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ABSTRACT

Quasi-Hyperbolic Present Bias: A Meta-Analysis*

Quasi-hyperbolic discounting is one of the most well-known and widely-used models to capture self-control problems in the economics literature. The underlying assumption of this model is that agents have a "present bias" toward current consumption such that all future rewards are downweighed relative to rewards in the present (in addition to standard exponential discounting for the length of delay). We report a meta-analytic dataset of estimates of the present bias parameter β based on searches of all major research databases (62 papers with 81 estimates in total). We find that the literature shows that people are on average present biased for both monetary rewards ($\beta = 0.82$, 95% confidence interval of [0.74, 0.90]) and nonmonetary rewards ($\beta = 0.66$, 95% confidence interval of [0.51, 0.85]) but that substantial heterogeneity exists across studies. The source of this heterogeneity comes from the subject pool, elicitation methodology, geographical location, payment method, mode of data collection (e.g. laboratory or field), and reward type. There is evidence of selective reporting and publication bias in the direction of overestimating the strength of present-bias (making β estimates smaller), but present bias still exists after correcting for these issues (for money $\beta = 0.87$ with 95% confidence interval of [0.82, 0.92] after correcting for selective reporting).

JEL Classification: C91, D12, D80, D91

Keywords: quasi-hyperbolic discounting, present bias, beta-delta model, meta-analysis

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1. Introduction

People often fail to follow their plans and instead prioritise immediate pleasures over long-term benefits (DellaVigna & Malmendier, 2006; Kaur, Kremer, & Mullainathan, 2015; Laibson, Repetto, & Tobacman, 1998). This is particularly evident in decisions about health (e.g. eating versus exercising), finances (e.g. saving for retirement versus consuming now for pleasure), and work and education (e.g. sticking to a schedule versus procrastinating). In economics and other disciplines, researchers commonly model such behaviours through time-inconsistent preferences. The dominant model of quasi-hyperbolic (or $\beta - \delta$) discounting (Laibson, 1997; O'Donoghue & Rabin, 1999) assumes that individuals have a "present bias" toward current consumption such that the value of all future rewards is downweighed by a constant factor $\beta < 1$, in addition to the standard exponential discounting of delayed rewards. Although quasi-hyperbolic discounting is commonly applied to explain problematic behaviours across a wide variety of domains, the extent to which the available empirical evidence supports this model has been the subject of some controversy.

In the early 2000s, it was widely accepted as a stylised fact in behavioural economics that people are present biased (Frederick, Loewenstein, & O'Donoghue, 2002) even though a precise estimate of β was not available. More general evidence consistent with non-exponential discount rates goes back as far as the early 1980s. Thaler (1981) found that the implicit discount rate over longer time horizons was lower than that over shorter time horizons, implying time inconsistency but without quantifying the magnitude of β (nor specifically supporting the quasi-hyperbolic model over other alternatives to standard exponential discounting). Similar evidence on time inconsistency is also well documented in early papers in psychology (Green, Fristoe, & Myerson, 1994; Kirby & Herrnstein, 1995; Millar & Navarick, 1984; Solnick et al., 1980). However, several notable recent studies that carefully control for confounding factors in the elicitation process (such as transaction costs and trust in the experimenter) found no present bias for monetary rewards (Andersen et al., 2014; Andreoni & Sprenger, 2012a; Augenblick, Niederle, & Sprenger, 2015). As a result, it is becoming a new stylised fact that present bias either does not exist for money or that it is an artefact of experimental design and procedures.

A meta-analysis can help to resolve whether present bias is indeed a real phenomenon. The possible reasons why there is no consensus in this literature are numerous and can be broadly classified into three factors: differences in the characteristics of participants, differences in the reward type, and differences in the experimental task. Many estimates of β are based on choices made by *students at top research universities*, a group that may not have serious problems of time inconsistency to begin with. Thus, one might hypothesize that estimates of β in a general adult population would be lower (i.e. present bias would be stronger). Moreover, estimates of β are usually derived from decisions over time-dated *monetary* payments, a methodology that has been questioned because it assumes that monetary payments are consumed immediately upon receipt (see Cohen et al. (2020) for a detailed discussion). If that is not the case, present bias for consumption rewards may be stronger than for money.

Finally, the experimental tasks used to elicit β (e.g. choice list versus Convex Time Budget (henceforth CTB) designs) may be a source of differences in estimates because different methods make different underlying assumptions, in particular regarding the nature of utility for consumption (see Cheung (2016) for discussion). Before 2008, researchers typically assumed that utility is linear. However, Andersen et al. (2008) demonstrated that if utility is in fact concave, then assuming it to be linear causes estimates of discounting parameters to be biased. Currently, even those elicitation methods that adjust for utility curvature differ in whether utility is estimated under certainty or risk. The CTB design (Andreoni & Sprenger, 2012a) estimates both utility curvature and discounting parameters from the one set of choices, in which the amounts of a reward and their receipt dates vary in each trial and no risk is involved. On the other hand, the joint elicitation approach (Andersen et al., 2008) infers utility curvature from choices over risky lotteries and discounting parameters from riskless temporal trade-offs. If utility over risky and riskless rewards are not the same (Abdellaoui et al., 2013; Andreoni & Sprenger, 2012b; Cheung, 2020), then estimates from joint elicitation are also potentially biased.

Given the widespread impact of the quasi-hyperbolic present-biased discounting model in applied and theoretical economics – as well as in many other social sciences and in policy – it is important to establish whether present bias is real, as well as to understand the sources of heterogeneity in present bias across different populations, reward types, and methodologies. A meta-analytic approach offers a principled, reproducible, and open-science method for accumulating scientific knowledge (Stanley, 2001; Stanley & Doucouliagos, 2012). In this paper, we report a quantitative meta-analysis using all existing empirical estimates of present-biased preferences.

Our comprehensive search for published papers and unpublished working papers from all major databases (Web of Science Core Collection, Scopus, PsycINFO, EconLit, PubMed, Research Papers in Economics, Social Science Research Network and Google Scholar) performed on 19 December 2018 returned 2,351 candidate articles (without duplicates). With thorough screening, we narrowed these papers down to what is now the largest dataset of present bias estimates (62 papers, 81 estimates[1]).

Contrary to the recent suggestion that there is no present bias for monetary rewards, we find statistically significant evidence of present bias towards money. Our uncorrected meta-analytic average β for monetary rewards (before accounting for selective reporting and publication bias) is 0.82 with 95% confidence interval of [0.74, 0.90]. Estimates of β for non-monetary rewards are generally smaller, implying stronger present bias: our uncorrected meta-analytic average β for non-monetary rewards is 0.66 with 95% confidence interval of [0.51, 0.85].

We find evidence of both selective reporting and publication bias. Using the trim-and-fill technique (Duval & Tweedie, 2000a, 2000b; Sutton et al., 2000) to correct for selective reporting (respectively, publication bias) yields a corrected average β of 0.87 (0.84) with 95% confidence interval of [0.82, 0.92] ([0.77, 0.92]) for monetary rewards, in each case slightly higher than the uncorrected meta-analytic average but still significantly less than one.

Finally, we find that estimates of β differ systematically with study characteristics. We find that present bias is stronger in the general adult population compared to university students, in studies using bank transfers for payments compared to using cash, and in European participants compared to North American ones. Perhaps surprisingly, whether choices are consequential or hypothetical has no significant effect on estimates of β. Estimates of β do not systematically vary based on whether the estimation model adjusted for utility curvature. In line with the large discussion on elicitation methods, we find that studies that use CTB methods are more likely to report estimates of β close to one compared to studies that use choice lists. However, this difference becomes insignificant when we control for a full set of covariates.

[1] Appendix 1 contains the reference list for the included papers.

Recently Imai, Rutter, & Camerer (2021) conducted a meta-analysis of present-bias estimates based *only* on articles that use the CTB elicitation method. In contrast to their study, our meta-analysis is not limited to papers that use CTB, resulting in a much larger dataset (62 versus 28 papers). Our approach also allows us to examine whether estimates of β vary with the elicitation method, an important methodological guide for future research on time preferences.

The rest of the paper is organised as follows: Section 2 describes how we identified relevant articles and constructed the dataset. Section 3 provides results and Section 4 discusses the implications of our results.

2. Data and methodology

2.1 *Theoretical framework*

The classical exponentially discounted utility model (Koopmans, 1960; Samuelson, 1937) assumes that an agent's intertemporal preferences are governed by a parameter δ, called the discount factor, and that when making a plan today she attaches a weight δ^t to the utility from consumption t periods in the future. The quasi-hyperbolic $\beta - \delta$ discounting model adds an extra discount ($\beta < 1$) to all future rewards ($t > 0$) to capture the observation that people are present biased. In the $\beta - \delta$ model, an agent (at time 0) values a consumption stream $(x_0, \dots, x_T)$ as:

$$U(x_0, \dots, x_T) = u(x_0) + \beta \sum_{t=1}^{T} \delta^t u(x_t)$$

where $0 < \delta < 1$ is the standard exponential discount factor, $0 < \beta < 1$ captures present bias, and $u(x_t)$ is the instantaneous utility of consumption at time t. When $\beta = 1$, there is no present bias, and the $\beta - \delta$ model converges to the standard exponential model.

2.2 *Identification and selection of relevant papers*

A thorough meta-analysis begins by casting a wide net to identify all relevant studies. Figure 1 illustrates the paper identification procedure which was pre-registered at the Open Science Framework. We conducted our search using all major databases that included both published papers (Web of Science Core Collection, Scopus, PsycINFO, EconLit, PubMed) as well as unpublished working papers and student theses (Research Papers in Economics, Social Science Research Network and Google Scholar) using two sets of search terms (topic keywords and methodology keywords).[2] The search returned 2,351 results (without duplicates) on 19 December 2018. Six research assistants were involved in a two-stage double-screening process. In each stage, each paper was independently classified by at least two research assistants. The authors then sampled 1/3 of the papers to verify that they were coded correctly.

In the title and abstract screening stage, we excluded papers that did not relate to time preference or had no empirical content (or both). This narrowed our database down to 716 papers. In the full-text eligibility screening, we excluded papers that did not report an estimate of β and where the original data could not be used by us to estimate β. We identified 74 papers that reported an estimate of β, and 42 additional papers for which the data could be used to estimate β. We emailed the authors of these 42 papers asking them to either share their original data with us or to estimate β and share their results with us. By 30 October 2020, the authors of three of these papers provided their datasets,[3] and our estimates of β using the provided datasets are included in this meta-analysis. After excluding papers for which the standard error of the present bias estimate could not be recovered, our database consists of 62 papers (50 with monetary rewards, 9 with non-monetary rewards such as food, real effort or health outcomes, and 3 with both monetary and non-monetary rewards).

[Insert Figure 1 here]

2.3 *Dataset construction*

Our primary variable of interest is the estimate of the present bias parameter β together with its standard error (which allows us to calculate the weight of a study in the meta-analysis). Studies differ in how they report this information. Some studies provide aggregate-level parameter estimates, while others provide summary statistics such as the mean or median of individual-

[2] Topic keywords are "beta-delta" OR "dynamic consistency" OR "dynamically consistent" OR "dynamic inconsistency" OR "dynamically inconsistent" OR "hyperbolic discount*" OR "non-constant discount*" OR "present bias*" OR "present-bias*" OR "future bias*" OR "quasi-hyperbolic" OR "self-control" OR "time consisten*" OR "time inconsisten*". Methodology keywords are elicit* OR estimat* OR experiment* OR measur* OR comput* OR "test*".
[3] They are Olivola & Wang (2016), Sopher & Sheth (2006) and Sutter et al. (2013).

level estimates, and some studies provide both. Our database includes all such available information with an indication of how the reported estimates were obtained. If estimates were derived from individual-level estimation, we transformed the standard deviation of the individual estimates into the standard error of the mean estimate. When standard errors for aggregate estimates were not reported directly, we reconstructed them from other available information such as t-ratio, or p-value (of the null hypothesis of no present bias, $\beta = 1$).

Some papers report more than one estimate of β. When a paper reported more than one estimate using both the full sample as well as its subsamples (e.g. males and females), we kept one estimate based on the full sample and did not include estimates for the subsamples. When a paper reported multiple estimates of β derived from the one dataset, we kept the estimate that is reported as the main result in the paper. Such procedures minimise interdependence resulting from the inclusion of multiple estimates of β from the same dataset in our analysis. However, when a paper reported more than one estimate of β as a result of collecting multiple datasets from a single sample (for example, when comparing different elicitation methods or different reward types in the same subjects), we included all of these estimates.[4] This allows us to test whether the choice of elicitation procedure or reward type affects the resulting estimate of β. Through this procedure, the 62 articles resulted in 81 estimates (68 for money and 13 for other rewards) used in our analysis.

To investigate potential publication bias, we coded whether a study was published. To investigate the sources of heterogeneity in estimates of β, our dataset captures methodological differences between studies, such as the characteristics of participants, the reward type, and the experimental task. These variables include subject pool (e.g. university students, children/teenagers, clinical populations), reward type (e.g. money, food, health outcomes), consequential versus hypothetical choice, elicitation method (e.g. choice list, CTB), utility curvature control (e.g. none, joint elicitation, CTB), estimation method (e.g. maximum likelihood, Tobit, non-linear least squares), study location (e.g. laboratory, field), continent, and discipline (see Appendix 2 for details).

3. Results

[4] For example, Andreoni, Kuhn, & Sprenger (2015) applied two distinct elicitation methods (CTB and joint elicitation) with the same subjects. In our dataset, we included both estimates of β, one for each elicitation method.

3.1 *Characteristics of papers and estimates*

Table 1 shows the characteristics of the papers. 45.0% of the papers were unpublished as at 19 December 2018. The dataset includes papers from a variety of disciplines: economics and business (90.3%), psychology (3.2%), neuroscience (3.2%), and medicine and psychiatry (3.2%). 76.0% of the papers reported estimates from developed countries, including one cross-country study (Wang et al., 2016). 75.8% of the studies were incentivised.

[Insert Table 1 here]

Table 2 presents the characteristics of the estimates. Most data (76%) were collected either from university students or the general adult population (with roughly equal numbers of estimates obtained from each of these groups). There are a small number of estimates from other populations such as clinical populations, or entrepreneurs. The choice list (Harrison et al., 2002) is the most popular elicitation method and accounts for 50% of estimates (this includes estimates obtained using joint elicitation methods (Andersen et al., 2008)). 28% of the estimates (and 40% of those collected after 2012) are obtained using the CTB method (Andreoni & Sprenger, 2012a) (Figure 2). Less than half of all estimates (but 57% of those collected after Andersen et al. (2008)) control for utility curvature; this includes all joint elicitation and CTB estimates. Finally, maximum likelihood (ML) and non-linear least squares (NLS) are the most popular estimation methods. Together, over 50% of estimates are obtained using one of these two techniques.

[Insert Table 2 and Figure 2 here]

3.2 *Descriptive analysis of present bias estimates*

The earliest estimate of β in our dataset is from 2009 (Brown et al., 2009) ($\beta = 0.87, SE = 0.396$). In Figure 3, we plot each estimate of β for money against publication year, with the estimation methods indicated by different markers. Over the years, there are increasing numbers of estimates of β and they appear to gradually trend toward one (indicating no present bias).

[Insert Figure 3 here]

For monetary rewards, the mean of the estimates is 0.86. Given the left skew in the distribution (Figure 4A and Table 3), the median of 0.96 is larger than the mean, indicating weaker present bias. 57% of the estimates are consistent with present bias (i.e. β significantly smaller than 1), 36% with no present bias (β not significantly different from 1) and 7% with future bias.

For non-monetary rewards, the mean estimate of β is 0.72, which is significantly smaller than β estimated for monetary rewards (two-sided *t*-test, $p < 0.01$). Due to the left skew in the distribution, the median of 0.86 is again larger than the mean (Figure 4B and Table 3). 77% of these estimates find present bias and 23% find no present bias.

[Insert Figure 4 and Table 3 here]

3.3 *Meta-analytic estimate of* β

The descriptive analysis of β in the preceding section does not take the precision of the estimates into account. To establish a proper "meta-analytic average" of β, we set up a random-effects model to make use of the standard error information associated with each estimate, separately for monetary and non-monetary rewards.

To estimate the average present bias for money, we use the following random-effects model (DerSimonian & Laird, 1986):

$$\beta_j = \beta_0 + \xi_j + \varepsilon_j$$

where β_j is the jth estimate of present-bias in our dataset. The observed present bias is decomposed into β_0 (the "true" present-bias parameter that is assumed to be common to all observations in the data) and the sampling errors $\xi_j \sim N(0, \tau^2)$ and $\varepsilon_j \sim \mathcal{N}(0,\ v_j^2)$, where τ^2 captures the unknown between-observation heterogeneity, beyond mere sampling variance, while the sampling variance v_j^2 is known. The random-effects estimate $\overline{\beta_0}^{RE}$ is a weighted average of the individual β_j:

$$\overline{\beta_0}^{RE} = \frac{\sum_{j=1}^{m} w_j \beta_j}{\sum_{j=1}^{m} w_j}$$

The weights are given by $w_j = 1/(v_j^2 + \hat{\tau}^2)$ where $\hat{\tau}^2$ is the estimate of τ^2 based on the DerSimonian and Laird method (DerSimonian & Laird, 1986). Estimates with higher precision (smaller standard errors) are given larger weights. As explained in Section 2.2, in some cases, our dataset includes multiple estimates of β from a single study, albeit not in cases where these were derived from the same underlying data. To account for potential correlation of estimates within a study, we use cluster-robust variance estimation.

For monetary rewards, the estimated overall mean of present bias is 0.82 with a 95% confidence interval of [0.74, 0.90].[5] The mean is significantly smaller than one, supporting the existence of present bias. Figure 5 shows the forest plot (Hedges & Olkin, 1985) of the estimates of β for monetary rewards in our dataset, with the overall meta-analytic estimate indicated by the diamond at the bottom of the figure. Each row represents a different estimate of β, but not necessarily a different paper. The size of each box represents the weight of that estimate in calculating $\overline{\beta_0}^{RE}$. The horizontal line around each box represents the 95% confidence interval of that estimate.

[Insert Figure 5 here]

For non-monetary rewards (food, real effort, health outcomes, and environmental outcomes), the meta-analytic estimate of present bias is 0.66 with a 95% confidence interval of [0.51, 0.85] (see Figure 6). Thus, consistent with the widely held view in the literature, we find a stronger present bias for non-monetary rewards. The confidence interval of β for non-monetary rewards is wider than for money because there are fewer estimates for non-monetary rewards.

[Insert Figure 6 here]

3.4 *Selective reporting and publication bias*

There are two distinct reporting biases that might lead our meta-analytic estimates of β to not be a true reflection of present bias. First, for whatever reason, authors might tend to report β only when it is significantly smaller than one. This would result in a *selective reporting* bias.

[5] We obtained similar results when use different weighting schemes (e.g. unit, sample size, Schmidt & Hunter, (2004)). The overall mean of $\overline{\beta_0}^{RE}$ is between 0.81 and 0.85, which are all significantly smaller than one.

Second, journals might tend to only publish papers with β smaller than one, resulting in a *publication bias*. For monetary rewards, we search for evidence of selective reporting and publication bias separately because the former is a result of authors' decisions while the latter is a joint result of journals' and authors' decisions. Since there are only a small number of estimates of β for non-monetary rewards, we search for evidence of selective reporting (but not publication bias) for non-monetary rewards.

The funnel plot is a useful device for detecting selective reporting and publication bias (Egger et al., 1997). This is a scatter plot of the estimates against their standard errors (with the scale reversed, such that estimates with smaller standard errors appear at the top). The 95% confidence interval is illustrated by a cone that fans out from the mean estimate: all estimates within this cone are not significantly different from the mean. To detect selective reporting for present bias for monetary rewards, the funnel plot in Figure 7A uses all estimates (published and unpublished) of β for monetary rewards in our database. The asymmetry in this plot suggests that there are "missing studies" that authors chose not to report: there are more observations to the bottom left of the graph compared to the right, indicating that estimates of β that are greater than the mean (0.82) and have large standard errors are less likely to be reported.

To formally test for selective reporting, we use the Egger test, a simple meta-regression of each estimate of β on its standard error (Egger et al., 1997):

$$\beta_{ij} = \alpha_0 + \alpha_1 * SE_{ij} + \varepsilon_{ij}.$$

where α_0 is the "true" effect when there is no selective reporting, and $\alpha_1 \neq 0$ indicates the existence of selective reporting. To account for heteroscedasticity, we use weighted least squares with the inverse of the variance ($1/SE_{ij}^2$) as the weight. If there is selective reporting in the direction we expect, the reported estimates of β will be negatively correlated with their standard errors as authors are more likely to report smaller estimates of β, even with large standard errors (less precision). The Egger test confirms the existence of selective reporting: $\alpha_1 = -1.57, p = 0.019$.

[Insert Figure 7 here]

The funnel plot in Figure 7B uses all estimates of β for non-monetary rewards. The symmetry of this plot and the Egger test ($\alpha_1 = -0.28, p = 0.81$) both indicate no evidence of selective reporting for non-monetary rewards.

To detect publication bias for monetary rewards, the funnel plot in Figure 7C uses only estimates for money from published papers in our database. Again, there is an asymmetry in the plot indicating that there that there are "missing studies" that failed to publish. The Egger test supports the existence of a publication bias in this literature: $\alpha_1 = -2.49$ ($p = 0.010$).

To correct for selective reporting and publication bias, we use the trim-and-fill technique (Duval & Tweedie, 2000a, 2000b; Sutton et al., 2000). The idea of this method is to first *trim* the studies that cause a funnel plot's asymmetry so that the overall estimate produced by the remaining studies can be considered minimally impacted by bias, and then to *fill* imputed missing studies in the funnel plot based on the bias-corrected overall estimate. For monetary rewards, after correcting for selective reporting, the overall mean of β is 0.87 with 95% confidence interval [0.82, 0.92]. After correcting for publication bias, the overall mean of β for monetary rewards is 0.84 with 95% confidence interval [0.77, 0.92].[6] These estimates of β are slightly higher than what we obtained before, but the conclusion that decision-makers show present bias still holds.

3.5 *Sources of heterogeneity in present bias estimates*

The I^2 statistic quantifies the amount of heterogeneity in the estimates of β relative to the total amount of variance in the observed β. This statistic is computed as:

$$I^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + s^2} \times 100\%$$

where $\hat{\tau}^2$ is the estimate of τ^2 (the unknown between-observation heterogeneity) and $s^2 = \frac{(m-1)\sum w_j}{(\sum w_j)^2 + \sum w_j^2}$ is the 'typical' sampling variance of the observed effect size with $w_j = \frac{1}{v_j^2}$ (where m is the number of estimates and w_j is weight of each estimate used to calculate the sampling variance).

[6] Our results for publication bias should be interpreted with caution for two reasons. Firstly, the analysis of publication bias is based on less data (only published estimates) than the analysis of selective reporting (both published and unpublished estimates). Secondly, some studies that were coded as unpublished in the dataset might in fact be published in the future, resulting in potential misspecification.

We find $I^2 = 100\%$ (Figure 5). This may be interpreted as indicating that all variance across studies is driven by unobserved between-observation heterogeneity rather than mere sampling variance. To explain this heterogeneity, we use a meta-regression model:

$$\beta_{ij} = \alpha_0 + \alpha_1 \cdot SE_{ij} + \gamma \boldsymbol{X_{ij}} + \varepsilon_{ij}$$

where $\boldsymbol{X}_{ij}$ is a vector of observable characteristics of the jth estimate from study i, and γ is the coefficient vector. Variables included in $\boldsymbol{X}_{ij}$ are categorized into (1) participant characteristics: subject pool (omitted category is university students), developing country dummy (omitted category is developed country), continents (omitted category is North America), and (2) methodology: utility curvature correction dummy (omitted category is no correction for utility curvature), elicitation method (omitted category is choice list), estimation method (omitted category is inference from switching point), payment method (omitted category is cash), consequential choice dummy (omitted category is hypothetical choice), study place (omitted category is laboratory), and discipline (omitted category is economics and business).[7] The results illustrate how participant characteristics and methodological variables affect the estimates of β.

In Table 4, we only consider estimates for money. We show the meta-regressions for each individual source of heterogeneity separately in Models (1) – (10), and for all sources together in Model (11). The baseline is an estimate of β obtained in a laboratory experiment conducted with university students from North America, not controlling for utility curvature, using a choice list design to elicit and inference from switching points to estimate β, using consequential choices paid in cash, and originating from the disciplines of economics and business.

Our key findings are that: Studies of the general adult population, or of special populations such as clinical samples, yield lower estimates of β (stronger present bias) compared to studies of students. Estimates from European samples are larger than estimates from North American samples. Controlling for utility curvature does not affect the estimate of β in the full model (Model (11)) but increases β in the reduced model (Model (4)). Estimates based on the CTB design are larger (closer to one) in the reduced model (Model (5)) relative to estimates based

[7] See Appendix 2 for details of the coding of these variables.

on choice list methods, but this is not significant in the full model (Model (11)).[8] The choice of estimation technique and whether choices are consequential or hypothetical do not significantly affect the estimate of β. Collecting data online tends to result in larger estimates of β (less present bias), while collecting data in schools or workplaces tends to result in lower estimates compared to the laboratory. Finally, studies that use bank transfers as the payment method report lower estimates of β compared to studies that use cash.

[Insert Table 4 here]

To examine whether the reward type has a significant effect on the estimated value of β, we use all estimates for both monetary and non-monetary rewards. Table 5 reports the results of a model where the variables of $\boldsymbol{X}_{ij}$ are the reward types (omitted category is money). We find that, compared to monetary rewards, individuals tend to show stronger present bias for real effort (6 estimates) and health outcomes (3 estimates). Directionally, we see the same result for food, however it is not significant (based on 2 estimates).

[Insert Table 5 here]

4. Discussion

People consistently fail to follow the plans they had made earlier, especially if the plans entail costs upfront but benefits in the future. People pledge to exercise more, eat healthier, become financially responsible or quit smoking starting at some future date but fail to follow through when this date arrives, often to their own frustration and disappointment. In behavioural economics, these self-control problems are usually captured using quasi-hyperbolic discounting. The central assumption is that people are "present-biased" toward current consumption. Despite the popularity of this model across multiple fields in decision sciences, to date the individual papers in the literature have not produced consistent evidence to support the existence of present bias, calling for a scientific re-examination of all existing empirical evidence.

[8] Imai et al. (2021) also used meta-analysis to estimate the overall "mean" of β for studies that use the CTB design. They documented that the average value of β is between 0.95 and 0.97. We replicate this finding. We find the average value of β using CTB design is 0.98 with 95% confidence interval between 0.95 and 1.00.

In this paper, we conducted a meta-analysis of 81 estimates of present bias (β) from 62 published and unpublished papers. For monetary rewards, the simple mean of the estimates is 0.86 and the median is 0.96. For primary rewards, such as food or real effort, the mean is 0.72 and the median is 0.86. Present bias is significantly stronger for primary rewards than for money. However, these simple summary statistics may present a distorted picture of present bias because they do not take the quality of the estimates into account and may potentially be driven by underpowered studies. Using a random-effects model that accounts for the standard errors of the estimates, we find that the meta-analytic average of β for monetary rewards is close to the simple mean. For monetary rewards, it is 0.82 with 95% confidence interval of [0.74, 0.90], and for primary rewards it is 0.66 with 95% confidence interval of [0.51, 0.85], indicating a statistically significant present bias for both monetary and primary rewards.

The relatively wide confidence intervals of the meta-analytic estimates signal a considerable heterogeneity across studies. Previous research speculated that experiments using time-dated monetary payments may yield higher estimates of β than experiments using non-monetary rewards because money need not be consumed immediately upon receipt. Consistent with this idea, Augenblick et al. (2015) found more present bias for effort than for monetary rewards. Our meta-regression further supports this hypothesis. We find that experiments in which participants make temporal trade-offs that involve effort or health outcomes yield smaller estimates of β (stronger present bias) than decisions about money. For food, we see the same result but the difference is not significant (but see also Cheung, Tymula, & Wang (2020), not included in this meta-analysis, who find stronger present bias for food than for money). On one hand, this evidence is in line with the idea that studies using financial flows may not appropriately estimate time preference because the quasi-hyperbolic discounting model is proposed to explain time preference over consumption (see Cohen et al. (2020) for detailed discussion). On the other hand, the fact that we find present bias for money suggests that concerns over the confounding effect of arbitrage in discounting experiments using monetary rewards may have been overstated (possibly because of the mismatch between experimental and market interest rates). It is surprising that the correlation of present bias across domains has not been more extensively studied, given the confidence with which researchers extrapolate from studies using one type of reward to completely different domains. The two existing studies provide dramatically different conclusions. Cheung, Tymula & Wang (2020) found robust correlation between present bias for money and food ($\rho = 0.60, p < 0.01$), whereas

Augenblick et al. (2015) found almost zero correlation of present bias between money and real effort ($\rho = -0.05, p = -0.66$). It is clear that more studies are needed to establish whether present bias is an individual specific trait that affects many decision domains and is correlated across these domains.

Focusing on studies of how people trade-off monetary payments across time, we find that estimates of present bias systematically vary with the characteristics of participants. It is possible that studies that found no or weak present bias could simply have selected a sample that does not have self-control problems. For example, one would expect students at top research universities to be particularly good at foregoing immediate pleasures for long term benefits, especially if they show up in the laboratory for the experimental session. In line with this argument, we find that studies with general adult samples yield stronger present bias compared to studies with university students, which may explain recent findings of no present bias for monetary rewards among university students (e.g. Andreoni & Sprenger (2012a)). In addition, participants from European countries show less present bias than participants from North America. In the future, we hope that more studies will include non-WEIRD (White, Educated, Industrialised, Rich and Democratic) participants (Henrich, Heine, & Norenzayan, 2010) from continents other than North America to provide a more complete picture of heterogeneity in present bias across populations.

Adjusting for utility curvature is perhaps the most important recent methodological advance in the study of temporal discounting (Andersen et al., 2008). We find that whether a study adjusts for non-linear utility does not affect the estimate of present bias. This suggests that the effect of adjusting for utility curvature may be reflected largely in estimates of the discount factor (δ) rather than in estimates of present bias (β) (see, for example, Andersen et al (2014)). A new methodological controversy is whether the correction for utility curvature should be done using data on risky or riskless choices. We find that the CTB method that estimates utility over riskless choices yields higher estimates of β (more closer to one, i.e. less present bias) than the joint elicitation method that uses utility estimated from risky choices. However, this effect becomes insignificant when we control for the full set of covariates, likely because of correlation between elicitation and estimation methods.[9]

[9] Papers that use the CTB design most commonly use NLS for estimation, while studies that use the joint elicitation approach usually use ML.

It may be surprising to experimental economists that we find that estimates of present bias do not depend on whether participants' choices were incentivised or hypothetical. Further research is needed to investigate to what extent this is due to the possibility that the incentives may not have been large enough. Finally, we find that relative to laboratory experiments, experiments conducted in schools or workplaces report lower estimates of β, while online experiments report higher β. These results remain significant when all other aspects of a study are controlled for. We find this result intuitive. Laboratory experiments require participants to take the initiative to sign up for the experiment and then come to the right place at the right time. Such procedures may lead to a selection bias as participants who show up to a previously scheduled experimental session on time are likely to have fewer problems with self-control. We recommend that future studies carefully consider selection bias in their experimental design.

It is important to note that all of our conclusions are based on the evidence that is available and thus can be distorted if there are biases in the reporting and publication process. Indeed, we find that there is both selective reporting and publication bias, with both authors being more likely to report and journals more likely to publish studies that find present bias. Nonetheless, we find that even though the estimate of β increases slightly after correcting for these biases, it is still significantly lower than 1.

Finally, we emphasise that while our meta-analysis provides evidence of time inconsistent preferences, it should not be treated as a test of the quasi-hyperbolic discounting model against other alternatives to standard exponential discounting. We chose to conduct this meta-analysis in the framework of the quasi-hyperbolic model due to its popularity and analytical convenience. However, there are other models, such as generalised hyperbolic discounting (e.g. Loewenstein & Prelec (1992)), that also capture time-inconsistent preferences. This meta-analysis provides support for time inconsistency in general but cannot differentiate between alternative models to provide support for one over another.

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Figure 1. Paper selection procedure

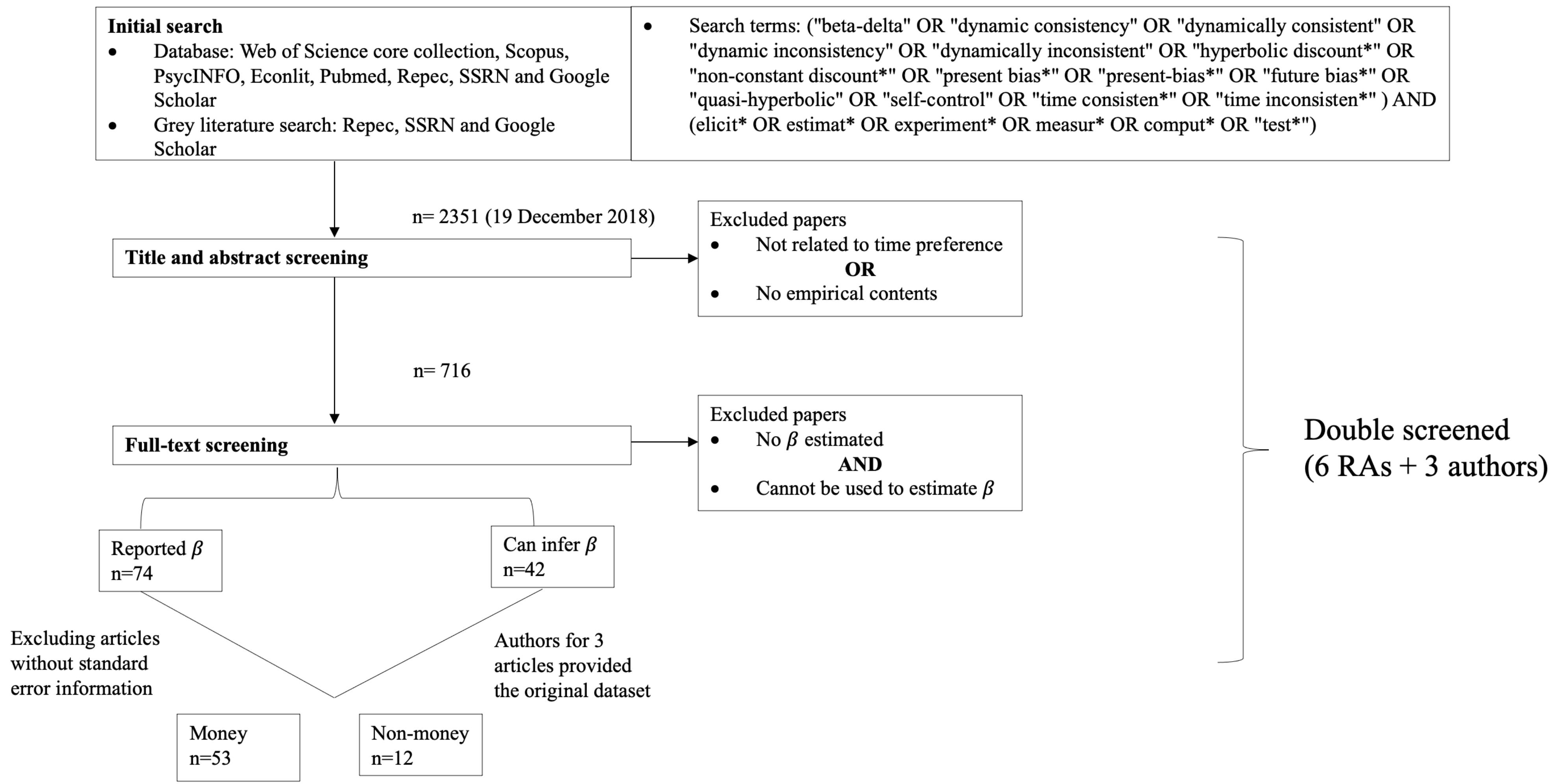


Figure 2. Elicitation methods by the year of publication and data collection. Numbers on top of each bar represent the total number of papers available in that year.

A. Elicitation methods over publication years.

B. Elicitation methods over collection years.

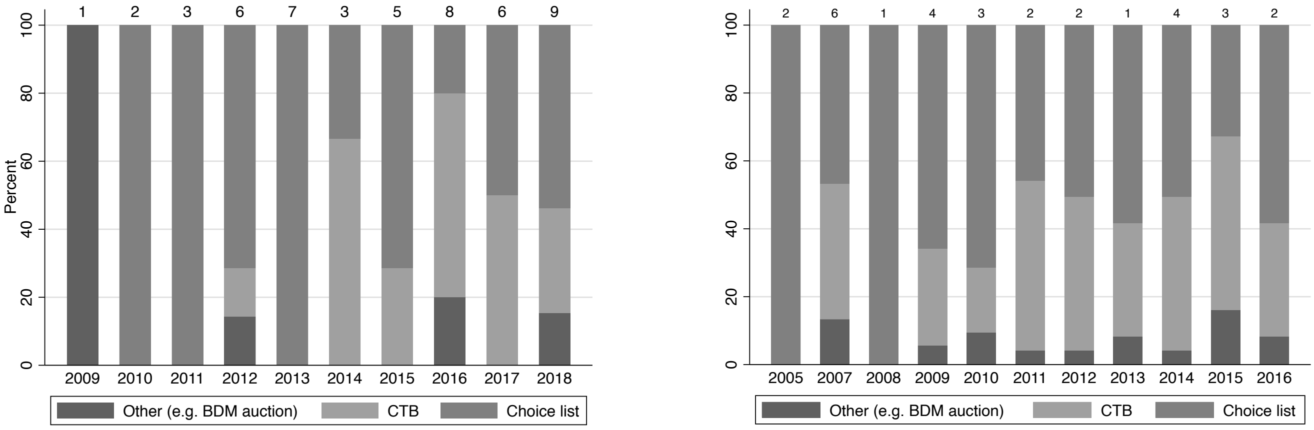


Figure 3. Estimates of β by the year of publication and data collection. Different elicitation methods are indicated by different markers. Jitter equals to 5. The dashed vertical line (year =2012) indicates when the CTB design was published.

A. Estimates of β over publication years

B. Estimates of β over experiment years

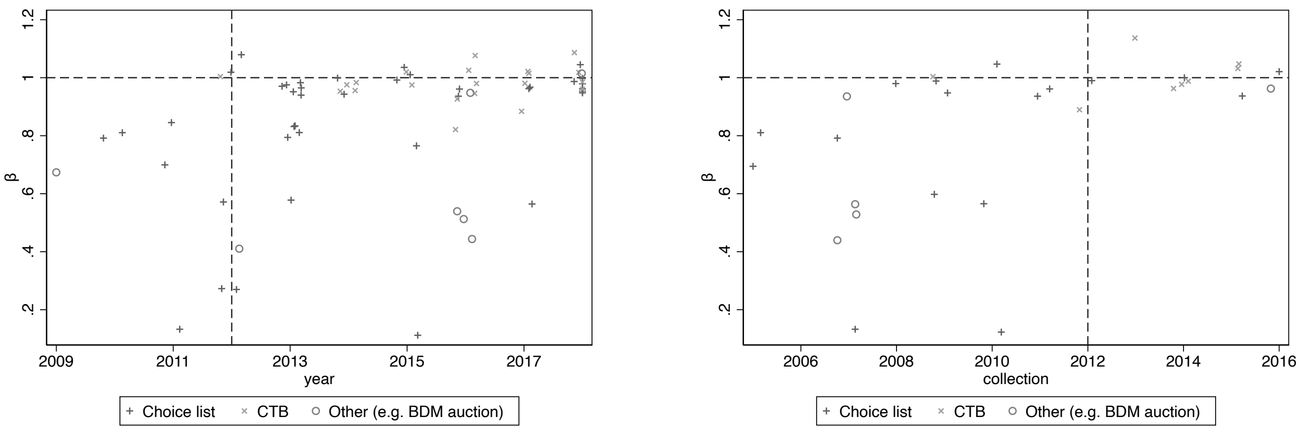


Figure 4. Distribution of β estimates in the literature. The fitted line is the normal density curve corresponding to the mean and standard deviation of the data shown.

A. Monetary rewards

B. Other reward types

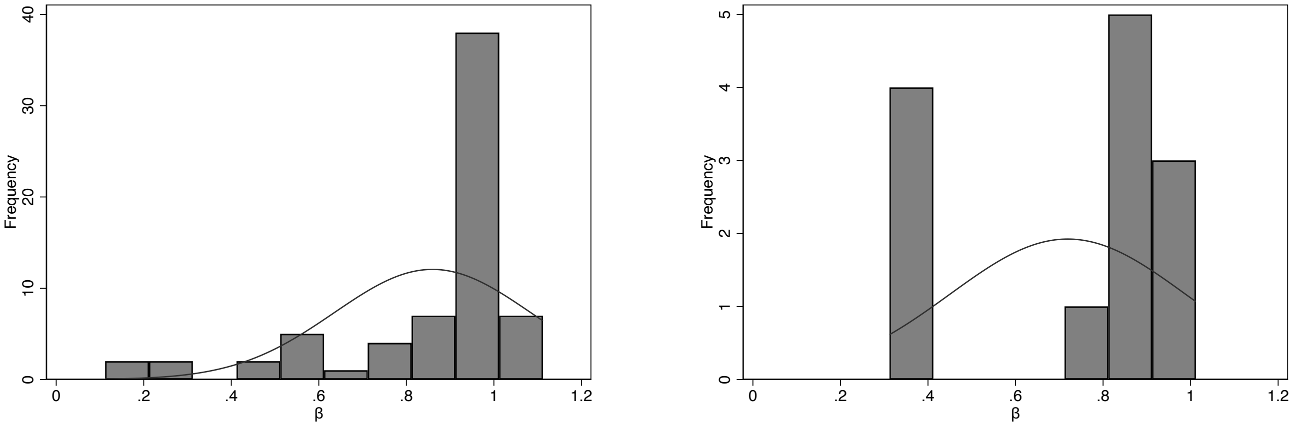


Figure 5. Forest plot of the estimates of β for monetary rewards. The vertical solid line indicates no present bias. There are 68 estimates from 53 papers. Each row is a different estimate but not necessarily a different study. Notes are added after colon to explain the difference between estimates that are from the same paper. The size of a box represents the weight of the estimate that is used to calculate the mean of β. The line on each box represents the confidence interval of that estimate. The diamond represents the meta-analytical average of β under random-effects framework.

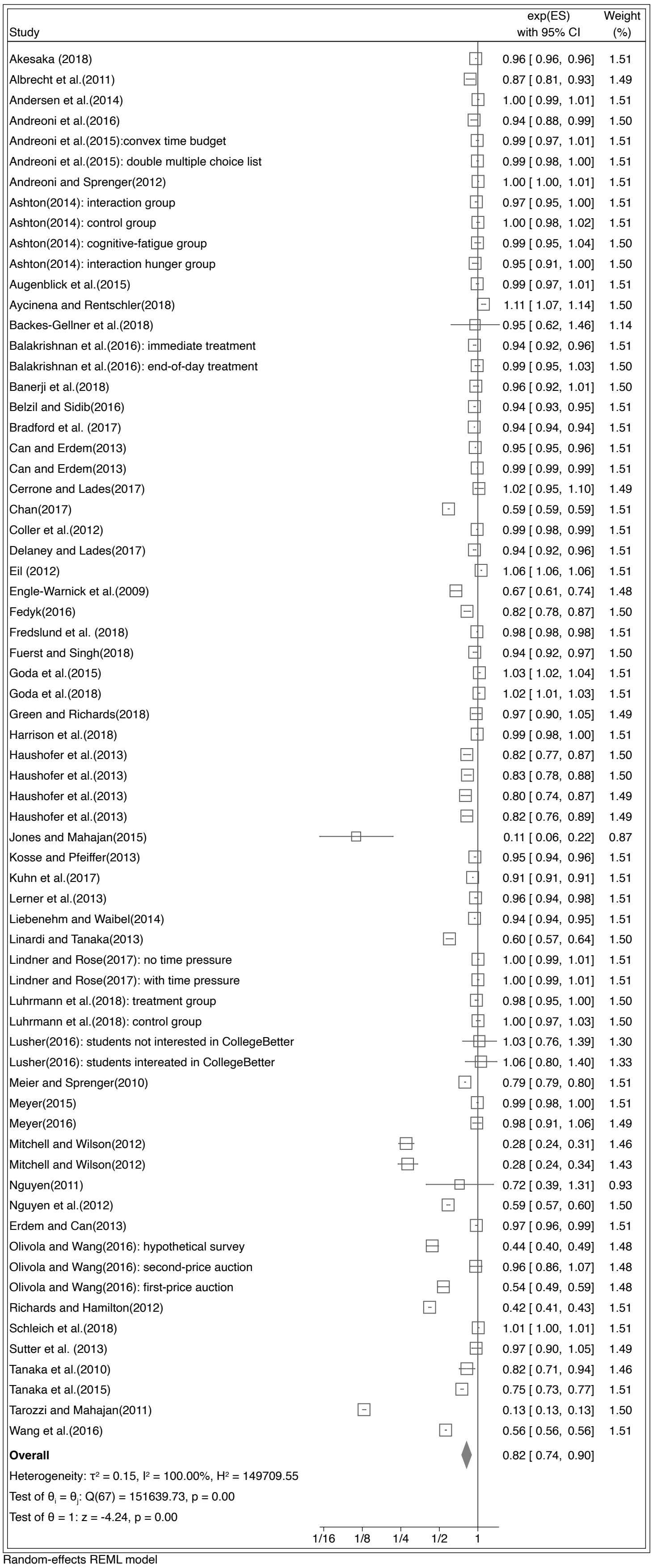


Figure 6. Forest plot of the estimates of β for other reward types. Reward type is indicated after the colon for each estimate. The vertical solid line indicates no present bias. There are 13 estimates from 9 papers. Each row is a different estimate but not necessarily a different study. The size of a box represents the weight of the estimate that is used to calculate the mean of β. The line on each box represents the confidence interval of that estimate. The diamond represents the meta-analytical average of β under random-effects framework.

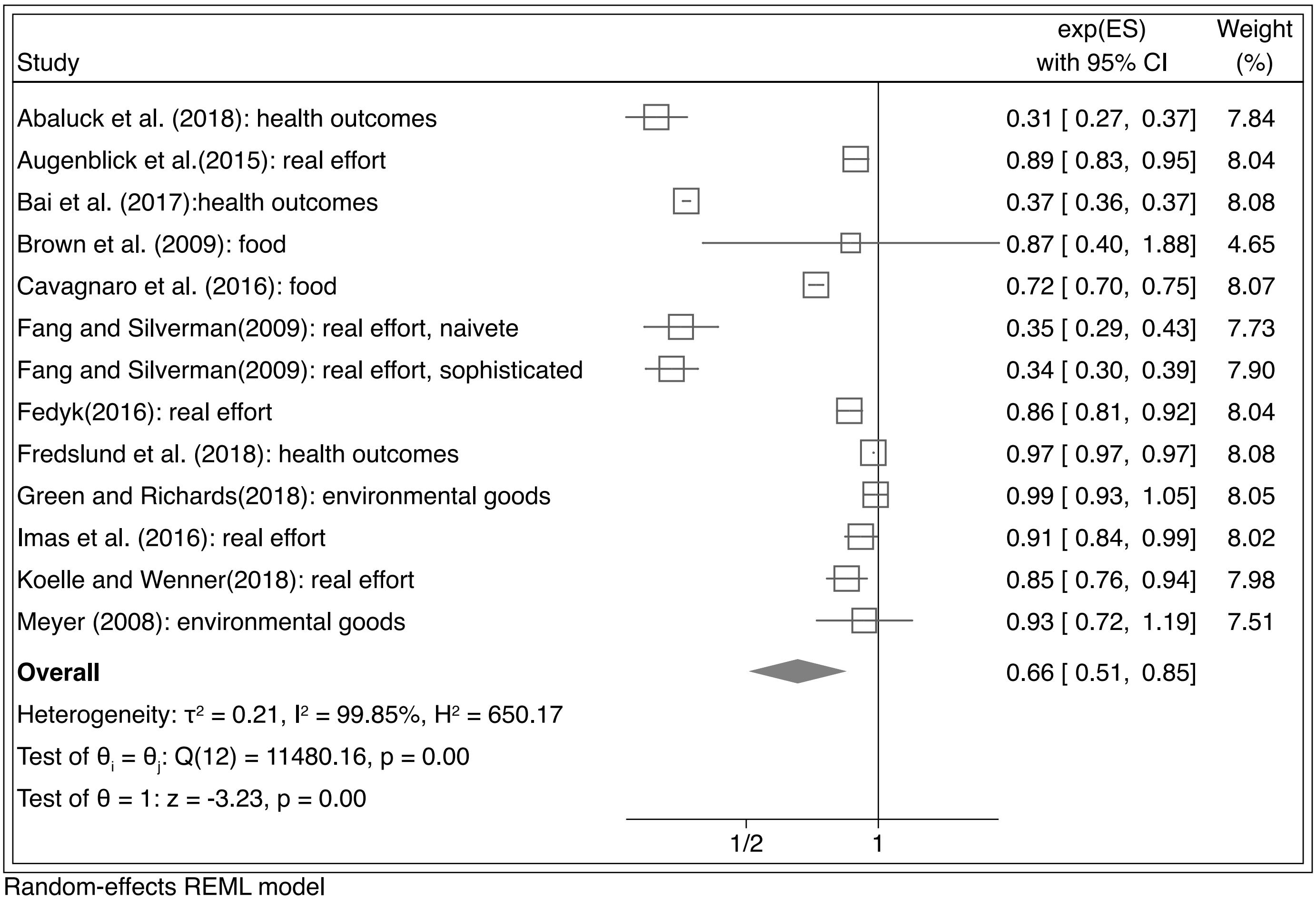
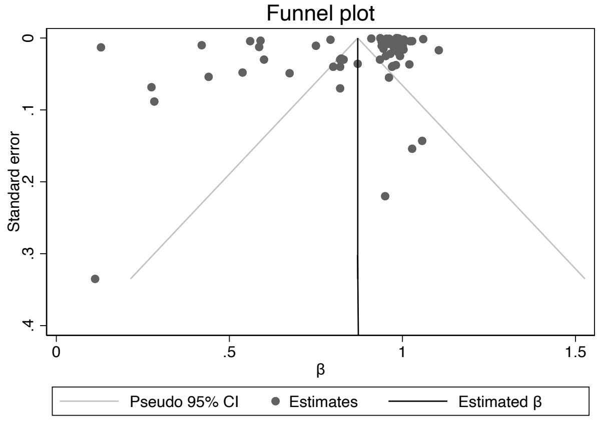
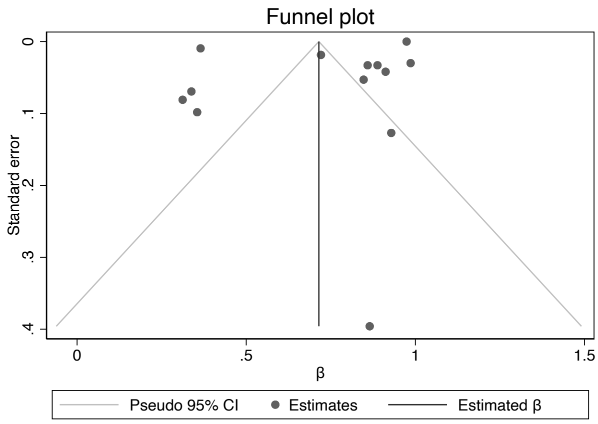


Figure 7. Selective reporting and publication bias. Estimates within the grey boundaries (arms) are consistent with the meta-analytic estimate of β using a two-sided test at the 5% significance level. The vertical black line is the meta-analytic β estimate.

A. Selective reporting (monetary rewards, all estimates in the dataset)



B. Selective reporting (non-monetary rewards, all estimates in the dataset)



C. Publication bias (monetary rewards, only estimates from published studies only)

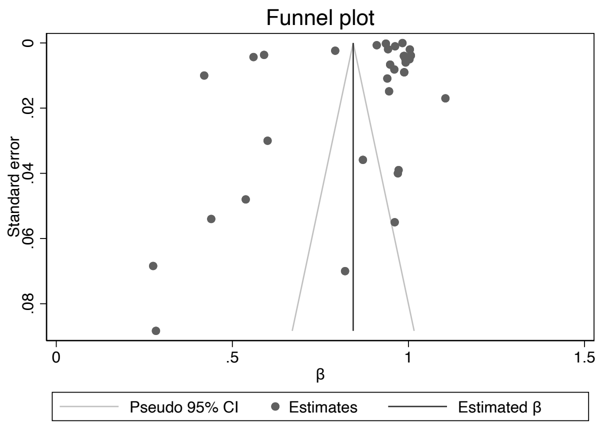


Table 1. Characteristics of papers.

	All studies		Money		Other reward types	
	Frequency	Proportion (%)	Frequency	Proportion (%)	Frequency	Proportion (%)
Total number of papers	62	100.00	53	100.00	12	100.00
Publication status						
Published in an academic journal	34	54.84	30	56.60	6	50.00
Unpublished working paper	28	45.16	23	43.40	6	50.00
Geographical location						
Developed country	47	75.81	39	73.58	11	91.67
Developing country	14	22.58	13	24.53	1	8.33
Both	1	1.61	1	1.89		
Consequential choice						
Incentivised	47	75.80	39	73.58	9	75.00
Hypothetical	15	24.19	14	26.42	3	25.00
Discipline						
Economics and Business	56	90.34	47	88.69	12	100.00
Psychology	2	3.22	2	3.77		
Neuroscience	2	3.22	2	3.77		
Medicine and psychiatry	2	3.22	2	3.77		
Reward type						
Money	50	80.65				
Food or beverage	2	3.23				
Real effort	3	4.84				
Health outcomes	2	3.23				
Other (e.g. environmental good)	2	3.23				
Multiple reward types	3	4.84				

Table 2. Data characteristics.

	All estimates		Money		Other reward types	
	Frequency	Proportion (%)	Frequency	Proportion (%)	Frequency	Proportion (%)
Total number of estimates	81	100.00	68	100.00	13	100.00
Subject type						
University students	30	37.04	25	36.76	5	38.46
General adult population	32	39.51	28	41.48	4	30.77
Adolescents and Children	5	6.17	5	7.35		
Other (e.g. clinical, entrepreneurs)	14	17.28	10	14.41	4	30.77
Elicitation						
Choice list	41	50.62	40	58.82	1	7.69
Convex time budget	23	28.40	21	30.88	2	15.38
Other (e.g. BDM auction)	17	20.98	7	10.30	10	76.93
Control for utility						
Yes	39	48.15	36	52.94	3	23.08
No	42	51.85	32	47.86	10	76.92
beta estimation						
Maximum likelihood	23	28.40	19	27.94	4	30.77
Inference from switching point	13	16.05	13	19.12		
OLS	7	8.64	6	8.82	1	7.69
NLS	23	28.40	22	32.35	1	7.69
Tobit	3	3.70	1	1.47	2	15.38
Other (e.g. interval censored)	12	14.81	7	10.29	5	38.46

Table 3. Summary statistics of reported $\boldsymbol{\beta}$.

Reward type	N	Mean	SD	Q25	Median	Q75	Min	Max
Money	68	0.86	0.22	0.82	0.96	0.99	0.11	1.11
Non-money	13	0.72	0.27	0.37	0.86	0.91	0.31	0.99

Table 4. A meta-regression of β for monetary rewards. The baseline is an estimate of β obtained from a laboratory experiment with university students in North America, that does not control for utility curvature, uses choice list and switching point to estimate beta, uses cash as payment, consequential choice and has been published in an economic/business journal. In Model (11), South America is perfectly collinear with Africa and thus is omitted.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Subject pool											
General adult	-0.0316										-0.1706*
	(0.0546)										(0.0816)
Children	0.0596										0.0780
	(0.1018)										(0.1241)
Other	-0.1774*										-0.3067***
	(0.0742)										(0.0907)
Developing country											
Developing		-0.0182									-0.0299
		(0.0603)									(0.1373)
Continents											
Europe			0.1003+								0.2486***
			(0.0584)								(0.0754)
Asia			-0.0055								0.1653
			(0.0692)								(0.1400)
South America			0.2661								
			(0.2025)								
Africa			0.0778								0.1437
			(0.1056)								(0.1711)
Utility curvature											
Yes				0.0825+							-0.0146
				(0.0486)							(0.0574)
Elicitation											
CTB					0.1263*						0.0263
					(0.0504)						(0.0740)
BDM auction					-0.1588*						-0.2316**

	(0.0721)						(0.0856)
Estimation							
ML		-0.0505					0.0285
		(0.0750)					(0.0946)
OLS		0.0041					-0.0079
		(0.0965)					(0.1299)
NLS		-0.0059					0.0458
		(0.0725)					(0.0927)
Tobit		0.2092					0.5281
		(0.2117)					(0.3217)
Other		-0.0941					-0.1700
		(0.0961)					(0.1083)
Payment method							
Cheque			0.1534				0.0015
			(0.1040)				(0.1092)
Bank transfer			0.0444				-0.2049+
			(0.1143)				(0.1177)
Gift card			0.1041				-0.0330
			(0.1042)				(0.1342)
Postal money order			-0.0654				0.1080
			(0.2024)				(0.1804)
Consequential choice							
No				0.0235			0.0010
				(0.0470)			(0.0606)
Study place							
Field					-0.0728		-0.1016
					(0.0633)		(0.0813)
Online					0.1068		0.2174*
					(0.0711)		(0.0865)
School/workplace					-0.1404		-0.3013*
					(0.1300)		(0.1332)

Discipline											
Psychology										0.0665	0.0822
										(0.1383)	(0.1421)
Neuroscience										0.1059	-0.1635
										(0.1395)	(0.1957)
Other										-0.3451**	-0.2480*
										(0.1192)	(0.1171)
constant	0.9101***	0.8314***	0.8551***	0.8958***	0.8780***	0.8389***	0.8574***	0.8541***	0.8781***	0.8835***	0.9266***
	(0.0401)	(0.0350)	(0.0296)	(0.0576)	(0.0278)	(0.0352)	(0.0273)	(0.0471)	(0.0302)	(0.0249)	(0.0797)
N	70	70	70	70	70	70	70	70	70	70	70

Standard errors in parentheses

+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 5. A meta-regression of β for different reward types. The reference group are the estimates for monetary rewards.

Food	-0.1033
	(0.1195)
Real effort	-0.1836+
	(0.0988)
Health outcome	-0.3081*
	(0.1239)
Other (environmental good, cleansed basin)	0.0725
	(0.0903)
constant	0.8698***
	(0.0258)
N	85

Standard errors in parentheses
+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Appendix 1. Reference list of included papers

Abaluck, J., Gruber, J., & Swanson, A. (2018). Prescription drug use under Medicare Part D: A linear model of nonlinear budget sets. *Journal of Public Economics*, *164*, 106–138.

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Appendix 2. Coding strategy

Variable name	Variable type	Codes/ Description
Experimental study	Dummy	1- Yes 0- No
Data type	Categorical	1- Experimental 2- Discounting questions embedded within a survey 3- Other
Reported β	Dummy	1- Yes 0- No
Estimation level	Categorical	1- Aggregate level 2- Individual level 3- Both
Aggregate β		Reported β at aggregate level, leave blank if not reported
Aggregate β se		Reported β standard error at aggregate level, leave blank if not reported
Individual β mean		Reported individual β mean, leave blank if not reported
Individual β median		Reported individual β median, leave blank if not reported
Individual β sd		Reported individual β standard deviation, leave blank if not reported
Individual β range		Reported individual β percentile, leave blank if not reported
Longitudinal design	Dummy	1- Yes 0- No
Attrition rate	Continuous	Only for longitudinal design
Zero FED	Dummy	1- there is front-end delay 0- no front-end delay
Immediate payment	Categorical	1- Immediately after the choice is made 2- Immediately at the end of study 3- On the same day 4- Not applicable, because the outcomes were hypothetical 5- Not reported
FED length	Continuous	All reported FED values e.g. when there is no FED and no variation in FED, the FED value is 0
BED length	Continuous	All reported BED lengths

Sample size	Continuous	Reported sample size
Subject pool	Categorical and free text (multiple responses)	1- University students 2- Adults 3- Adolescents 4- Children 5- Clinical populations 6- Animals 7- Other (specify)
Geographical location	Free text	Reported country and/or states
Developed country	Dummy	1- Yes 0- No
Study place	Categorical and free text	1- Laboratory 2- Field 3- Online 4- School/workplace 5- Clinical setting 6- Other
Reward type	Categorical (multiple responses) and free text	1- Money 2- Food 3- Real effort 4- Consumption good 5- Health outcomes 6- Other (specify)
Real	Dummy	1- Yes 0- No (i.e. Hypothetical)
Payment medium	Categorical and free text	1- Cash 2- Cheque 3- Bank transfer 4- Gift card/voucher 5- Postal money order 6- Other (specify)
Future payment	Categorical and free text	1- same reward delivery method for sooner and later rewards 0- different (specify)
Future payment risk	Dummy	1- control for it 0- no control
Elicitation procedure	Categorical and free text	1- Multiple choice list 2- Titration 3- Convex time budget 4- WTP (BDM auction) 5- Matching task 6- Other (specify)
Utility control	Dummy	1- Yes 0- No
Utility control method	Categorical	1- risk preference 2- probability equivalence 3- intertemporal substitution (include CTB)

		4- “direct” method 5- Other (specify)
Estimation	Categorical	1- Ad hoc 2- Maximum likelihood 3- Censored regression model 4- Ordinary least squares 5- Non-linear least squares 6- Other (specify)
Publish	Dummy	1- Academic journal 2- Unpublished working paper 3- Other (specify)
SCImago ranking	Continuous	SCImago quartile rankin
SCImago H index	Continuous	SCImago H index
SCImago score	Continuous	SCImago SJR score
Discipline	Categorical and free text	1- Economics and business 2- Psychology 3- Neuroscience 4- Biology 5- Other (specify) 6- Unknown since the study has not been published yet