | |
| | (1) | (2) | (3) | (4) | (5) |
| Opaque treatments | 13.6*** | 0.065** | 0.99 | 3.07 | -0.59 |
| | (1.40) | (0.03) | (1.89) | (2.20) | (2.35) |
| Time delay (years) | | | -6.88*** | | |
| | | | (0.18) | | |
| Time delay (years) × Opaque treatments | | | -1.92*** | | |
| | | | (0.34) | | |
| 1 if one long interval | | | | -8.58*** | |
| | | | | (0.63) | |
| 1 if one long interval × Opaque treatments | | | | -7.99*** | |
| | | | | (1.30) | |
| 1 if front-end delay | | | | | -3.06*** |
| | | | | | (0.99) |
| 1 if front-end delay × Opaque treatments | | | | | 5.32*** |
| | | | | | (1.86) |
| Payment amount FE | Yes | Yes | Yes | Yes | Yes |
| Subadditivity set FE | No | No | No | Yes | Yes |
| Observations | 11364 | 3788 | 11364 | 2818 | 3465 |
| $R^2$ | 0.06 | 0.01 | 0.18 | 0.04 | 0.01 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. In columns (1) and (3), the sample consists of all decisions in the *Delay Noise* and *Opaque* treatments. In column (2), the sample includes all sets of repeated decisions shown to a subject. In column (4), the sample consists of two observations per subject: their implied annual discounting over the long (composite) interval and their implied discounting over the two shorter intervals. In column (5), the sample includes those two decisions per subject that have a front-end delay structure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Population-level estimates of $\beta - \delta$ model

| | *Delay & Mirror* | | *Delay Noise* | | | | | *Opaque* | *Voucher Noise* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Delay (1) | Mirror (2) | All (3) | CU=0 (4) | CU>0 (5) | Incons.=0 (6) | Incons.>0 (7) | All (8) | All (9) | CU=0 (10) | CU>0 (11) | Incons.=0 (12) | Incons.>0 (13) |
| $\hat{\beta}$ | .774 | .846 | .76 | .872 | .721 | .822 | .75 | .72 | .882 | .953 | .854 | .957 | .865 |
| $\hat{\delta}$ | .982 | .96 | .978 | .973 | .98 | .983 | .977 | .989 | .942 | .955 | .941 | .968 | .936 |

*Notes.* Population-level estimates of a $\beta - \delta$ model (eq. (2)). Columns (1) and (2) use the first-assigned treatment only, based on $N = 254$ subjects in *Delay* and $N = 246$ subjects in *Mirror*. Columns (3), (8) and (9) include all subjects in the respective treatments: $N = 645$ in *Delay Noise*, $N = 302$ in *Opaque* and $N = 500$ in *Voucher Noise*. All other columns are based on sample splits of the corresponding treatments. Non-linear least squares estimates.

Table 10: Choice inconsistencies in *Mirror*

| | *Dependent variable:* Implied annual discounting (in %) | |
|---|---|---|
| Phenomenon: | Short-run discounting | Decreasing impatience |
| | (1) | (2) |
| Inconsistent decision | 17.8*** | 12.7*** |
| | (3.86) | (3.90) |
| Number of recursions (in years) | | -2.64*** |
| | | (0.51) |
| Number of recursions (in years) × Inconsistent decision | | -3.07*** |
| | | (0.53) |
| Payment amount FE | Yes | Yes |
| Observations | 417 | 3408 |
| $R^2$ | 0.09 | 0.21 |

*Notes.* OLS estimates, robust standard errors (in parentheses) are clustered at the subject level. Regressions include sets of repeated decisions shown to a subject. Column (1) includes decisions with one recursion only, column (2) includes decisions involving any number of recursions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# C Experimental Instructions

## C.1 Instructions for *Delay & Mirror* Experiment

### C.1.1 First-assigned treatment: *Delay*

#### Delayed Choices

In this part of the study you will **choose between various hypothetical payments, which pay different amounts at different points in time**. An example decision is between the following two hypothetical payments.

| Option A | Option B |
|---|---|
| $100.00 in 3 months | $90.00 now |

In this example we are asking you (hypothetically) would you rather be paid $100 in three months (Option A) or $90 right now (Option B).

For all hypothetical payments in this study, please treat them as if you know you will receive them with certainty, even if they are delayed. That is, please assume there is no risk that you wouldn't actually get paid. Further, assume all payments were made by leaving a check in your mailbox which you can cash at the specified date.

For this part of the experiment, there are no right wrong answers, because how much you like an option depends on your personal taste. Just <u>try your best to think hard about what you'd really prefer</u>.

## The Choice List

On your decision screen, you will be asked to choose which of two payment options you prefer. You will see choice lists such as the one below, where **each row is a separate choice**.

In every list, the left-hand option (Option A) is a delayed payment that is identical in all rows. The right-hand side option (Option B) is a payment with an *earlier payment date than Option A*. The earlier, right-hand side payment increases as you go down the list. To make a choice just click on the option you prefer for each choice (i.e. for each row), highlighting your choice yellow. **An effective way to complete these choice lists is to determine in which row you like to switch from preferring Option A to preferring Option B.**

| | Option A | Option B |
|---|---|---|
| 1 | $40.00 in 3 months | $2.00 now |
| 2 | $40.00 in 3 months | $4.00 now |
| 3 | $40.00 in 3 months | $6.00 now |
| 4 | $40.00 in 3 months | $8.00 now |
| 5 | $40.00 in 3 months | $10.00 now |
| 6 | $40.00 in 3 months | $12.00 now |
| 7 | $40.00 in 3 months | $14.00 now |
| 8 | $40.00 in 3 months | $16.00 now |
| 9 | $40.00 in 3 months | $18.00 now |
| 10 | $40.00 in 3 months | $20.00 now |
| 11 | $40.00 in 3 months | $22.00 now |
| 12 | $40.00 in 3 months | $24.00 now |
| 13 | $40.00 in 3 months | $26.00 now |
| 14 | $40.00 in 3 months | $28.00 now |
| 15 | $40.00 in 3 months | $30.00 now |
| 16 | $40.00 in 3 months | $32.00 now |
| 17 | $40.00 in 3 months | $34.00 now |
| 18 | $40.00 in 3 months | $36.00 now |
| 19 | $40.00 in 3 months | $38.00 now |
| 20 | $40.00 in 3 months | $40.00 now |

**Auto-completion:** The table auto-completes your choices so you don't have to click through all of the rows. You do not have to start at the top of the table. If you select Option A in any one row, we assume you will also prefer Option A in all rows *above* that row. If you select Option B in any one row, we assume that you will also prefer Option B in all rows *below* that row.

## Next Part

In the next part of the experiment, we are going to have you make a **very different kind of decision**, also using choice lists.

Instead of making hypothetical decision about money paid out at various points in time (as in Part 1) **we will have you make real money decisions paid as a bonus today.** Specifically, we will ask you to choose between monetary amounts that are shrunk to varying degrees, using a choice list like the one you used in Part 1. The difference is, we will really pay some of you these amounts today!

### C.1.2 First-assigned treatment: *Mirror*

## Shrunk Choices

In this part of the study you will **choose between various payments (actually paid to you today), which will first be shrunk (reduced in value) some number of times.** An example decision is between the following two payments.

| Option A | Option B |
|---|---|
| $100.00 shrunk 3 times | $90.00 |

Each time a payment is shrunk (as in Option A), its dollar value falls by 4% meaning it shrinks to only 96% of the dollar value from the previous step. For example

- If $100 is shrunk only 1 time, we would pay you 96% of $100 or $96.
- If $100 is shrunk in only 2 time, we would pay you 96% of 96% of $100 or $92.16
- If $100 is shrunk in only 3 time, we would pay you 96% of 96% of 96% of $100 or $88.47

And so on. So, in the example, if you chose Option A ($100 shrunk 3 times), you would earn $88.47. On the other hand, Option B isn't shrunk at all so it just pays the $90 shown (any time we don't mention shrinking for a payment, that means the payment is not shrunk at all).

At the end of the experiment we will randomly select 20% of participants to actually be paid their earnings as a bonus today from a randomly selected choice.

## The Choice List

On your decision screen, you will be asked to choose which of two payment options you prefer. You will see choice lists such as the one below, where **each row is a separate choice**.

In every list, the left-hand option (Option A) is a delayed payment that is identical in all rows. The right-hand side option (Option B) is a payment with an *earlier payment date than Option A*. The earlier, right-hand side payment increases as you go down the list. To make a choice just click on the option you prefer for each choice (i.e. for each row), highlighting your choice yellow. **An effective way to complete these choice lists is to determine in which row you like to switch from preferring Option A to preferring Option B.**

| | Option A | Option B |
|---|---|---|
| 1 | $40.00 in 3 months | $2.00 now |
| 2 | $40.00 in 3 months | $4.00 now |
| 3 | $40.00 in 3 months | $6.00 now |
| 4 | $40.00 in 3 months | $8.00 now |
| 5 | $40.00 in 3 months | $10.00 now |
| 6 | $40.00 in 3 months | $12.00 now |
| 7 | $40.00 in 3 months | $14.00 now |
| 8 | $40.00 in 3 months | $16.00 now |
| 9 | $40.00 in 3 months | $18.00 now |
| 10 | $40.00 in 3 months | $20.00 now |
| 11 | $40.00 in 3 months | $22.00 now |
| 12 | $40.00 in 3 months | $24.00 now |
| 13 | $40.00 in 3 months | $26.00 now |
| 14 | $40.00 in 3 months | $28.00 now |
| 18 | $40.00 in 3 months | $36.00 now |
| 19 | $40.00 in 3 months | $38.00 now |
| 20 | $40.00 in 3 months | $40.00 now |

**Auto-completion:** The table auto-completes your choices so you don't have to click through all of the rows. You do not have to start at the top of the table. If you select Option A in any one row, we assume you will also prefer Option A in all rows *above* that row. If you select Option B in any one row, we assume that you will also prefer Option B in all rows *below* that row.

## Next Part

In the next part of the experiment, we are going to have you make a **very different kind of decision**, also using choice lists.

Instead of making real money decisions about money shrunk to various degrees (as in Part 1) **we will have you make hypothetical money decisions about money amounts paid to you at various points in time.** Specifically, we will ask you to choose between monetary amounts paid sooner versus later, using a choice list like the one you used in Part 1. We won't actually pay you based on your choices in this part, but just want to understand when you'd hypothetically rather be paid various combinations of money.

## C.2 Instructions for *Delay Noise*

### Part 1 of this study: Instructions (1/3)

Please read these instructions carefully. There will be comprehension checks. If you fail these checks, you will immediately be excluded from the study and you will not receive the completion payment.

In this part of the study, you will **choose between various hypothetical payments, which pay different amounts of money at different points in time**. An example decision is between the following two hypothetical payments:

**In 30 days: $ 40** OR **Today: $ 12**

For all hypothetical payments in this study, please treat them as if you knew that you would receive them with certainty, even if they are delayed. That is, please assume that there is no risk that you wouldn't actually get paid. Further assume that all payments were made by leaving a check in your mailbox.

Throughout the experiment, there are no right or wrong answers, because how much you like an option depends on your personal taste. There will be two types of decision screens.

### Decision screen 1

On decision screen 1, you will be asked to choose which of two payment options you prefer. You will see choice lists such as the one below, where each row is a separate choice. In every list, the left-hand side option (Option A) is a delayed payment that is identical in all rows. The right-hand side option (Option B) is a payment *with an earlier payment date than Option A*. The earlier, right-hand side payment increases as you go down the list. **An effective way to complete these choice lists is to determine in which row you would like to switch from preferring Option A to preferring Option B.**

Based on where you switch from Option A to Option B in this list, we assess which amount at the early payment date (Option B) you value as much as the amount specified at the later payment date (Option A). For example, in the choice list below, you would value $40 in 30 days somewhere between $12 and $14 today, because this is where switching occurs.

| Option A | | | Option B |
|---|---|---|---|
| | ◉ | ○ | **Today: $2** |
| | ◉ | ○ | **Today: $4** |
| | ◉ | ○ | **Today: $6** |
| | ◉ | ○ | **Today: $8** |
| | ◉ | ○ | **Today: $10** |
| | ◉ | ○ | **Today: $12** |
| | ○ | ◉ | **Today: $14** |
| | ○ | ◉ | **Today: $16** |
| | ○ | ◉ | **Today: $18** |
| **In 30 days: $40** | ○ | ◉ | **Today: $20** |
| | ○ | ◉ | **Today: $22** |
| | ○ | ◉ | **Today: $24** |
| | ○ | ◉ | **Today: $26** |
| | ○ | ◉ | **Today: $28** |
| | ○ | ◉ | **Today: $30** |
| | ○ | ◉ | **Today: $32** |
| | ○ | ◉ | **Today: $34** |
| | ○ | ◉ | **Today: $36** |
| | ○ | ◉ | **Today: $38** |
| | ○ | ◉ | **Today: $40** |

On the next page, you will see an example choice list, and you can practice making your selections.

Click "Next" to proceed to the example page.

## Part 1 of this study: Instructions (2/3)

**Auto-completion**: The table auto-completes your choices so you don't have to click through all of the rows. You do not have to start at the top of the table. If you select Option A in any one row, we assume that you will also prefer Option A in all rows *above* that row. If you select Option B in any one row, we assume that you will also prefer Option B in all rows *below* that row.

| Option A | | | Option B |
|---|---|---|---|
| | ○ | ○ | **Today: $2** |
| | ○ | ○ | **Today: $4** |
| | ○ | ○ | **Today: $6** |
| | ○ | ○ | **Today: $8** |
| | ○ | ○ | **Today: $10** |
| | ○ | ○ | **Today: $12** |
| | ○ | ○ | **Today: $14** |
| | ○ | ○ | **Today: $16** |
| | ○ | ○ | **Today: $18** |
| **In 30 days: $40** | ○ | ○ | **Today: $20** |
| | ○ | ○ | **Today: $22** |
| | ○ | ○ | **Today: $24** |
| | ○ | ○ | **Today: $26** |
| | ○ | ○ | **Today: $28** |
| | ○ | ○ | **Today: $30** |
| | ○ | ○ | **Today: $32** |
| | ○ | ○ | **Today: $34** |
| | ○ | ○ | **Today: $36** |
| | ○ | ○ | **Today: $38** |
| | ○ | ○ | **Today: $40** |

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## Part 1 of this study: Instructions (3/3)

### Decision screen 2

When you fill out a choice list, you may feel **uncertain about whether you prefer the left or right payment option**. On decision screen 2, we will ask you to select a button to indicate **how certain** you are how much money the larger later payment is worth to you in terms of dollars at the earlier payment date.

In answering this question, we ask you to assume that you would receive both payment options with certainty. We are interested in **your uncertainty about your own preferences regarding these payments**, not in your potential uncertainty about whether you would actually receive the money.

### Example

Suppose that on the first decision screen you indicated that you valued $40 in 30 days somewhere between $12 and $14 today. Your second decision screen would look like this.

**How certain** are you that you actually value $40 **in 30 days** somewhere between $12 and $14 **today**?

| ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0% | 5% | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |

**very uncertain** **completely certain**

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## Comprehension questions

The questions below test your understanding of the instructions.

**Important:** If you fail to answer any one of these questions correctly, you will not be allowed to participate in the study.

1. Which of the following statements is true?

   - ○ In making my decisions, I am asked to assume that I will actually receive all payments as indicated, regardless of whether they take place now or in the future.
   - ○ In making my decisions, I am asked to assume that it is less likely that I will actually receive payments that are meant to take place in the future.
   - ○ In making my decisions, I am asked to assume that it is less likely that I will actually receive payments that are meant to take place now.

2. Suppose you are 80% certain that your decisions actually correspond to how much the different choice options are worth to you. Which button should you click in this case?

   | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
   |---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
   | 0% | 5% | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |

   **very uncertain** **completely certain**

3. When we ask you how certain you are about how much different payments are worth to you at different points in time, then which type of uncertainty are we interested in?

   - ○ Uncertainty about whether I would actually receive the payments.
   - ○ Uncertainty about how much I value the payments, assuming that I know I would receive them with certainty.

## C.3 Instructions for *Voucher Noise*

### Part 1 of this study: Instructions (1/4)

Please read these instructions carefully. There will be comprehension checks. If you fail these checks, we will have to exclude you from the study and you will not receive the completion payment.

In this part of the study, you will **choose between different UberEats food delivery vouchers. These vouchers will vary along two dimensions**:

- **The vouchers will have different values**
- **The vouchers will be valid at different points in time**

### How do the vouchers work?

Each voucher is valid for food delivery during a period of only seven days. A voucher can be used starting **from the indicated date**, and **it remains valid for exactly 7 days after** that date. Specifically, the vouchers work as follows:

- If you win a voucher, you will be informed about the voucher amount and the validity period on the last page of this study. You will then be asked to provide an email address associated with an UberEats account. The voucher will directly be credited to the corresponding UberEats account within the next 10 hours.
- However, the voucher amount **can only be spent during the validity period** of the voucher.
- Vouchers can be used to order from the entire range of restaurants, cafes, and bars that partner with UberEats in your area.
- You do not need to worry about forgetting the validity period: **UberEats will automatically send reminders** about your voucher 24 hours before the validity period starts and 24 hours before it ends.

### What decisions will you be asked to make?

An example decision is between the following two vouchers:

**Valid in 30 days: $40 Voucher** OR **Valid today: $20 Voucher**

The left-hand side voucher carries an amount of $40 and can be spent in the 7-day period starting in 30 days from now. The right-hand side voucher is for an amount of only $20, but can be spent in the 7-day period starting immediately.

Throughout the experiment, there are no right or wrong answers because how much you like a voucher depends on your personal taste.

# Part 1 of this study: Instructions (2/4)

## Decision screen 1

On decision screen 1, you will be asked to choose which of two vouchers you prefer. You will see choice lists such as the one below, where each row is a separate choice. In every list, the left-hand side option (Voucher A) is a voucher that is identical in all rows. The right-hand side option (Voucher B) is a voucher *with an earlier validity period than Voucher A*. The amount associated with the earlier, right-hand side voucher increases as you go down the list. **An effective way to complete these choice lists is to determine in which row you would like to switch from preferring Voucher A to preferring Voucher B.**

Based on where you switch from Voucher A to Voucher B in this list, we assess which voucher amount in the early validity period (Voucher B) you value as much as the voucher amount specified in the later validity period (Voucher A). For example, in the choice list below, you would value a $40 voucher that is valid in 30 days somewhere between a $12 and a $14 voucher that is valid today, because this is where switching occurs.

| Voucher A | | | Voucher B |
|---|---|---|---|
| | ● | ○ | Valid Today: $2 Voucher |
| | ● | ○ | Valid Today: $4 Voucher |
| | ● | ○ | Valid Today: $6 Voucher |
| | ● | ○ | Valid Today: $8 Voucher |
| | ● | ○ | Valid Today: $10 Voucher |
| | ● | ○ | Valid Today: $12 Voucher |
| | ○ | ● | Valid Today: $14 Voucher |
| | ○ | ● | Valid Today: $16 Voucher |
| | ○ | ● | Valid Today: $18 Voucher |
| Valid In 30 days: $40 Voucher | ○ | ● | Valid Today: $20 Voucher |
| | ○ | ● | Valid Today: $22 Voucher |
| | ○ | ● | Valid Today: $24 Voucher |
| | ○ | ● | Valid Today: $26 Voucher |
| | ○ | ● | Valid Today: $28 Voucher |
| | ○ | ● | Valid Today: $30 Voucher |
| | ○ | ● | Valid Today: $32 Voucher |
| | ○ | ● | Valid Today: $34 Voucher |
| | ○ | ● | Valid Today: $36 Voucher |
| | ○ | ● | Valid Today: $38 Voucher |
| | ○ | ● | Valid Today: $40 Voucher |

If you are selected to receive an additional reward from part 1 of the study, your reward will be determined as follows:
Your choice in a randomly selected row of a randomly selected choice list determines the amount of your personal voucher. Each choice list and each row are equally likely to get selected.

**Important:**

- Your choices may matter for real money! If you are selected to receive a bonus, one of your choices will actually be implemented, and your decision will determine which type of voucher you receive.
- Since only one of your decisions will be randomly selected to count, you should consider each choice list independently of the others. There is no point in strategizing across decisions.

On the next page, you will see an example choice list, and you can practice making your selections.

Click "Next" to proceed to the example page.

# Part 1 of this study: Instructions (3/4)

**Auto-completion**: The table auto-completes your choices so you don't have to click through all of the rows. You do not have to start at the top of the table. If you select Voucher A in any one row, we assume that you will also prefer Voucher A in all *above* that row. If you select Voucher B in any one row, we assume that you will also prefer Voucher B in all rows *below* that row.

Reminder: both vouchers are valid for 7 days starting on the day indicated for each voucher.

| Voucher A | | | Voucher B |
|---|---|---|---|
| | ○ | ○ | **Valid today: $2 Voucher** |
| | ○ | ○ | **Valid today: $4 Voucher** |
| | ○ | ○ | **Valid today: $6 Voucher** |
| | ○ | ○ | **Valid today: $8 Voucher** |
| | ○ | ○ | **Valid today: $10 Voucher** |
| | ○ | ○ | **Valid today: $12 Voucher** |
| | ○ | ○ | **Valid today: $14 Voucher** |
| | ○ | ○ | **Valid today: $16 Voucher** |
| | ○ | ○ | **Valid today: $18 Voucher** |
| **Valid in 30 days: $40 Voucher** | ○ | ○ | **Valid today: $20 Voucher** |
| | ○ | ○ | **Valid today: $22 Voucher** |
| | ○ | ○ | **Valid today: $24 Voucher** |
| | ○ | ○ | **Valid today: $26 Voucher** |
| | ○ | ○ | **Valid today: $28 Voucher** |
| | ○ | ○ | **Valid today: $30 Voucher** |
| | ○ | ○ | **Valid today: $32 Voucher** |
| | ○ | ○ | **Valid today: $34 Voucher** |
| | ○ | ○ | **Valid today: $36 Voucher** |
| | ○ | ○ | **Valid today: $38 Voucher** |
| | ○ | ○ | **Valid today: $40 Voucher** |

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# Part 1 of this study: Instructions (4/4)

## Decision screen 2

When you fill out a choice list, you may feel **uncertain about whether you prefer the left or right voucher**. On decision screen 2, we will ask you to select a button to indicate **how certain** you are about how much the larger voucher amount with the later validity period is worth to you in terms of voucher credit that can be spent in the earlier validity period.

## Example

Suppose that on the first decision screen you indicated that you value a $40 voucher that is valid in 30 days somewhere between a $12 and a $14 voucher that is valid today. Your second decision screen would look like this.

**How certain** are you that you actually value a $40 voucher that is valid **in 30 days** somewhere between a $12 and a $14 voucher that is valid **today**?

| ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0% | 5% | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |

**very uncertain** **completely certain**

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## Comprehension questions

The questions below test your understanding of the instructions.

**Important:** If you fail to answer any one of these questions correctly, you will not be allowed to participate in the study, and you will not receive the completion payment.

1. Which of the following statements about the voucher below is true?

   **Valid in 1 month: $30 Voucher**

   - ○ This voucher can be used to order food starting from today until no later than 1 month.
   - ○ This voucher can be used to order food any time after 1 month. The validity period has no end date.
   - ○ This voucher can be used to order food in the 7-day period starting in 1 month.

2. Suppose you are 80% certain that your decisions actually correspond to how much the different voucher options are worth to you.

   Which button should you click in this case?

   | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
   |---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
   | 0% | 5% | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% | 95% | 100% |

   **very uncertain** **completely certain**

3. Which of the following statements is true?

   - ○ Even if the validity period starts in the future, my voucher will be credited to my UberEats account shortly after the experiment. I do not have to remember the validity period because UberEats will send me reminders.
   - ○ If the validity period of the voucher starts in the future, I should expect to get my voucher credited to my UberEats account only shortly before the validity period starts. I have to memorize the validity period, otherwise I may forget to use the voucher amount. There is also some risk that I will not actually receive the voucher.