

# Temptation: Immediacy and certainty<sup>\*</sup>

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**Abstract** Is an option especially tempting when it is both immediate and certain? I test the effect of risk on the present-bias factor given quasi-hyperbolic discounting. In my experiment workers allocate about thirty to fifty minutes of real-effort tasks between two weeks. I study dynamic consistency by comparing choices made two days in advance of the work-day with choices made when work is imminent. My novel design permits estimation of present bias using a decision with a consequence that is both immediate and certain. I find greater present bias when the consequence is certain. This finding has implications for any economic decision involving a present-biased decision-maker, including labor contracting and consumer good pricing. I offer a methodological remedy for experimental economists.

*JEL Codes* C91, D80, D90

**Keywords** present bias, dynamic inconsistency, quasi-hyperbolic discounting, time preferences, risk preferences, immediacy effect, certainty effect, experimental economics

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# 1 Introduction

While risk and time preferences are fundamental to the theory of decision-making, much remains unknown about the interplay between these two dimensions. A future prospect is inherently risky if any circumstance may arise that precludes consumption of the consequence. This implies that outcomes are obtained with certainty only if obtained without delay. Accordingly a preference for certain outcomes results in a preference for immediate outcomes. Conversely, the introduction of risk may especially diminish the appeal of an immediate reward, relative to a delayed reward. I explore in this paper such an interaction between immediacy and certainty with an experiment of dynamic decision-making over risky and delayed prospects.

Present-biased preferences explain oft-bemoaned consumer behavior, such as the failure to meet one's own physical exercise goals and the over-utilization of credit-card debt (Royer, Stehr, and Sydnor 2015; Meier and Sprenger 2010). Firms exploit consumer present bias and successfully extract welfare (DellaVigna and Malmendier 2004). Meanwhile, incentives, commitment devices, and other interventions may (or may not) help consumers improve their long-term welfare (Ashraf, Karlan, and Yin 2006; Carrera et al. 2022). A better understanding of present bias assists this body of research.

As an example, my study informs labor contract design, especially those used in the modern gig economy. Consider drivers for ride-hail companies—these workers face decisions similar to those of the workers in my experiment. Ride-hail companies carefully withhold selective information (such as ride length or destination) when offering a gig to a driver and require commitment prior to revealing all of these ride details (Rana 2020). Such uncertainty in a spot labor contract theoretically affects labor supply; my results confirm that a present-biased worker with a weekly income target may procrastinate less given greater uncertainty.

My novel experimental design allows estimation of present bias for subjects making a single decision with a certain consequence. This is in contrast to a baseline treatment that implements an allocation choice made on a randomly-selected day and at a randomly-selected intertemporal price ratio, in accord with prevailing experimental methodology.

Workers in my experiment allocate a workload between two weeks. Each worker first makes allocation decisions two days before the first workday. Each worker then returns on the first workday and makes identical decisions with the work being imminent. If a worker is present-biased, she will in advance choose some allocation between the two weeks, but then on the first workday, prefer an allocation with less work for the present day. In my experiment, once the implementation mechanism selects a particular allocation, the worker must complete the tasks allocated to each week to earn a substantial bonus payment.

Ultimately I find that the immediacy effect is significantly attenuated by the introduction of risk. Specifically, the quasi-hyperbolic present-bias factor  $\beta$  becomes smaller with the elimination of risk, implying greater myopia. In my experiment, when a workload allocation is implemented with certainty, subjects on average discount the future by a factor of  $\hat{\beta} = 0.581$  relative to the present. In the baseline treatment that uses prevailing experimental methodology, I find no statistically significant present bias, with  $\hat{\beta} = 1.009$  when each decision has a 10% implementation probability.

These findings underscore the importance of decision-theoretic frameworks that permit interaction between dimensions of risk and time. The findings also suggest that studies of tempting goods may necessitate decisions with temporally salient and certain consequences; researchers should keep this in mind when designing either lab or field experiments. Further, risk introduced by randomized incentive mechanisms—common experimental methodology—may require augmentation of decisions with certain consequences. I offer such a methodological remedy.

## 2 Background

To model intertemporal decision-making, Samuelson (1937) introduced *exponential discounted utility* (DU), which describes how an individual values utility flows (of consumption goods, such as leisure) that occur over time. If utility flows  $u(x_{t+\tau})$  result from consumption  $x_{t+\tau}$  at time  $t + \tau \in \mathbb{N}$ , given a constant discount factor  $\delta \in [0, 1]$ , the model gives an intertemporal value at time  $t$  of

$$U_t^{\text{DU}} = \sum_{\tau=0} \delta^\tau u(x_{t+\tau}). \quad (1)$$

A decision-maker with this value function will make *dynamically consistent* choices, assuming that the felicity function  $u$  is time-invariant (Halevy 2015).

To capture a preference for immediate utility, Laibson (1997) introduces the present-bias factor  $\beta \geq 0$  to discount all future utility flows contra present utility. The resultant *quasi-hyperbolic discounted utility* (QHD) has an intertemporal value at time  $t$  of

$$U_t^{\text{QHD}} = u(x_t) + \beta \sum_{\tau=1} \delta^\tau u(x_{t+\tau}). \quad (2)$$

$\beta < 1$  describes a preference for immediacy, also referred to as *present bias*. This is an example of *diminishing sensitivity to delay*—an individual is more impatient regarding a delay in felicity that happens immediately relative to a delay that occurs in the future. Meanwhile, some individuals may exhibit future bias, with  $\beta > 1$ .

A decision-maker with  $\beta \neq 1$  will make *dynamically inconsistent* choices. A decision-maker with  $\beta < 1$  ( $\beta > 1$ ) will continually revise consumption plans to achieve greater (lesser) felicity in the present moment relative to her prior plans.

## 2.1 Diminishing sensitivity to risk and delay

Let a simple gamble  $(x \circ p)$  be a prospect that obtains  $x$  with probability  $p$ . Given the independence axiom of expected utility theory (EUT), a preference relation is maintained if prospect probabilities are multiplied by a common ratio (Machina 1982). Consider

$$\begin{array}{llll} \text{Menu } \mathcal{A}: & a = (1 \circ 0.9) & \text{or} & a' = (2 \circ 0.6); & \text{and} \\ \text{Menu } \mathcal{B}: & b = (1 \circ 0.6) & \text{or} & b' = (2 \circ 0.4). \end{array}$$

Under EUT,  $a$  is weakly preferred to  $a'$  if and only if  $b$  is weakly preferred to  $b'$ .

Allais (1953) presented empirical violations of this result (see also Kahneman and Tversky 1979). The *common ratio effect* describes a preference reversal in which a decision-maker is indifferent between two prospects, but when the prospect probabilities are scaled down by a common ratio, she then strictly prefers the riskier option (e.g.,  $a \sim a'$  and  $b < b'$ ).

The *certainty effect* is a special case of the common ratio effect when one prospect obtains with probability one. For example, consider

$$\begin{array}{llll} \text{Menu } \mathcal{C}: & c = (3 \circ 1.0) & \text{or} & c' = (4 \circ 0.8); & \text{and} \\ \text{Menu } \mathcal{R}: & r = (3 \circ 0.5) & \text{or} & r' = (4 \circ 0.4). \end{array}$$

If a decision-maker is indifferent between  $c$  and  $c'$  but strictly prefers  $r'$  over  $r$ , she may simply possess diminishing sensitivity to risk as described by the common ratio effect, or she may have a disproportionate preference for a certain outcome.

Prelec and Loewenstein (1991) note equivalent results regarding time delay using discounted utility. Following Halevy (2008), let us simply interpret  $\delta$  in equation (1) as a failure risk imposed by a unit-time delay that precludes consumption of the consequence (e.g.,  $\delta$  might be one's probability of death in every time period). Under DU, a decision-maker

weakly prefers one intertemporal consumption plan to another if and only if this preference is maintained with an additional arbitrary time delay.

Consider a daily survival probability of 0.8. Let us reinterpret the previous menus as

Menu  $\tilde{C}$ :  $C = 3$  now                      or                       $C' = 4$  in 1 day;                      and  
Menu  $\tilde{R}$ :  $R = 3$  in 3 days                      or                       $R' = 4$  in 4 days.<sup>1</sup>

The *common difference effect* describes a preference reversal in which a decision-maker is indifferent between two intertemporal consumption plans, but when an arbitrary time delay is added to each, she then becomes more patient (e.g.,  $C \sim C'$  and  $R < R'$ ).

The *immediacy effect* is a special case of the common difference effect, when only immediate consumption varies between plans. In equation (2), QHD describes an immediacy effect if  $\beta < 1$ . Chakraborty, Halevy, and Saito (2020) fully characterize the relationship between the immediacy effect (including under QHD) and the certainty effect.<sup>2</sup>

In this sense, a decision-maker only obtains a prospect with certainty when also obtained without delay. Any time delay plausibly eliminates a certainty effect, and similarly any risk plausibly eliminates an immediacy effect. I endeavor to experimentally test the significance of this interaction.

## 2.2 Evidence of risk moderating present bias

At least three studies have shown that risk moderates present bias using hypothetical or nearly-hypothetical monetary incentives.

Keren and Roelofsma (1995) conduct a between-subject full-factorial experiment with

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<sup>1</sup>With approximation, 0.5 is the probability of surviving  $\ln 0.5 / \ln 0.8 \approx 3$  days, and 0.4 is the probability of surviving  $\ln 0.4 / \ln 0.8 \approx 4$  days.

<sup>2</sup>Epper and Fehr-Duda (2018), Baucells and Heukamp (2010), and Green and Myerson (2004) also explore this relationship.

hypothetical monetary stakes, wherein subjects choose between \$50 and \$55 with a four-week delay. When prizes obtain with certainty, 82% of subjects prefer \$50 immediately over \$55 in four weeks, while only 37% of subjects prefer \$50 in twenty-six weeks over \$55 in thirty weeks, thereby demonstrating present bias at certainty. When prizes obtain with probability one-half, 39% of subjects prefer \$50 immediately over \$55 in four weeks, and 33% of subjects prefer \$50 in twenty-six weeks over \$55 in thirty weeks, failing to show significant present bias.

Weber and Chapman (2005) confirm these findings, again with hypothetical monetary stakes. Baucells and Heukamp (2010) also find that risk moderates present bias with highly-diluted monetary incentives, implementing only three of 3,757 decisions.<sup>3</sup>

However the methodologies employed may not appropriately identify the effect of interest. Hypothetical decisions lack incentive, relying solely on framing and contingent reasoning. Similarly, extremely low probabilities of implementation may dilute the stated probability of the prospects due to isolation failure (which I discuss in section 2.4). Finally, monetary earnings do not necessarily translate to consumption as in the intertemporal models of equations (1) and (2); an individual would need to be extremely liquidity-constrained to trade a few dollars of earnings for a good to be consumed the same day.

Models of present bias are often used to study self-control failure of visceral urges (Cheung, Tymula, and Wang 2021), which are plausibly best elicited with an immediate and certain consequence. For example, many studies of sequential games find costly punishment more prevalent upon eliciting a direct-response action instead of a conditional strategy (Brandts and Charness 2011), perhaps due to a preference for exacting *unconditional* (*i.e.*, certain) revenge.

My study is the first to use truly immediate and certain consequences in studying present bias. I avoid concerns associated with hypothetical decisions, long-shot implementation,

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<sup>3</sup>Three of 221 subjects are selected, each of whom has one of their seventeen decisions implemented.

and monetary stakes, thereby establishing an ideal method for capturing present bias.

### 2.3 Empirical estimates of present bias

While many studies have used monetary rewards to measure present bias, Andreoni and Sprenger (2012) pioneered the “convex time budget” (CTB) methodology, which elicits monetary-prize allocations between two time periods at various interest rates, thereby allowing risk preferences and QHD parameters to be estimated jointly.<sup>4</sup> However, monetary earnings may not adequately capture consumption utility in the absence of liquidity constraints and decision isolation. Augenblick, Niederle, and Sprenger (2015) address this concern with CTB decisions in which individuals allocate real-effort tasks across time (other studies have used alternative primary rewards, such as food).

The meta-analysis by Imai, Rutter, and Camerer (2021) finds no evidence of present bias in monetary rewards, while finding a mean bias-corrected present-bias factor  $\beta$  between 0.90 and 0.99 in real-effort tasks. While the specific value depends on the particular bias correction, present bias is also highly context-dependent.<sup>5</sup>

### 2.4 Decision framing, isolation, and implementation

A typical subject in an economics experiment makes many decisions. Historically many experiments implement many or all decisions, but this method can yield data rife with wealth effects, hedging, and other confounds (Charness, Gneezy, and Halladay 2016). Con-

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<sup>4</sup>See Cheung, Tymula, and Wang (2021) for a nice review of estimates of present bias using various methodologies. For more on these other methodologies used to elicit time and risk preferences, see Andersen et al. (2008), Cheung (2016, 2020), and Abdellaoui et al. (2013).

<sup>5</sup>While Imai, Rutter, and Camerer (2021) restrict their focus to twenty-eight studies that use the CTB methodology, Cheung, Tymula, and Wang (2021) offer a meta-analysis which includes studies that use other methodologies such as the joint-elicitation methodology (Andersen et al. 2008). Xueting Wang has informed me that a forthcoming revision of Cheung, Tymula, and Wang (2021) will present results that are qualitatively consistent with those of Imai, Rutter, and Camerer (2021).



sequently most experiments now implement one randomly-selected decision, thus avoiding such complementarity between outcomes (Azrieli, Chambers, and Healy 2018). Yet implementing one decision at random is not a panacea; many subjects still fail to isolate each decision.<sup>6</sup>

Non-expected utility rationalizes isolation failure when a subject views a set of decisions as comprising a single optimization problem. For example, given a Holt and Laury (2002) choice list, a subject is often able to secure a certain outcome by choosing every safe option. Freeman, Halevy, and Kneeland (2019) find evidence of the certainty effect when comparing pairwise choices to choice-list data. Freeman and Mayraz (2019) find evidence of the Allais paradox with the effect independent of the mechanism used.

Freeman and Mayraz (2019) find that presentation has the largest impact on isolation. Brown and Healy (2018) display decisions separately and reclaim incentive compatibility.

### 3 Experimental design

The present study compares present bias between a risky consequence and a certain consequence. I implement one decision to avoid complementarity (see section 2.4), which must be implemented with certainty in the respective treatment. To obtain useful choice data from a single implemented decision, I use the CTB methodology (see section 2.3). To induce an immediate (primary) reward, I ask subjects to allocate a budget of real-effort tasks between two weeks.

The experiment consists of three sessions: Monday (day zero), Wednesday (day two), and the following Wednesday (day nine). Every subject earns \$1.50 per session, which must be completed between noon and midnight. I immediately disqualify subjects who miss a

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<sup>6</sup>See Starmer and Sugden (1991), Beattie and Loomes (1997), Cubitt, Starmer, and Sugden (1998), and Cox, Sadiraj, and Schmidt (2015).

deadline. Every subject that completes all three sessions earns a \$5 bonus.

Each session begins with ten mandatory tasks, providing salient experience and a fixed baseline effort-level on each day. Each task asks the subject to count the number of zero digits in a sixteen-digit binary string and enter this count into an adjacent text field (figure 1a). The subject must remedy any incorrect response for successful submission.

Following the mandatory tasks on day zero and day two, each subject chooses an allocation of 360 tasks between day two and day nine at each of five substitution rates (the 360-task budget has day-two value). Each decision is presented individually to elicit a tentative choice (figure 1b), which are then juxtaposed on a single page (figure 1c) for any adjustment.

Accordingly, let  $e_{i,d}^t$  denote effort chosen at rate  $R_i$  on decision-day  $d$  to be expended on workday  $t$ . For example,  $e_{4,0}^{\text{day two}}$  is the effort chosen at rate  $R_4$  on day zero to be worked on day two. Each subject faces the constraint

$$e_{i,d}^{\text{day two}} + R_i e_{i,d}^{\text{day nine}} = 360, \text{ for each } R_i \in \mathcal{R} := \langle 1.25, 0.75, 1, 1.5, 0.5 \rangle \text{ and } d \in \{0, 2\}.$$

Some rates  $R_i$  (which can also be interpreted as productivity ratios or gross interest rates) entail substantial income effects. For example, at  $R_4 = 1.5$ , a subject may choose to delay all 360 tasks on day two to only 240 tasks on day nine. Yet if a subject delays all 360 tasks at  $R_5 = 0.5$ , she would need to complete 720 tasks on day nine. Randomly-selected subjects receive a rate sequence in reverse order.

### 3.1 Treatments

I implement a  $2 \times 2$  factorial between-subject design. I inform all subjects that a decision from either day zero or day two will be selected with equal probability (figure 1d).

The baseline treatment implements one of the ten decisions with uniform probability. Subjects with this treatment have uncertainty regarding the day and the rate selected. Each

**PRACTICE MODE** The correct answers are already filled in to save you time.

### Complete 10 required rows of counting

Please count the number of zeros ("0") on each line and enter it in the box.

Each row will be marked correct or incorrect. You must correct errors before submission.

Row No.	String	Count ("0")
1	1000110011100011	8
2	1000010100000001	12
3	1110001110000011	8
4	0100110010101111	7
5	0000100010101110	10
6	1101001011001010	8
7	00001100101010001	10
8	1011100110010010	8
9	1110110100011111	5
10	0110001100111001	8

Check responses and save

(a) Task interface

**PRACTICE MODE** You will not have to work these tasks.

### Split workload between Wed, Oct 30 and Wed, Nov 6

You're making five decisions on how to split the workload for Wed, Oct 30. You'll make five more similar decisions on that day.

A coin flip will determine whether a decision made today or a decision made on Wed, Oct 30 will be selected to actually matter.

One of today's five decisions may be randomly selected to actually split your workload.

The odds of each decision being the decision-that-matters are **10%**.

Trade-off	Wed, Oct 30	Wed, Nov 6
1 to 0.5	360 rows	0 rows
1 to 0.75	274 rows	115 rows
1 to 1	139 rows	221 rows
1 to 1.25	40 rows	256 rows
1 to 1.5	0 rows	240 rows

Please review your choices and make any final changes.

Finalize

(c) Allocation interface, presented juxtaposed

**PRACTICE MODE** You will not have to work these tasks.

### Split workload between Wed, Oct 30 and Wed, Nov 6

Choose how you want to split your workload of 360 rows of counting (in addition to the required 10 rows per workday).

In this scenario, **working 1 more row next week reduces work by 1 row(s) this week.**

You're making five decisions on how to split the workload for Wed, Oct 30. You'll make five more similar decisions on that day.

A coin flip will determine whether a decision made today or a decision made on Wed, Oct 30 will be selected to actually matter.

One of today's five decisions may be randomly selected to actually split your workload.

The odds of this decision being the decision-that-matters are **10%**.

Wed, Oct 30	Wed, Nov 6
139 rows	221 rows

Try moving the slider around to see how this trade-off rate splits your workload.

If this choice were selected to actually matter, your work schedule would be:

Sun, Oct 27	Mon, Oct 28 (today)	Tue, Oct 29	Wed, Oct 30 10 rows required + 139 rows chosen	Thu, Oct 31	Fri, Nov 1	Sat, Nov 2
Sun, Nov 3	Mon, Nov 4	Tue, Nov 5	Wed, Nov 6 10 rows required + 221 rows chosen	Thu, Nov 7	Fri, Nov 8	Sat, Nov 9

You will be able to adjust this decision before finalizing it.

Continue

(b) Allocation interface, presented separately

**PRACTICE MODE**

### How today's decisions are used

You made decisions about splitting work between this Wednesday and next Wednesday.

You will make similar decisions again Wednesday. One day will be selected for its decisions to actually matter.

Sun, Oct 27	Mon, Oct 28 (today)	Tue, Oct 29	Wed, Oct 30 Decisions made	Thu, Oct 31	Fri, Nov 1	Sat, Nov 2
Sun, Nov 3	Mon, Nov 4	Tue, Nov 5	Wed, Nov 6 Decisions made	Thu, Nov 7	Fri, Nov 8	Sat, Nov 9

You just made five decisions about how to split work between these days

Choice No.	Trade-off	Wed, Oct 30	Wed, Nov 6
1	1 to 0.5	360 rows	0 rows
2	1 to 0.75	274 rows	115 rows
3	1 to 1	139 rows	221 rows
4	1 to 1.25	40 rows	247 rows
5	1 to 1.5	0 rows	240 rows

You will make five similar decisions Wednesday

Choice No.	Trade-off	Wed, Oct 30	Wed, Nov 6
1	1 to 0.5	x rows	x rows
2	1 to 0.75	x rows	x rows
3	1 to 1	x rows	x rows
4	1 to 1.25	x rows	x rows
5	1 to 1.5	x rows	x rows

After you make decisions Wednesday, a coin-toss will select which day's decisions are used

Choice No.	Trade-off	Wed, Oct 30	Wed, Nov 6
1	1 to 0.5	360 rows	0 rows
2	1 to 0.75	274 rows	115 rows
3	1 to 1	139 rows	221 rows
4	1 to 1.25	40 rows	247 rows
5	1 to 1.5	0 rows	240 rows

Choice No.	Trade-off	Wed, Oct 30	Wed, Nov 6
1	1 to 0.5	x rows	x rows
2	1 to 0.75	x rows	x rows
3	1 to 1	x rows	x rows
4	1 to 1.25	x rows	x rows
5	1 to 1.5	x rows	x rows

Reveal

(d) Day selection mechanism interface

Figure 1: Experimental interface

Table 1: Probability of decision implementation

Treatment	Decision chosen on	
	day $d = 0$	day $d = 2$
Baseline	1/10	1/10
Certain Day	1/10	1/5
Certain Rate	1/2	1/2
Certain Rate, Certain Day	1/2	1

*Note:* Probabilities of implementation of the effort allocation choice  $e_{2,d}$  (chosen on decision-day  $d$  at rate  $R_2 = 1.25$ ).

decision in this *Risky Rate, Risky Day* treatment thus has a 10% implementation probability.

The *Certain Rate (CR)* treatment dimension eliminates risk regarding the rate to be implemented. In this treatment, subjects are informed that  $R_2 = 1.25$  will certainly be implemented; decisions for all prices  $R_i \neq 1.25$  are hypothetical, which I exclude from my analysis.

The *Certain Day (CD)* treatment dimension eliminates risk regarding the day from which a decision is selected. I inform subjects in this treatment that I will reveal the randomly-selected day *before* their day-two decisions. Accordingly, the day to be implemented is risky for *all* subjects on day zero, but certain for subjects with CD treatment on day two. Half of the subjects with this treatment learn that their day-two decisions are hypothetical; I exclude all hypothetical decisions from analysis and compensate by doubling the sample size of the CD dimension.<sup>7</sup>

Table 1 shows decision implementation probability by treatment cell  $T$ .

My primary interest is the interaction of Certain Rate and Certain Day treatments. On day zero subjects know that their choice at  $R_2 = 1.25$  made on either day zero or made on day two will be selected with certainty. Then on day two, prior to making a decision, subjects

<sup>7</sup>I considered this alternate design: If day zero is selected, inform after day-two decisions; if day two is selected, inform before day-two decisions. I rejected this design because subjects would lack complete prior information about the timing of the resolution of risk.

learn from which day a decision will be selected. Subjects who learn day two is selected thus make a decision on day two that is certainly implemented. That is, these subjects choose their impending same-day effort level, knowing this choice will be implemented with certainty, with the tasks due imminently. I hypothesize that present bias is more pronounced under certainty than under risk.

### 3.2 Interface

I carefully designed the interface to bolster subjects' understanding of the choice process and the implementation mechanism. The interface guides every subject through a complete practice round at the beginning of each session before the real decisions and tasks.

**Day selection** The interface shows each subject a list of their practice choices made on each decision-day (figure 1d). Upon clicking the button to proceed, the page visualizes random selection between the two decision-days by alternately highlighting the lists in quick succession before the highlight settles on one day as being selected. Every subject simulates two practice coin-flips: the first trial selects the alternate decision-day, then the second selects the present day. The remainder of the practice round uses the choices made in the present session.

**Rate selection** The interface next shows each subject the five practice choices made on the present day, arranged in a table similar to the juxtaposed allocation page (figure 1c). Subjects with Certain Rate treatment see row four permanently highlighted and a reminder that only choices at this rate will be implemented. Other subjects see no highlight at first, but upon clicking the button to proceed, a roulette-wheel sequence highlights each row quickly in succession. After traversing the table twice, the highlight settles on a randomly-selected decision.

With a practice allocation selected, subjects view a practice task interface that requests the corresponding amount of work to be completed on the present day. Subjects then exit the practice round and begin an identical sequence with real decisions and tasks.

## 4 Model and methodology

Assuming quasi-hyperbolic discounting, within-day power-function effort costs, and background effort of  $\omega$ , on each decision-day  $d = 0$  and  $d = 2$  the decision-maker optimizes

$$\min_{e_{i,d}^t} \beta^{\mathbb{1}(d=0)} (e_{i,d}^2 + \omega)^\alpha + \beta \delta^7 (e_{i,d}^9 + \omega)^\alpha, \text{ subject to } e_i^2 + R_i e_i^9 = 360, \quad (3)$$

choosing effort  $e_{i,d}^t$  for each price ratio  $R_i \in \{0.5, 0.75, 1, 1.25, 1.5\}$  and workday  $t \in \{2, 9\}$ . This model uses  $\delta$  as a daily discount factor, while  $\beta$  discounts future-day effort. Assuming the independence axiom, the resultant intertemporal Euler equation is:

$$\left( \frac{e_{i,d}^2 + \omega}{e_{i,d}^9 + \omega} \right)^{\alpha-1} = \frac{\beta^{\mathbb{1}(d=2)} \delta^7}{R_i} \quad (4)$$

(Lawrance 1991). Logarithms linearize this equation as

$$\underbrace{\ln \frac{e_{i,d}^2 + \omega}{e_{i,d}^9 + \omega}}_{=: E_{i,d}} = \underbrace{\frac{\ln \delta}{\alpha - 1}}_{=: \theta_{\text{delay}}} 7 + \underbrace{\frac{-1}{\alpha - 1} \ln R_i}_{=: \theta_{\text{lnrate}}} + \underbrace{\frac{\ln \beta}{\alpha - 1}}_{=: \theta_{\text{present}}} \underbrace{\mathbb{1}(d = 2)}_{=: \mathbb{1}(\text{pr})}. \quad (5)$$

Let us define the variables as shown under braces in equation (5) to simplify notation. An additive error term produces an estimatable reduced-form, with  $s$  indexing subjects:

$$E_{i,d,s} = \theta_{\text{delay}} 7 + \theta_{\text{lnrate}} \ln R_i + \theta_{\text{present}} \mathbb{1}(\text{pr})_d + \varepsilon_{i,d,s}. \quad (6)$$

Let  $\mathbb{1}(\text{cr})$  indicate Certain Rate treatment and  $\mathbb{1}(\text{cd})$  Certain Day treatment. We interact the full-factorial of these with the present-workday indicator,  $\mathbb{1}(d = 2)$ , to obtain an estimatable pooled reduced-form regression model:

$$E_{i,d,s} = \theta_{\text{delay}}7 + \theta_{\text{lnrate}} \ln R_i + \theta_{\text{present}} \mathbb{1}(d = 2)_d + \theta_{\text{cr}} \mathbb{1}(\text{cr})_s \mathbb{1}(d = 2)_d + \theta_{\text{cd}} \mathbb{1}(\text{cd})_s \mathbb{1}(d = 2)_d + \theta_{\text{cr,cd}} \mathbb{1}(\text{cr})_s \mathbb{1}(\text{cd})_s \mathbb{1}(d = 2)_d + \varepsilon_{i,d,s}. \quad (7)$$

This specification allows recovery of  $\beta_T$  that varies by treatment cell  $T$  (the supplement offers details).

## 4.1 Hypotheses

My primary hypothesis is that an interaction exists between the immediacy effect and the certainty effect. That is, present bias at certainty differs from present bias with risk. The baseline treatment with risk regarding the rate and risk regarding the decision-day is standard in the literature, here with each decision having an implementation probability of 1/10. When treated with Certain Rate and Certain Day, the day-two choice for  $R_2 = 1.25$  is implemented with certainty (probability of one).

**Hypothesis 1** *Present-bias is more intense under implementation certainty (with both Certain Rate and Certain Day treatment) than when the decision involves both types of risk (decision-day and rate both unrealized), in which each decision has an implementation probability of 1/10:  $\beta_{\text{cr,cd}} < \beta$ .*

For completeness I further hypothesize that present bias at certainty differs from present bias with any uncertainty—that is, with only one dimension of risk.

**Hypothesis 2** *Present-bias is more intense under implementation certainty than when the decision involves rate risk but has decision-day certainty (implementation probability of 1/5):*

$$\beta_{cr,cd} < \beta_{cd}.$$

**Hypothesis 3** *Present-bias is more intense under implementation certainty than when the decision involves decision-day risk but has rate certainty (implementation probability of 1/2):*

$$\beta_{cr,cd} < \beta_{cr}.$$

I do not hypothesize further how the type of risk may matter. For example, controlling for the implementation probability, perhaps risk regarding the rate is most influential, perhaps driven by the income effect of the price ratios. Research regarding types of risk and underlying mechanisms is left to future research.

## 4.2 Statistical methodology

Each subject allocates 360 tasks (in day-two valuation) between day two and day nine at various price ratios. Each subject must also complete ten mandatory real-effort tasks on each day. A subject might most prefer a negative effort allocation to a workday (that is, a net gain of leisure on that day), which my environment does not facilitate: the environment bounds elicited day-two effort such that  $e_{i,d}^2 \in [0, 360]$  for all rates  $R_i$  on each decision-day  $d$ . A two-limit Tobit model accommodates this censoring.

To estimate the model with a power cost function  $c(e) := (e + \omega)^\alpha$ , we must specify some background effort  $\omega > 0$ . The primary analysis will use  $\omega = 10$  as the background effort, corresponding to the mandatory daily tasks. Subjects may perform other tasks throughout the day that we might wish to include in  $\omega$ ; my supplement offers results that demonstrate robustness to various background effort levels.

## 4.3 Identification of present bias

As represented by the factor  $\beta$ , present bias is identified from a two-day window. On Monday, day zero, I assume that subjects view both Wednesday, day two, and the next Wednes-



day, day nine, as part of the future. Then on day two, I assume that subjects view that same day as the present and continue to view day nine as the future.

One could reasonably argue that Monday and Wednesday of the same week may both feel relatively present, while the following week may feel relatively distant. This would imply that present bias would be better identified from a week-long delay, as in Augenblick, Niederle, and Sprenger (2015). However, this is an empirical question, and Augenblick (2018) studies exactly how present bias varies with short delays. Using similar real-effort tasks, he finds that present bias quickly diminishes within three days, with two days capturing most present bias. In the present study, the use of a two-day window will yield conservative estimates of  $\beta$  (biased upward). A week-long delay might more accurately identify present bias, but likely at the cost of greater attrition. Regardless, in the present study I simply intend to use average treatment effects to test my hypotheses.

#### 4.4 Identification of discounting

The daily discount factor  $\delta$  exponentially discounts the future. In this environment, we identify  $\delta$  (jointly with  $\alpha$ ) using variation in the rate  $R_i$ .

Suppose that marginal cost of effort is constant within a day, so that the effort-cost convexity parameter  $\alpha = 1$ . Then the ratio  $\delta^7/R_i$  determines how a decision-maker allocates her workload between day two and day nine. If  $\delta^7/R_i = 1$ , she is indifferent to how the workload is split; otherwise she will allocate the entire workload to a single day. For example, if she discounts the future ( $\delta < 1$ ) but she can trade day-two and day-nine work one-for-one (when  $R_i = 1$ ), she will choose to do all of the work on day nine.

Instead, assume that the decision-maker has an increasing marginal cost of within-day effort, so that  $\alpha > 1$ . Then if  $R_i = 1$  and  $\delta = 1$ , she would divide the workload evenly between day two and day nine. This is because she values smoothing effort between workdays, since

additional within-day effort becomes more costly. Then as either the rate  $R_i$  or the discount factor  $\delta$  changes, the decision-maker will choose a different workload split between day two and day nine, balancing the benefit of smoothing effort against the inferior rate.

Because  $\delta^7/R_i$  and effort-cost convexity  $\alpha$  jointly explain allocation between workdays,  $\alpha$  and  $\delta$  are jointly identified by rate  $R_i$  variation.

## 4.5 Between- and within-subject identification

My novel experimental design and identification strategy permits estimation of the present-bias factor  $\beta$  with some subjects making only two incentivized decisions (the interaction of Certain Rate and Certain Day treatments). This is possible because effort-cost convexity  $\alpha$  and the discount factor  $\delta$  are estimated with the pooled regression, relying on variation in rate  $R_i$  from Risky Rate treatment. Meanwhile,  $\beta_T$  is estimated between-subjects for each treatment cell  $T$ .<sup>8</sup>

Other researchers who wish to evaluate present bias under certainty need not implement my full-factorial design. My design will identify  $\alpha$ ,  $\delta$ , and  $\beta_T$  with only two treatment cells: a cell with Risky Rate and a cell with Certain Rate and Certain Day. The cell with Risky Rate can use either Risky Day or Certain Day; however the latter requires a larger sample to achieve the same statistical power if the study excludes hypothetical decisions and avoids deception. For my present study I implement a full-factorial design to investigate each dimension.

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<sup>8</sup>While within-subject estimation of the present-bias factor is possible, each point-estimate  $\beta_s$  would rely on only two observations,  $e_{1,0}$  and  $e_{1,2}$ , per subject  $s$  given Certain Rate treatment.

## 5 Results

I recruited subjects from an online piece-rate labor marketplace with an equivalent median hourly wage under \$5 and jobs that commonly involve transcribing invoices or tagging photographs (Newman 2019).<sup>9</sup> I described my “multi-day counting project” as three sessions with a combined 30–50 minutes of tasks which paid \$1.50 for each session and a \$5 bonus for completing all three. Given that the experiment involves tasks similar to those typical of the marketplace, it is a *framed field experiment* (Harrison and List 2004).

My instructions provided sample tasks, explained the task allocation process, and stressed the three dates of participation: Monday 28 October 2019 (day zero), Wednesday 30 October (day two), and Wednesday 6 November (day nine). Consenting subjects answered an eight-question comprehension survey which paid \$1.50 regardless of the responses (the supplement provides all experimental instruments).

Of the 389 comprehension survey submissions, 220 provided informed consent and only correct responses; I enrolled these subjects in my experiment. Of these 220 subjects, 206 (93.6%) enrolled in and completed day-zero decisions. From this first session to the last, sample attrition was only 26 of 206 subjects (12.6%).<sup>10</sup> The median subject completed a combined 340 tasks in 36 minutes (with quartiles  $q_1 = 28$  and  $q_3 = 47$  minutes).

### 5.1 Descriptive results

While log-effort-ratio is the correctly specified choice variable given the model in equation (3), let us consider a more intuitive outcome: day-two effort-share  $\varphi := e_{i,d}^2/360$ . Because the Certain Price treatment only incentivizes  $R_2 = 1.25$ , I only analyze choice data at

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<sup>9</sup>On Amazon Mechanical Turk I sampled residents of the United States and Canada with at least 1,000 jobs completed with 98% approval.

<sup>10</sup>On day two, 192 subjects (93.2%) returned and completed that day’s decisions. One of each subject’s ten decisions was implemented, upon which 188 subjects (97.9%) completed the selected day-two effort. Finally, on day nine, 180 subjects (95.7%) returned and completed the session, thus earning the completion bonus.

this rate. Note that because day-nine effort is more productive than day-two effort at this rate, effort is split evenly between workdays when  $e_{2,d}^2 = e_{2,d}^9 = 160$  and thus  $\varphi = 160/360 = 0.44$ .

Figure 2 offers histograms of effort-share choices by treatment. Given an effort-share choice in advance of the workday (day zero), a smaller choice on the workday itself (day two) suggests present bias. Thus this graph illustrates present bias if the outlined bars shift to the left of the solid bars.

We see a striking feature at 0.0–0.10: in treatments with at least one certainty treatment, many subjects choose a day-two allocation much different than their day-zero allocation. On day two, with work imminent, they choose to exert 0.0–0.10 of effort on day two. Compare the filled bar against the outlined bar for the 0.0–0.10 bin in each treatment; more subjects choose an allocation in this bin on day two (when the work is imminent) relative to day zero (when the work is distant) with either certainty treatment.

This simple descriptive graph intuitively suggests evidence of present bias in at least some treatments. We now turn to regression analysis to make use of all incentivized choice data.

## 5.2 Regression results

We now consider the regression results as presented in table 2 and figure 3. We notably find no present bias in the baseline treatment. Meanwhile, relative to the baseline treatment with risk, present bias under certainty is vastly different economically. With a point-estimate of 0.58 under certainty, subjects value the present 1.7 times as much as they value the future.

We reject the null hypothesis that  $\beta_{cr,cd} = \beta$  at  $p < 0.001$ . This provides clear evidence that the introduction of a substantial amount of risk significantly moderates present bias.

We also find that addition of risk in the rate dimension alone also drastically moderates present bias relative to the baseline, rejecting  $\beta_{cr,cd} = \beta_{cd}$  with  $p = 0.005$ . However we do

Figure 2: Histograms of effort-share chosen for day two at  $R_2 = 1.25$  for each treatment

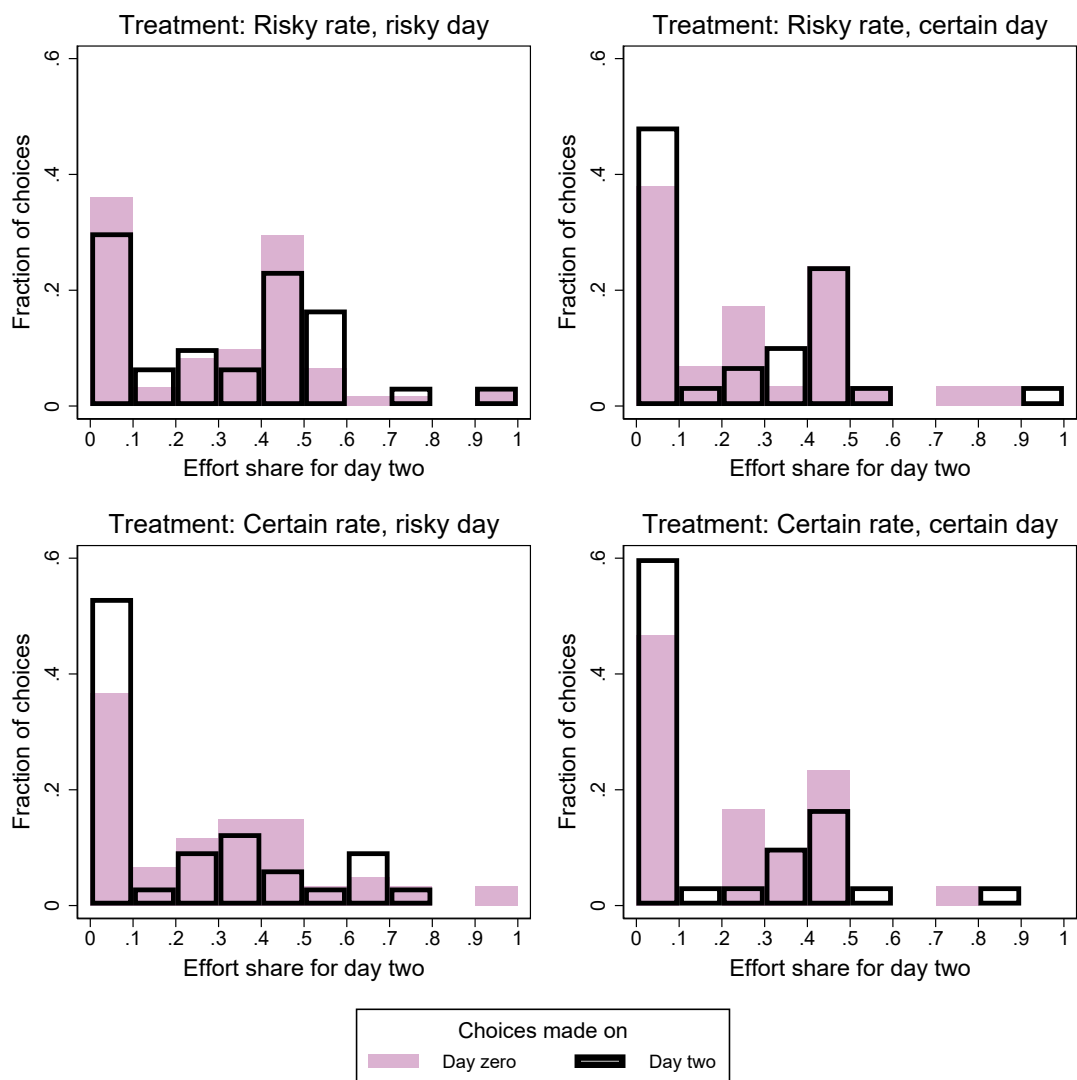
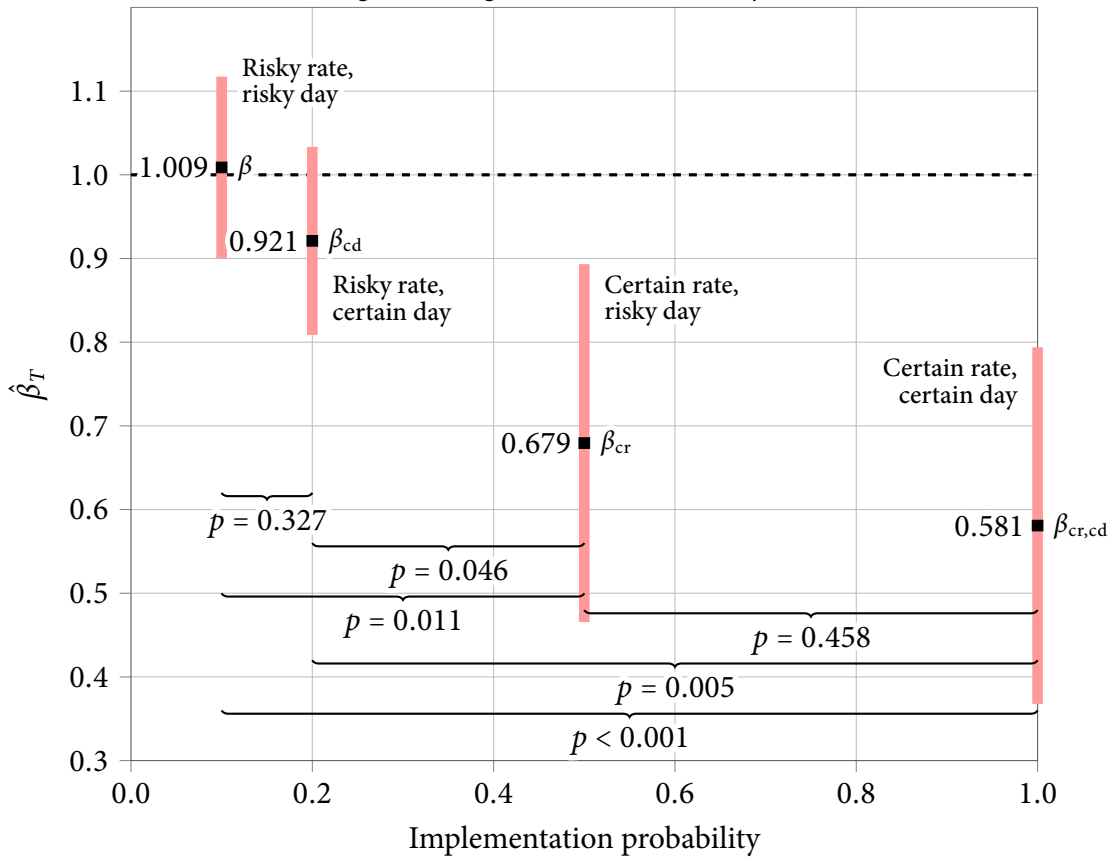


Table 2: Regression results

Param.	Estim.	Std. Err.	$p$ -value of $\chi^2_1$ test that parameter equals			
			1	$\beta$	$\beta_{cd}$	$\beta_{cr}$
$\beta_{cr,cd}$	0.581	(0.108)	< 0.001	< 0.001	0.005	0.458
$\beta_{cr}$	0.679	(0.109)	0.003	0.011	0.046	
$\beta_{cd}$	0.921	(0.057)	0.166	0.327		
$\beta$	1.009	(0.055)	0.873			
$\delta$	0.986	(0.004)	0.001			
$\alpha$	1.282	(0.045)	< 0.001			

Note: 897 observations (161 left- and 95 right-censored) from 180 subjects. Robust standard errors in parentheses are clustered on subject using a two-limit Tobit model.

Figure 3: Regression estimates of  $\beta_T$



not find a similar result in comparing certainty to the addition of risk in the decision-day dimension, failing to reject that  $\beta_{\text{cr,cd}} = \beta_{\text{cr}}$  with  $p = 0.458$ . Recall that with Certain Rate treatment, we rely on only two observations per subject; otherwise we have ten observations per subject. Indeed the standard errors for  $\beta$  with Certain Rate treatment are roughly double those in the other treatments, suggesting that a larger sample may reveal significance.

Beyond concerns of statistical power, we can conjecture that the implementation probability plays an important role (figure 3). When making a day-two decision with Certain Rate and Risky Day treatments, subjects know that their present decision will be selected by one side of a coin flip. This might make the decision sufficiently salient to preserve a high degree of present bias, especially with only a single incentivized decision on each day. Regardless, the testing of such hypotheses and underlying mechanisms is left to future work.

### 5.3 Additional considerations

#### Attrition bias

While sample attrition (12.6%) was remarkably low for an online experiment across ten days, we should look for evidence of selective attrition. For example, Certain Rate treatment might have lower attrition as it guarantees an income effect, whereas the Risky Rate treatment does not in expectation.

Only four subjects completed day-two decisions but did not complete the implemented day-two effort level. Two of these made only hypothetical decisions on day two and are thus excluded from the analysis. Both remaining subjects had Certain Rate treatment. We conclude that attrition during day two was orthogonal to rate resolution.

Attrition between day two and day nine of eight subjects was highly balanced across treatments and rate selection.

### Effort-cost curvature

We reject the hypothesis that  $\alpha \geq 1$  with  $p < 0.001$ , satisfying the second-order condition for equation (3). The results are robust to background effort  $\omega$  of greater orders of magnitude, appropriate for having already worked prior to the sessions (see the supplement).

## 6 Conclusion

This study of dynamic inconsistency in real-effort provision finds that risk diminishes the intensity of present bias. This includes uncertainty that arises from random-implementation mechanisms popular among experimental economists. My experiment varies the implementation mechanism, thereby altering the probability of decision implementation. The novel design permits pooled estimation of the present-bias factor in each of four treatment cells, including one that implements a single decision with certainty.

The effect of certainty on present bias is striking. Under certainty I estimate  $\hat{\beta}_{cr,cd} = 0.581$ , while the baseline treatment finds no significant present bias with a point-estimate of  $\hat{\beta} = 1.009$ . These results present a remarkable treatment effect: risk significantly moderates present bias.

While most other studies find present bias in real-effort, some do not (Imai, Rutter, and Camerer 2021). The replication study of Augenblick, Niederle, and Sprenger (2015) is similar to my baseline treatment, using the same implementation mechanism, one-week delay, and similar interest rates. They estimate  $\hat{\beta} = 0.892$  with  $p = 0.05$  for University of California students transcribing blurry Greek letters. My subjects, being workers in an online marketplace, may have substituted effort in my session with effort in other jobs. Nevertheless the treatment effect suggests that the implementation mechanism affects present bias.

Experiments that seek an accurate point-estimate of the present-bias factor should include a decision with substantial immediate and certain consequences. If complementari-



ties between consequences do not pose a serious concern, the experiment might reasonably implement multiple such decisions.

My findings underscore the importance of unifying theories of time and risk, notably Chakraborty, Halevy, and Saito (2020) (see section 2.1 and footnote 2). Conversely, in testing decision-theoretic models, researchers should mind their incentive mechanisms and use decisions implemented with certainty when appropriate.

Empirical work on tempting goods may require decisions with salient and certain consequences, a potentially-critical design element for any study employing experimental methods. Such work might study models of self-control, the effectiveness of commitment devices, or any application that depends on present-biased preferences.

Uncertainty may interact with non-stationary time preferences, leading to different behavior in strategic interactions. For example, in labor contracts firms may exploit present bias with (un)certainly regarding compensation, effective productivity, or job duration.

Clearly the field of behavioral economics has much yet to learn about present bias, temptation, and related interventions. Continual improvement of experimental methodology will aid this pursuit.

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