A meta-analysis of quasi-hyperbolic discounting

Stephen L. Cheung,[a] Agnieszka Tymula[a] and Xueting Wang[b,*]

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Abstract: In economics, quasi-hyperbolic discounting is one of the most well-known and widely-used models to capture problems of self-control. The model's underlying assumption 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). We report meta-analytic estimates of the present bias parameter β (89 papers with 109 estimates) and the discount factor δ (90 estimates drawn from the same papers). After correcting for selective reporting, we find a slight present bias for monetary rewards ($\beta = 0.98$ with 95% confidence interval of [0.979, 0.981]). The present bias for non-monetary rewards is much stronger ($\beta = 0.68$ with a 95% confidence interval of [0.57, 0.82]). We find substantial heterogeneity in estimates across studies, which stems from variations in elicitation methodology, study location, and reward type. Our insights contribute to the understanding of quasi-hyperbolic discounting and also underscore the intricate interplay of factors influencing temporal preferences.

Keywords: quasi-hyperbolic discounting; present bias; discount factor; beta-delta model; meta-analysis

JEL codes: C91, D12, D80, D91

Affiliation:

[a] School of Economics, The University of Sydney, Australia.
[b] School of Economics, Finance, and Marketing, RMIT University, Australia.

[*]Corresponding author. Email: xueting.wang@rmit.edu.au

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1. Introduction

Self-control is a critical attribute within the realm of managerial economics, as it plays a pivotal role in decision-making processes and overall organisational success. Managers must exercise self-control when faced with myriad choices that can have profound implications for their companies. The ability to resist immediate gratification in favour of long-term strategic objectives is essential in allocating resources efficiently and making optimal investment decisions. Furthermore, self-control is vital in maintaining discipline within teams, ensuring adherence to established budgets and timelines, and fostering a culture of accountability. From a managerial perspective, the practice of self-control not only enhances individual leadership effectiveness but also cultivates an environment conducive to sustained growth and competitiveness.

Regrettably, 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 work and education (e.g. sticking to a schedule versus procrastinating), finances (e.g. saving and investing for later versus consuming now for pleasure), and health (e.g. eating unhealthy food versus exercising). 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 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 procedure (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.

The second parameter in the quasi-hyperbolic model is the discount factor δ which captures long-run discounting. The history of estimating δ is longer than that of β as the exponential discounting model has been used since the early 20th century (Samuelson, 1937). Despite decades of work and dozens of experiments devoted to eliciting time preferences, there is no consensus on how to best measure discounting (Andreoni, Kuhn, & Sprenger, 2015). It is safe to say that the discount factor differs across individuals and its estimates vary a great deal throughout the literature, sometimes by orders of magnitude (Coller & Williams, 1999; Frederick et al., 2002).

In this paper, we provide the first scientifically synthesised evidence summarising estimates of both the β and δ parameters of the quasi-hyperbolic model. A meta-analysis of β can help to resolve whether present bias is indeed a real phenomenon. A meta-analysis of δ can shed light on why estimates seem to vary so much across studies. The possible reasons why there is no consensus in the literature are numerous and can be broadly classified into three categories: differences in the characteristics of participants, differences in the reward type, and differences in the experimental task.

Firstly, many estimates of time preferences are based on choices made by students at top research universities, a group that may not have serious problems with time inconsistency or impatience to begin with. Thus, one might conjecture that estimates of both β and δ in a general adult population may be lower (i.e. they might be more present biased and impatient). Secondly, estimates of β and δ are usually derived from decisions over time-dated monetary payments, a methodology that has been questioned because it assumes that monetary rewards are consumed immediately upon receipt (see Cohen et al. (2020) for a detailed discussion). If that is not the case, present bias and impatience may be stronger for consumption rewards than for money.

Finally, the experimental tasks (e.g. choice list design versus Convex Time Budget, henceforth CTB) 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 biases the estimates of discounting parameters. Currently, even those methods that adjust for utility curvature differ in whether utility is estimated from choices under certainty or risk. The CTB design (Andreoni & Sprenger, 2012a) estimates both utility curvature and discounting parameters from a single task, 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 popularity of the quasi-hyperbolic 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 and if so how strong, as well as to understand the sources of heterogeneity in both present bias and long-run discounting 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 systematic meta-analysis drawing upon a comprehensive database of estimates of both the β and δ parameters of the quasi-hyperbolic discounting model.

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 (89 papers and 109 estimates, of which 89 estimates are for money and

20 are for other reward types).[1] From the same set of papers, we also have a matched dataset of 90 estimates of the (annualised) discount factor (75 for money and 15 for other rewards).[2]

For monetary rewards, using 89 estimates from 74 papers, our uncorrected meta-analytic average β is 0.91 with 95% confidence interval of [0.87, 0.95]. This indicates statistically significant evidence of present bias for money, contrary to the emerging consensus in the recent literature. However, we also find evidence of selective reporting in the estimates of β for monetary rewards. Using standard methods to correct for selective reporting yields a corrected average β of 0.98 with 95% confidence interval of [0.979, 0.981]; while this indicates much less pronounced present bias, it is still significantly less than one. Estimates of β for non-monetary rewards are much smaller, implying stronger present bias: using 20 estimates from 18 papers, our meta-analytic average β for non-monetary rewards is 0.68 with 95% confidence interval of [0.57, 0.82]. We found no evidence of selective reporting of β for non-monetary rewards.

In our heterogeneity analysis, we find that estimates of β differ systematically based on study characteristics. Both meta regression analysis and Bayesian model averaging reveal that online studies are associated with larger estimates of β (indicating less present bias) than laboratory experiments. Perhaps surprisingly, the estimation technique and whether choices are incentivised or hypothetical do not affect the estimates of β.

Imai, Rutter, & Camerer (2021) report a meta-analysis of present-bias estimates based *only* on papers that use the CTB method. Because our meta-analysis is not limited to the CTB design, we report a much larger dataset (89 versus 28 papers). We are also able to examine whether estimates of β vary with the elicitation method, an important methodological guide for future research. Both meta-analyses find that β is significantly less than one and smaller for non-monetary than for monetary rewards. However, our conclusions differ regarding selective reporting and heterogeneity analysis. We compare our results to those of Imai, Rutter, & Camerer (2021) in more detail in our discussion.

[1] Appendix A contains the full list of included papers.

[2] We have fewer estimates of δ than for β because some studies do not estimate δ or assume it to be equal to one (e.g. Abaluck, Gruber, & Swanson (2018), Cavagnaro et al. (2016)).

Turning to δ, using 75 estimates from 62 papers for monetary rewards, the estimated overall mean annual discount factor is 0.84 with a 95% confidence interval of [0.80, 0.89]. This corresponds to an annual discount rate of 19.05%. We find evidence of selective reporting in estimates of δ for monetary rewards. Using standard methods to correct for selective reporting, the mean of δ is 0.99 with 95% confidence interval [0.989, 0.991]. This corresponds to an annual discount rate of 1.01%. For non-monetary rewards, using 15 estimates from 13 papers, the meta-analytic average δ is 0.95 (corresponding an annual discount rate of 5.26%) with 95% confidence interval of [0.90, 1.01]. We found no evidence of selective reporting of δ for non-monetary rewards. Both meta regression analysis and Bayesian model averaging indicate that geographical location has strong impact on the discount factor. In particular, African samples are more impatient than North American ones.

The closest work to our meta-analysis of δ is the meta-analysis of discount rates by (Matousek, Havranek, & Irsova, 2022). Whereas we focus on estimates of δ that are obtained in conjunction with β, their dataset includes studies that do not estimate any present-bias parameter. Moreover, even where a study estimates a quasi-hyperbolic function, they collapse the estimates of β and δ into a single measure of the discount rate (see their footnote 2). For both these reasons, their measure of the discount rate combines the effects of both present bias and long-run discounting. This explains why they find much more long-run discounting than we do: Matousek, Havranek & Irsova (2022) report an uncorrected mean annual discount rate of 80%, while their corrected mean is 33%.

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

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:

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

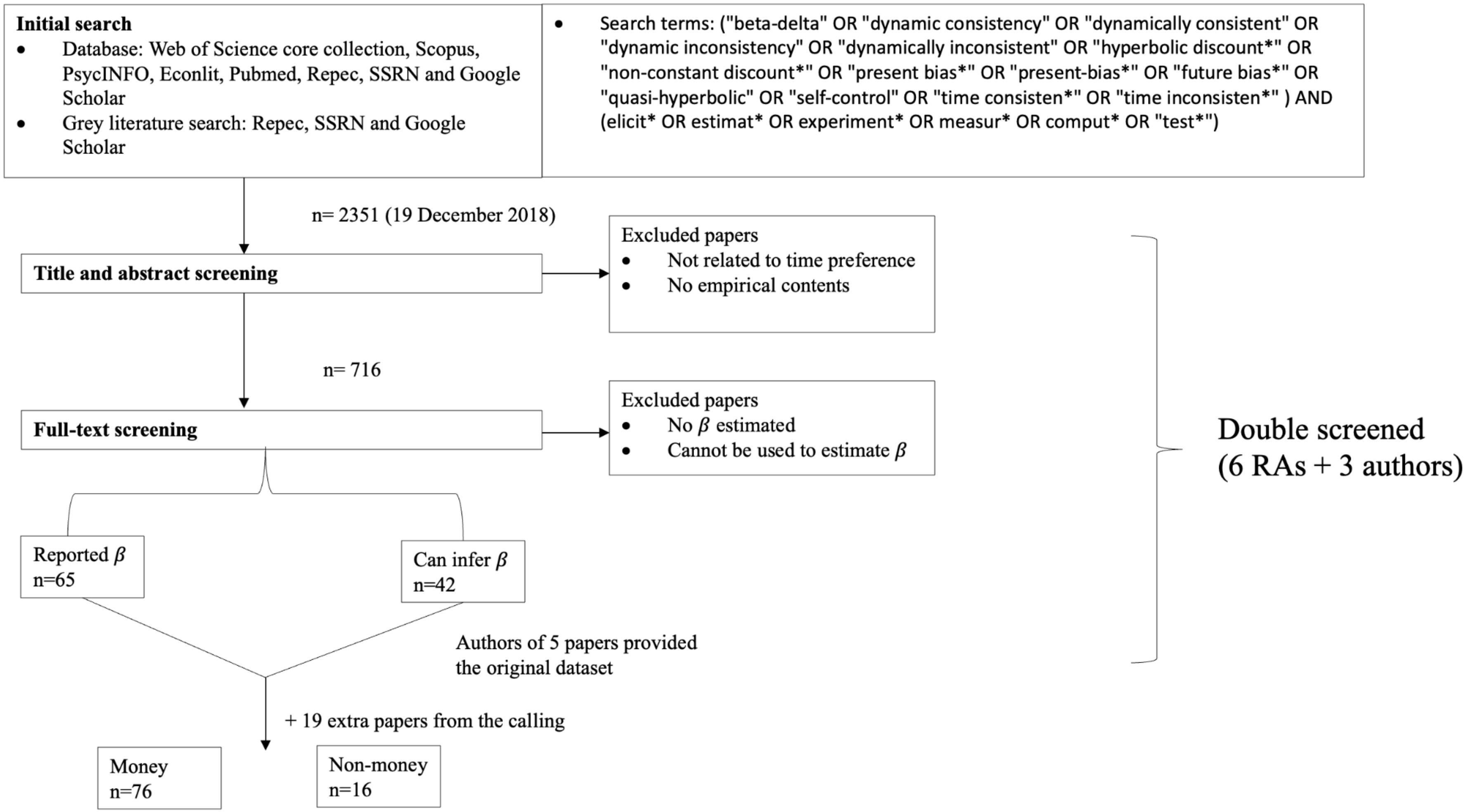
where $0 < \delta < 1$ is the standard exponential discount factor, $0 < \beta < 1$ captures present bias, and $u(x_t)$ is the instantaneous utility of consumption at time t. When $\beta = 1$, there is no present bias, and the $\beta - \delta$ model converges to the standard exponential model.

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 our search 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).[3] 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.

[3] 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*".

Figure 1. Paper selection procedure



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 65 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 29 May 2023, the authors of five of these papers provided their datasets,[4] and our estimates of β and δ using the provided datasets are included in this meta-analysis. To ensure the comprehensiveness of our database search, we shared our list of papers in the ESA Google Discussion Group and called for missing papers if recognised. By 17 August 2021, we added 19 extra papers to our database. As a result, our database contains 89 papers (73 with monetary rewards, 18 with non-monetary rewards such as food, real effort or health outcomes, including 2 with both monetary and non-monetary rewards).

2.3 *Dataset construction*

Our primary variable of interest is the estimate of the present bias parameter β together with its standard error (essential for weighting studies in the meta-analysis). Studies differ in how they report this information. Some studies provide aggregate-level parameter estimates, while other studies provide summary statistics such as the mean or median of individual-level estimates, and some 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, $\beta = 1$). Our dataset contains six estimates of β (and seven of δ) for which standard errors are missing; we outline our approach to addressing this issue in Section 3.2.2.

[4] They are Denant-Boemont, Diecidue, & L'Haridon (2017), Glimcher, Kable, & Louie (2007), Olivola & Wang (2016), Sopher & Sheth (2006) and Sutter, et al. (2013).

Some papers report more than one estimate of β. When a paper reported more than one estimate representing 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 a single 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 within subjects), we included all of these estimates.[5] This allows us to examine whether the choice of elicitation procedure or reward type affects the resulting estimate of β. Through this procedure, the 89 articles resulted in 109 estimates of β (89 for money and 20 for other rewards) used in our analysis.

The second variable of interest is the estimate of δ which is commonly estimated jointly with β in this literature. Employing a similar methodology for dataset construction as with β, we collected 97 estimates of δ (82 for money and 15 for other rewards) from the same set of papers from which we collected the estimates of β. Among these, 84 were explicitly reported as discount factors while the remaining 13 were reported as discount rates. We used discount rates to calculate the corresponding discount factors using standard formulas. We annualised all discount factors, and applied the delta method to compute standard errors when discount factors had to be recalculated.

To investigate the sources of heterogeneity in estimates of β and δ, 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), incentivised versus hypothetical choice, elicitation method (e.g. choice list, CTB), whether and how a study controls for utility curvature (e.g. none, joint elicitation, CTB), estimation method (e.g. maximum likelihood, Tobit, non-linear least squares), timing of the sooner payment (e.g. paid immediately), study location (e.g. laboratory, field), continent, and discipline (see Appendix B for details).

[5] 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. Results

3.1 *Characteristics of papers and estimates*

Table 1 provides an overview of the key characteristics of the 89 papers included in our analysis. As of June 16, 2023, 29% of the papers were unpublished. The dataset includes papers largely from the disciplines of economics and business (85%) while the remaining 15% are from other disciplines such as psychology and neuroscience. 74% of the papers reported estimates from developed countries, including one cross-country study (Wang, Rieger, & Hens, 2016). The majority (81%) of the studies were incentivised.

Table 2 presents the characteristics of the 109 estimates of β. Most data (85%) were collected either from university students or the general adult population (with roughly equal numbers of estimates obtained from these two groups). There are a small number of estimates from other populations such as clinical populations, or entrepreneurs. The choice list (Harrison, Lau, & Williams, 2002) is the most popular elicitation method and accounts for 45% of estimates (this includes estimates obtained using joint elicitation methods (Andersen et al., 2008). 42% of the estimates (and 48% of those collected after 2012) are obtained using the CTB method (Andreoni & Sprenger, 2012a) (Figure 2). More than one half of all estimates (64% of those collected after 2008) control for utility curvature; this includes both joint elicitation and CTB estimates. Finally, maximum likelihood (ML) and non-linear least squares (NLS) are the most popular estimation methods. Together, over 55% of estimates are obtained using one of these two techniques.

Table 1. Characteristics of papers.

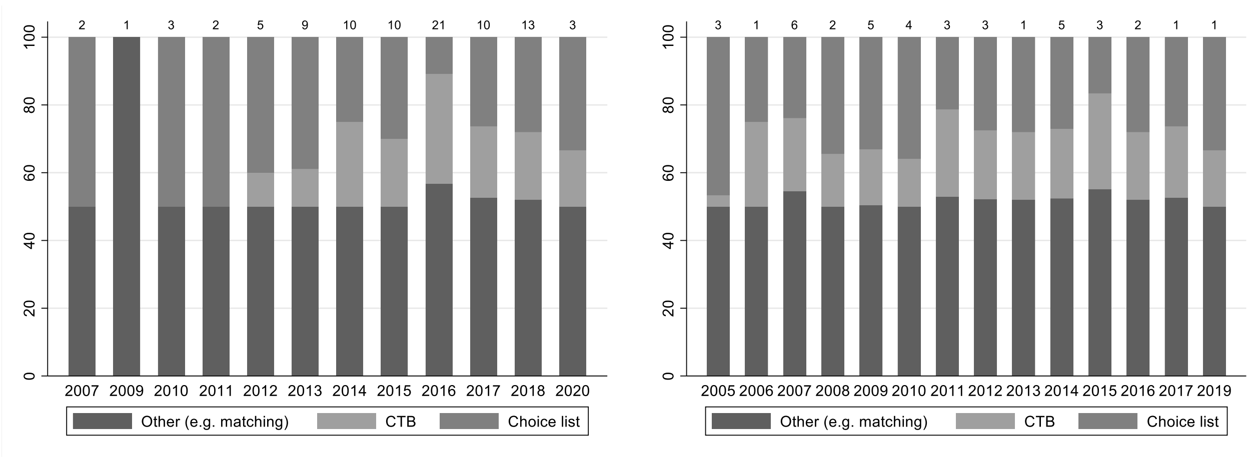
	All studies		Money		Other reward types	
	Frequency	Proportion (%)	Frequency	Proportion (%)	Frequency	Proportion (%)
Total number of papers	89	100.00	73	100.00	18	100.00
Publication status						
Published in an academic journal	63	70.79	53	72.60	12	66.67
Unpublished working paper	26	29.21	20	27.40	6	33.33
Discipline						
Economics and Business	76	85.40	62	84.93	14	77.78
Other disciplines (e.g. psychology, neuroscience)	13	14.60	11	15.07	4	22.22
Geographical location						
Developed country	66	74.16	53	72.60	15	83.33
Developing country	22	24.72	19	26.03	3	16.67
Both	1	1.12	1	1.37		
Consequential choice						
Incentivised	72	80.90	57	78.08	16	88.89
Hypothetical	17	19.10	16	21.92	2	11.11
Reward type						
Money	73					
Food or beverage	3					
Real effort	11					
Other outcomes (e.g health outcomes, environmental outcomes)	4					
Multiple reward types	2					

Table 2. Data characteristics of β estimates.

	All estimates		Money		Other reward types	
	Frequency	Proportion (%)	Frequency	Proportion (%)	Frequency	Proportion (%)
Total number of estimates (β)	109	100.00	89	100.00	20	100.00
Subject type						
University students	45	41.28	37	41.57	8	40.00
General adults	48	44.04	42	47.19	6	30.00
Adolescents and Children	8	7.34	6	6.74	2	10.00
Other adults (e.g. clinical, entrepreneurs)	8	7.34	4	4.50	4	20.00
Elicitation						
Choice list	49	44.95	47	52.81	2	10.00
Convex time budget	46	42.20	34	38.20	12	60.00
Other (e.g. BDM auction, matching)	14	12.85	8	8.99	6	30.00
Control for utility						
Yes	68	62.39	56	62.92	12	60.00
No	41	37.61	33	37.08	8	40.00
β estimation						
Maximum likelihood	30	27.52	25	28.09	5	25.00
Inference from switching point	19	17.43	17	19.10	2	10.00
OLS	6	5.50	3	3.37	3	15.00
NLS	32	29.36	29	32.58	3	15.00
Multinomial logit	4	3.67	2	2.25	2	10.00
Tobit	18	16.51	13	14.61	5	25.00

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

A. Elicitation methods by publication year B. Elicitation methods by year of data collection



3.2 *Analysis of present bias estimates*

3.2.1 *Descriptive analysis of present bias estimates*

The earliest estimates of β for money in our dataset are from 2007: Glimcher, Kable, & Louie (2007) ($\beta = 1.152, SE = 0.051$; estimated by us using data supplied by the authors) and Meier & Sprenger (2007)[6] ($\beta = 0.924, SE$ not reported). In Figure 3, we illustrate the evolution of β estimates for money over the years, plotting each estimate against the year of publication in a journal or as a working paper for unpublished papers (Figure 3A) and against the year of data collection (Figure 3B). Different markers denote different elicitation methods. Over the years, there are increasing numbers of estimates of β and they appear to gradually trend toward one (indicating no present bias).

For monetary rewards, the mean of the estimates is 0.92. Given the left skew in the distribution (Table 3 and Figure 4A), the median of 0.97 indicates weaker present bias than the mean. 51% of the estimates are consistent with present bias (β significantly smaller than 1), 33% with no present bias (β not significantly different from 1) and 16% with future bias.

[6] The published version is Meier & Sprenger (2010).

Figure 3. Estimates of β by 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 by publication year B. Estimates of β by year of data collection

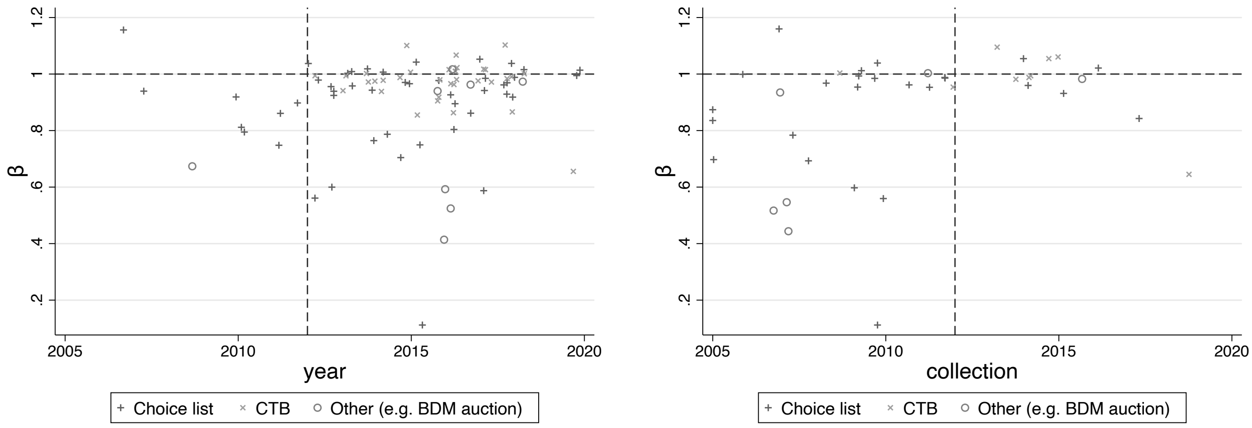
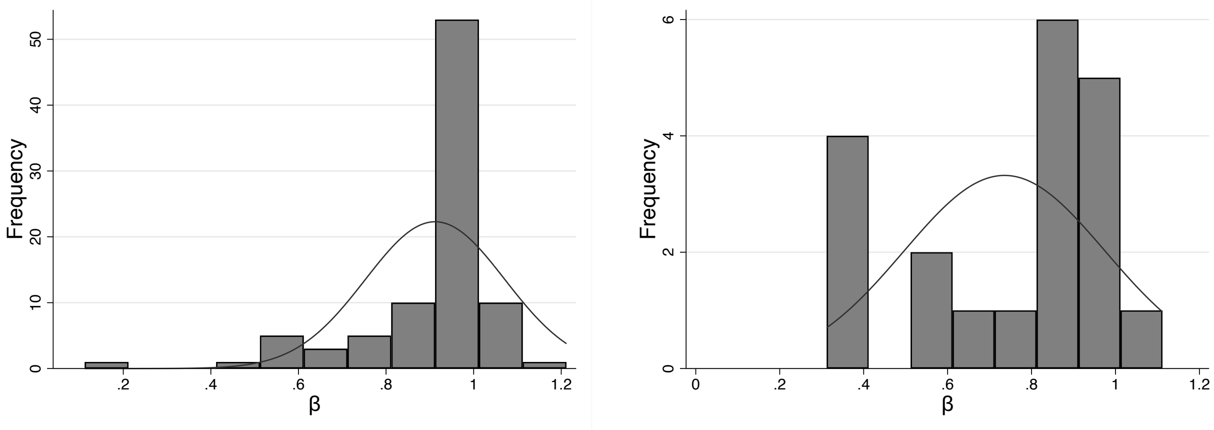


Table 3. Summary statistics of reported β.

Reward type	N	Mean	SD	Q25	Median	Q75	Min	Max
Money	89	0.92	0.16	0.88	0.97	0.99	0.11	1.15
Non-money	20	0.74	0.24	0.54	0.83	0.92	0.31	1.04

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. Non-monetary rewards



For non-monetary rewards, the mean estimate of β is 0.74, 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 0.83 is again larger than the mean (Table 3 and Figure 4B). 80% of these estimates find present bias and 20% find no present bias.

3.2.2 *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.[7]

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 dataset) 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 (1986) method. 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.

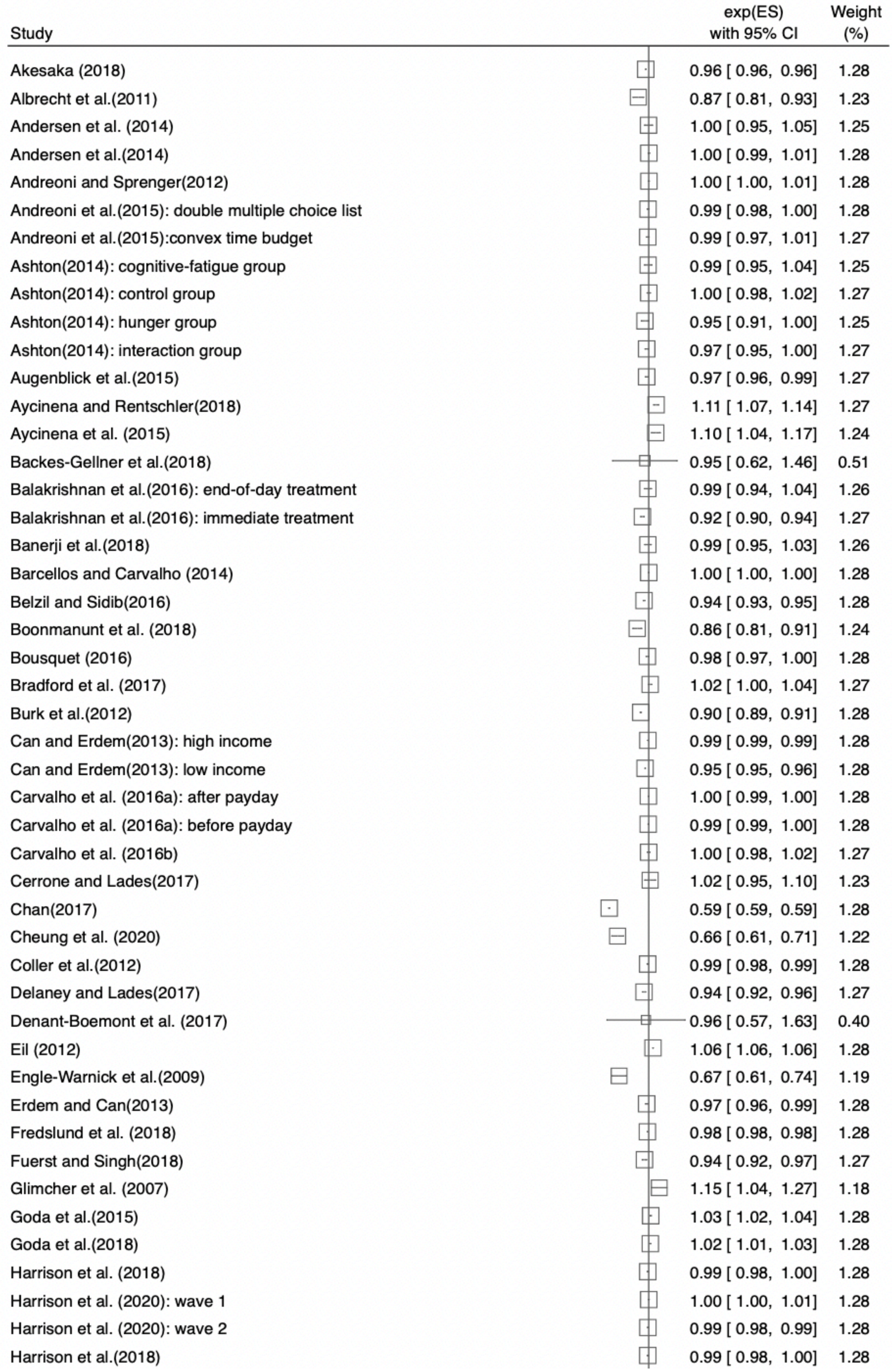
[7] 6 (7) out of 89 (82) of the estimates of β (δ) for money are missing standard errors. In the main text, we exclude these estimates from our meta-analysis. In Appendix D, we impute the missing standard errors following the methodology outlined in Brown et al. (2023) and conduct meta-analysis of β and δ using all available data. We find that this yields qualitatively similar results to those presented in the text.

For monetary rewards, the estimated overall mean of present bias is 0.91 with a 95% confidence interval of [0.87, 0.95].[8] The mean is significantly smaller than one, indicating the existence of present bias in the quasi-hyperbolic model. 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.

For non-monetary rewards (food, real effort, health outcomes, and environmental outcomes), the meta-analytic estimate of present bias is 0.68 with a 95% confidence interval of [0.57, 0.82] (see Figure 6). Thus, consistent with a 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.

[8] We obtain similar results using different weighting schemes (e.g. unit, sample size, Schmidt & Hunter (2004)). The overall mean of $\overline{\beta_0}^{RE}$ is between 0.89 and 0.93 and all estimates are significantly smaller than one.

Figure 5. Forest plot of estimates of β for monetary rewards. The vertical solid line indicates no present bias. There are 83 estimates from 69 papers. Each row is a different estimate but not necessarily a different study. Notes after the colon explain differences between estimates from the same paper. The size of the box represents the weight of an estimate in calculating the mean of β. The line on each box represents the confidence interval of that estimate. The diamond represents the random-effects meta-analytic average of β.



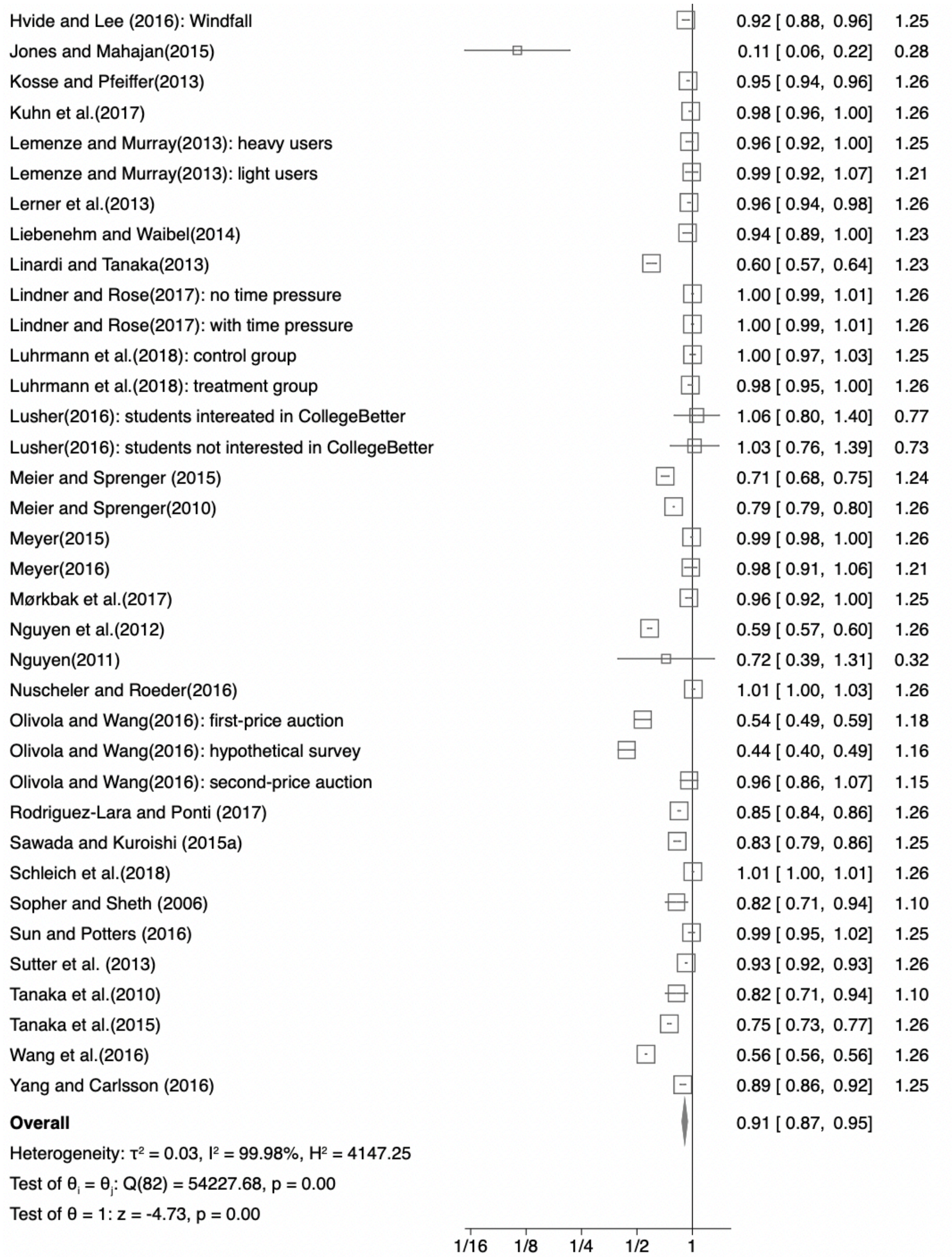
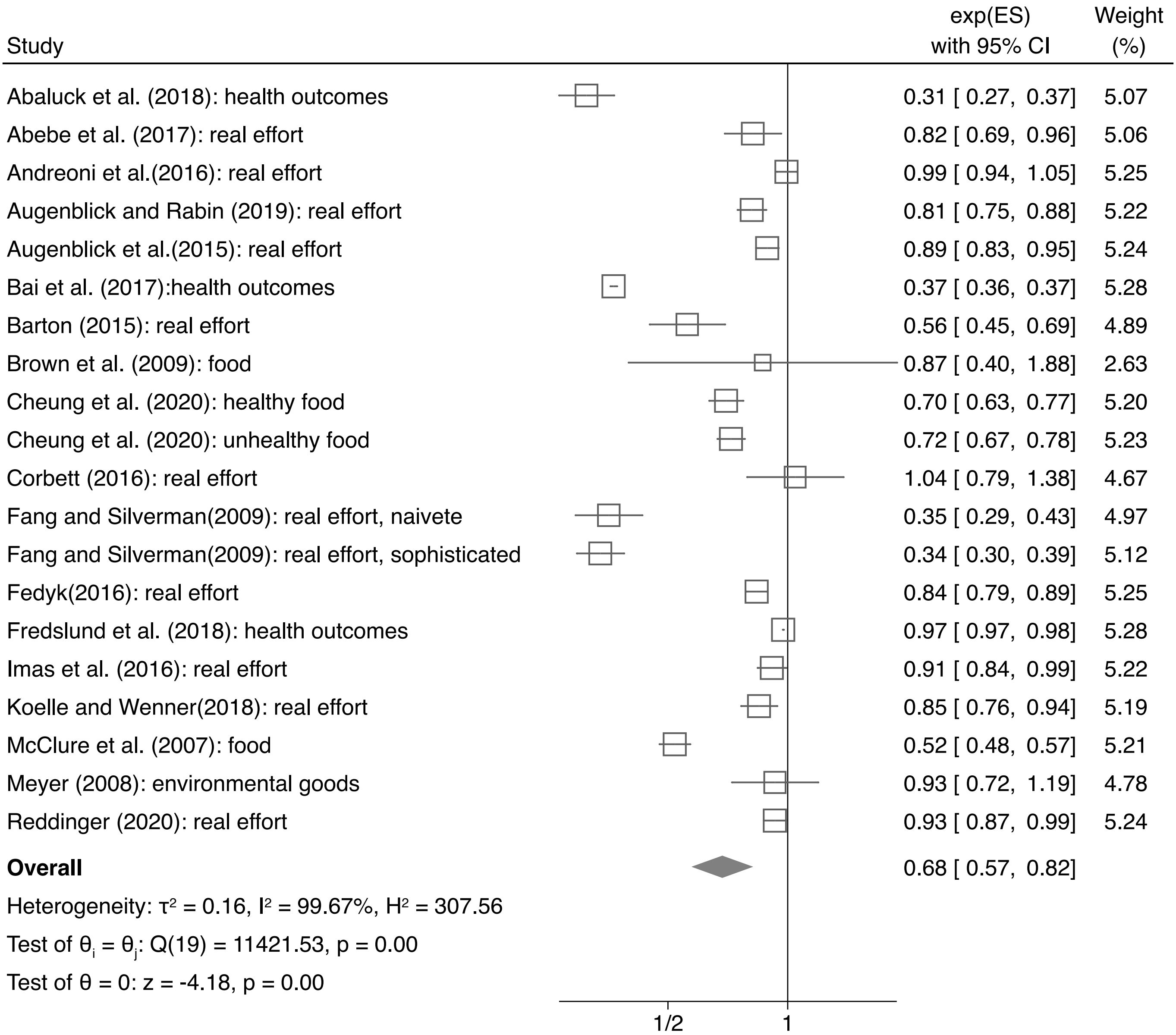

Hvide and Lee (2016): Windfall 0.92 [0.88, 0.96] 1.25
Jones and Mahajan(2015) 0.11 [0.06, 0.22] 0.28
Kosse and Pfeiffer(2013) 0.95 [0.94, 0.96] 1.26
Kuhn et al.(2017) 0.98 [0.96, 1.00] 1.26
Lemenze and Murray(2013): heavy users 0.96 [0.92, 1.00] 1.25
Lemenze and Murray(2013): light users 0.99 [0.92, 1.07] 1.21
Lerner et al.(2013) 0.96 [0.94, 0.98] 1.26
Liebenehm and Waibel(2014) 0.94 [0.89, 1.00] 1.23
Linardi and Tanaka(2013) 0.60 [0.57, 0.64] 1.23
Lindner and Rose(2017): no time pressure 1.00 [0.99, 1.01] 1.26
Lindner and Rose(2017): with time pressure 1.00 [0.99, 1.01] 1.26
Luhrmann et al.(2018): control group 1.00 [0.97, 1.03] 1.25
Luhrmann et al.(2018): treatment group 0.98 [0.95, 1.00] 1.26
Lusher(2016): students intereated in CollegeBetter 1.06 [0.80, 1.40] 0.77
Lusher(2016): students not interested in CollegeBetter 1.03 [0.76, 1.39] 0.73
Meier and Sprenger (2015) 0.71 [0.68, 0.75] 1.24
Meier and Sprenger(2010) 0.79 [0.79, 0.80] 1.26
Meyer(2015) 0.99 [0.98, 1.00] 1.26
Meyer(2016) 0.98 [0.91, 1.06] 1.21
Mørkbak et al.(2017) 0.96 [0.92, 1.00] 1.25
Nguyen et al.(2012) 0.59 [0.57, 0.60] 1.26
Nguyen(2011) 0.72 [0.39, 1.31] 0.32
Nuscheler and Roeder(2016) 1.01 [1.00, 1.03] 1.26
Olivola and Wang(2016): first-price auction 0.54 [0.49, 0.59] 1.18
Olivola and Wang(2016): hypothetical survey 0.44 [0.40, 0.49] 1.16
Olivola and Wang(2016): second-price auction 0.96 [0.86, 1.07] 1.15
Rodriguez-Lara and Ponti (2017) 0.85 [0.84, 0.86] 1.26
Sawada and Kuroishi (2015a) 0.83 [0.79, 0.86] 1.25
Schleich et al.(2018) 1.01 [1.00, 1.01] 1.26
Sopher and Sheth (2006) 0.82 [0.71, 0.94] 1.10
Sun and Potters (2016) 0.99 [0.95, 1.02] 1.25
Sutter et al. (2013) 0.93 [0.92, 0.93] 1.26
Tanaka et al.(2010) 0.82 [0.71, 0.94] 1.10
Tanaka et al.(2015) 0.75 [0.73, 0.77] 1.26
Wang et al.(2016) 0.56 [0.56, 0.56] 1.26
Yang and Carlsson (2016) 0.89 [0.86, 0.92] 1.25
Overall 0.91 [0.87, 0.95]
Heterogeneity: τ² = 0.03, I² = 99.98%, H² = 4147.25
Test of θi = θj: Q(82) = 54227.68, p = 0.00
Test of θ = 1: z = -4.73, p = 0.00
1/16 1/8 1/4 1/2 1

Figure 6. Forest plot of estimates of β for non-monetary rewards. Reward type is indicated after the colon for each estimate. The vertical solid line indicates no present bias. There are 20 estimates from 18 papers. Each row is a different estimate but not necessarily a different study. The size of the box represents the weight of an estimate in calculating the mean of β. The line on each box represents the confidence interval of that estimate. The diamond represents the random-effects meta-analytic average of β.



3.2.3 *Selective reporting of* β

In theoretical work, the assumption that $\beta < 1$ is commonly invoked to explain phenomena such as loss of self-control (O'Donoghue & Rabin, 1999), while $\beta = 1$ represents the normative model of exponential discounting. On the other hand, an estimate of $\beta > 1$ is likely to be viewed with suspicion and authors may be reluctant to report such findings. This would result in a *selective reporting* bias, leading our meta-analytic estimates of β to not be a true reflection of present bias.

The funnel plot is a useful device for detecting selective reporting (Egger et al., 1997). It 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 represented by a cone that fans out from the mean estimate: all estimates within this cone are not significantly different from the mean. The funnel plot in Figure 7A is based on all estimates (published and unpublished) of β for monetary rewards in our database. The asymmetry in this plot suggests that there are "missing studies": 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 of 0.91 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):

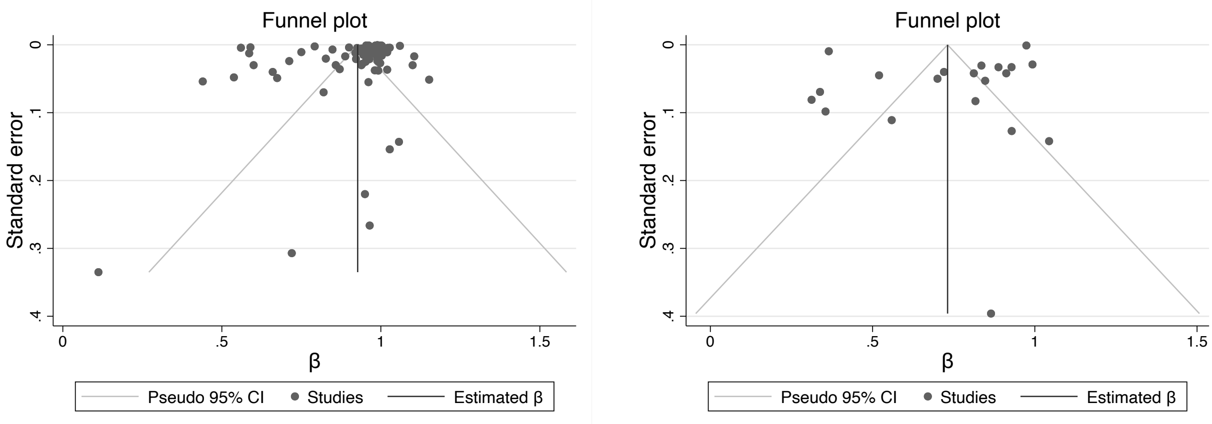
$$\beta_{ij} = \alpha_0 + \alpha_1 * SE_{ij} + \varepsilon_{ij}.$$

where α_0 is the "true" effect when there is no selective reporting, and $\alpha_1 \neq 0$ indicates the presence 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 in this literature: $\alpha_1 = -0.92, p = 0.04$.

The funnel plot in Figure 7B uses all estimates of β for non-monetary rewards. The symmetry of this plot and the Egger test ($\alpha_1 = -0.12, p = 0.90$) both indicate no evidence of selective reporting for non-monetary rewards.

Figure 7. Selective reporting of $\boldsymbol{\beta}$. 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 estimate of β.

A. Monetary rewards B. Non-monetary rewards



To correct for selective reporting in the estimates for money, 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 0.98 with 95% confidence interval [0.979, 0.981]. As some authors have questioned the performance of the trim-and-fill technique (Hong & Reed, 2021), we also use the selection models technique (Iyengar & Greenhouse, 1988), commonly used to correct for selective reporting in the science literature, and obtain an identical point estimate of 0.98 and 95% confidence interval [0.980, 0.981]. To summarise, the estimate of $\beta = 0.98$ is larger than the uncorrected value of 0.91 which we obtain when we do not adjust for selective reporting (indicating less present bias), but the conclusion that there is a slight present bias under the $\beta - \delta$ model still holds.

3.2.4 *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).

We find $I^2 = 99.98\%$ (Figure 5). This indicates that almost all variance across studies is driven by unobserved between-observation heterogeneity rather than mere sampling variance. To explain this heterogeneity, we firstly 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 categorised 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 variables: utility curvature correction dummy (omitted category is no correction for utility curvature), dummy for using intertemporal substitution for utility curvature correction (omitted category is using a risk preference measure to correct for utility curvature, including double choice list), incentivised choice dummy (omitted category is hypothetical choice), individual estimation dummy (omitted category is estimation at the aggregate level), elicitation method (omitted category is choice list), estimation method (omitted category is inference from switching points), sooner payment availability (omitted category is where the sooner payment on trials that do not involve a front-end delay is paid and accessible immediately), payment method (omitted category is cash), study location (omitted category is laboratory), and discipline (omitted category is economics and business).[9] The results illustrate how participant characteristics and methodological variables affect the estimates of β.

In Appendix C Table C.1, we consider estimates for money and report meta-regressions for each source of heterogeneity separately in Models (1) – (11), identifying variables that exhibit statistical significance at the 10% level or greater. We find that controlling for utility curvature increases the estimated value of β, implying less present bias, while estimation at the individual or aggregate level, as well as the incentivised or hypothetical nature of choices do not significantly affect estimates of β (Model (5)). Estimates based on the CTB design are larger

[9] See Appendix B for details of the coding of these variables.

(indicating less present bias) relative to ones based on choice list methods, but estimates tend to be smaller when using other elicitation methods such as matching tasks (Model (6)).[10] Estimates obtained using Tobit estimation are larger compared to ones inferred from switching points (Model (7)). The timing of immediate payments significantly affects the estimated value of β: when immediate payment is made on the same day as the experiment but is not immediately accessible (e.g., through a bank transfer), the estimates are larger, indicating less present bias, compared to immediately accessible payments (Model (8)).[11] Studies using bank transfer report larger estimates of β compared to those using cash (Model (9)). Finally, estimates of β are smaller in studies conducted in schools or workplaces than in laboratory studies (Model (10)). Overall, we find that 14.97% of the between-observation variance is explained by the covariates.[12]

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 C.2 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 food (4 estimates), real effort (12 estimates), and health and environmental outcomes (4 estimates).

3.2.5 *Bayesian model averaging for β*

The above meta-regression analysis faces the challenge that not all variables that are included are equally important. Some may be redundant, and including such variables can reduce the precision of the point estimates for the important variables (Matousek, Havranek & Irsova, 2022)). Consequently, we face extensive model uncertainty, a typical feature of meta-regression analysis. To address this issue, we employ Bayesian model averaging (BMA), as proposed by Raftery, Madigan, & Hoeting (1997), to identify which variables are most likely to influence β. To do this, BMA estimates many models that span the entire space of all

[10] Imai, Rutter, & Camerer (2021) also use meta-analysis to estimate the overall "mean" of β, limited only to studies that use the CTB design. They find that the average value of β is between 0.95 and 0.97. We find similar results: the average value of β using the CTB design is 0.94 with 95% confidence interval between 0.90 and 0.97.
[11] Conversely, when "immediate" payment is made on a different day for logistical reasons, estimates of β are in fact smaller. This counterintuitive finding may indicate that this variable reflects the influence of other aspects of low study quality, which in turn contribute to a finding of stronger present bias.
[12] As a robustness check, in Appendix E, we cluster standard errors at the author level instead of the study level. Since several researchers co-authored multiple studies in our dataset, the results of these studies might not be independent. We identified 57 author clusters with no overlapping co-authors. The results remain qualitatively consistent with those obtained from clustering at the study level.

possible combinations of explanatory variables in our dataset. Using this approach, we construct a weighted average of estimated coefficients, leveraging posterior model probabilities obtained using Bayes' theorem. BMA also produces posterior inclusion probabilities (PIP) for each variable, reflecting the cumulative posterior model probability of all models in which a variable is included. Recent applications of BMA in the meta-analysis of behavioural economics parameters include studies by (Brown et al., 2023; Imai, Rutter, & Camerer, 2021; Matousek, Havranek & Irsova, 2022). We follow the established practice of these studies by assuming a uniform model prior.[13]

We estimate our BMA analysis using Stata 18. The results of this analysis are visualised in Figure 8, with variables displayed on the vertical axis and sorted by PIP, such that the more important variables appear at the top of the figure. The horizontal axis represents individual regression models sorted by posterior model probability (PMP), from left to right. The PMP reflects how well a model fits the data relative to its size; the width of each column is proportional to the PMP. The colours of individual cells indicate the sign of the corresponding regression coefficients, with darker gray indicating a positive sign and lighter gray a negative sign. Blank cells indicate that the variable was not included in a given model. Table 4 provides numerical results from BMA, including the posterior mean and standard deviation for each variable, along with the PIP.

We find that three variables have PIPs above 50%: standard error, Online, and Europe. Consistent with our analysis of selective reporting in Section 3.2.3, we find that standard errors are robustly negatively correlated with estimates of β, even when accounting for 27 additional study and estimate characteristics. This finding reiterates the importance of controlling for potential selective reporting in meta-regression analysis. Additionally, in line with the results of our meta-regression analyses, we find that online studies are associated with larger estimates of β (indicating less present bias) than laboratory experiments. The BMA analysis also supports our conclusion that the choice of estimation technique and whether choices are incentivised or hypothetical do not affect the estimates of β. Unlike in the meta-regression, we find that geographic location is likely to affect the estimate of β, with larger estimates for European than for North American samples.

[13] Further details on BMA can be found in Raftery, Madigan, & Hoeting (1997) and Steel (2020). Although BMA can be sensitive to the choice of priors, we verify that while varying the model prior assumption can influence the PIPs, it does not affect the identification of the most important covariates.

Figure 8. Model inclusion in Bayesian model averaging for $\boldsymbol{\beta}$. The response variable is the estimate of β reported in a study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities. The estimation is based on a uniform model prior. Darker gray depicts variables with a positive estimated sign. Lighter gray depicts variables with a negative estimated sign. Variables with no color are not included in the given model. The numerical results of the BMA exercise are reported in Table 4.

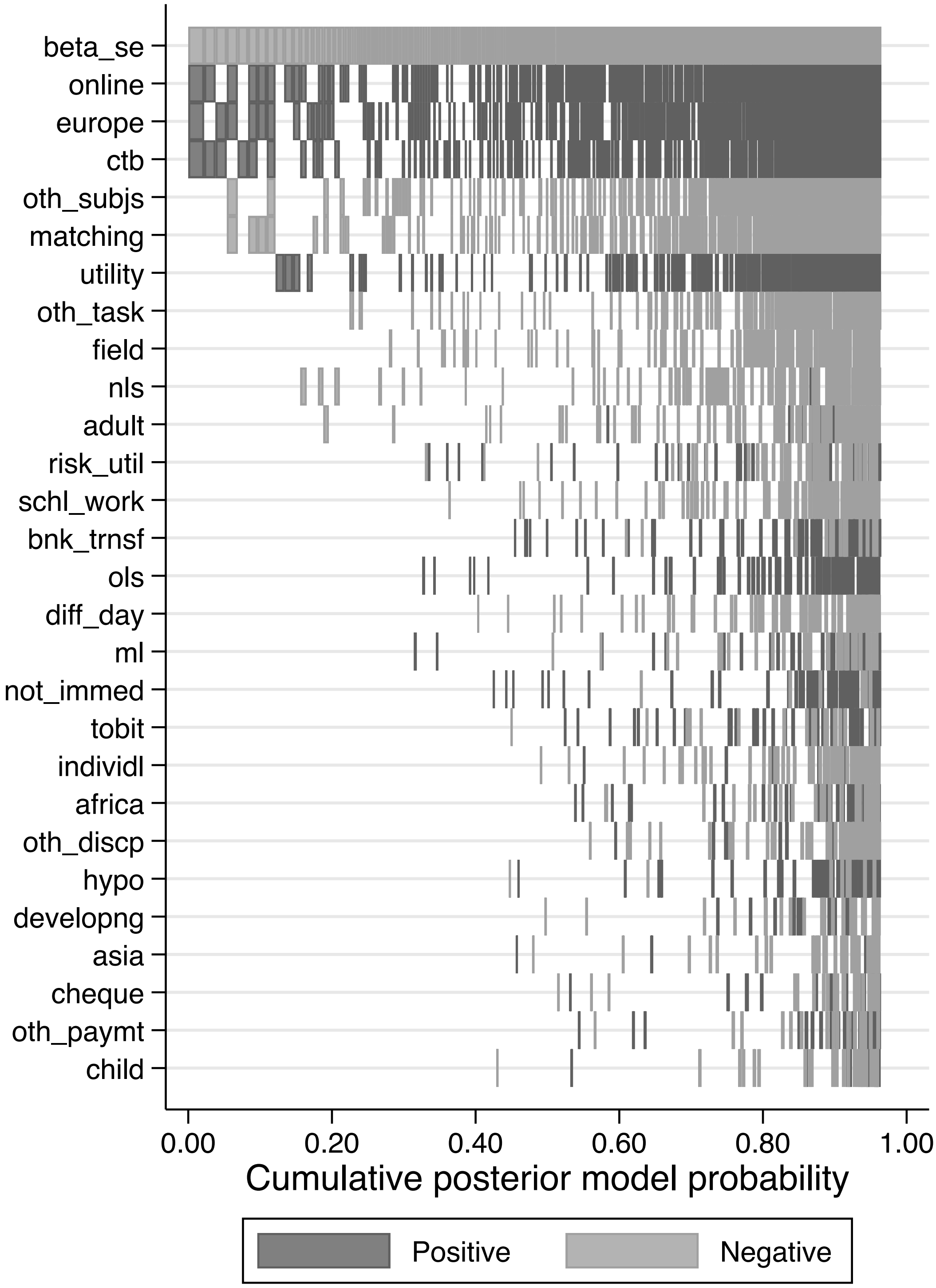


Table 4. BMA results for reported $\boldsymbol{\beta}$. The response variable is the estimate of present bias (β). Bayesian model averaging is performed using a uniform model prior.

Variables	Post.mean	Post.SD	PIP
SE	-0.8076	0.2879	0.9789
Subject pool			
General adults	-0.0022	0.0134	0.0741
Children	-0.0002	0.0088	0.0168
Other adults	-0.0513	0.0835	0.3484
Developing country			
Developing	-0.0001	0.0075	0.0229
Continents			
Europe	0.0415	0.0447	0.5598
Asia	-0.0006	0.0082	0.0222
Africa	0.0002	0.0121	0.0305
Methodological variables			
Utility	0.0188	0.0379	0.2437
Intertemporal substitution for utility	-0.0001	0.0159	0.0649
Hypothetical	0.0007	0.0086	0.0269
Individual	-0.0007	0.0091	0.0352
Elicitation			
CTB	0.0372	0.0482	0.4509
Matching	-0.0438	0.0699	0.3473
Other elicitation (BDM, observational data, other tasks)	-0.0284	0.0912	0.1246
Estimation			
ML	0.0005	0.0098	0.0408
OLS	0.0055	0.0312	0.0525
NLS	-0.0061	0.0225	0.1023
Tobit	0.0003	0.0121	0.0381
Soon payment availability			
Same day but not immediately accessible	0.0011	0.0980	0.0391
Different day	-0.0021	0.0163	0.0433
Payment method			
Cheque	0.0000	0.0078	0.0216
Bank transfer	0.0011	0.0111	0.0535
Gift card/ voucher	0.0000	0.0099	0.0212
Study place			
Field	-0.0058	0.0204	0.1144
Online	0.0630	0.0635	0.5911
School/workplace	-0.0035	0.0208	0.0591
Discipline			
Other discipline (psychology, neuroscience, biology, etc.)	-0.0002	0.0061	0.0303
constant	0.9058	0.0397	1
N	83		

3.3 *Analysis of discount factor estimates*

3.3.1 *Descriptive analysis of discount factor estimates*

For monetary rewards, the average estimate of the annual discount factor is 0.86 (equivalent to an annual discount rate of 16.28%). Given the left skew in the distribution (Table 5 and Figure 9A), the median discount factor of 0.93 is larger than the mean, indicating less discounting (an annual discount rate of 7.53%). For non-monetary rewards, the mean estimate of δ is 0.96 (annual discount rate of 4.17%), which is significantly larger than δ estimated for monetary rewards (two-sided t-test, $p = 0.05$), indicating less long-run discounting of non-monetary rewards. Again, the median of 0.98 (annual discount rate of 2.04%) is greater than the mean, reflecting the left skew in the distribution (Table 5 and Figure 9B).

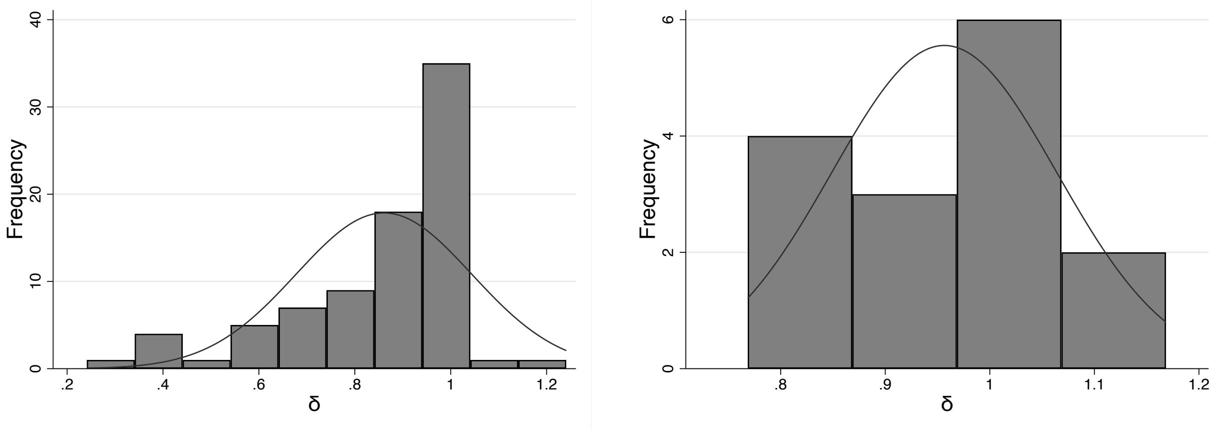
Table 5. Summary statistics of reported δ.

Reward type	N	Mean	SD	Q25	Median	Q75	Min	Max
Money	75	0.86	0.19	0.78	0.93	0.99	0.24	1.16
Non-money	15	0.96	0.11	0.87	0.98	1.01	0.77	1.12

Figure 9. Distribution of δ 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. Non-monetary rewards



3.3.2 *Meta-analytic estimate of* δ

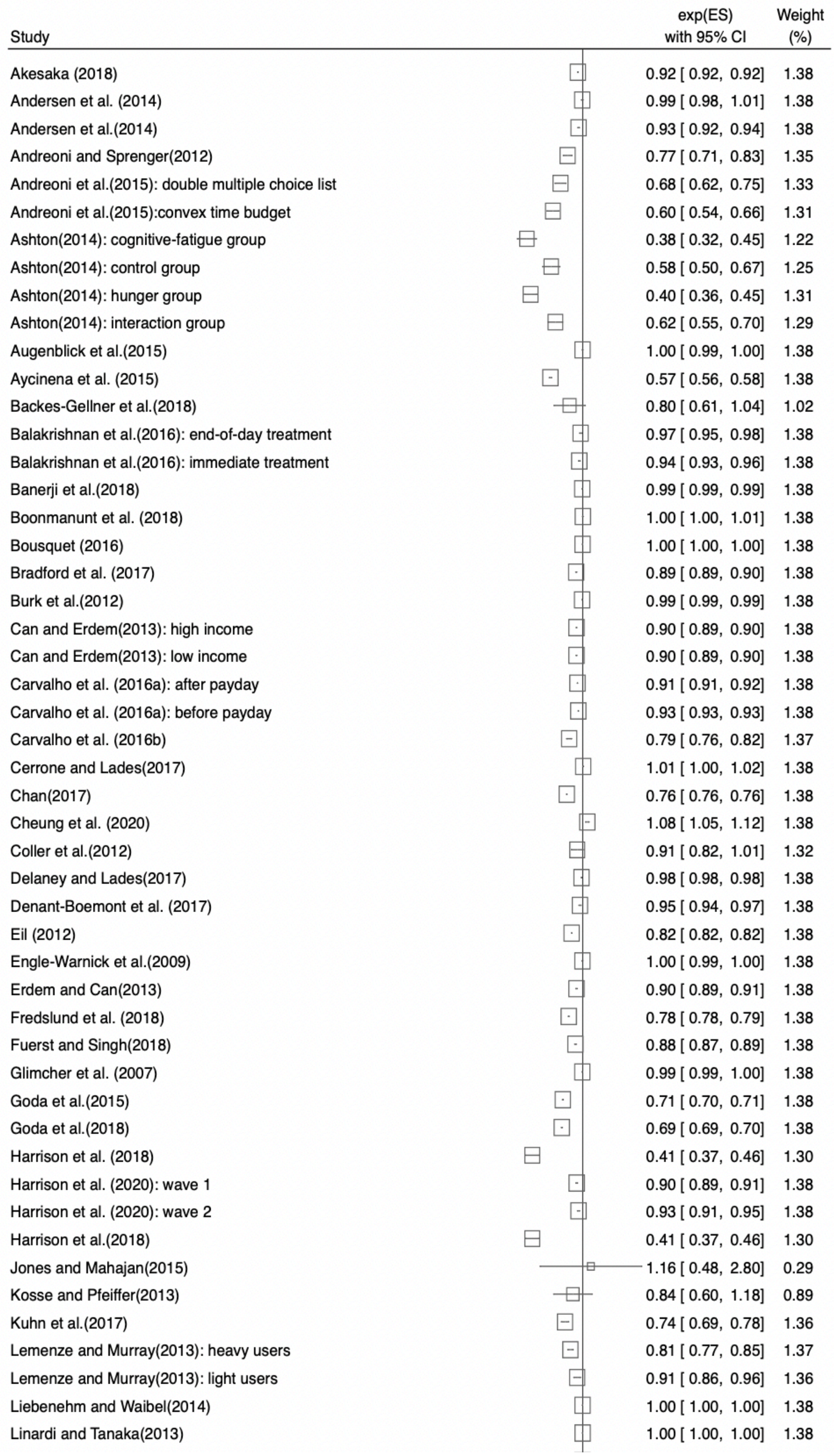
To account for the precision associated with each δ estimate, we set up a random-effects model to calculate a meta-analytic average of the annual discount factor, separately for monetary and non-monetary rewards.

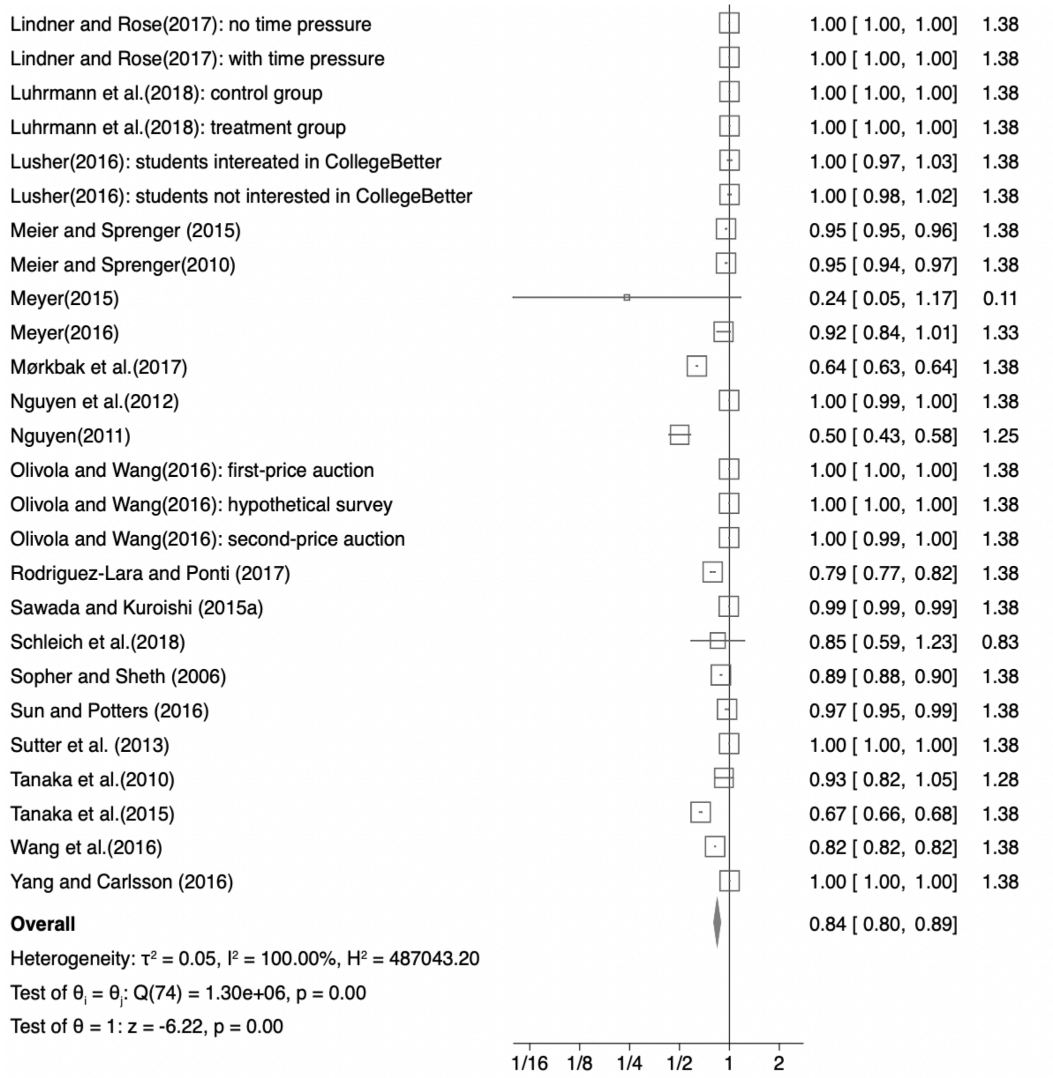
For monetary rewards, the estimated overall mean of the annual discount factor is 0.84 with a 95% confidence interval of [0.80, 0.89].[14] This is equivalent to an annual discount rate of 19.05%. The mean is significantly smaller than one, indicating impatience for money. Figure 10 shows the forest plot (Hedges & Olkin, 1985) of the estimates of δ for monetary rewards in our dataset, with the overall meta-analytic estimate indicated by the diamond at the bottom of the figure.

For non-monetary rewards, the meta-analytic estimate of δ is 0.95 (equivalent to an annual discount rate of 5.26%) with a 95% confidence interval of [0.90, 1.01] (see Figure 11). This indicates that the estimate of δ is not significantly different from one, implying negligible discounting of non-monetary rewards in the long run, however the wider confidence interval again reflects the smaller number of estimates for non-monetary rewards. The finding of a larger δ for non-monetary rewards indicates a higher degree of patience when it comes to consumption goods. On the other hand, a smaller δ for money indicates faster discounting, with individuals placing greater value on early monetary rewards rather than waiting for delayed ones.

[14] We obtained similar results using different weighting schemes (e.g. unit, sample size, Schmidt & Hunter, (2004)). The overall mean of $\overline{\delta_0}^{RE}$ is between 0.83 and 0.86 and all estimates are significantly smaller than one.

Figure 10. Forest plot of estimates of δ for monetary rewards. The vertical solid line indicates no discounting. There are 75 estimates from 66 papers. Each row is a different estimate but not necessarily a different study. Notes after the colon explain differences between estimates from the same paper. The size of the box represents the weight of an estimate in calculating the mean of δ. The line on each box represents the confidence interval of that estimate. The diamond represents the random-effects meta-analytic average of δ.




Lindner and Rose(2017): no time pressure 1.00 [1.00, 1.00] 1.38
Lindner and Rose(2017): with time pressure 1.00 [1.00, 1.00] 1.38
Luhrmann et al.(2018): control group 1.00 [1.00, 1.00] 1.38
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Meyer(2016) 0.92 [0.84, 1.01] 1.33
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Nguyen et al.(2012) 1.00 [0.99, 1.00] 1.38
Nguyen(2011) 0.50 [0.43, 0.58] 1.25
Olivola and Wang(2016): first-price auction 1.00 [1.00, 1.00] 1.38
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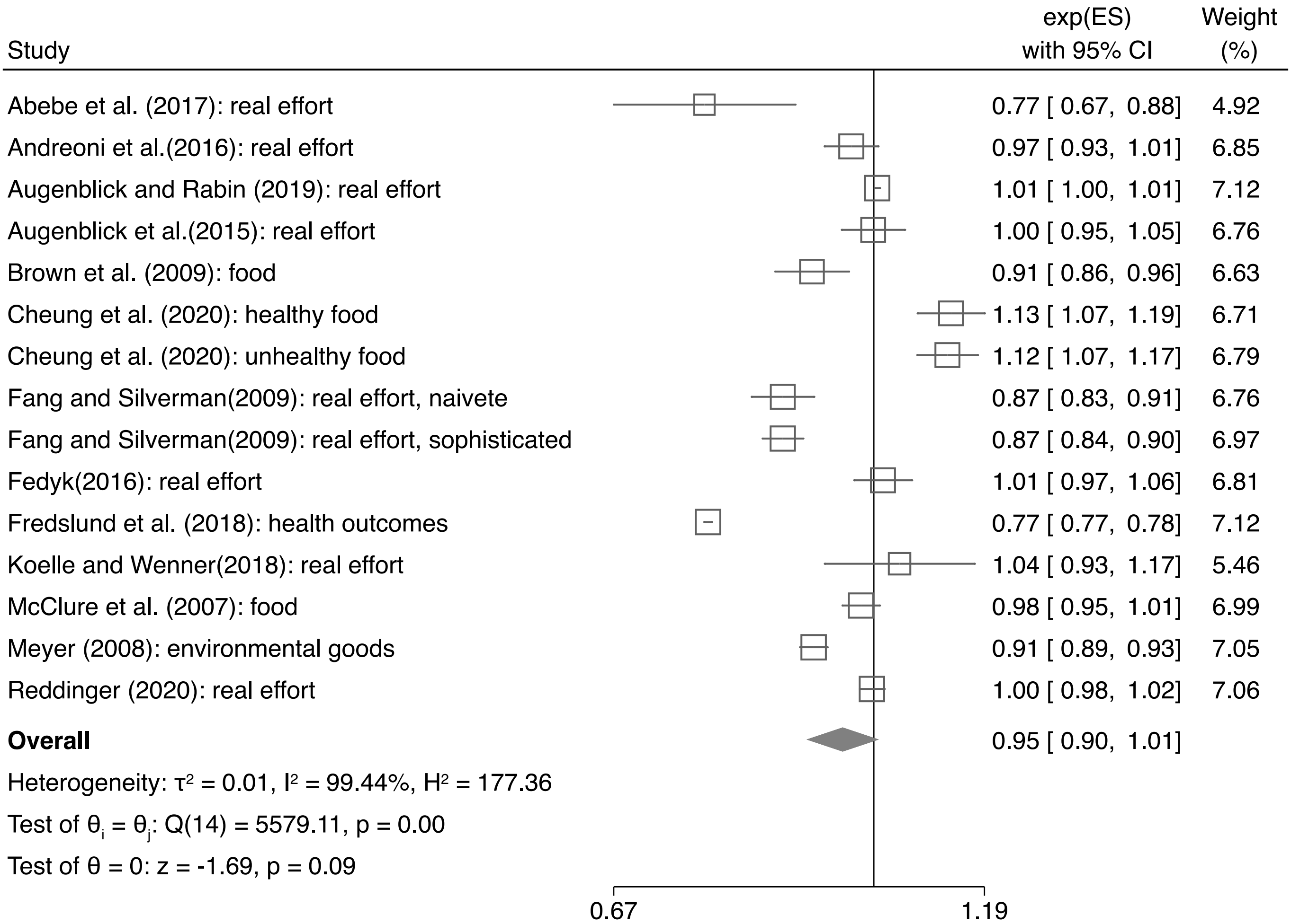
Rodriguez-Lara and Ponti (2017) 0.79 [0.77, 0.82] 1.38
Sawada and Kuroishi (2015a) 0.99 [0.99, 0.99] 1.38
Schleich et al.(2018) 0.85 [0.59, 1.23] 0.83
Sopher and Sheth (2006) 0.89 [0.88, 0.90] 1.38
Sun and Potters (2016) 0.97 [0.95, 0.99] 1.38
Sutter et al. (2013) 1.00 [1.00, 1.00] 1.38
Tanaka et al.(2010) 0.93 [0.82, 1.05] 1.28
Tanaka et al.(2015) 0.67 [0.66, 0.68] 1.38
Wang et al.(2016) 0.82 [0.82, 0.82] 1.38
Yang and Carlsson (2016) 1.00 [1.00, 1.00] 1.38
Overall 0.84 [0.80, 0.89]
Heterogeneity: $\tau^2 = 0.05$, $I^2 = 100.00\%$, $H^2 = 487043.20$
Test of $\theta_i = \theta_j$: Q(74) = 1.30e+06, p = 0.00
Test of $\theta = 1$: z = -6.22, p = 0.00
1/16 1/8 1/4 1/2 1 2

Figure 11. Forest plot of estimates of δ for non-monetary rewards. Reward type is indicated after the colon for each estimate. The vertical solid line indicates zero discounting. There are 15 estimates from 13 papers. Each row is a different estimate but not necessarily a different study. The size of the box represents the weight of an estimate in calculating the mean of δ. The line on each box represents the confidence interval of that estimate. The diamond represents the random-effects meta-analytic average of δ.



3.3.3 *Selective reporting of* δ

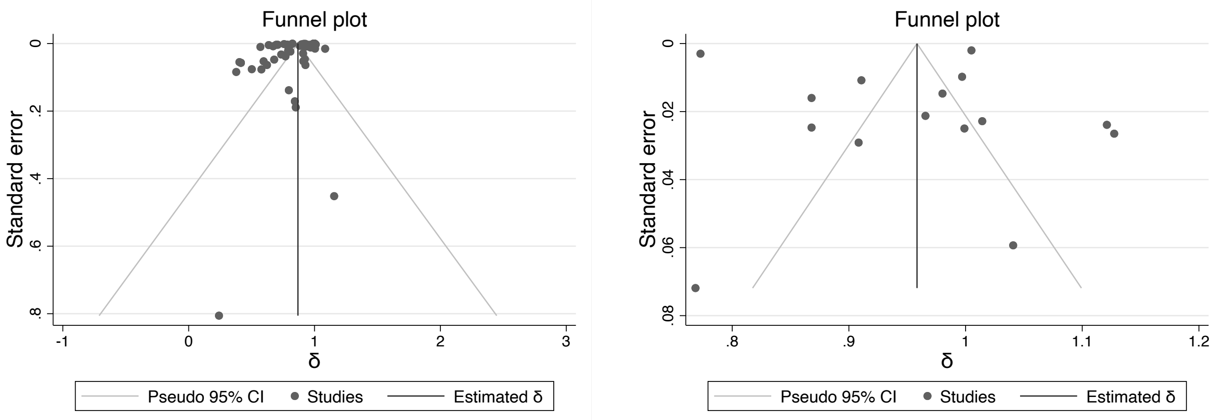
Selective reporting of estimates, typically those that are intuitive and statistically significant, is a known concern in empirical research. In the case of δ, authors might be reluctant to report estimates larger than one as this implies negative discounting, with later rewards valued more highly than sooner ones. The asymmetry in the funnel plot in Figure 12 confirms this intuition. To formally test for selective reporting, we use the Egger test (Egger et al., 1997) which confirms the presence of selective reporting: $\alpha_1 = -1.93, p < 0.01$. Using the trim-and-fill technique (Duval & Tweedie, 2000a, 2000b; Sutton et al., 2000) and the selection models technique (Iyengar & Greenhouse, 1988) to correct for selective reporting yields the same result. After correction, the overall mean of δ is 0.99 with 95% confidence interval [0.989, 0.991]. This corresponds to an annual discount rate of 1.01%.[15]

The funnel plot in Figure 12B includes all estimates of δ for non-monetary rewards. The symmetry of this plot and the Egger test ($\alpha_1 = -0.12, p = 0.94$) both indicate no evidence of selective reporting for non-monetary rewards.

Figure 12. Selective reporting. Estimates within the grey boundaries (arms) are consistent with the meta-analytic estimate of δ using a two-sided test at the 5% significance level. The vertical black line is the meta-analytic estimate of δ.

A. Monetary rewards

B. Non-monetary rewards



[15] Matousek, Havranek & Irsova (2022) also found a significant correlation between estimates and standard errors at the 10% level, and their corrected mean of the annual discount rate (33%) is smaller than the uncorrected mean (86%). In contrast to Matousek, Havranek & Irsova (2022), our meta-analysis of the long-run discount factor only includes studies that simultaneously estimate the present-bias parameter β. This likely explains why we find much less long-run discounting than they do: in studies that do not account separately for present bias, the effect of β will instead be captured by a lower value of δ, or equivalently a larger annual discount rate.

3.3.4 *Sources of heterogeneity in discount factor estimates*

The observed heterogeneity in discount factor estimates is substantial, as indicated by the I^2 statistic equal to 100% (Figure 10). This indicates that the variance across studies is entirely driven by unobservable differences between observations, rather than mere sampling variability. To explain this heterogeneity, we use a meta-regression model:

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

where $\boldsymbol{X}_{ij}$ is the vector of observable characteristics of the *j*th estimate from study i, and γ is the coefficient vector. Variables included in $\boldsymbol{X}_{ij}$ are the same as in our meta-regression models for β. The results illustrate how participant characteristics and methodological variables affect the estimates of δ.

In Table C.3, we consider estimates for money and use meta-regressions to assess each individual source of heterogeneity in Models (1) – (11). We find that the characteristics of participants significantly affect the estimates of δ. Estimates of δ for children are larger than for university students (Model (2)), indicating that children discount less than university students. Estimates from European and Asian samples are larger than estimates from North American samples, while estimates from African samples are smaller (Model (4)). The covariates collectively explain approximately 14.97% of the between-observation variance.

To examine whether the reward type has a significant effect on the estimated value of δ, we use all estimates for both monetary and non-monetary rewards. Table C.4 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 be more patient for food. There is no significant difference in estimates of δ between monetary rewards and other reward types including real effort, health outcomes and environmental outcomes.

Figure 13 and Table 6 present the results obtained using BMA. This reconfirms the evidence of selective reporting in discount factor estimates. Even after accounting for 27 additional study-related factors, the standard errors continue to be robustly negatively correlated with estimates of δ. We note that estimation at the individual or aggregate level, and whether the choices are incentivised or hypothetical are unlikely to be important factors that affect estimates of δ. Furthermore, African samples are more impatient than North American ones.

Figure 13. Model inclusion in Bayesian model averaging for *δ*. The response variable is the estimate of δ reported in a study. The columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities. The estimation is based on a uniform model prior. Darker gray depicts variables with a positive estimated sign. Lighter gray depicts variables with a negative estimated sign. Variables with no color are not included in the given model. The numerical results of the BMA exercise are reported in Table 6.

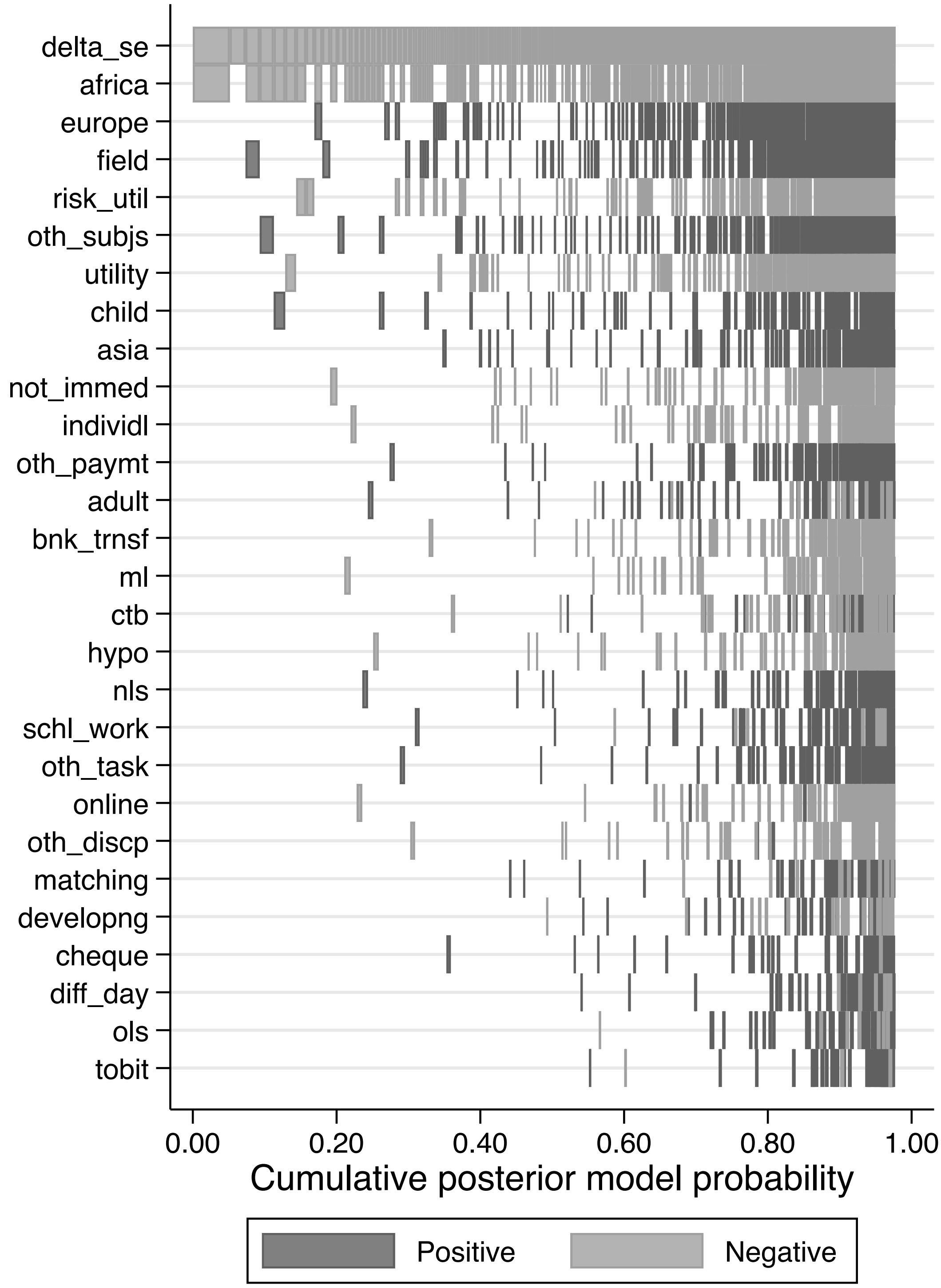


Table 6. BMA results for reported $\boldsymbol{\delta}$. The response variable is the estimate of the annual discount factor (δ). Bayesian model averaging is performed using a uniform model prior.

Variables	Post.mean	Post.SD	PIP
SE	-0.6216	0.1857	0.9979
Subject pool			
General adults	0.0019	0.0136	0.0598
Children	0.0116	0.0424	0.1055
Other adults	0.0256	0.0651	0.0191
Developing country			
Developing	-0.0004	0.0178	0.0305
Continents			
Europe	0.0202	0.0420	0.2613
Asia	0.0069	0.0301	0.0809
Africa	-0.1104	0.1072	0.6132
Methodological variables			
Utility	-0.0126	0.0337	0.1733
Intertemporal substitution for utility	-0.0162	0.0393	0.2026
Hypothetical	-0.0018	0.0135	0.0486
Individual	-0.0032	0.0175	0.0763
Elicitation			
CTB	0.0005	0.0132	0.0495
Matching	0.0015	0.0168	0.0337
Other elicitation (BDM, observational data, other tasks)	0.0062	0.0468	0.0422
Estimation			
ML	-0.0023	0.0144	0.0529
OLS	0.0007	0.0163	0.0208
NLS	0.0017	0.0123	0.0459
Tobit	0.0007	0.0108	0.0191
Soon payment availability			
Same day but not immediately accessible	-0.0032	0.0171	0.0769
Different day	0.0008	0.0121	0.0219
Payment method			
Cheque	0.0006	0.0112	0.0281
Bank transfer	-0.0017	0.0141	0.0593
Gift card/ voucher	0.0044	0.0264	0.0671
Study place			
Field	0.1437	0.0337	0.214
Online	-0.0014	0.0139	0.0416
School/workplace	0.0015	0.0178	0.0439
Discipline			
Other discipline (psychology, neuroscience, biology, etc.)	-0.0006	0.0087	0.0414
constant	0.8875	0.0379	1
N	75		

4 Discussion

Managers and people in general consistently fail to follow the plans they had made earlier both in the workplace and in their private lives, especially if the plans entail costs upfront but benefits in the future. They pledge to be more financially responsible, prioritise long-term goals, focus on research and development, as well as to exercise more, eat healthier, 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, in addition to long-term discounting for the length of delay. Despite the popularity of this model across multiple fields in decision sciences, to date the literature has not produced consistent evidence about the existence of present bias and the level of patience, calling for a scientific re-examination of the existing empirical evidence.

In this paper, we conducted a meta-analysis of the two parameters in quasi-hyperbolic discounting, β and δ. We use a random-effects model that accounts for the standard errors of the estimates to calculate the meta-analytic average of both parameters. Using 109 estimates of present bias (β) from 89 published and unpublished papers, we find the meta-analytic average β for monetary rewards (after correcting for selective-reporting) is 0.98 with 95% confidence interval of [0.979, 0.981]. For primary rewards we do not find evidence of selective reporting, and the meta-analytic average is 0.68 with 95% confidence interval of [0.57, 0.82]. We thus find statistically significant present bias for both monetary and primary rewards.

The closest work to our meta-analysis of β is by Imai, Rutter and Camerer (2021), who focus on the present-bias parameter *only* estimated using the convex time budget protocol (resulting a smaller dataset of 28 articles). They do not find selective reporting of β for money, and find the average β for money is 0.98, differing significantly from one at the 5% level. This coincides with our estimate for money that corrects for selective reporting. They also document a smaller β (stronger present bias) for non-monetary rewards (real effort) than for monetary rewards, however they find selective reporting for real effort. In contrast, our meta-analysis includes a wider range of non-monetary rewards and does not find evidence of selective reporting.

Using 90 estimates from the same set of studies of the annual discount factor (δ) for monetary rewards, we find the meta-analytic average δ after correcting for selective reporting is 0.99 (equivalent to an annual discount rate of 1.01%) with 95% confidence interval of [0.989, 0.991]. For primary rewards we do not find evidence of selective reporting, and the meta-analytic average is 0.95 (equivalent to an annual discount rate of 5.26%) with 95% confidence interval of [0.90, 1.01]. We thus find impatience for both monetary and primary rewards.

The closest work to our meta-analysis of δ is by Matousek, Harvanek and Irsova (2022). After correcting for selective reporting their mean annual discount rate is 33%, which is much larger than ours. This reflects the fact that their measure of the discount rate combines the effects of both present bias and long-run impatience. This is the case both because they include studies that do not account for β, and because for those studies that estimate both β and δ they collapse the two parameters into a single measure of the discount rate (see their footnote 2).

Previous research has 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, Niederle & Sprenger (2015) found stronger present bias for real effort than for monetary rewards. Our results further support this hypothesis. We find that experiments in which participants make temporal trade-offs that involve food, effort or health outcomes yield smaller estimates of β (stronger present bias) than decisions about 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 a slight present bias for money may suggest that concerns over the confounding effect of arbitrage in discounting experiments using monetary rewards are not completely absent (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 (2022) found robust correlation between present bias for money and food ($\rho = 0.60, p < 0.01$), whereas Augenblick, Niederle &

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

Turning to δ, after correcting for selective reporting in estimates using money, we find a trend toward greater impatience for primary rewards compared to monetary incentives. This aligns with the findings of several studies that have compared discounting across reward types outside the framework of quasi-hyperbolic discounting, such as (Estle et al., 2007; Reuben, Sapienza, & Zingales, 2010 and Ubfal, 2016). These studies have reported similar patterns, reinforcing and validating our observed result.

Using both meta regression analysis and Bayesian modelling averaging, we find that estimates of present bias for money 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 might conjecture that students at top research universities are particularly good at foregoing immediate pleasures for long term benefits, especially if they have enough self-control to show up in the laboratory for the experimental session. However our analysis did not support this hypothesis. For β, we find that participants from European countries show less present bias than participants from North America, while for δ, participants from Africa are more impatient than those from North America. In the future, we hope that more studies will include non-WEIRD (Western, Educated, Industrialised, Rich and Democratic) participants (Henrich, Heine, & Norenzayan, 2010) to provide a more complete picture of heterogeneity in discounting behaviour across populations.

Adjusting for utility curvature is perhaps the most important recent methodological controversy in the study of temporal discounting (Andersen et al., 2008). We indeed find that whether a study adjusts for non-linear utility affects the estimate of present bias. Studies that adjust for utility curvature present higher estimates of β than studies that do not. A new methodological debate 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 (closer to one, i.e. less present bias) than the joint elicitation method that uses utility estimated from risky choices. Even though the rationale for adjusting for utility curvature ought to apply equally to the estimation of δ, our findings indicate that it in fact has no significant effect. This aligns with the findings of other recent studies outside the framework of quasi-hyperbolic discounting that find near-linear utility in choice over time (Abdellaoui et al., 2013; Cheung, 2020).

It may be surprising to experimental economists that we find that estimates of present bias and the discount factor do not depend on whether 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 compared to using cash for payment, experiments using bank transfer report higher β. We find this result intuitive. Experiments using cash potentially require participants to return to collect payments at a future date. Such procedures may favour the choice of immediate payments for reasons unrelated to participants' underlying economic preferences. Thus, we recommend that studies carefully consider payment method and controls for transaction cost in their experimental design.

Another important issue in the measurement of present bias concerns the definition of "now" (Balakrishnan, Haushofer, & Jakiela, 2020). We find that when immediate payment is made on the day of the experiment but is not immediately accessible (e.g., through a bank transfer), the estimates of β are larger (less present biased) compared to immediately accessible payments. Our findings here surprisingly diverge from those reported by Imai, Rutter & Camerer (2021). Nonetheless, our Bayesian Model Averaging (BMA) analysis indicates that, despite its observed effect on estimates, the timing of immediate payments is unlikely to be a critical moderator in determining the magnitude of β.

It is important to emphasise that our conclusions are based on the evidence that is available and thus can be distorted by biases in the reporting and publication process. Our analysis reveals a pattern of selective reporting, wherein studies that support present bias and discounting for money are more likely to be reported. Upon correction for these biases, our results demonstrate an increase in the estimate of β for money from 0.91 to 0.98; however, the estimate remains significantly less than 1. Similarly, the estimate of δ for money increases from 0.84 to 0.99 after correction (reflecting less discounting), yet it remains significantly less than 1. With these adjustments we provide a clearer picture of the role of present bias and discounting even in the face of potential reporting biases in the literature. Interestingly, we did not find any evidence of selective reporting, of either β or δ, for non-monetary rewards.

Our results can also be used to shed light on a reformulation of the quasi-hyperbolic model, recently proposed by Bleichrodt, Potter van Loon, & Prelec (2022). They transform the traditional beta-delta parametrisation of the model to delta-tau, where tau is defined by $\tau = \frac{ln\beta}{ln\delta}$. Since tau is the value that solves $\beta = \delta^{\tau}$, it has a simple intuition: the degree of present bias is equivalent to the effect of having to wait an additional τ periods for a delayed payoff. Since our dataset contains matched estimates of β and δ, as well as their standard errors, we are able to derive τ for the vast majority of studies, and use the delta method to derive its standard error.

Using 66 estimates from 54 studies, we compute a meta-analytic average τ of 0.24 for monetary rewards, with 95% confidence interval [0.13, 0.46]. Since our measure of δ is annualised, this implies that the availability of an immediate monetary reward is equivalent to having to wait roughly three more months to receive a delayed alternative. For non-monetary rewards, using 14 estimates from 12 studies, our meta-analytic average τ is 0.46 with 95% confidence interval [0.09, 2.30]. While this is less precisely estimated owing to fewer observations, it implies that the availability of an immediate primary reward is equivalent to waiting an extra 5.5 months for a delayed alternative, again indicating stronger present bias for non-monetary rewards.

An implication of this analysis is that the severity of present bias should not be judged from the estimate of β alone but should be interpreted in light of the associated estimate of δ. Thus, while our uncorrected mean β of 0.91 for money might suggest only modest present bias, when translated into τ equivalent to three added months of back-end delay it is arguably more consequential. Against this, we caution that we find selective reporting of both β and δ for monetary rewards, and it is *a priori* unclear what is the net effect of this upon measures of τ.

Finally, we emphasise that while our meta-analysis provides evidence of time inconsistent preferences, it should not be interpreted as a test of the quasi-hyperbolic discounting model against other alternatives to standard exponential discounting. We note, firstly, that *any* discount function other than the standard exponential will necessarily generate time inconsistency. Secondly, while theoretical work has proposed a rich array of alternative models (for example, Bleichrodt, Rohde, & Wakker, 2009; Ebert & Prelec, 2007; Loewenstein & Prelec, 1992; Read, 2001; Scholten & Read, 2006, 2010), these models are often motivated by behavioural phenomena quite distinct from the pattern of present bias for which the quasi-hyperbolic model is typically invoked.

Thirdly, and most salient to this meta-analysis, in practice the bulk of empirical research seeking to quantify the parameters of specific discount functions has focused on much narrower classes of models. Specifically, research in economics focuses largely on the exponential and quasi-hyperbolic models, while research in psychology typically estimates either the simple hyperbolic model (Mazur, 1987), or occasionally one of its hyperboloid generalisations (Green, Fry, & Myerson, 1994; Rachlin, 2006). The challenge is that these models are identified using quite distinct experimental designs. The β parameter of quasi-hyperbolic discounting is identified by varying the presence or absence of a front-end delay, often accompanied by minimal variation in back-end delay lengths. By contrast, identifying the k parameter of hyperbolic discounting requires extensive variation in back-end delays, but does not require any front-end delay. As a result, most datasets in the literature can be used to estimate only one but not both of these popular models.

Faced with this challenge, the meta-analysis by Matousek, Havranek & Irsova (2022) collapses estimates of several different discount functions into a single measure of the discount rate, in effect treating all estimates as if they were generated by an exponential model. Their approach thus allows them to quantify the *magnitude* of discounting, but not its *source*. By conducting our meta-analysis within the framework of the quasi-hyperbolic model, we are at least able to distinguish the two sources recognised within that model, namely present bias and long-run discounting. Moreover, the model has proven popular especially within economics owing to its parsimony, ease of interpretation and analytical tractability. We find support for time inconsistency as viewed through the lens of this model, and especially so for non-monetary rewards. However, we reiterate that our results should not be interpreted as support for the model itself against other alternative formulations. For this, we await future studies using richer designs than most of the ones considered here.

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