Information Processing and the Anomalies of Risk and Time*

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Abstract

A growing body of cognitive models attributes many canonical behavioral anomalies to frictions in information processing. Guided by a model of imprecise cognition, we experimentally show that merely changing the way information on payoffs, probabilities and time delays is presented to subjects produces a rich array of predictable, sizable and parallel effects on risky and intertemporal choice. As predicted, superficial changes to framing cause key anomalies like probability-dependence, decreasing impatience, small-stakes risk aversion and present bias to *shrink, disappear or even reverse* on average, suggesting that such anomalies may be, to a significant degree, outgrowths of cognitive frictions rather than of stable preferences.

Keywords: noisy cognition; risk-taking; delay-discounting

1 Introduction

A growing literature suggests that cognitive frictions — imperfections in the way the brain processes information — can account for a number of important regularities in behavioral economics. Most importantly, a number of cognitive models suggest that cognitive frictions may be responsible for many of the key anomalies documented in the literature, including many of the signature anomalies of risk and time. Less directly, unlike traditional preference-maximization models, these cognitive models also create immediate scope for *framing effects*. Since the way information is presented can influence how (and how well) it is processed by the brain, we should expect the severity of anomalies — to whatever extent they are indeed generated by cognitive frictions — to be influenced

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by the way information is framed. In this paper, we make use of this implication to empirically investigate the role cognitive frictions play in several of the literature's key anomalies.

Guided by a "noisy cognition" model, we show that simply by altering the way we present information on payoffs, probabilities and time delays in standard experiments (e.g., by changing the denomination of payments or switching from numeric to visual presentations of quantitative information), we can *attenuate, eliminate or even reverse* some of the core behavioral anomalies from the domains of risk and time in systematic and parallel ways. Since these kinds of framing effects are implications of cognitive explanations for these anomalies — but *not* of preference-based explanations — our results provide a novel strain of evidence that canonical anomalies like insensitivity to probabilities (à la probability weighting), insensitivity to time delays (à la hyperbolic discounting), subadditivity, present bias, small stakes risk aversion, stake effects for risk and the absolute magnitude effect may be (at least to a significant extent) driven by information processing frictions rather than by stable preferences. We show that these framing effects match distinctive — and often counterintuitive — predictions of the cognitive model we used to motivate and design our experiment.

Cognitive frictions and anomalies. Our investigation is organized and guided by a model of imprecise cognition. Like related models, ours is rooted in the idea that choice behavior is shaped by (i) the noisy way the brain processes and stores information and (ii) by the optimal strategies the brain deploys to cope with this imprecision. In particular, because choice primitives like payoffs, probabilities and time delays are processed and represented imprecisely neuronally, the brain combines internal representations of these primitives with prior beliefs about their value in a Bayesian manner, producing *systematic distortions* in choice due to Bayesian compression. Because of this compression, cognitive noise does not average out, but instead produces systematic biases.

As we show in Section 2, this cognitive compression can account for a number of famous, seemingly disconnected anomalies in the domains of risk and time for parallel reasons.[1] For instance, noise-generated compression will produce insensitivity to probabilities (the empirical basis for models of probability weighting) in the domain of risk for the same

[1] See Prelec and Loewenstein (1991) for an early discussion of the parallels between anomalies in the domains of risk and time.

reason it produces insensitivity to payment delays (the empirical basis of models of hyperbolic discounting) in the domain of time. Likewise, the same frictions that produce small-stakes risk aversion also produce exaggerated impatience and present bias in the domain of time. Finally, these frictions immediately predict that long-documented payoff magnitude effects from both the domains of risk and time arise for parallel reasons that are rooted, not in payoff magnitudes themselves, but in the imprecision associated with processing less commonly encountered magnitudes.

Crucially, our model makes highly distinctive predictions about *why* noise generates these anomalies and therefore *how* changes in cognitive imprecision should affect them. As our model makes clear, most of the preceding anomalies aren't a consequence of *too much* cognitive noise, but rather of a disbalance in the noisiness of probability (or delay) processing *relative to* the noisiness of payoff processing. Because of this, comparative statics of our model suggest that *increasing* the precision with which probabilities (or time delays) are processed should have the same qualitative effect on the severity of most of these anomalies as *decreasing* the precision with which payoffs are processed. In other words, our model predicts that we can reduce the severity of anomalies either by reducing the severity of cognitive frictions (surrounding probabilities/delays) or by increasing them (with respect to payoffs)! This highlights a key point that runs through our study: seemingly neoclassical behavior is not necessarily evidence of greater rationality, but simply emerges whenever (i) probabilities (or delays) and (ii) payoffs are processed with similar imprecision.

Framing as an empirical instrument. To test the proposition that parallel information processing frictions are drivers of many of the signature anomalies of risk and time, we make use of another key implication of cognitive models: that behavior should be influenced by payoff-irrelevant aspects of the way information is presented. The cognitive imprecision at the heart of our model stems from processing frictions like difficulties processing unfamiliar or complex information; allocation of scarce cognitive resources based on prior experiences; and the way the brain uses salience or associations to allocate limited funds of attention across primitives of a problem. Since these kinds of frictions are influenced by the way information is presented, manipulating the way payoffs, probabilities and time delays are framed to subjects will tend to alter the *relative noise* associated with these primitives and (according to our model) thereby alter the severity of many key anomalies in the domains of risk and time in parallel ways.

In our experiment, described in Section 3, subjects make a number of binary choices either between lotteries (risky choice experiments) or between payments made at sooner or later dates (intertemporal choice experiments). The key manipulation in our design is that we vary the framing of payoffs, probabilities and time delays in superficial ways that we, nonetheless, hypothesized would alter the relative precision with which these quantities are processed. First, we vary whether we describe *identical payoff amounts* (in both lotteries and intertemporal choices) in terms of British pounds or pence. Motivated by evidence of "numerical adaptation" (people more precisely process and represent numerical information at scales they are more often exposed to; Khaw, Li and Woodford, 2021; Frydman and Jin, 2022; Garagnani and Vieider, 2025), we predict that the pence denomination will decrease the cognitive precision of payoffs relative to pounds, even though the payoff amounts themselves are identical. Second, we vary whether we describe *the same quantitative information* (about probabilities or time delays) visually rather than numerically — a change to framing that we predict will systematically *increase* the cognitive precision associated with probabilities and time delays.[2] Again, our model makes the distinctive (and counterintuitive) prediction that both *increasing* the cognitive precision of probabilities/delays (by presenting information visually) and *decreasing* the cognitive precision of payoffs (by changing from pounds to pence) will have the same qualitative effect of reducing the severity of parallel anomalies in the domains of risk and time.

We argue that this method for assessing the role cognitive frictions play in anomalies makes for a particularly powerful test precisely because these manipulations are not substantive: under the lens of any rational preference-based model (including standard descriptive behavioral models), these framing manipulations leave the task unchanged and therefore should have no effect on behavior. Because of this, evidence that these manipulations have *any* systematic effects on risky or intertemporal choice immediately

[2]In risky choice tasks we vary whether likelihoods are framed using percentages vs. 10 numbered balls pictured on the subject's screen, while in intertemporal choice, we vary whether time delays of payments are given with numbers (of weeks) vs. lines visualizing the length of the payment delay. This manipulation relies on the intuition that visual displays help people to grasp information faster and with less cognitive effort, thereby increasing the representational precision in quick tradeoffs. For instance, Bouchouicha, Li and Vieider (2025) show that visual displays reduce the asymmetry in the precision with which gains and losses are represented, thereby systematically shifting choice patterns over mixed gain-loss gambles.

suggests that information processing frictions likely play an important role in shaping behavior in these domains, regardless of whether the effects match the predictions of the specific cognitive model we used to motivate and design our experiment. However, because we also designed the experiment around a specific cognitive model — one that makes distinctive comparative statics predictions — our experiment *also* poses a test of the specific imprecise cognition mechanism that animates our model.[3,4]

Findings. In Section 4 we show that the way information is presented has strong and parallel effects on behavior in both the domains of risk and time. What's more, these effects match a rich array of distinctive comparative static effects predicted by our imprecise cognition model. Decreasing cognitive precision around payoffs (by manipulating payoff denominations) or increasing cognitive precision around probabilities/delays (by using visualizations) *both* significantly reduce (i) probability insensitivies (à la "probability weighting") in the domain of risk and (ii) delay insensitivities (à la "hyperbolic discounting")[5] in the domain of time. Likewise, each of these same manipulations (i) alter the severity of small stakes risk aversion in risky choice and (ii) reduce both overall impatience and present bias in intertemporal choice, just as our model predicts. Finally, manipulations of payoff denominations replicate canonical "stakes effects" in both the domains of risk and time (i.e., the "absolute magnitude effect") without actually changing the magnitudes of monetary rewards.

Importantly, these framing effects are powerful enough that, when combined, they *eliminate or reverse* some of the most important anomalies documented in the behavioral time

[3]Technically, our experiment poses a joint test of (i) our cognitive model and (ii) our hypotheses about how framing should influence cognitive noise. Although these hypotheses are well-motivated (and have some empirical backing), what exactly causes imprecision in internal representations and where the boundary conditions of such imprecision may lay remains under-investigated at this point. We return to this important question in the Discussion.

[4]Another subtle (but important) advantage of our test is that it is robust to potential "cognitive spillovers" because of the relative nature of the main predictions the model makes. If a manipulation meant to, e.g., increase the cognitive precision of probabilities (by providing visualizations) simultaneously draws attention away from and thus reduces the cognitive precision of payoffs, the qualitative comparative static prediction is identical. Similarly, if a manipulation meant to decrease cognitive precision of payoffs (by switching from pound to pence descriptions) shifts attention to probabilities, increasing precision, the qualitative predictions are unchanged. The fact that predicted cognitive noise effects run in opposite directions for probabilities/delays vs. payoffs therefore makes our predicted framing effects easier to measure.

[5]Our model predicts (and we find strong evidence supporting this prediction) that this occurs because it eliminates subadditivity (Read, 2001), the main driver of insensitivity in our data; by contrast we find no evidence of strongly declining impatience — impatience declining systematically as a given time delay is pushed farther and farther into the future — an alternative candidate driver of the same phenomenon (Prelec, 2004).

and risk literatures on average. For instance, systematic insensitivity to changes in probabilities (the empirical basis for theories of probability weighting) disappears (and even slightly *reverses* to *over*sensitivity) when framing manipulations are used to maximize probability precision and reduce payoff precision. Similarly, insensitivity to delays (the empirical basis for theories of hyperbolic discounting) virtually disappears at the median, leading to near-exponential discounting when framing is used to maximize delay precision while at the same time reducing payoff precision. Finally, the same manipulation causes subadditivity also to disappear, while present bias (the core anomaly described in models of quasi-hyperbolic discounting) is severely reduced. The fact that we can eliminate systematic evidence for these canonical anomalies simply by manipulating framing under the guidance of cognitive models suggests that many of the most important regularities in behavioral economics may be largely (or even entirely) driven by imperfections in information processing rather than rational responses to preferences.

Implications. We think there are three main implications of these results. First, our findings inform long-running debates in the literature on how to interpret behavioral preference models (e.g., prospect theory, the $\beta - \delta$ model etc.) designed to describe and account for some of the literature's most important behavioral anomalies. The literature has long been ambivalent on whether these models should be interpreted as (i) descriptions of systematic errors due to limitations in human cognition or (ii) as (potentially welfare-relevant) descriptions of true tastes for risk or delayed rewards. For instance, prospect theory parameters are often treated by the literature as preference parameters but another tradition (beginning with Kahneman and Tversky, 1979, themselves) interprets many of its parameters as describing, instead, behavioral consequences of (unmodeled) perceptual frictions (see Wakker, 2010). Similar debates surround behavioral intertemporal choice models, where discount functionals are sometimes interpreted as preference primitives and sometimes as reflections of psychological or perceptual processes. We interpret the fact that cognitively-motivated changes to framing can eliminate or reverse many of the key anomalies motivating these models as strong evidence in favor of a cognitive error interpretation (i).

Second, because of this, our findings also highlight the promise of complementing descriptive behavioral models with explicit cognitive models. Expected utility theory (von Neumann and Morgenstern, 1944; Savage, 1954), discounted utility theory (Samuelson, 1937), and their behavioral extensions (e.g., Kahneman and Tversky, 1979; Loewenstein and Prelec, 1992) make no predictions about how behavior should change when the presentation of identical choice primitives varies. As long as the underlying outcomes, probabilities, and delays remain the same, these models presume that behavior is governed by stable, exogenous preferences and therefore invariant to format. Because of this, they cannot account for or predictively anticipate framing effects that clearly have first-order influences on behavior. As we show, cognitive models often make rich and highly distinctive predictions about these effects that bear out in data and therefore can be used to shore up the predictive limitations of more descriptive models. By (effectively) providing cognitive micro-foundations for parameters in standard behavioral models, explicit cognitive models can predict how these parameters can be expected to be shaped by (and change due to) payoff-irrelevant factors.

Finally, our results point to a consilience between a number of behavioral anomalies that have typically been treated as domain-specific and therefore unrelated to one another. For instance, our finding that key behaviors respond in nearly identical ways to virtually identical manipulations of framing in the very different domains of risk and time suggests that *factors that are not specific to either risk or time* play a fundamental role in shaping behavior in these domains. Since the levers that produce these effects are motivated and predicted by a cognitive model, our results suggest that domain-general cognitive frictions may be responsible for this link between anomalies across domains. Likewise, within-domain, behaviors that are seemingly distinct (e.g., subadditivity and present bias, or average risk aversion and likelihood insensitivity) are in fact linked to one another by cognitive frictions. Finally, because mere manipulations of presentation generate these effects, our results also link framing anomalies to the signature anomalies of risk and time. Indeed, under the lens of our noisy cognition model, many key anomalies of risk and time *are* framing effects — behavioral responses to payoff irrelevant aspects of the choice environment. All of these point to the possibility that the anomalies that scaffold behavioral economics may have a significantly more parsimonious structure than is generally realized — promising news for the positive project of economics.

1.1 Relation to the literature

Our work connects to a growing literature studying the cognitive foundations of economic behavior (Enke, 2024). This literature considers both theoretically and empirically how limitations in attention (Bordalo, Gennaioli and Shleifer, 2012; Gabaix, 2019; Maćkowiak, Matějka and Wiederholt, 2023), memory (Bordalo, Gennaioli and Shleifer, 2020; Bordalo et al., 2023; Enke, Schwerter and Zimmermann, 2024; Graeber, Roth and Zimmermann, 2024), available time (Alós-Ferrer, Buckenmaier and Garagnani, 2020; Frydman and Krajbich, 2022) and computational ability (Woodford, 2020; Oprea, 2024*a*) — and adaptations to these constraints like salience effects (Bordalo, Gennaioli and Shleifer, 2022; Li and Camerer, 2022), cuing (Jiang et al., 2025; Gennaioli et al., 2024), comparative thinking (Arieli, Ben-Ami and Rubinstein, 2011; Bushong, Rabin and Schwartzstein, 2021; Shubatt and Yang, 2024; Graeber and Enke, 2026), behavioral attenuation (Enke et al., 2024) and heuristics (Mullainathan, Schwartzstein and Shleifer, 2008; Bordalo et al., 2016) — shape belief formation and decision-making. The goal of this literature is not only to produce more accurate accounts of the psychological drivers of economic behavior, but also to create models that improve our ability to positively predict and normatively interpret that behavior.

One theme from this literature that connects to our study is that anomalies identified in the prior literature can often be explained as outgrowths of cognitive frictions, and that these frictions are often domain-general, generating similar behavioral patterns in seemingly dissimilar contexts.[6] We provide a novel source of evidence for both suppositions, showing that superficial changes to the way information on primitives are presented produces large and systematic changes to a number of classic anomalies, and that these changes are parallel in the two very different domains (risk and time), suggesting a shared, domain-general mechanism.

Another important theme, also mirrored in our study, is that cognitive constraints cause behavior to be sometimes highly sensitive to payoff-irrelevant aspects of the choice envi-

[6] For example, Enke et al. (2024) document that behavioral attenuation underlies a wide range of empirical regularities in domains as varied as risk, time, consumption-savings, effort supply, taxes, fairness, prediction, and strategic games. Similarly, salience-based accounts have been used to organize choice and belief patterns across consumer choice, risky choice, and stereotyping (Bordalo, Gennaioli and Shleifer, 2012; 2013; Bordalo et al., 2016), and memory-based accounts have been used to organize phenomena across belief formation, finance, macro and discrimination (Bordalo, Gennaioli and Shleifer, 2020; Bordalo et al., 2023; Enke, Schwerter and Zimmermann, 2024; Jiang et al., 2025; Gennaioli et al., 2024; Miserocchi, 2023).

ronment. For instance, a growing literature shows that bottom-up salience of pieces of information can have significant impacts on behavior (Bordalo, Gennaioli and Shleifer, 2012; Frydman and Mormann, 2018; Frydman and Wang, 2020; Li and Camerer, 2022; Bose et al., 2022; Bohren et al., 2024). The complexity of information can have similar effects (Oprea, 2020; 2024*a*; Enke and Shubatt, 2023; Salant and Spenkuch, 2025; Puri, 2025; de Clippel et al., 2024). Finally, because of the way the brain distributes information, familiarity with and expectations regarding types of information can impact how well it is processed (Malmendier and Nagel, 2011; 2016; Khaw, Li and Woodford, 2021; Frydman and Jin, 2022; Heng, Woodford and Polania, 2023; Garagnani and Vieider, 2025). Our framing manipulations are, in part, inspired by this body of work because they rely on the idea that attention, complexity and familiarity shape the way cognitive precision is allocated.

Imprecise cognition and optimal information processing. Within the literature on cognitive economics, our work is most connected to a sub-literature that models choices as optimal responses to noisy information processing. Natenzon (2019) shows how correlated perceptual noise can explain attraction and compromise effects. Khaw, Li and Woodford (2021) model small-stakes risk aversion as arising from noisy number perception. Enke and Graeber (2023) show that regression to the mean in certainty equivalent lists relates to measures of cognitive uncertainty, while Oprea (2024*b*) and Enke, Graeber and Oprea (2024) demonstrate how complexity alone can generate choice patterns typically associated with risk or time preferences and Enke and Shubatt (2023) document the drivers of lottery complexity. Dean et al. (2026) show how imprecise beliefs can create scope for reference point effects. Our paper also relates to evolutionary and constraint-based accounts of decision-making (Friedman, 1989; Robson, 2001*b*;*a*; Netzer, 2009; Steiner and Stewart, 2016; Herold and Netzer, 2023; Netzer et al., 2025). Our closest connections are to models that view probability distortions as emerging from noisy cognition (Zhang, Ren and Maloney, 2020; Frydman and Jin, 2023; Khaw, Li and Woodford, 2023). Relative to these papers, our contribution is (i) to study how changes to the *processing* of new information (rather than, e.g., changes to prior expectations) influence behavior; (ii) to emphasize (and empirically demonstrate) the importance of payoff noise (in addition to probability noise) for shaping the degree of probability weighting that occurs; and (iii) to show that the same patterns extend to delay discounting in a parallel way.

Instability of measured preferences. Our experimental manipulations connect to a long tradition documenting the instability of elicited risk and time preferences. Slovic (1964) first showed that levels of risk-taking can vary systematically across choice architectures. Violations of procedure invariance — the principle that risk and time tradeoffs should be independent of the elicitation method, and which is built into virtually all high-level behavioral models — have since proven widespread (e.g., Loomes and Pogrebna, 2014; Crosetto and Filippin, 2015; Mata et al., 2018; Imai et al., 2025). Preference reversals have been documented between choice and valuation tasks (Lichtenstein and Slovic, 1971; Grether and Plott, 1979; Bouchouicha et al., 2024), and within choice lists depending on which attribute is varied (Hershey and Schoemaker, 1985; Feldman and Ferraro, 2023; Shubatt and Yang, 2024). In contrast to these studies, the patterns we document arise *within identical binary choice tasks*. This makes them particularly challenging for preference-based models resting on utility-maximization, which assume that such choices reveal stable taste-based transformations of objective primitives.

A particularly relevant literature on preference instability studies how visual or structural presentation formats affect risk and time choices. Several papers investigate whether presenting probabilities or outcomes visually influences risk-taking, typically in choice lists. Friedman et al. (2022) find that visual displays tend to move behavior toward risk neutrality. Castillo and Starmer (2023) vary the visual representation of both probabilities and rewards using a rich set of certainty equivalents and find attenuated utility curvature. Estepa-Mohedano and Espinosa (2023) report decreased risk aversion when rewards are displayed with money bills, though not when probabilities are displayed visually (see also Habib et al., 2017). Segovia et al. (2025) combine visual displays with eye-tracking and find no systematic effects. The time-domain literature reveals similar themes. Read et al. (2005) find that using calendar dates reduces discount rates and eliminates apparent hyperbolicity; Ebert and Prelec (2007) illustrate the "fragility" of delay perception; and Zauberman et al. (2009) show that average subjective time perceptions can organize several discounting regularities. Our design extends this work by manipulating both delays and outcomes, by examining not only delays from the present but also delays from up-front delays, and by using a model that predicts why each manipulation should matter.

2 Choices under risk and time as Bayesian inference

Noisy cognition models study how imperfections in information processing shape behavior. A central premise, grounded in neuroscience, is that the brain processes economic quantities — such as payoffs, probabilities, and time delays — with frictions, generating imprecise internal signals rather than exact values. When decoding internal representations to make decisions, the brain combines these signals with prior beliefs or expectations in a Bayesian manner, effectively *inferring* the underlying quantities they represent. The Bayesian compression in this inference process induces systematic distortions in decision quantities, which can generate many of the choice patterns documented as anomalies in behavioral economics. Building on Vieider (2024*b*) and Vieider (2023), we apply a common imprecise processing model to risky and intertemporal choice and use it to derive parallel predictions across the two domains.

2.1 Cognitive frictions in representations of risk and time

As in our experiment, consider two standard binary choice environments. In the domain of risk, individuals choose between a lottery paying x with probability p and y otherwise, denoted $(x, p; y)$, and a sure outcome c. In the domain of time, individuals choose between a smaller-sooner amount S received at time τ_s and a larger-later amount L received at time $\tau_\ell > \tau_s$.

Under risk, we assume that decision-makers trade off the log-odds in favor of winning (earning $x > y$) against the relative log cost–benefit ratio, choosing the lottery whenever

$$\ln \frac{p}{1-p} \geq \ln \frac{c-y}{x-c}.$$

This is simply equivalent to choosing the lottery whenever expected benefits exceed expected costs, $p(x-c) \geq (1-p)(c-y)$.[7]

In the domain of time, we make an analogous assumption. Decision-makers choose the smaller-sooner reward whenever the 'log-time odds' exceed the log reward ratio,

$$\ln \frac{p_s}{p_\ell} \geq \ln \frac{L}{S},$$

[7]We thus assume that, in the absence of noise, decision-makers maximize expected value under risk. While stable preferences may also shape such tradeoffs, this normalization allows us to isolate the effects of noisy cognition. Incorporating preference parameters would not alter the qualitative predictions derived below.

where $p_s \triangleq e^{-\tau_s}$ and $p_\ell \triangleq e^{-\tau_\ell}$. This condition is equivalent to the comparison of exponentially discounted values, $e^{-\tau_s} S \geq e^{-\tau_\ell} L$.[8]

These representations have a close structural parallel: in both domains, choice can be expressed as a comparison between a log-odds term and a log reward ratio — log-odds of winning versus relative payoffs under risk, and log-time odds versus relative rewards under time. This formulation treats choice as a direct tradeoff between two competing pieces of relevant information in each domain. In the risk domain, this comparison has the form of a log-likelihood ratio test, closely related to evidence accumulation frameworks in signal detection theory (Green, Swets et al., 1966; Gold and Shadlen, 2001). In the time domain, instead of an additively separable representation of discounting it involves a joint comparison of delays and rewards, closely related to Scholten, Read and Sanborn (2014).[9]

Before making use of log-odds and log-reward ratios to inform decisions, these quantities have to be processed and represented by the brain and we assume the brain does this imperfectly (imprecisely). Let z denote a choice-relevant quantity (i.e. log-odds or log reward ratios). The brain observes an *imprecise internal representation* r_z, drawn from a likelihood centered at $\ln z$ with variance ν_z^2.[10] Prior beliefs over such quantities are given by $\ln z \sim \mathcal{N}(\ln \zeta, \sigma_z^2)$. Bayesian updating optimally combines these noisy representation with prior beliefs about their quantities, yielding

$$\mathbb{E}[\ln z \mid r_z] = \frac{\lambda_z}{\lambda_z + \xi_z}\, r_z + \frac{\xi_z}{\lambda_z + \xi_z}\, \ln \zeta,$$

where $\lambda_z = \nu_z^{-2}$ and $\xi_z = \sigma_z^{-2}$ denote the precision of the signal and the prior, respectively. The value of z is thus inferred by the brain from a precision-weighted combination of the signal and the prior.

Let $\hat{z}(r_z) \triangleq \mathbb{E}[\ln z \mid r_z]$ denote the posterior expectation. Repeated over many trials with

[8] As in the risk domain, we abstract from preference parameters to focus on inference-driven distortions; introducing such parameters would not affect the predictions that follow.

[9] Eye-tracking evidence supports the attribute-wise tradeoffs described by this model in both domains, showing that subjects actively compare probability or delay information with reward information when making choices (Arieli, Ben-Ami and Rubinstein, 2011).

[10] Although, we model internal representations as noisy, it is important to emphasize that we are agnostic about where in cognition this noise enters. While it is possible that this noise enters due to imprecise numerical perception or imperfections in working memory, it is also possible for it to enter when the decision maker is manipulating, aggregating or comparing quantities to inform choice.

the same true primitive z, the posterior's expected estimate is

$$\mathbb{E}[\hat{z}(r_z) \mid z] = \frac{\lambda_z}{\lambda_z + \xi_z} \ln z + \frac{\xi_z}{\lambda_z + \xi_z} \ln \zeta.$$

This is the familiar Bayesian regression toward the prior mean, and it is optimal in the precise sense of minimizing mean squared error across many trials (Ma, Kording and Goldreich, 2023). Here and throughout, we assume that the brain processes and stores information in log space, with Gaussian noise. While unnecessary for our qualitative predictions, these assumptions are standard in the cognitive noise literature because they (i) match evidence from the neurophysical literature and (ii) make our analysis more tractable.[11]

2.2 Risky and intertemporal choice

The inference described above is applied separately to each primitive entering choice: log-odds and log cost–benefit ratios under risk, and log delays and log-transformed reward ratios under time. Under risk, choice trades off inferred log-odds against inferred log reward ratios; under time, the analogous tradeoff is between inferred log delays and inferred twice-log-transformed reward ratios. The log transformations make it easy to additively aggregate information from different sources (Gold and Shadlen, 2001; 2002), and provide for efficient neural representations on a compressed scale that make optimal use of scarce neural resources (Dehaene, 2003; Khaw, Li and Woodford, 2021). They further ensure that the posterior can be obtained by a simple linear combination of evidence and prior, which means that the operation can be easily performed by neural networks, thus ensuring neural realism.

After rearranging (see Online Appendix A for a step-wise derivation), the probability of

[11]These assumptions are not only tractable, they are also consistent with efficient evidence accumulation (Gold and Shadlen, 2001; 2002) and with neurophysiological evidence on numerical coding (Dehaene, 2003; Nieder, 2016). This conjugate structure yields closed-form expressions while preserving the key qualitative features of Bayesian inference. Gaussian representations in log-odds or log-reward ratio space arise naturally under mild assumptions, for example when probability assessments derive from Binomial–Beta processes (Atchison and Shen, 1980; Oprea and Vieider, 2024). Simulations in Gold and Shadlen (2001) suggest that the qualitative predictions are robust across a wide class of unimodal representations, and such formulations are widely used in models of noisy cognition (Khaw, Li and Woodford, 2021).

choosing the risky lottery $(x,p;y)$ over the sure amount c can be written as:

$$p[(x,p;y)\succ c]=\Phi\left[\frac{\frac{\gamma}{\beta}\ln\left(\frac{p}{1-p}\right)+\frac{1-\gamma}{\beta}\ln(\eta)-\ln\left(\frac{c-y}{x-c}\right)-\frac{1-\beta}{\beta}\ln(\kappa)}{\sqrt{\left(\frac{\gamma}{\beta}\right)^2\frac{1}{\lambda_p}+\frac{1}{\lambda_o}}}\right], \tag{1}$$

where λ_p and λ_o denote the precision of log-odds and log cost–benefit representations, and where $\ln(\eta)$ and $\ln(\kappa)$ denote prior expectations about log-odds and log-cost benefits, respectively. The parameters $\gamma\triangleq\frac{\lambda_p}{\lambda_p+\xi_p}$ and $\beta\triangleq\frac{\lambda_o}{\lambda_o+\xi_o}$ are *evidence weights*, capturing the weight conferred on each piece of evidence relative to the respective priors. Higher precision in log-odds representations increases γ, raising the influence of observed probabilities in choice, while lower precision compresses log-odds toward the prior mean. The same applies to β for relative rewards.

A directly parallel expression obtains for intertemporal choice. Writing the time log-odds as $\ell-s$ (with $s=\tau_s+1$ when $\tau_s>0$ and $s=0$ otherwise, and $\ell=\tau_\ell+1$), the probability of choosing the smaller–sooner option is

$$p[(S,\tau_s)\succ(L,\tau_\ell)]=\Phi\left[\frac{\frac{\widehat{\gamma}}{\widehat{\beta}}\ln(\ell-s)+\frac{1-\widehat{\gamma}}{\widehat{\beta}}\ln(\theta)-\ln\left(\ln\frac{L}{S}\right)-\frac{1-\widehat{\beta}}{\widehat{\beta}}\ln(\rho)}{\sqrt{\left(\frac{\widehat{\gamma}}{\widehat{\beta}}\right)^2\frac{1}{\lambda_t}+\frac{1}{\lambda_r}}}\right], \tag{2}$$

where $\widehat{\gamma}\triangleq\frac{\lambda_t}{\lambda_t+\xi_t}$ and $\widehat{\beta}\triangleq\frac{\lambda_r}{\lambda_r+\xi_r}$ are the evidence weights for delays and reward ratios, and where $\ln(\theta)$ and $\ln(\rho)$ denote prior expectations over delays and reward ratios. The interpretation mirrors that under risk. The addition of 1 to the time delays serves to preserve the numerical efficiency and resource-saving rationale of the neural log representation, since it prevents the number to be represented from going to minus infinity as the time delay approaches zero.[12]

The key observation is that both domains share a common structure: choices depend on a precision-weighted comparison of two imprecisely processed and represented attributes — probabilities versus outcomes under risk, and delays versus rewards under time. In both cases, behavior exhibits constant-elasticity comparative statics. We now examine

[12]Such numbers are routinely added in the literature to log-coded numbers (Petzschner and Glasauer, 2011; Howard and Shankar, 2018). While the choice of an integer value of 1 is somewhat arbitrary, it here serves to limit our degrees of freedom, which would be increased by making this an additional constant to be estimated.

these implications in detail.

2.3 Imprecise Processing and Anomalies

The choice equations described above suggest that cognitive precision fundamentally and similarly influences behavior in both the domains of risk and time: changes to cognitive precision (such as those we propose with the manipulations in our experiment, below) can intensify, attenuate, eliminate or even reverse some of the signature behavioral patterns in both domains. Because of this, by altering the precision with which various pieces of attribute information are internally represented and processed, we can shift the weight placed on presented information relative to subjects' prior beliefs. The experiment described in the next section uses this implication to assess the theory.

A crucial aspect of our model is that cognitive noise generates *joint* predicted effects across multiple behavioral dimensions at once, altering multiple anomalies simultaneously. In particular changes in representational precision are predicted to simultaneously affect (i) sensitivity to probabilities and time delays (the basis of core models like probability weighting and hyperbolic discounting), as well as (ii) average risk aversion and impatience (including present bias). These effects arise from a common source — precision-based re-weightings of the influence of signals vs. priors — and therefore cannot vary independently. As a result, the model delivers a rich but tightly structured set of predictions, in which different behavioral quantities are expected to co-move in systematic and testable ways that are highly parallel across risk and time.

1. Insensitivity to probabilities and delays ("probability weighting" and "hyperbolic discounting"). The first implication of equations (1) and (2) is that they imply insensitivity to probabilities and time delays, and that both will change in parallel, systematic ways with the nature of cognitive imprecisions. Taking the derivative of log-rewards with respect to log-odds, we measure how much relative rewards must change when the odds of winning change in order to maintain indifference:

$$\partial \ln\left(\tfrac{c-y}{x-c}\right) / \partial \ln\left(\tfrac{p}{1-p}\right) = \gamma/\beta.$$

For time, the analogous object is the derivative of the transformed reward ratio at indifference with respect to log-time odds,

$$\partial \ln\!\left(\ln \tfrac{L}{S}\right) / \partial \ln(\ell - s) = \widehat{\gamma}/\widehat{\beta}.$$

Sensitivity of choices to probabilities and time delays are thus governed by the elasticities γ/β and $\widehat{\gamma}/\widehat{\beta}$, respectively. The canonical anomalies of insensitivity to probabilities (the basis of "probability weighting") and insensitivity to time delays (the basis of "hyperbolicity") thus obtain whenever $\gamma < \beta$ and $\widehat{\gamma} < \widehat{\beta}$ — whenever probability and delay representations are less precise than reward representations.

Figure 1 illustrates the behavioral predictions of the model under shifts in the relative precision of probability or delay versus reward representations (which, in our experiment, we will attempt to induce via framing manipulations). Standard probability-dependence in risk-taking (relative risk aversion increasing in probabilities) is expected whenever probabilities are represented less precisely than rewards, so that $\gamma/\beta < 1$ (low-sensitivity case in Panel A). *Ceteris paribus*, any manipulation of the choice environment that increases the precision of log-odds representations, λ_p, thereby increasing γ, will increase sensitivity to probabilities (high-sensitivity case in Panel A). A fully parallel prediction holds for time. Standard decreasing impatience for delays from the present ($s = 0$) arises whenever delays are represented less precisely than rewards, so that $\widehat{\gamma}/\widehat{\beta} < 1$ (low-sensitivity case in Panel B).

Crucially, these sensitivities are governed by *relative* precision. The same increase in sensitivity to probabilities and time delays is obtained when the precision of reward representations (λ_o and λ_r) *declines*, thereby *decreasing* β and $\widehat{\beta}$. This yields a striking prediction: behavior can move closer to seemingly neoclassical benchmarks not only by improving the precision of probability and delay representations, but also by *reducing* the precision with which rewards are encoded.

2. Subadditivity. Under our model the preceding insensitivity to time delays (and thus the declining measured impatience typically attributed to "hyperbolicity") is in fact driven by subadditive discounting (Read, 2001), whereby discount factors over longer horizons exceed the product of discount factors over subintervals. This is a pattern that violates exponential discounting, as well as hyperbolic-type models. Increasing the

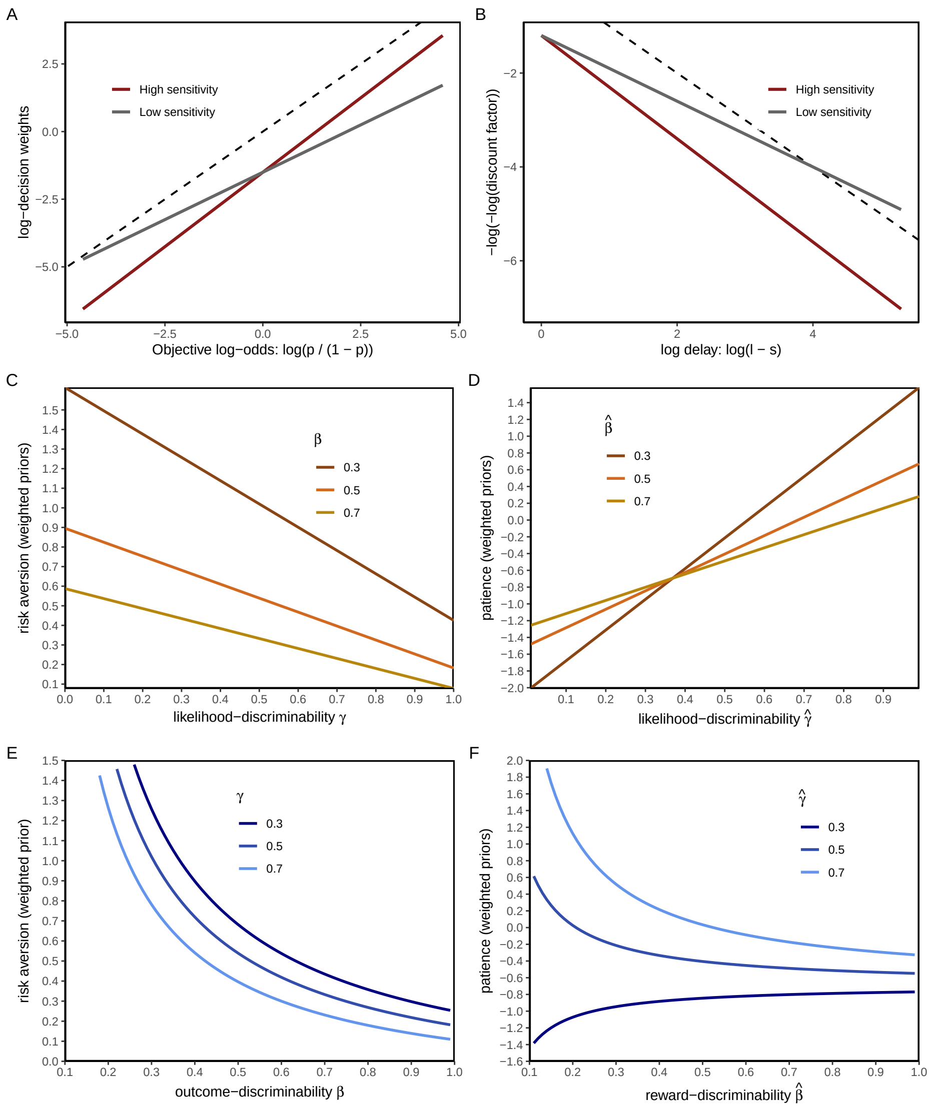

Figure 1: Predicted behavioral changes as relative precision shifts

The figure shows simulated changes in the slopes γ/β (probability sensitivity; Panel A) and $\widehat{\gamma}/\widehat{\beta}$ (delay sensitivity; Panel B) upon changes in the Bayesian evidence weights. Panel C illustrates the effect of changes in γ on average risk aversion, and Panel D illustrates changes in patience following changes in $\widehat{\gamma}$. Panel E illustrates the effect of changes in β on risk aversion, and Panel F illustrates changes in patience following changes in $\widehat{\beta}$. Simulations in Panels C and E are based on $\eta = 0.7$ and $\kappa = 1.2$; simulations in panel D and F are based on $\theta = 3$ and $\rho = 2$.

precision of delay representations, λ_t, and hence $\widehat{\gamma}$, raises sensitivity to time delays (high-sensitivity case in Panel B), thereby attenuating decreasing impatience from the present by reducing subadditivity. Because of this, the same forces that reduce insensitivities to time delays simultaneously reduce subadditivity in discounting.

3. Small-stakes risk aversion and exaggerated impatience. The relative precision with which log-odds or log-delays versus log reward ratios are internally represented not only affects *sensitivity*, but also *average levels* of risk aversion and impatience. To see this, consider the elasticity of the indifferent outcome term with respect to prior means. For risk, the elasticity with respect to the prior expectation of log-odds, $\ln(\eta)$, is $(1-\gamma)/\beta$; for time, the corresponding elasticity with respect to the prior expectation of delays, $\ln(\theta)$, is $(1-\widehat{\gamma})/\widehat{\beta}$. These elasticities determine how strongly prior beliefs about probabilities and delays shape behavior, and thus how risk aversion and impatience respond to these priors. Because these terms enter multiplicatively to $ln(\eta)$ and $ln(\theta)$, the direction and magnitude of their effects depend on whether η and θ are greater or smaller than one — a point we return to below. Analogously, the elasticities with respect to the prior expectation of the log cost–benefit ratio, $\ln(\kappa)$, and the twice-log-transformed reward ratio, $\ln(\rho)$, are $(1-\beta)/\beta$ and $(1-\widehat{\beta})/\widehat{\beta}$, respectively. These elasticities are jointly determined by the precision of the underlying representations.

In our model, despite assuming risk-neutral and exponential discounting preferences, risk aversion, impatience, and present bias can emerge from the interaction of noisy signals with prior beliefs about probabilities and about the relative size of costs and benefits. Although the absolute level of risk aversion and impatience depends on the latent prior means $\ln(\eta)$, $\ln(\kappa)$, $\ln(\theta)$, and $\ln(\rho)$, these priors are naturally interpretable as *environmental expectations* and should therefore be invariant across manipulations of cognitive noise (as in our experimental treatments, below). Effects of manipulations of cognitive noise are predicted to "work" because changes in representational precision alter the elasticity with which these priors enter choice. For risk, we assume that decision-makers are pessimistic about the odds of winning ($\eta < 1$), consistent with the prevalence of risk aversion in typical experimental tasks. Increasing the precision of probability representations, λ_p, raises γ and thereby reduces the elasticity $(1-\gamma)/\beta$ with respect to $\ln(\eta)$. This attenuates the influence of pessimistic probability beliefs and increases average risk-taking (Panel C). For time, we assume $\theta > 1$, reflecting the fact that the smallest delay expressible in integer units is positive. Increasing the precision of delay representations, λ_t, raises $\widehat{\gamma}$ and reduces the elasticity $(1-\widehat{\gamma})/\widehat{\beta}$ with respect to $\ln(\theta)$. This compresses perceived delays toward unity and increases patience (Panel D). In both domains, these effects are strongest when reward precision (λ_o and λ_r) is low, so that β and $\widehat{\beta}$ are small.[13]

[13]This prediction obtains because β and $\widehat{\beta}$ scale the overall elasticity to the evidence, that is they scale elasticity to the probability/delay prior (through $(1-\gamma)/\beta$ and $(1-\widehat{\gamma})/\widehat{\beta}$) and to the reward prior

Similarly, manipulations of the precision attached to *rewards* also influences levels of risk aversion and impatience. For risk, we assume pessimistic priors over log cost–benefit ratios, $\kappa > 1$, consistent with pervasive risk aversion observed in experiments. Lowering the precision with which rewards are internally represented, λ_o, decreases β and thereby increases the elasticity $(1 - \beta)/\beta$. This reduces the compression of κ toward one, amplifying pessimistic beliefs about relative costs and benefits and increasing risk aversion (Panel E). For time, we assume $\rho > 1$, reflecting that larger-later rewards substantially exceed smaller-sooner rewards in the experimental environment. This is natural in our design: the larger-later reward is fixed at £22, whereas the smaller-sooner reward ranges from £1 to £21. The choice environment therefore induces a prior expectation that delayed rewards exceed sooner rewards by a meaningful margin. Lowering the precision with which rewards are represented, λ_r, decreases $\widehat{\beta}$ and increases $(1-\widehat{\beta})/\widehat{\beta}$. This reduces the compression of ρ toward one, amplifying optimistic beliefs about future rewards and increasing patience (Panel F). Thus, in both domains, reductions in reward precision increase the influence of prior beliefs, but with opposite behavioral implications: increased pessimism over outcomes raises risk aversion, whereas increased optimism over future rewards raises patience. This asymmetry arises from the directional structure of the underlying priors, rather than from any difference in the underlying mechanism.

4. Present Bias. In the domain of time, in addition to influencing average levels of patience our model predicts that representational noise governs the anomaly of *present bias*. When $\tau_s = 0$, the model adds a minimal delay of one week to τ_ℓ, which is thus replaced by $\ell = \tau_\ell + 1$ — an aspect of the model that prevents the log-time delay to go to minus infinity as $\tau_\ell \to 0$ — a commonly used feature in the modeling of logarithmic coding (Petzschner and Glasauer, 2011; Howard and Shankar, 2018). Far from being a mere modeling convenience, this is essential for the resource-saving rationale of neural log-coding, and thus serves to preserve neural realism. However, an immediate consequence is that it suggests that cognitive imprecision will increase *present bias* (Vieider, 2023). In this sense, present bias is an outgrowth of efficient neural representations, which introduces distortions as delays become very small. Crucially, under the lens of the model, the magnitude of present bias is tied mechanically to patience: any treat-

(through $(1 - \beta)/\beta$ and $(1 - \widehat{\beta})/\widehat{\beta}$). This differs from changes in γ and $\widehat{\gamma}$, which control the *relative elasticity* to the evidence and the probability/delay prior.

ment that increases patience (higher $\widehat{\gamma}$ or lower $\widehat{\beta}$) is predicted to also reduce present bias.

5. Stake-effects on risk aversion and patience. An immediate consequence of this effect of imprecision is that it generates the famous anomaly of small-stakes risk aversion: risk aversion in laboratory experiments appears at stakes that are too small to be attributable to utility curvature à la expected utility theory (Rabin, 2000; Rabin and Thaler, 2001). The parallel anomaly in the delay-discounting domain is small-stake impatience: discount rates measured in typical lab paradigms are often implausibly large relative to real-world behavior and market borrowing rates (Frederick, Loewenstein and O'Donoghue, 2002; Cubitt and Read, 2007). Furthermore, relative risk aversion is typically found to increase in stakes (Holt and Laury, 2002; Fehr-Duda et al., 2010; Bouchouicha and Vieider, 2017), whereas impatience tends to decrease in stakes (Thaler, 1981; Loewenstein and Thaler, 1989, often called the "absolute magnitude effect"). These patterns are difficult to reconcile within a coherent utility-based framework, as increasing risk aversion in stakes requires utility exhibiting decreasing elasticity, whereas increasing patience requires increasing elasticity (Loewenstein and Prelec, 1992).

Our model provides a unified cognitive account of these patterns. Changes in representational precision affect behavior through two distinct channels. First, changes in γ and $\widehat{\gamma}$ reallocate elasticity between signals and priors, altering sensitivity without substantially changing overall responsiveness. Second, changes in β and $\widehat{\beta}$ scale the overall responsiveness of the decision rule by increasing the *total elasticity* applied to prior beliefs. Changes in risk aversion and patience arise through this second channel. Reductions in reward precision decrease β and $\widehat{\beta}$, thereby increasing the elasticities with which priors enter choice. This amplifies the influence of prior beliefs about outcomes and rewards, generating stronger deviations from benchmark behavior even at small stakes.

An immediate implication is that the model generates stakes effects even if actual preferences are insensitive to stakes and (crucially for our experiment) even if actual stakes don't change. Increasing monetary stakes typically increases the numerical magnitude of the quantities participants must process, which can reduce the precision of reward representations (Frydman and Jin, 2022; Garagnani and Vieider, 2025). Through the scaling channel governed by β, this increases the influence of prior beliefs: in the risk domain, amplifying pessimistic beliefs about costs and benefits raises measured risk aversion, while in the time domain, amplifying optimistic beliefs about future rewards increases patience. Rather than requiring conflicting forms of utility curvature, our model predicts that stake effects in risk and time emerge as parallel consequences of changes in representational precision. One implication is that changing the numerical magnitude of the *description* of payoffs should have the same qualitative effects as actual increases in payoffs. Our pounds-to-pence manipulation in the experiment below leverages exactly this implication and therefore tests this further implication of the model.

3 Experimental Design and Predictions

In order to better understand the role information processing frictions play in the anomalies discussed in Section 2, we conduct an experiment that attempts to exogenously manipulate the precision with which payoffs, probabilities and time delays are cognitively processed and represented. As we discuss in Section 3.1, our experiment is rooted in standard binary choice tasks in the domains of risk and time that match both the prior literature and the setup of our model. The key thing we manipulate in the design (discussed 3.2) is the superficial *framing* of payoffs, probabilities and time delays. The way this information is presented to subjects shouldn't influence behavior under standard maximization models, but should have an influence (possibly a strong influence) under models of constrained information processing. We discuss these predicted implications in Section 3.4.

3.1 Experimental Tasks

The tasks we used in the experiment were deliberately conventional and closely track the binary choices described in Section 2. In the domain of risk, each participant made 143 binary choices, each between a lottery and a sure amount. Lotteries paid £ 22 with probability $p \in \{0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9\}$ and zero otherwise. For each probability, the sure amount ranged from £ 1 to £ 21. This rich set of stimuli allows us to estimate nonparametric choice proportions for every lottery and thereby measure the anomalies discussed Section 2. In the domain of time, each participant made 252 choices, again selected to allow us to measure standard intertemporal choice anomalies. This resulted in 12 delay pairs. First, we chose seven delays from the present, equally spaced in log space: 1, 2, 4, 8, 16, 32, and 64 weeks. These allow us to plot nonparametric discount functions directly analogous to the log-odds plots used to assess treatment effects in the risk experiment. To this set, we added delays that permit direct measurement of specific behavioral components: (i) *subadditivity*, by comparing discount factors for longer delays (2, 4, 8, and 16 weeks) to the product of discount factors for their constituent subperiods; (ii) *present bias*, by comparing short delays from the present to identical delays preceded by an up-front delay; and (iii) *decreasing discount rates*, by comparing identical 4-week delays embedded at increasing distances into the future. The later outcome was always fixed at £22. The sooner outcome varied between £1 and £21 in increments of £1, paralleling the design used for risk and enabling us to estimate nonparametric stochastic approximations of discount factors.

3.2 Framing Manipulations

In order to understand how cognitive frictions influence the anomalies of risk and time, we manipulate the *framing* of the primitives of these tasks. In particular, guided by our model, we aimed to manipulate the way payoffs, probabilities and time delays are presented to subjects *without changing anything of quantitative substance*. Following the predictions in Section 2 our aim with these manipulations is to *increase* the relative precision with which probabilities and time delays are processed and (ii) *decrease* the relative precision with which payoffs are processed. Both of these manipulations are predicted to *reduce* the severity of most of the anomalies discussed in Section 2, and should have particularly strong negative effect on their severity when combined.

Although cognitive models strongly imply that details of presentation will shape how (and how well) information is processed, there is only limited direct evidence (and even less theoretical guidance) to date to inform our selection of framing manipulations for this purpose.[14] Nonetheless, the framing manipulations we selected for this purpose were motivated not only by strong intuition but also by findings from the prior literature, and we deliberately used directly parallel manipulations in both the domains of risk and time. Panels A and E of Figure 2 shows our baseline design (for the domains of risk and time, respectively) in which (i) payoffs are described in British pounds and (ii) probabilities and time delays are both presented *numerically*. We manipulate both (i) and (ii), aiming

[14]Indeed, we view the building of stronger theory and the collecting of richer data to better understand the way framing helps or hinders the quality of information process to be an important frontier in the literature.

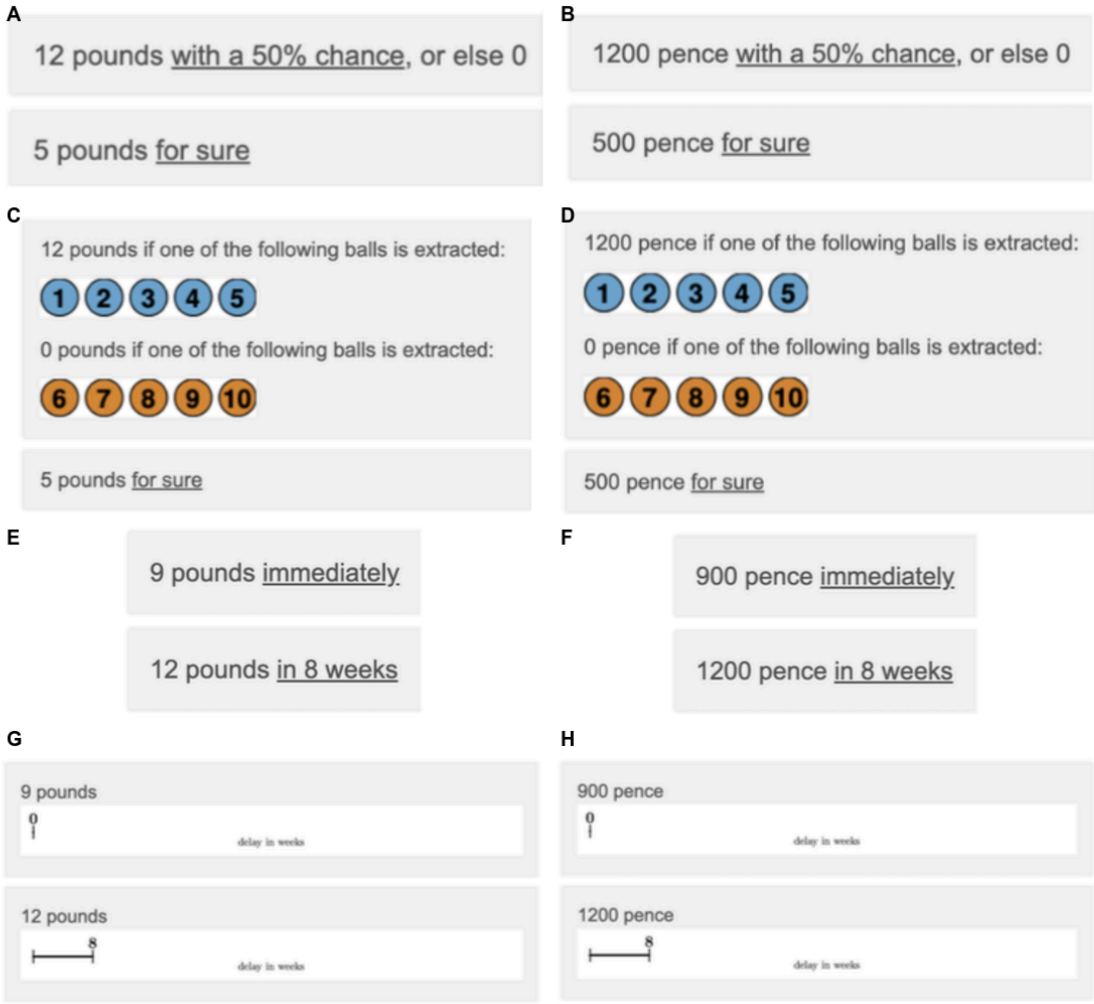

Figure 2: Screenshots from the four experimental treatments. The top row shows textual presentations and the bottom row visual presentations. Within each row, the first two columns correspond to risky choice and the last two to intertemporal choice, each shown in pounds and pence.

to reduce the magnitude of anomalies in both domains.

First, in order to *decrease* the precision with which payoffs are processed, we switched from describing payoffs in terms of British pounds to describing the same payoffs in terms of British pence. Doing this increases the numbers the subject must process by two orders of magnitude. Panels B and F of Figure 2 give an example of this manipulation.

We expect this manipulation to decrease payoff precision for several reasons. First, there is significant evidence that people less precisely process quantities they are less accustomed to because brains tend to allocate scarce cognitive resources where they are expected to matter most (Robson, 2001*a*;*b*; Netzer, 2009; Heng, Woodford and Polania, 2023; Frydman and Jin, 2022). Noisy cognition models in particular are founded on the idea that approximate numerical representations are tuned specifically to numerical ranges encountered frequently in one's decision environment. Because of this, payments denominated in British pounds can be expected to be more precisely represented.[15] Second, this manipulation may have the additional effect of driving subjects to pay less attention to less manageable, larger payoff numbers and more attention to more manageable, smaller percentage and time delay numbers, thereby reducing the precision attached to payoffs relative to probabilities/delays.

Second, in order to *increase* the precision with which probabilities and time-delays are processed we switched from describing these quantities numerically to describing them *visually*. Instead of presenting these quantities numerically (textually) as percentages, we describe them visually via a frequentist representation by presenting ten colored and numbered balls on subjects' screens. Similarly, we switch from describing time delays in weeks using textual numbers only, to describing them with a visualization of the length of the delay in the form of a horizontal line segment in addition to these numbers. These manipulations are visualized in panels C-D and G-H of Figure 2.

We expect this manipulation to increase probability and delay precision, again, for several reasons. First, there is some evidence that people have difficulty processing quantities like

[15] Indeed, Garagnani and Vieider (2025) show that a representative sample of British subjects make systematically more errors (in the form of first order stochastic dominance violations in decisions under risk) when identical values are expressed in large numerical units. By contrast, representative sample of Japanese subjects —where 1 GB pounds corresponds to approximately 180 Yen— made more errors when identical stakes are mapped into *small numerical units*. People (for sound neurological reasons) seem to be adapted to specific numerical ranges, and outcomes denominated in more frequently encountered numbers are internally represented with greater precision.

probabilities and delays numerically. Hoffrage et al. (2002) argue that people are typically maladapted for understanding abstract probability descriptions, and that using easily understood frequentist representations — such as an urn with colored balls, or frequency tables — can aid the understanding of probabilities. Similar forces may shape the process of time delays. Discussing the inherent 'fragility of time', Ebert and Prelec (2007) propose inter alia a visual display to represent time delays, showing that it increases sensitivity to delays of increasing length from the present. Several of the framing interventions in the previous literature — reviewed above — have used visual displays to try to manipulate valuations in choice lists. Thus, we hypothesize that visualization reduces the costs of processing information. Second, again, visuals may attract more attention as in the bottom-up salience literature (Bordalo, Gennaioli and Shleifer, 2012; 2013; 2022; Li and Camerer, 2022). By making a specific piece of information more visually salient, subjects may dwell longer on that dimension which has been shown to increase consideration paid to the object of increased attention (Arieli, Ben-Ami and Rubinstein, 2011; Pachur et al., 2018; Hirmas, Engelmann and Weele, 2024). We expect this to increase the relative precision assigned to probabilities and delays.[16]

In our experiment, in both the domains of risk and time, we study all four combinations of presentation pictured in Figure 2: (i) pounds vs. pence presentation of payoffs and (ii) numeric vs. visual presentation of probabilities/delays. Subjects are assigned to only one domain (risk or time) and one presentation setting (pounds or pence, numeric or visual) resulting in 8 total between-subjects treatments (4 under risk and 4 under time).

3.3 Implementation Details

We ran the experiment on Prolific UK, targeting 100 participants in each of the eight treatment conditions (800 total). Choices were presented one per screen in randomized order, with the position of the lottery and sure option also randomized in the domain of risk. The median completion time was 14 minutes for risk and 18 minutes for time. Participants received fixed compensation in line with Prolific policies. In addition, one in

[16] Indeed, in noisy cognition models, allowing for repeated extractions of signals r can be expected to increase the precision of the signal as a function of the square root of the number of draws. Our predicted effects may thus arise either because of an increase in the ease of processing visual information, or because of a salience-driven shift in relative attention (e.g., decreasing noise attached to probabilities/delays and simultaneously increasing the noise attached to payoffs), or indeed both. While we cannot test this here based on our behavioral choice data, both of these mechanisms are fully coherent with our hypotheses, which concern the purely the precision with which one dimension is internally represented and processed *relative to the other*.

ten participants was randomly selected for a bonus payment based on a randomly chosen choice. Immediate payments were executed directly after the experiment. Future payments were guaranteed by Ghent University (whose logo was displayed throughout the experiment) and participants were informed that they would receive a confirmation message specifying the amount, payment date, and contact information for the researchers. Participants were explicitly encouraged to reach out with any questions concerning future payments.

3.4 What Can We Learn from this Design?

We designed this experiment to test the hypothesis that information processing frictions play an important role in generating classic choice anomalies at three distinct levels. These levels overlap, with each having progressively sharper implications and making stronger demands on the data than the previous one.

1. Systematic effects. First, because our manipulations are superficial, altering nothing more than the way information is presented, our primary treatments should have *no effect* on behavior under rational, maximization models (including preference-based interpretations of standard *behavioral* models). Because of this, evidence that any of the anomalies measured by our design are systematically attenuated or intensified by our treatments is evidence that the anomaly is generated (at least to some extent) by imperfections in information processing in our data. Thus, even without specifying a particular model of information processing frictions, our experiment tests the broad hypothesis that cognitive frictions meaningfully shape choice in these canonical environments.

2. Parallel effects. Second, because we designed our experiment to directly compare several facially similar anomalies in the domains of risk and time (e.g., probability and delay insensitivity, exaggerated risk aversion and impatience), our experiment also tests the sharper hypothesis that domain-general cognitive frictions are jointly responsible for similar anomalies across the two domains. Indeed, the reason we manipulate framing in parallel ways in the two domains is to sharply test the hypothesis that parallel information processing frictions are similarly responsible for parallel anomalies. Under the hypothesis that these anomalies are driven by domain-specific factors linked to risk and time rather than to domain-general information processing frictions — i.e., to the degree similarities between these parallel anomalies is coincidental or accidental — we have no reason to expect parallel responses to our manipulations in the two domains. However, to the degree that similar framing manipulations have similar impacts on parallel anomalies in the domains of risk and time, we have evidence that domain-general cognitive frictions may be jointly responsible for such anomalies in the two domains.

3. Imprecise cognition effects. Third, because our imprecise cognition model makes a number of sharp (and often counterintuitive) predictions, our experiment also serves as a demanding test of our model (and by extension the premises behind noisy cognition models more generally). Indeed, as we outline in Section 2, the model makes numerous *simultaneous* predictions on the effects of increasing probabilities/delay noise and decreasing payoff noise on probability insensitivity, delay insensitivity, small stakes risk aversion, exaggerated impatience, present bias, the absolute magnitude effect and payoff-increasing risk aversion. Because of this, our experiment serves as a joint test of our predictions concerning the effects of framing on cognitive noise, and our predictions about the way noise shapes many anomalies in both the domains of risk and time.

First, we predict that switching to a visual presentation will increase the precision with which log-odds and log-delays will be coded relative to rewards, increasing the elasticities γ/β and $\widehat{\gamma}/\widehat{\beta}$, and decreasing elasticities to the respective priors, $(1-\gamma)/\beta$ and $(1-\widehat{\gamma})/\widehat{\beta}$. Because of this, our model predicts that when we switch from numeric to visual framing:

- probability-insensitivity (in the domain of risk) and time-insensitivity (in the domain of time) will both decrease, in parallel
- average risk aversion (in the domain of risk) and average impatience (in the domain of time) will both decrease
- present bias and subadditivity will both decrease in the domain of time

Second, we predict that switching to denominating rewards in pence instead of pounds will decrease the precision of reward coding (relative to noise in probabilities/delays), thereby once more increasing the elasticities γ/β and $\widehat{\gamma}/\widehat{\beta}$. Given that β and $\widehat{\beta}$ scale overall elasticity, their decrease will further increase elasticities to all prior means, yielding the following behavioral predictions:

- probability-insensitivity (in the domain of risk) and time-insensitivity (in the domain of time) will both decrease, in parallel

- average risk aversion will increase (mimicking canonical "stake effects" for risk) while average impatience will *decrease* (mimicking canonical "stake effects" for time)
- present bias and subadditivity will both decrease in the domain of time

4 Results

In Section 4.1 we examine the effects of our attempt to *increase* the precision with which probabilities and delays are coded by using visualizations, while in Section 4.2 we examine the effects of our attempts to *decrease* the precision with which payoffs are coded by denominating rewards in pence. In Section 4.3 we examine the combined effect of these two manipulations which we expect to create particularly strong treatment effects. Throughout the analysis, we use non-parametric indices (introduced as they appear in the text) to show measured treatment effects on anomalies. We conduct statistical tests using reduced-form logistic regressions, reported in Online Appendix C. Unless otherwise noted, all reported effects are statistically significant at the 5% level.[17]

4.1 Increasing precision: visualizations of probabilities and delays

Figure 3 presents the effects of switching to visual displays of probabilities and delays, averaging over the pounds versus pence manipulations.

Insensitivity to probabilities and delays. Our first main prediction is that reducing noise in processing by presenting them visually will significantly reduce subjects' insensitivity to probabilities (the basis of models of "probability weighting") and time delays (the basis of models of "hyperbolic discounting").

Panel A summarizes average choice proportions by treatment by plotting the log-odds of choosing the lottery against the objective log-odds of winning.[18,19] Values of the log-

[17]When comparing data to normative benchmarks (e.g., unit sensitivity to probabilities or exponential discounting), we generally conservatively focus on nonparametric indices. The effects detected in the logistic regressions reported in the Online Appendix tend to be at least as strong as those shown by these indices, and stronger in some cases.

[18]When choices are well-behaved — exhibiting either a single switching point or multiple switches clustered around the indifference point — the resulting nonparametric choice proportions can be meaningfully compared to the objective log-odds.

[19]Throughout, we adjust nonparametric choice proportions to account for the fact that each lottery is compared to 21 sure amounts from £1 through £21. Specifically, we multiply the observed choice

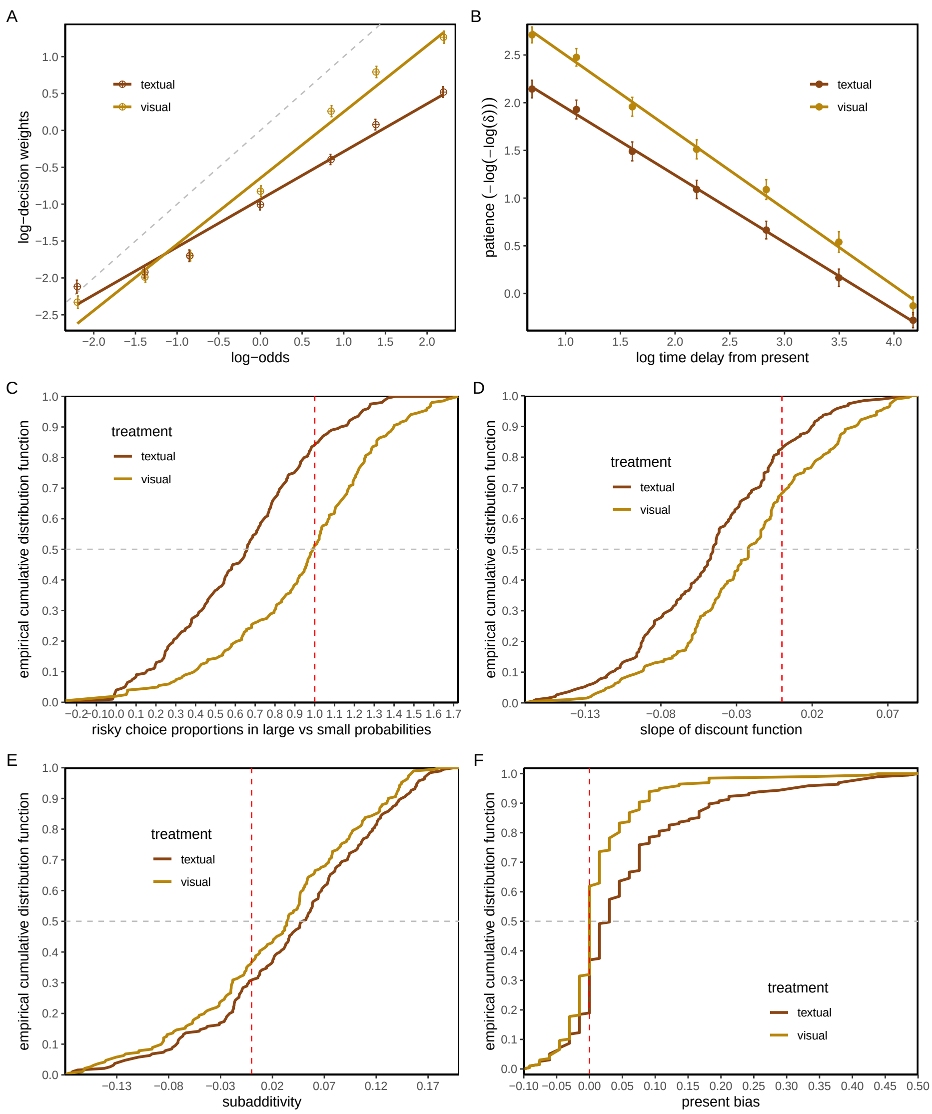

Figure 3: Effect of visual vs textual displays for risk and time

Panel A shows a plot of the objective log-odds on the x-axis against the log-odds of the average lottery choice proportions on the y-axis by treatment. Panel B plots the log-delay against minus the log of minus the log of the choice proportion for the larger–later option. Vertical bars indicate 1 standard error. Panel C shows an index capturing likelihood-sensitivity, constructed by taking the difference in lottery choice proportions between large and small probabilities at the individual level, and normalizing by division with the probability difference. Panel D shows an index of decreasing impatience, calculated as the choice proportion for the later option for a given delay, minus the choice proportion for half that delay, squared. Panel E shows an index of subadditivity, taking the difference of the choice proportion for a given delay and the product of two or more sub-delays. Panel F plots an index of present bias, comparing choice proportions for a given delay from the present to choice proportions for the same delay from an up-front delay. Some observations may have been dropped to improve the visual display.

odds of choice proportions above the objective log-odds indicate risk-seeking behavior, while values below indicate risk aversion. In the baseline percentage treatments, we observe strong probability insensitivity, reflected in a relatively flat slope. Switching to visual presentations of probabilities substantially attenuates this pattern: the fitted line becomes markedly steeper and approximately parallel to the 45-degree line, indicating near-unit sensitivity ($\gamma/\beta \approx 1$). Thus our efforts to reduce probability noise cause probability insensitivity to largely disappear. Panel B shows parallel results in the domain of time by presenting average choice proportions for the larger-later option as a function of delays from the present, plotted on the log–log scale implied by the model. The function fitted to the visual data is both steeper and more elevated than that for the textual condition, indicating greater sensitivity to time delays and higher patience. Overall, these twin effects closely match the model's predictions: visual displays increase sensitivity to probabilities and delays while simultaneously shifting average behavior in the predicted direction.

Panels C and D examine these same insensitivities at the individual level in the domains of risk and time, respectively. To test for changes in likelihood sensitivity, γ/β, without imposing functional-form restrictions, we construct a simple nonparametric index. For any pair of probabilities $p_H > p_L$, the index is defined as the difference in choice proportions between the two probabilities, normalized by the objective probability difference. An index of 1 corresponds to perfect sensitivity (the EUT benchmark), values below 1 indicate insensitivity (as in inverse-S probability weighting), and values above 1 indicate oversensitivity (apparent relative risk aversion decreasing in p). We compute this index for the probability pairs $(0.9, 0.1)$, $(0.8, 0.2)$, and $(0.7, 0.3)$, and average across pairs for each participant. Panel C of Figure 3 shows the distribution of this index across subjects. The empirical CDF for the visual treatment lies uniformly to the right of that for the percentage treatment, indicating greater likelihood sensitivity under visual probability displays. Most participants in the percentage condition exhibit pronounced insensitivity, whereas the median participant in the visual condition is close to unit sensitivity and thus roughly neoclassical. Indeed, oversensitivity and undersensitivity occur with roughly equal frequency in the visual condition, suggesting that insensitivity is no longer a systematic characteristic of the data.

proportion by $21/22 + 0.5/22$, which normalizes the proportion so that, under a single switching point, it corresponds to the normalized certainty equivalent ${}^{ce}/_{x}$.

Panel D presents the distribution of a similar individual-level steepness index for time, defined as the average of $d_{t/2}^2 - d_t$ across all eligible delay pairs. This index captures how the discount curve flattens with increasing delays: a value of 1 corresponds to the neoclassical exponential benchmark, values below 1 reflect decreasing impatience, and values above 1 indicate oversensitivity to delays. The index is clearly larger in the visual condition, indicating greater time sensitivity. Indeed evidence of insensitivity is cut in half for the median subject. This echoes the findings of Ebert and Prelec (2007), who similarly report increased sensitivity when delays are represented visually.

Result 1. *When we use visualizations to improve the cognitive precision of probabilities, we substantially reduce the anomaly of likelihood insensitivity (à la probability weighting). Similarly, using the same manipulation to increase the cognitive precision of delays substantially reduces the anomaly of delay insensitivity (à la hyperbolicity).*

Subadditivity. In contrast to related accounts (e.g., Ebert and Prelec, 2007), our model attributes the apparent time-insensitivity in Panels B and D to subadditivity, a consequence of cognitive noise. Panel E presents the empirical CDF of a nonparametric index of subadditivity, constructed as the average of $d_t - d_{0,t/2} \cdot d_{t/2,t}$ across all applicable delays. Visual displays substantially reduce subadditivity. By contrast, we find no evidence of strongly decreasing discount rates: using constant 4-week delays from 4, 8, and 12 weeks, differences are statistically insignificant ($p \geq 0.135$ in all comparisons, see Online Appendix B). This supports the interpretation that subadditivity — rather than sharply decreasing discount rates — drives the "hyperbolic" patterns observed with non-visual displays in Panels A and B.

Result 2. *When we use visualizations to increase the cognitive precision of delays, we reduce the anomaly of subadditivity. Delay insensitivity is driven by this subadditivity in our data and we find no corresponding evidence that insensitivity is driven by strongly decreasing discount rates.*

Average risk aversion and impatience. Our model predicts that reducing probability or payoff noise will influence not only the sensitivity of choices, but also levels. The function fit to the risk data in Panel A shows higher elevation at even odds upon provision of a visual aid, suggesting a reduction in small-stakes risk aversion in accordance with our model's predictions (logit results in Online Appendix C confirm that this is a significant effect). In parallel, the delay-discounting function in Panel B is more elevated when a visual aid is provided, indicating lower levels of impatience. Thus, we find evidence that, indeed, small-stake risk aversion and impatience are significantly influenced by cognitive noise.

Result 3. *When we use visualizations to increase the cognitive precision of probabilities, we significantly reduce measured risk aversion. When we use visualizations to increase the precision of delays we decrease measured impatience.*

Present bias. Finally, our model predicts that present bias will be modulated by cognitive noise. Indeed, we hypothesized that visualization should reduce delay discriminability ($\widehat{\gamma}$) and thereby reduce both overall impatience and present bias in concert. Panel F plots the distributions of individual-level measures of an index of present bias, defined as the average difference $d_{t,2t} - d_{0,t}$ across comparable delay pairs. The vertical dotted line shows the no-present bias benchmark. The plot shows that, consistent with this prediction, visualizations cause a sharp reduction in present bias. In fact, for the median subject the manipulation causes present bias to disappear.

Result 4. *Using visualization to increase the precision of delays significantly reduces the severity of present bias.*

4.2 Decreasing precision: showing rewards in pence instead of pounds

Perhaps the most counterintuitive (and therefore distinctive) implication of our noisy cognition account is its prediction that *reducing* the precision of payoffs should have parallel effects to *increasing* the precision of probabilities or delays. This is because for most of the anomalies we consider, it is the noise in the latter *relative to* the former that generates the anomaly. As a result, reducing the quality of information processing (with respect to payoffs) can be as effective at reducing the severity of anomalies as increasing the quality of information processing (with respect to probabilities/delays). Because this implication is particularly distinctive, it allows for a particularly sharp test of the noisy cognition explanation for these anomalies. Figure 4 presents the effects of denominating rewards in pence versus pounds for risk and time, averaging over the textual versus visual manipulation.

Sensitivity to probabilities and delays. Panel A again plots the aggregate log-odds of choosing the lottery against the objective log-odds by treatment, together with fitted linear regression lines. In the pounds condition, the slope is well below one, revealing pronounced insensitivity to probabilities. When we switch to the pence condition, however, the fitted line grows much steeper and thus more sensitive to probabilities. This increase in probability sensitivity (via γ/β) is exactly what the model predicts when outcome-discriminability β decreases. Panel B displays the nonparametric discount patterns for delays from the present and we find strong evidence for our predictions concerning the effects of increasing reward noise. The discount function in the pence condition is clearly steeper than in the pounds condition, indicating increased time-sensitivity.

Panel C examines sensitivity to probabilities at the individual level. The distribution for the pence condition lies uniformly to the right of that for the pounds condition, confirming higher likelihood-sensitivity under risk. Indeed, the median subject is almost perfectly calibrated, treating probabilities linearly. Panel D shows an equivalent sensitivity index for delays from the present. Sensitivity to time delays is markedly increased when rewards are denominated in pence rather than pounds. Panel E complements this with the distribution of the subadditivity index: denominating rewards in pence substantially reduces subadditivity, and the effect is large. In line with our earlier results, we again find no evidence of strongly decreasing discount rates.

Importantly, these results imply that behavior moves *closer* to the rationality benchmark of linear probability treatment (as in expected utility theory) and of exponential discounting when outcome assessments become *less precise* — a counterintuitive hallmark prediction of noisy-cognition models that is difficult to reconcile with stable preference-based accounts.

Present bias. Our model also predicts that increasing payoff noise will reduce the anomaly of present bias. Panel F shows the empirical CDFs of the present-bias index. The curve for the pence condition lies uniformly to the left of the curve for the pounds condition ($p = 0.001$), and, in parallel with our findings from use of the visual display,

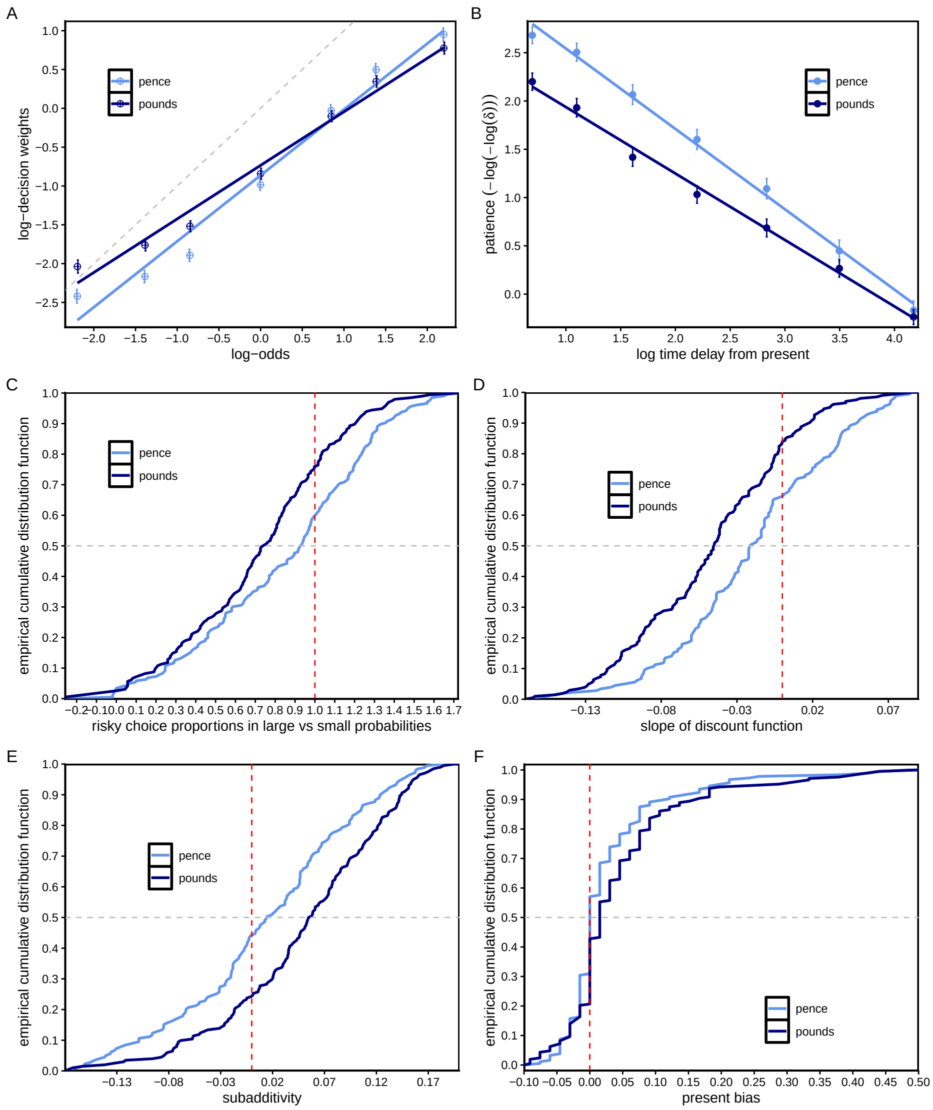

Figure 4: Effect of rewards in pounds vs pence for risk and time

Panel A shows a plot of the objective log-odds on the x-axis against the log-odds of the average lottery choice proportions on the y-axis by treatment. Panel B plots the log-delay against minus the log of minus the log of the choice proportion for the larger–later option. Vertical bars indicate 1 standard error. Panel C shows an index capturing likelihood-sensitivity, constructed by taking the difference in lottery choice proportions between large and small probabilities at the individual level, and normalizing by division with the probability difference. Panel D shows an index of decreasing impatience, calculated as the choice proportion for the later option for a given delay, minus the choice proportion for half that delay, squared. Panel E shows an index of subadditivity, taking the difference of the choice proportion for a given delay and the product of two or more sub-delays. Panel F plots an index of present bias, comparing choice proportions for a given delay from the present to choice proportions for the same delay from an up-front delay. Some observations may have been dropped to improve the visual display.

present bias disappears for the median subject.

Result 5. *Reducing the cognitive precision of payoffs by denominating them in pence has the same effect as increasing the precision of probabilities and delays using visualizations. This worsening of the processing of payoffs causes insensitivity to both probabilities and time delays to diminish, along with the anomalies of subadditivity and present bias in the domain of time.*

Canonical stake effects for risk and time. We also find evidence that this same manipulation supports our predictions concerning the effects of reducing payoff precision in risk and time. Here, however — in contrast to the predicted effects of the pence manipulation on insensitivity, and the predicted effects of the visualization of probabilities and delays — our model predicts the pence manipulation will produce *opposite* effects on average behavior in the two domains. Looking again at risky choice in panel A of Figure 4, at even odds (log-odds = 0) the line for the pence condition lies lower than for the pounds condition, indicating increased risk aversion for 50–50 gambles (significant at 10% level). This pattern is exactly what the model predicts when outcome-discriminability β decreases: pessimistic reward priors exert a stronger downward pull on overall risk-taking, leading to an *increase* in risk aversion. For time, however, the function is clearly higher at delays equal to one (log-delay = 0), indicating *lower* impatience when rewards are denominated in pence and the precision of reward-encoding declines. The data therefore reproduces the hallmark *absolute magnitude effect* — larger nominal amounts yielding lower discount rates (Thaler, 1981) — despite the fact that the underlying monetary stakes are identical and only the *numerical scale* is varied.

Our finding that two opposing classic rewards patterns — risk aversion increasing in stakes and impatience decreasing — are reproduced with mere manipulations of numeric (rather than true payoff) magnitude helps to resolve an enduring mystery in the literature. Both phenomena have proved difficult to organize under the lens of a consistent utility function, since one (risk) requires decreasing and the other (time) increasing elasticity of utility. In our model, elasticity towards reward priors, $(1-\beta)/\beta$ and $(1-\widehat{\beta})/\widehat{\beta}$, increases as β and $\widehat{\beta}$ decline. Since reward priors capture pessimism for risk (expected costs exceed expected benefits of the lottery) and optimism for time (later rewards are expected to be considerably larger than sooner rewards), this consistent change in elasticity produces effects in opposite directions. Our evidence in support of this account thus supports the hypothesis that these seemingly distinct anomalous stakes effects are, at least in part, a consequence of the *similar* way cognitive noise is influenced by larger numerical magnitudes.

Result 6. *Increasing the numerical magnitude of payoff numbers reproduces (i) the famous absolute magnitude effect in the domain of time and (ii) increasing risk aversion in the domain of risk. The fact that this occurs without changing actual rewards supports the hypothesis that noisy cognition is at least partially responsible for these anomalies.*

4.3 Combined effect of visualization and pence denomination

As the previous subsections show, our efforts to alter γ and $\widehat{\gamma}$ (by providing visual aids for probabilities and time delays) and β and $\widehat{\beta}$ (by manipulating the denomination in which rewards are described) each lead to significant changes in the severity of the anomalies we designed our experiment to study. For most of these anomalies, our model predicts that these effects will be intensified when we jointly increase the precision of probabilities/delays and decrease the precision of payoffs. This is because for most of our predictions it is the relative precision of probabilities/delays and payoffs that determines the severity of the anomaly.[20] For instance, because sensitivity to probabilities and delays depends on the ratios γ/β and $\widehat{\gamma}/\widehat{\beta}$ the conjunction of the two manipulations should lead to a particularly sizable effect on this anomaly. To study this accumulation of effect, we compare the predicted extremes for these anomalies by comparing the treatment in which (i) probabilities and time delays are presented textually with outcomes in pounds (where probability/delay precision is minimized and payoff precision maximized) to the treatment in which (ii) probabilities and delays are visualized and rewards are represented in pence (where probability/delay precision is maximized and payoff precision minimized).

Panel A of Figure 5 shows results on probability insensitivity and reveals very strong effects. In the percentage–pounds condition, the fitted slope is well below one: probability sensitivity is low, and apparent risk aversion increases with the log-odds of the lottery. As

[20] The one exception is overall levels of risk aversion. For this, the effects of visual displays and pence-denomination go in opposite directions, they cancel one another out to a great extent so that the joint predicted effect is ambiguous. For overall levels of impatience, however, the direction of the effects go in the same direction, so that we once more expect the effect of the two interventions to cumulate. This is yet another distinctive prediction of the model.

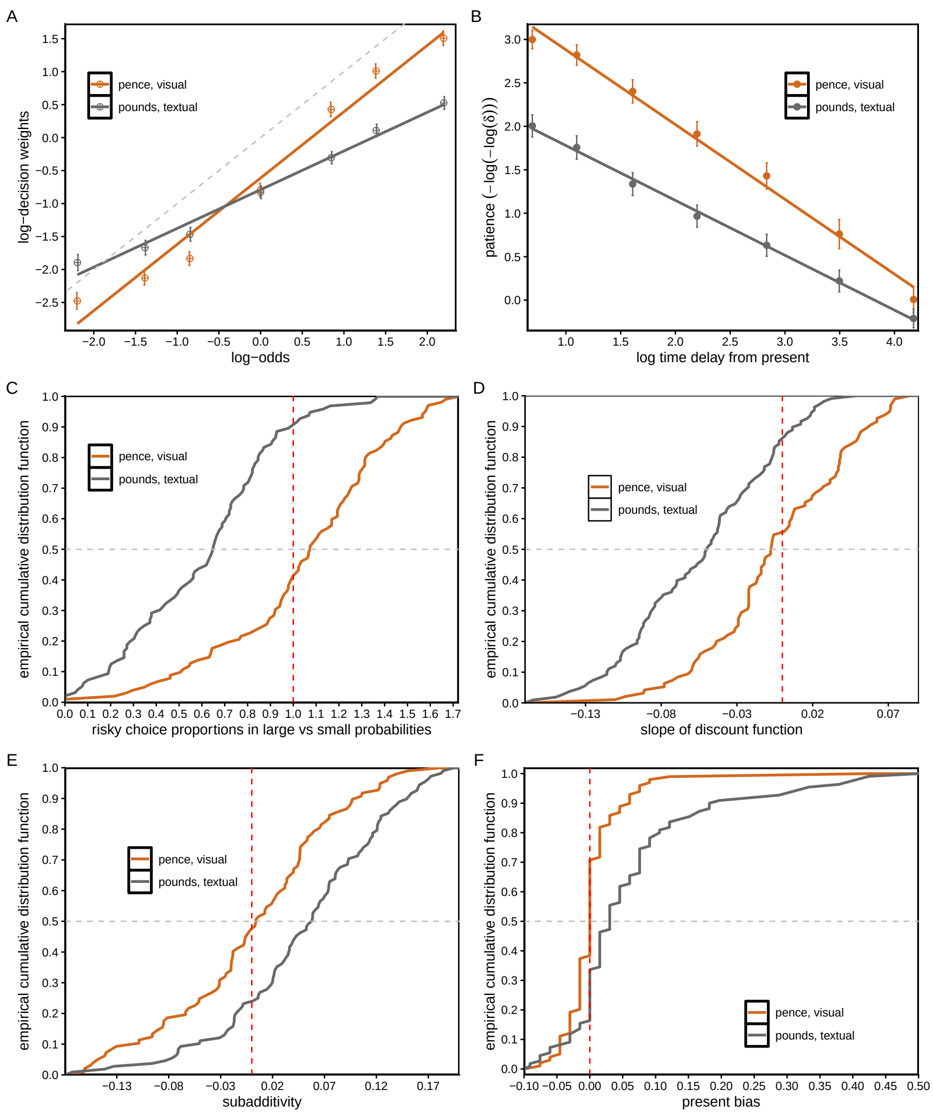

Figure 5: Effect of rewards in pounds vs pence for risk and time

Panel A shows a plot of the objective log-odds on the x-axis against the log-odds of the average lottery choice proportions on the y-axis by treatment. Panel B plots the log-delay against minus the log of minus the log of the choice proportion for the larger–later option. Vertical bars indicate 1 standard error. Panel C shows an index capturing likelihood-sensitivity, constructed by taking the difference in lottery choice proportions between large and small probabilities at the individual level, and normalizing by division with the probability difference. Panel D shows an index of decreasing impatience, calculated as the choice proportion for the later option for az given delay, minus the choice proportion for half that delay, squared. Panel E shows an index of subadditivity, taking the difference of the choice proportion for a given delay and the product of two or more sub-delays. Panel F plots an index of present bias, comparing choice proportions for a given delay from the present to choice proportions for the same delay from an up-front delay. Some observations may have been dropped to improve the visual display.

expected, this reproduces classic probability insensitivity (as in typical inverse-S shaped measures of probability weighting). In the visual–pence condition, the anomaly not only disappears, it actually *reverses.* Participants exhibit the strongest apparent risk aversion at the smallest probability ($p = 0.1$), and this declines as p increases — i.e. risk-taking *increases* with the probability of winning. Thus, when these effects are accumulated, subjects become *over*sensitive to probabilities ($\gamma/\beta > 1$) – a pattern that our model predicts when probability noise is reduced and reward noise increased to a sufficient extent (i.e. for $\gamma > \beta$). Panel B show parallel results for the nonparametric discount functions. The differences between the two conditions are dramatic: the visual–pence treatment produces a much steeper discount function — indicating substantially greater time-sensitivity.

Panels C and D show the empirical CDFs of the sensitivity indices for risk and time, respectively. The distribution for the visual–pence condition lies uniformly to the right of the textual–pounds condition, confirming substantially higher sensitivity to probabilities and time delays in the visual-pence condition. For risk, the median subject is now oversensitive to probabilities. For time, the median subject comes arbitrarily close to the exponential discounting, meaning apparent "hyperbolic" discounting virtually disappears for the median subject (indeed, logit analysis in the appendix suggests this reverses to oversensitivity, just as in risk). Panel E reports the empirical CDFs of the subadditivity index and shows a sharp decline in subadditivity in visual–pence. The median subject in textual–pounds exhibits substantial subadditivity, whereas the median subject in visual–pence is almost perfectly calibrated, showing minimal deviation from additivity over time intervals. Despite these anomalies disappearing or reversing as systematic phenomena, subject-level data remains highly heterogeneous in visual–pence, just as in textual–pounds.

Panel F shows the empirical CDFs for present bias. Present bias is prevalent in the textual–pounds condition but substantially reduced in the visual–pence condition ($p = 0.002$), once more disappearing for the median subject. This matches the model's prediction — and the earlier aggregate results — that increases in patience resulting from reward noise should be especially pronounced in the visual-delay condition, thereby strongly attenuating present bias.

Finally, the data matches a distinctive asymmetry predicted by noisy cognition. As panel

B shows, the effects of our two manipulations reinforce one another in influencing levels of impatience, producing a particularly large shift in the domain of time. However, as panel B shows, the same is not true in overall levels of risk aversion where we should instead expect the effects of our visual and pence manipulations to conflict. The model thus predicts not only parallel effects across the domains of risk and time, but also where this parallelism should break down.

Result 7. *Probability insensitivity, delay insensitivity, subadditivity and present bias largely disappear or (in some cases) even reverse statistically and on average when risk/delay noise is minimized and payoff noise maximized.*

These results illustrate an important implication of our manipulations: the sizable shifts we observe in these anomalies reflects a shift in the relative precision with which different dimensions are encoded, rather than a shift towards globally "better decision-making". The fact that average or median choice patterns coincide with normative benchmarks such as exponential discounting or expected utility maximization is thus accidental, and obtains when the imprecision in probability/delay coding and in reward coding are roughly in balance. This is yet another strand of evidence that choice behavior (and the anomalies it generates) is unlikely to reflect the maximization of standard preferences, but instead details of the way information is processed by the decision-maker.[21]

Finally, in Online Appendix B , we show that our data reveal patterns resulting from subtler predictions of the model concerning interaction effects of noise manipulations. For instance, as predicted, visual manipulations have stronger effects on both sensitivity and levels of risk aversion or impatience when the imprecision of payoffs is high (e.g., the pence condition), in both the domains of risk and time. Conversely, we also document increased effects of the pence-vs-pounds manipulation in the time domain when delays are displayed visually — again following the prediction of the model. The model predictions are thus reflected in the data to a remarkable degree.

[21] See also Vieider (2025), for evidence showing that such supposedly-neoclassical behavior often exhibits peak choice variability — a key stochastic choice prediction of our model.

5 Discussion and Conclusion

We can characterize our findings in three ways, highlighting what we think are three primary implications of this research.

First, we find that superficial changes in the way we present information about economic primitives like payoffs, probabilities and time delays to subjects have large and systematic effects on many of the signature anomalies in behavioral economics including probability insensitivity (the basis of models of "probability weighting"), delay insensitivity (the basis of models of "hyperbolic discounting"), small stakes risk aversion, exaggerated impatience, the absolute magnitude effect, subadditive discounting and present bias. The fact that these canonical behavioral patterns are highly sensitive to payoff-irrelevant factors suggests that they are unlikely to be pure outgrowths of the maximization of stable preferences: models of utility maximization (including behavioral ones) do not predict sensitivity to payoff-irrelevant aspects of the way information is presented. Instead, our results serve as evidence that many classic anomalies, in both the domains of risk and time, are likely (at least to a significant extent) a consequence of limitations in decision makers' ability to process information.[22]

Second, we find that similar framing manipulations affect parallel anomalies in the domains of risk and time in similar ways. For instance, we find that probability insensitivity (á la probability weighting) in the domain of risk and delay insensitivity (á la hyperbolic discounting) in the domain of time, respond very similarly to parallel manipulations in the framing of payoffs or probabilities/delays. Similarly, we find that overall levels of risk aversion and overall levels of impatience respond similarly to parallel manipulations in the presentation of probabilities and time delays, respectively. The parallel way framing manipulations impact the anomalies of risk and time suggests that many of these anomalies may have less to do with risk or time, per se, than with shared information processing frictions that constrain decisions similarly in the two very different settings. Our results therefore suggest that behavioral economics may have a far more parsimo-

[22] As we emphasize in the introduction, we view cognitive explanations like ours as *complements* to standard descriptive models like prospect theory and the $\beta - \delta$ model rather than substitutes. The literature has long debated whether these models should be interpreted literally as descriptions of non-standard tastes for risk and delay or instead as descriptions of a suite of cognitive adaptations. Our findings support the latter interpretation and suggest that models like ours can allow us to endogenize parameters from descriptive behavioral models and explain why those parameters change in response to payoff-irrelevant factors.

nious structure than is typically appreciated because many of it's key patterns may have closely related cognitive foundations.[23]

Third, we find that our treatment effects match a distinctive fingerprint of behavioral effects predicted by the model of imprecise cognition that we used to design our experiment. Given our motivating hypotheses concerning the way cognitive noise should be influenced by framing, our treatment effects correspond remarkably well to the key comparative statics predictions of our model. Not only does our model predict that *improving* the quality of information processing (with respect to probabilities and delays) will lessen the severity of anomalies, but also, less intuitively, that *worsening* the quality of information processing (surrounding payoffs) will often have the same effect. The fact that this counterintuitive symmetry strongly bears out in our data (modulo our choice of framing manipulations), in both the domain of risk and time, constitutes particularly strong evidence for the imprecise cognition mechanism animating our model. Our findings therefore speak to the promise of imprecise cognition models as tools for explaining and predicting human behavior.

Indeed, our findings serve especially to emphasize a subtle but important implication of these (and other) cognitive models. To the degree that we expect people to be subject to *some* cognitive limitations, we should be cautious about interpreting evidence of neoclassical behavior as evidence of rationality. In our model, for instance, neoclassical behavior (e.g., well-calibrated likelihood or delay sensitivity) occurs whenever cognitive imperfections *similarly* afflict the processing of probabilities/delays and payoffs while anomalies occur when these imperfections are, instead, asymmetric. In some of our treatments we can lessen or eliminate anomalies, restoring relatively neoclassical behavior but this is not, in general, a consequence of our having restored economic rationality. Indeed, as we show, we can as easily push behavior towards neoclassical benchmarks by *worsening* cognitive frictions as by *lessening* them!

Although our experiment uses framing effects to influence behavior under the guidance of a cognitive model, it is important to emphasize that our experiment was not designed

[23] Indeed, because the cognitive frictions we study are not domain-specific, there are reasons to expect framing manipulations like ours to have effects on behavior in domains beyond those of risk and time. Enke et al. (2024) provide evidence that the insensitivities underlying some of the key anomalies of risk and time we study occur also in many other economic decision settings and we speculate that framing may have similar effects in many of these settings.

to give us much systematic insight into the scope or boundaries of such effects. We use framing manipulations in our experiment as treatment instruments to identify the role cognitive limitations play in behavioral anomalies, and our own selection of manipulations were derived not from a developed theory of frames but from strong intuition and prior findings in the literature about what features seemed likely to influence cognitive noise. Although we suspect that many other systematic manipulations of cognitive frictions via framing are possible, our experiment, by design, gives us limited insight into what they are or how easily they can be uncovered.[24] Nonetheless, we believe our results point to the potential of cognitive models for better understanding framing. Indeed, on the basis of our findings, we believe building and testing models of framing effects, rooted in information processing frictions, is an important frontier for the literature, and is a natural next step in this research.

Finally, although our experiment was designed with reference to a specific class of cognitive models (cognitive imprecision models), we believe our results point to the potential importance of a broader set of cognitive forces for interpreting, explaining and predicting human behavior. For instance, although our findings are well-explained by a model of cognitive imprecision (as in Khaw, Li and Woodford, 2021), the distribution of precision may well be shaped by other cognitive factors such as limited attention and the way framing shapes the relative salience of probabilities/delays vs. payoffs (as in Bordalo, Gennaioli and Shleifer, 2012; 2013; 2022; Li and Camerer, 2022). Likewise, our experiments were conducted with subjects who had a particular array of cognitive capacities available for the experiment (subjects in an online pool), while other pools of subjects may have differing resources available, altering both the intensity of these anomalies and the efficacy of framing in altering cognitive resource allocations.[25] Because of this our findings point especially at the importance of using cognitive models and empirical tests of them to better understanding how the supply of information processing (by decision makers) interacts with the demand for information processing (by tasks and the way they are framed) to shape economic behavior.

[24] Though see Bouchouicha, Li and Vieider, 2025 for evidence that visualizations of *payoffs* (rather than probabilities) produces predictable effects on risk-taking in mixed gain-loss lotteries, as predicted by imprecise cognition models.

[25] For instance, anomalies like probability weighting are substantially smaller with more cognitively sophisticated subjects (Donkers, Melenberg and Van Soest, 2001; L'Haridon and Vieider, 2019; Choi et al., 2022).

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ONLINE APPENDIX

A Step-wise model derivation

We model perception of a generic choice attribute z. The decision maker receives an unbiased but imprecise signal $r_z \sim \mathcal{N}(ln(z), \nu_z^2)$, where ν_z^2 is the error variance of the signal, and we define $\lambda_z \triangleq \nu_z^{-2}$ as the precision of the signal. The decision-maker holds prior beliefs about the distribution of choice quantities in the environment given by $ln(z) \sim \mathcal{N}(\mu_z, \sigma_z^2)$, with $\xi_z \triangleq \sigma_z^{-2}$ the precision of the prior. The decision maker subsequently decodes the noisy signal by combining it with the prior in a Bayesian inference process, yielding the posterior mean

$$\mathbb{E}[ln(z)|r_z] = \frac{\lambda_z}{\lambda_z + \xi_z} r_z + \frac{\xi_z}{\lambda_z + \xi_z} \mu_z.$$

While determining the decision, this posterior mean is not directly observable to the experimenter. The best we can thus do is to average over many repeated trials involving the same choice attributes to characterize average behavior. Given that r_z is unbiased, this allows us to to obtain the following response distribution:

$$\mathbb{E}\left[\mathbb{E}[ln(z)|r_z]\big|z\right] = \frac{\lambda_z}{\lambda_z + \xi_z} ln(z) + \frac{\xi_z}{\lambda_z + \xi_z} \mu_z,$$

where the signal has been replaced by its mean. The proof follows trivially from the property of the normal distribution whereby $n \sim \mathcal{N}(m, s)$ implies $a + bn \sim \mathcal{N}(a + bm, b^2 s^2)$.

The final step is to substitute the relevant quantities for z and to trade off different attributes as specified in the choice rules shown in the main text. We here show the derivation for risk (the derivation for time is identical). Define $\gamma \triangleq \frac{\lambda_p}{\lambda_p + \xi_p}$ as the evidence weight put on the true log-odds in the Bayesian inference process, where the subscript p indicates probabilities and $\frac{\xi_z}{\lambda_z + \xi_z} = 1 - \gamma$. Equivalently, define $\beta \triangleq \frac{\lambda_o}{\lambda_o + \xi_o}$, where o stands for outcomes, i.e. the cost-benefit ratio. Trading off the attributes involves choosing the risky wager whenever $\gamma r_p + (1 - \gamma) ln(\eta) > \beta r_o + (1 - \beta) ln(\kappa)$, with the prior means defined as in the main text. Rewriting the choice equation as $\gamma r_p - \beta r_o - [(1 - \beta) ln(\kappa) + (\gamma -) ln(\eta)] > 0$ and defining $[(1 - \beta) ln(\kappa) + (\gamma -) ln(\eta)] \triangleq ln(\theta)$, we can again apply the properties of the normal distribution to arrive at the response distribution:

$$\gamma\, r_p - \beta\, r_o - ln(\theta) \sim \mathcal{N}\left(\gamma\, ln\left(\frac{p}{1-p}\right) - \beta\, ln\left(\frac{c-y}{x-c}\right) - ln(\theta)\ ,\ \gamma^2/\lambda_p + \beta^2/\lambda_o\right).$$

The version in the main Probit equation in the main text obtains equivalently, by first dividing everything by β in $\gamma r_p - \beta r_o - [(1-\beta)ln(\kappa) + (\gamma -)ln(\eta)] > 0$ and then following the same steps.

B Additional nonparametric results

B.1 Interaction effects

In addition to the effects highlighted in the main text, our simulations in figure 1 make a number of predictions on interaction effects between parameters that are particularly empirically diagnostic of our model. In particular, for both risk and time, the effect of the visual manipulation on risk aversion and impatience are predicted to be strongest when reward discriminability β and $\widehat{\beta}$ are low. This is because reward-discriminability β and $\widehat{\beta}$ acts as a scaling parameter, modulating overall elasticity, including with respect to probabilities and delays, as well as to all prior expectations. Probability-discriminability γ and delay-discriminability $\widehat{\gamma}$, on the other hand, modulate the relative elasticity to evidence and prior.

These effects show up prominently in our data. Figure 6, Panels A and B, show the effect of the visual manipulation when rewards are denominated in pounds vs pence, respectively. When rewards are denominated in pence, sensitivity to probabilities is generally more pronounced, as seen above. In addition, both the effect of the visual display on sensitivity to probabilities and the effect of the visual display on the increase in risk-taking at even odds are more pronounced. We observe a similar effect for time, shown in panels C and D. When rewards are denominated in pence, the effect of the visual display on patience are much more pronounced, consistently with the overall increase in elasticity when the precision of reward coding is low.

Finally, there is an effect specific to time whereby the treatment effect of denominating rewards in pence ought to be strongest when delays are displayed visually and hence encoded relatively precisely. This effect, too, is clearly present in our data, as can be

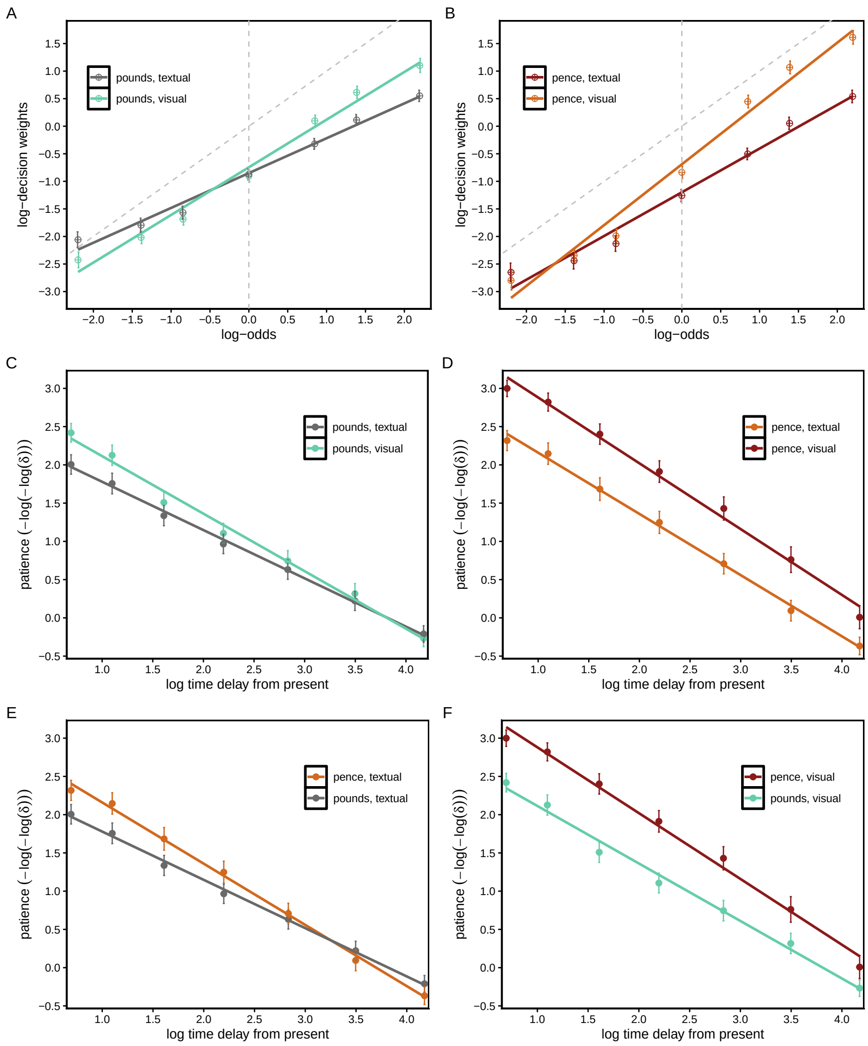

Figure 6: Interaction effects

Panel A shows the effects of the visual versus textual display of probabilities when rewards are denominated in pounds, and Panel B shows the effect of the sale treatment when rewards are denominated in pence. Panels C and D show effects of the visual vs textual time display for pounds and pence; respectively. Panels E and F show the effect of the pounds vs pence manipulation under textual displays and visual displays of time delays, respectively.

seen when comparing Panels E and F.

bigskip

Result 8. *Interactions between our manipulations of probability/delay noise and payoff noise are strikingly similar to distinctive predictions made by noisy cognition models.*

B.2 Strongly decreasing impatience

Here we show additional nonparametric results. In particular, figure 7 shows the effect of pushing given delay, $\tau_\ell - \tau_s$ farther into the future, starting from an initial up-front delay. This serves to test whether patience is strongly decreasing, in the sense of Prelec (2004). The index is constructed by including all pairwise comparison of 4-week delays, subtracting the earlier choice proportions from the later ones, and averaging over all comparisons. Values of the index larger than 1 thus indicate strongly decreasing impatience away from immediate delays, values of 1 constant impatience, and values lower than 1 strongly increasing impatience.

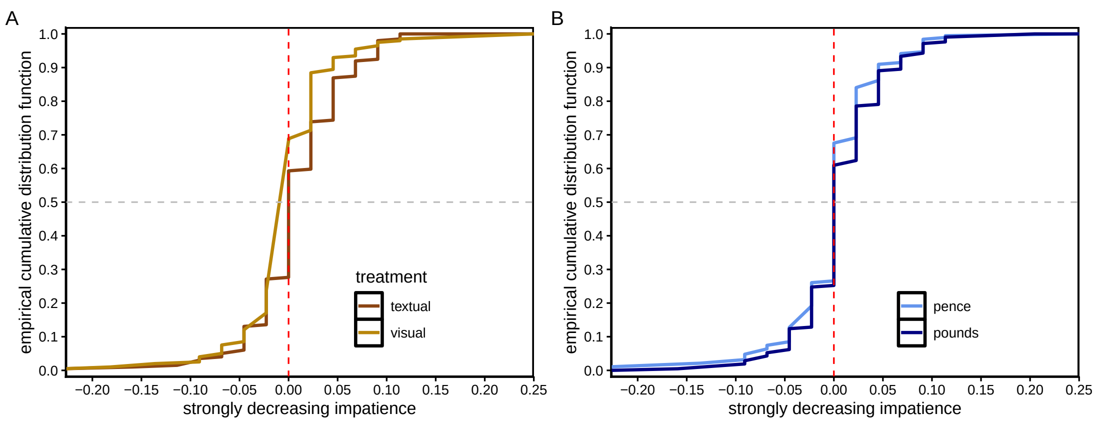

Figure 7: Strongly decreasing impatience

Panel A compares the index in the textual and the visual treatment. The median subject does not exhibit any changes in impatience as the up-front delay increases, and there is no difference between treatments ($p = 0.150$, Wilcoxon ranksum test). Panel B shows the equivalent comparison for pounds versus pence. Once again, the median subject in both treatments exhibits no changes in patience, and there is no treatment effect ($p = 0.242$).

C Reduced form logistic regressions

C.1 Regression model and code

To more rigorously test the model predictions in a model-free way, we use a reduced form logistic regression model. That is, we model

$$log\left(\frac{p_r}{1-p_r}\right) = \beta_0 + \beta_1 lo + \zeta_n,$$

where p_r is the probability of choosing risky/later option, and lo indicates the objective log-odds (or log time-delay). The coefficient on the log-odds or log-time delay is thus the reduced-form equivalent of the elasticities γ/β and $\widehat{\gamma}/\widehat{\beta}$. The intercept parameter β_0 is the reduced-form equivalent of the overall contribution from the priors.

The regression parameters β_0 and β_1 may be treatment-specific. The parameters ζ_n are individual-level hierarchical intercepts, which serve to cluster the error at the subject level. We estimate the regression using Bayesian techniques in Stan. We check convergence by making sure that there are no divergent iterations, by checking the Rhat statistic, and by visually examining the mixing of the simulation chains.

C.2 Risk: textual vs visual, pounds vs pence

Table 1 shows the results. Regression 1 examines the effect of the visual treatment only, while averaging over the pounds vs pence manipulation. The pure treatment effect — indicating the effect on risk taking propensity for even odds — shows a positive effect. The interaction between the visual treatment and the log-odds also shows a positive effect. Both effects line up with those predicted by the model. The total elasticity to log-odds in the visual treatment can furthermore be seen to exceed 1, showing a reversal of the canonical likelihood-insensitivity documented in the textual treatment.

Regression (2) examines the effects of the pounds vs pence manipulation. Expressing rewards in pence decreases the intercept (an effect that is significant at the 10% level). It also *increases* elasticity towards the log-odds, which again overshoot the unitary benchmark case of expected utility theory.

Regression (3) adds both treatments at once. All effects remain stable, indicating that the effects of the two treatments do indeed cumulate. Regression (4) further adds interaction

dep. var:	**choice of lottery over sure**			
	reg. (1)	reg. (2)	reg. (3)	reg. (4)
intercept	−1.274	−0.983	−1.184	−1.036
	(0.088)	(0.090)	(0.105)	(0.125)
visual	0.392		0.399	0.109
	(0.128)		(0.124)	(0.180)
pence		−0.236	−0.203	−0.488
		(0.127)	(0.116)	(0.174)
visual * pence				0.568
				(0.250)
log-odds	0.873	0.907	0.750	0.773
	(0.013)	(0.013)	(0.015)	(0.017)
log-odds * visual	0.326		0.323	0.271
	(0.019)		(0.019)	(0.025)
log-odds * pence		0.270	0.266	0.214
		(0.019)	(0.019)	(0.026)
log-odds * visual * pence				0.120
				(0.038)
observations	58,947	58,947	58,947	58,947
subjects (clusters)	401	401	401	401

Table 1: Regression analysis of risk-taking

The table shows Bayesian Logistic regressions of risk-taking on a number of independent variables. Errors are clustered at the subject level using random intercepts.

effects between the treatments. The effect of the visual aid on risk-taking is not significant in the pounds treatment, but very strong in the pence condition — just as predicted by our simulations in figure 1. The effect of the visual treatment on elasticity to the log-odds is also much more pronounced when outcomes are denominated in pence, again as predicted by β acting as a scaling factor for overall elasticity in our model.

C.3 Time: textual vs visual, pounds vs pence

To more rigorously test the model predictions empirically in a model-free way, we use a reduced form logistic regression model just as for risk. That is, we regress the log-odds of choosing the larger-later amount on predictors including the log-delay, a dummy whether the sooner payout is immediate, the two treatments, and the interaction between these variables.

Table 2 shows the results. Regression (1) shows the effects of displaying a visual aid for the time delay. This results in increased patience, as shown by the simple treat-

dep. var:	**choice of larger-later**			
	reg. (1)	reg. (2)	reg. (3)	reg. (4)
intercept	3.174	3.069	2.761	2.953
	(0.135)	(0.135)	(0.152)	(0.186)
visual	0.668		0.693	0.263
	(0.191)		(0.192)	(0.271)
pence		0.963	0.909	0.504
		(0.202)	(0.185)	(0.268)
visual * pence				0.882
				(0.372)
log-delay	−0.893	−0.870	−0.783	−0.810
	(0.012)	(0.012)	(0.015)	(0.017)
log-delay * visual	−0.193		−0.193	−0.132
	(0.019)		(0.019)	(0.025)
log-delay * pence		−0.258	−0.261	−0.193
		(0.029)	(0.019)	(0.026)
log-delay * visual * pence				−0.165
				(0.040)
immediate	−0.679	−0.612	−0.789	−0.749
	(0.029)	(0.029)	(0.035)	(0.039)
immediate * visual	0.386		0.396	0.304
	(0.045)		(0.045)	(0.058)
immediate * pence		0.256	0.271	0.172
		(0.045)	(0.045)	(0.060)
immediate * visual * pence				0.254
				(0.092)
observations	100,296	100,296	100,296	100,296
subjects (clusters)	398	398	398	398

Table 2: Regression analysis of patience

The table shows Bayesian Logistic regressions of risk-taking on a number of independent variables. Errors are clustered at the subject level using random intercepts.

ment effect. The interaction with the log-time delay furthermore shows a significantly negative effect, indicating a steeper discount function in the visual treatment. This effect is indeed string enough that the canonical pattern of time-insensitivity reverses, with excess-sensitivity prevailing in the visual treatment. Immediate payouts result in reduced patience in general, but providing a visual display reduces this effect, thus proceeding in lock-step with overall patience, as predicted by our model. Regression (2) shows parallel effects for the pence treatment: displaying outcomes in pence results in heightened patience, a steeper function — which once again overshoots the exponential benchmark — and reduced present bias.

Regression (3) controls for both treatments at once. It shows that the treatments indeed both show these effects independently of the orthogonal manipulation. Regression (4) further adds interaction effects. These show, once more, that the effect of the visual manipulation on overall patience, on the elasticity of choice proportions to log-delays, and on the reduction of present bias is strongest when outcomes are denominated in pence, highlighting once the predicted scaling effect of reducing the precision in reward-representations.

D Structural estimations

D.1 Estimation model

We estimate the model using a Bayesian hierarchical structure in Stan (Carpenter et al., 2017). Hyperpriors are chosen such as to be mildly regularizing, and the model is put on a common prior variance scale to allow for separate identification of the parameters γ and α ($\widehat{\gamma}$ and $\widehat{\alpha}$ for time), while allowing coding precision to freely adjust. Nonetheless we caution that separate identification of the parameters is much harder to achieve for time delays than under risk, given the lopsided nature of the 'time log-odds' cut off at 0, which make it impossible to obtain the same orthogonality in choice stimuli under time delays as we use in risk. The structural results for time thus ought to be consumed cautiously.

The individual-level parameters are estimated using the two models reproduced here below. Vieider (2024*a*) provides a tutorial on the estimation of Bayesian hierarchical decision-making models in Stan and R. We estimate a global model encompassing all treatment conditions. Coding noise (precision) parameters receive condition-specific means, whereas the parameters of the prior do not. Note that this serves to restrict our degrees of freedom: by explicitly modeling the parameters of the prior as common to the different conditions, we prevent them from easily adjusting, and thereby take away degrees of freedom. All coding noise parameters are allowed to be specific to all manipulations, even when a given manipulation is not predicted to affecta certain parameter.

The code for risk takes the following form:

```
data {
```

```
    int<lower=1> N;
    int<lower=1> N_id;
    array[N] int id;
    array[N] real high;
    array[N] real low;
    array[N] real sure;
    array[N] real p;
    array[N] int choice_risky;
    array[N_id] int condition;  // 1-4, condition index per subject
}

transformed data {
    array[N] real lcb;
    array[N] real llr;
    for (i in 1:N) {
        lcb[i] = log( (sure[i] - low[i]) / (high[i] - sure[i]) );
        llr[i] = log( p[i] / (1 - p[i]) );
    }
}

parameters {
    matrix[2, 4] mus_noise;   // population means for nup (row 1), nuo (row 2): condition-specific
    vector[3] mus_prior;       // population means for sigma, eta, xi: common across conditions
    vector<lower=0>[5] tau;
    cholesky_factor_corr[5] L_omega;
    array[N_id] vector[5] Z;
}

transformed parameters {
    matrix[5,5] Rho = L_omega * L_omega';
    array[N_id] vector[5] theta;
    vector<lower=0>[N_id] nup;
    vector<lower=0>[N_id] nuo;
    vector<lower=0>[N_id] sigma;
    vector<lower=0>[N_id] eta;
    vector<lower=0>[N_id] xi;

    vector<lower=0>[N_id] alpha;
```

```
    vector<lower=0>[N_id] gamma;
    vector<lower=0>[N_id] omega;

    for (n_id in 1:N_id) {
        vector[5] mus_id;
        mus_id[1] = mus_noise[1, condition[n_id]];  // nup: condition-specific
        mus_id[2] = mus_noise[2, condition[n_id]];  // nuo: condition-specific
        mus_id[3] = mus_prior[1];                   // sigma: common
        mus_id[4] = mus_prior[2];                   // eta: common
        mus_id[5] = mus_prior[3];                   // xi: common

        theta[n_id] = mus_id + diag_pre_multiply(tau, L_omega) * Z[n_id];

        nup[n_id]   = exp(theta[n_id, 1]);
        nuo[n_id]   = exp(theta[n_id, 2]);
        sigma[n_id] = exp(theta[n_id, 3]);
        eta[n_id]   = exp(theta[n_id, 4]);
        xi[n_id]    = exp(theta[n_id, 5]);

        alpha[n_id] = sigma[n_id]^2 / ( sigma[n_id]^2 + nuo[n_id]^2 );
        gamma[n_id] = sigma[n_id]^2 / ( sigma[n_id]^2 + nup[n_id]^2 );
        omega[n_id] = sqrt( nuo[n_id]^2 * alpha[n_id]^2 + nup[n_id]^2 * gamma[n_id]^2 );
    }
}

model {
    vector[N] udiff;

    // hyperpriors
    tau ~ exponential(1);
    L_omega ~ lkj_corr_cholesky(1);

    // population means: noise parameters, one prior per condition cell
    for (k in 1:4)
        mus_noise[:, k] ~ normal(0, 2);

    // population means: prior parameters, common
```

```
    mus_prior ~ normal(0, 2);

    // non-centered individual effects
    for (n_id in 1:N_id)
        Z[n_id] ~ std_normal();

    // likelihood
    for (i in 1:N) {
        udiff[i] = ( gamma[id[i]] * llr[i] + (1 - gamma[id[i]]) * log(eta[id[i]])
                   - ( alpha[id[i]] * lcb[i] + (1 - alpha[id[i]]) * log(xi[id[i]]) ) )
                   / omega[id[i]];
        choice_risky[i] ~ bernoulli( Phi( udiff[i] ) );
    }
}

generated quantities {
    vector[N] log_lik;
    vector[N] udiff;

    for (i in 1:N) {
        udiff[i] = ( gamma[id[i]] * llr[i] + (1 - gamma[id[i]]) * log(eta[id[i]])
                   - ( alpha[id[i]] * lcb[i] + (1 - alpha[id[i]]) * log(xi[id[i]]) ) )
                   / omega[id[i]];
        log_lik[i] = bernoulli_lpmf( choice_risky[i] | Phi( udiff[i] ) );
    }

    // individual-level derived quantities
    vector[N_id] ga;
    vector[N_id] prior;
    vector[N_id] ra;

    for (i in 1:N_id) {
        ga[i]    = gamma[i] / alpha[i];
        prior[i] = eta[i]^(gamma[i] - 1) * xi[i]^(1 - alpha[i]);
        ra[i]    = ( eta[i]^(gamma[i] - 1) * xi[i]^(1 - alpha[i]) )^(1 / alpha[i]);
```

```
    }
}
```

The code for time delays takes the following form:

```
data {
    int<lower=1> N;
    int<lower=1> N_id;
    array[N] int id;
    array[N] real large;
    array[N] real small;
    array[N] real sooner;
    array[N] real later;
    array[N] int choice_later;
    array[N] int immediate;
    array[N_id] int condition;  // 1-4, condition index per subject
}

transformed data {
    array[N] real lldf;
    for (i in 1:N)
        lldf[i] = log( log( large[i] / small[i] ) );
}

parameters {
    matrix[2, 4] mus_noise;   // population means for nut (row 1), nur (
        row 2): condition-specific
    vector[3] mus_prior;       // population means for sigma, eta, rho:
        common across conditions
    vector<lower=0>[5] tau_s;
    cholesky_factor_corr[5] L_omega_s;
    array[N_id] vector[5] Z_s;
}

transformed parameters {
    array[N_id] vector[5] theta;
    vector<lower=0>[N_id] nut;
    vector<lower=0>[N_id] nur;
    vector<lower=0>[N_id] sigma;
    vector<lower=0>[N_id] eta;
    vector<lower=0>[N_id] rho;
```

```
    vector<lower=0>[N_id] gamma;
    vector<lower=0>[N_id] alpha;
    vector<lower=0>[N_id] delta;
    vector<lower=0>[N_id] omega;

    for (n_id in 1:N_id) {
        vector[5] mus_id;
        mus_id[1] = mus_noise[1, condition[n_id]];  // nut: condition-specific
        mus_id[2] = mus_noise[2, condition[n_id]];  // nur: condition-specific
        mus_id[3] = mus_prior[1];                   // sigma: common
        mus_id[4] = mus_prior[2];                   // eta: common
        mus_id[5] = mus_prior[3];                   // rho: common

        theta[n_id] = mus_id + diag_pre_multiply(tau_s, L_omega_s) * Z_s[n_id];

        nut[n_id]   = exp(theta[n_id, 1]);
        nur[n_id]   = exp(theta[n_id, 2]);
        sigma[n_id] = exp(theta[n_id, 3]);
        eta[n_id]   = exp(theta[n_id, 4]);
        rho[n_id]   = exp(theta[n_id, 5]);

        gamma[n_id] = sigma[n_id]^2 / ( sigma[n_id]^2 + nut[n_id]^2 );
        alpha[n_id] = sigma[n_id]^2 / ( sigma[n_id]^2 + nur[n_id]^2 );
        delta[n_id] = eta[n_id]^(1 - gamma[n_id]) * rho[n_id]^(alpha[n_id] - 1);
        omega[n_id] = sqrt( nur[n_id]^2 * alpha[n_id]^2 + nut[n_id]^2 * gamma[n_id]^2 );
    }
}

model {
    vector[N] udiff;
    vector[N] delay;

    // hyperpriors
    tau_s ~ exponential(1);
    L_omega_s ~ lkj_corr_cholesky(1);
```

```

    // population means: noise parameters, one prior per condition cell
    for (k in 1:4)
        mus_noise[:, k] ~ normal(0, 2);

    // population means: prior parameters, common
    mus_prior ~ normal(0, 2);

    // non-centered individual effects
    for (n_id in 1:N_id)
        Z_s[n_id] ~ std_normal();

    // likelihood
    for (i in 1:N) {
        delay[i] = (later[i] - sooner[i]) + immediate[i];
        udiff[i] = ( alpha[id[i]] * lldf[i] + (1 - alpha[id[i]]) * log(
            rho[id[i]] )
                    - ( gamma[id[i]] * log( delay[i] )
                    + (1 - gamma[id[i]]) * log( eta[id[i]] ) ) ) / omega[
                        id[i]];
        choice_later[i] ~ bernoulli( Phi( udiff[i] ) );
    }
}

generated quantities {
    vector[N] log_lik;
    vector[N] udiff;
    vector[N] delay;
    vector[N_id] ga;
    vector[N_id] imp;
    matrix[5,5] Rho_s = L_omega_s * L_omega_s';

    for (i in 1:N) {
        delay[i] = (later[i] - sooner[i]) + immediate[i];
        udiff[i] = ( alpha[id[i]] * lldf[i] + (1 - alpha[id[i]]) * log(
            rho[id[i]] )
                    - ( gamma[id[i]] * log( delay[i] )
                    + (1 - gamma[id[i]]) * log( eta[id[i]] ) ) ) / omega[
                        id[i]];
        log_lik[i] = bernoulli_lpmf( choice_later[i] | Phi( udiff[i] ) );
```

```
    }

    for (n in 1:N_id) {
        ga[n]  = gamma[n] / alpha[n];
        imp[n] = delta[n]^(1 / alpha[n]);
    }
}
```

D.2 Structural results visual manipulation

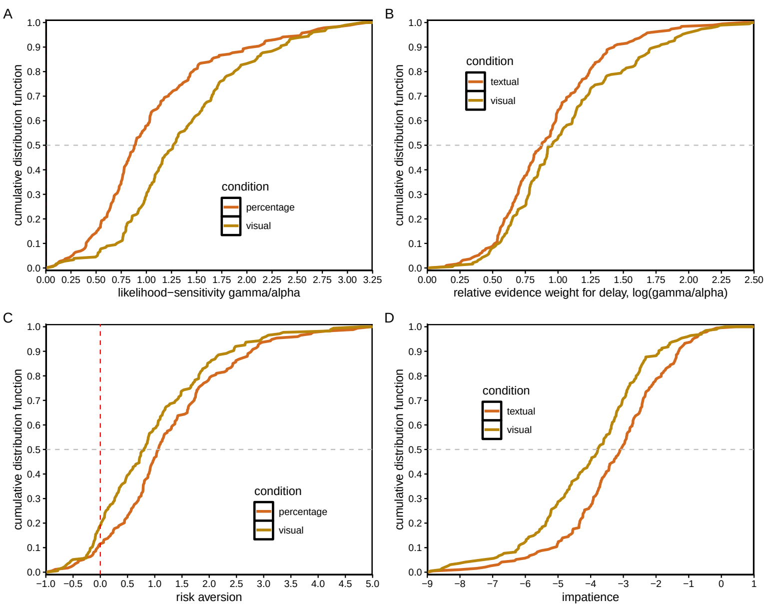

Figure 8: Structural parameter estimates for visual vs textual displays

We start by presenting the effects of the visual manipulation, shown in Figure 8. All panels show empirical cumulative distribution-functions of individual-level (hierarchical) means of the posteriors. Panel A shows the eCDFs of the evidence elasticity γ/β for risk. The distribution for the visual treatment lies clearly to the right of the distribution for the percentage or textual treatment ($p < 0.001$, Wilcoxon test on individual-level parameter means). The same is the case for the eCDF of the elqsticity to time delays, $\widehat{\gamma}/\widehat{\beta}$, shown in panel B. The treatment effect is again pronounced, and highly significant ($p = 0.017$).

Panels C and D show the treatment effects on risk aversion and impatience, respectively, i.e. on the whole contribution from the weighted priors. Risk aversion is clearly lower in the visual condition ($p = 0.007$). The same holds true for impatience, which is again lower in the visual condition ($p < 0.001$).

D.3 Structural results for pounds vs pence

Figure 9 shows the structural parameter distributions for the pounds vs pence manipulation. Panels A and B show elasticities γ/β to log-odds and $\widehat{\gamma}/\widehat{\beta}$ to log delays, respectively. In both cases, denominating outcomes in pence increases elasticity significantly compared to outcomes denominated in pounds ($p < 0.001$).

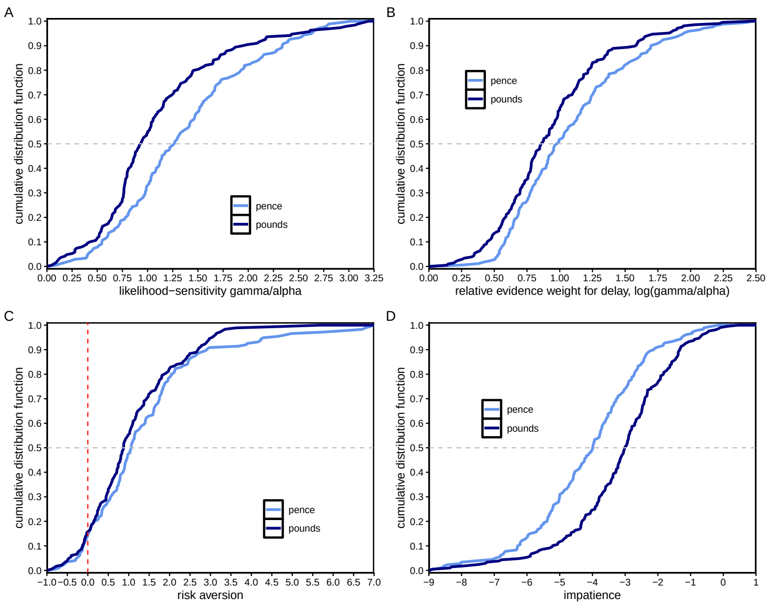

Figure 9: Structural parameter estimates for pounds vs pence

Panels C and D show the effects on risk aversion and impatience, respectively. Risk aversion is significantly larger in the pence condition ($p = 0.007$). Impatience, on the other hand, is again reduced in the pence condition ($p < 0.001$).

E Instructions

E.1 Instructions for risk

Thank you for taking part in this study. We will ask you to take repeated decisions involving lotteries. On each screen, you will be asked to choose between **a lottery** and **a sure amount of money**. Chances of winning the prize in the lottery are **always indicated as numbered balls out of 10**. Monetary payments are **always indicated in pounds**. There are no right or wrong answers–we a purely interested in your preferences.

Here is an example of a choice task:

Please indicate your choice

12 pounds if one of the following balls is extracted:

0 pounds if one of the following balls is extracted:

5 pounds for sure

In the example above, you are asked to choose between a lottery paying 12 pounds if a ball with a number between 1 and 5 inclusive is extracted, and a sure payment of 5 pounds.

If this is the randomly selected choice paid for real:
- If you selected the **sure amount**, we will pay you that amount

- If you selected the **lottery**, we will draw a ball from a bag containing 10 sequentially numbered balls. If the ball extracted bears a number between 1 and 5 inclusive, we will pay you the prize. If the ball contains a number between 6 and 10 inclusive, we will pay you nothing.

You will be presented repeatedly with such tasks, and you are asked to indicate your choice for each one of those tasks. Notice that **both the amounts and the numbers of balls attached to the prize may change from screen to screen**. Please consider the information carefully and choose your preferred option.

E.2 Instructions for time

Thank you for taking part in this study. We will ask you to take repeated decisions involving time delays.

On each screen, you will be asked to choose between an amount of money that is paid at **a sooner moment in time**, and an amount that is paid **at a later moment in time**. Time delays are **always indicated in weeks from today**. The time delays are depicted using **solid lines of length proportional to the length of the time delay**. The number above the endpoint of the line indicates the delay in weeks from today. Monetary payments are **always indicated in pence**.

There are no right or wrong answers – we are only interested in your preferences.

Here is an example of a choice task:

Please indicate your choice

In the example above, you are asked to choose between an option paying 900 pence in 0 weeks (that is, **immediately**), and an option paying 1200 pence in 8 weeks from today.

<u>If this is the randomly selected choice pair for real</u>:
- If you selected the **immediate payout**, we will pay you the amount as soon as this study is over

- If you selected the **payout in 8 weeks**, we will send you a message confirming the amount and date of the payout. The message will also contain our contact details, which you can use in case you have any questions about the payment. You will **receive the payment exactly 8 weeks from today**.

You will be presented repeatedly with such tasks, and you are asked to indicate your choice for each one of those tasks. Notice that **both the amounts and the time delays involved may change from screen to screen**. Please consider the information carefully and choose your preferred option.