Online Appendix

Meta-Analysis of Empirical Estimates of Loss Aversion

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A Data

A.1 Paper Search and Inclusion

We searched for relevant papers on the scientific citation indexing database Web of Science. We used, after several trial-and-error to fine-tune, the following combination of query terms.

```
(     (loss AND avers*)
 OR  "loss aversion coefficient"
 OR  "loss aversion index"
 OR  ("loss avers*" AND ("willingness to pay" OR "willingness to accept")))
                           AND
    (estimat* OR measur* OR experiment* OR survey)
```

FIGURE A.1: Keywords used in the search.

The initial search, made in the Summer of 2017, returned total hits of 1,547 papers. As a first step of paper identification, we went through titles and abstracts and threw out 833 papers that were irrelevant to our study. We then read the remaining papers, applied our inclusion criteria based on the content, and coded information. Finally, we posted a message on the email list of the Economic Science Association to ask for relevant papers (in February 2018).
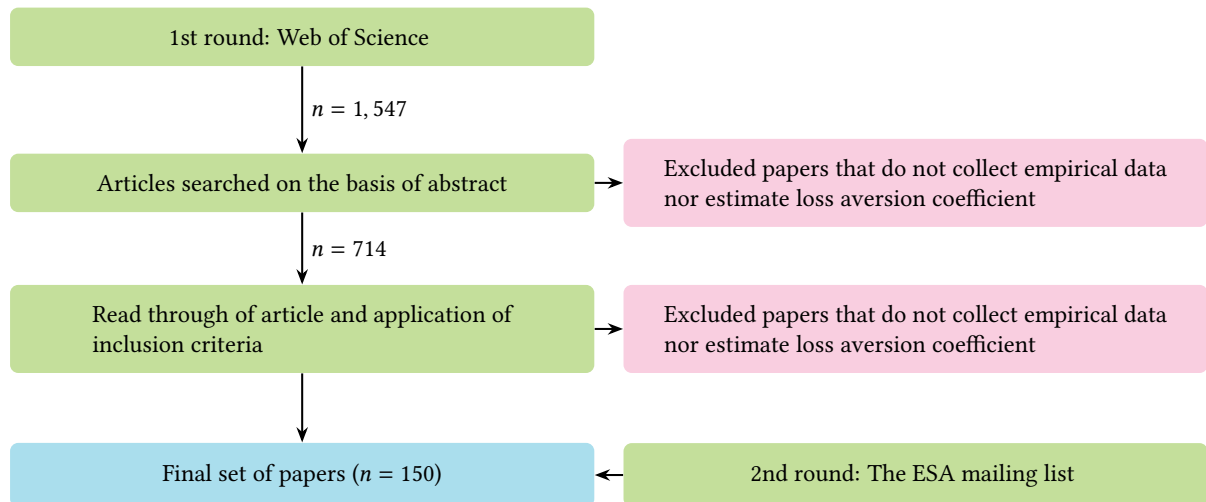

FIGURE A.2: Paper search and data construction.

A.2 Coded Variables

TABLE A.1: List of coded variables.

Variable	Description
Atricle meta data	
`main_title`	Title of the paper
`main_lastnames`	Last names of the authors
`main_firstnames`	First names of the authors
`main_published`	= 1 if published
`main_yearpub`	Year of publication
`main_journal`	Journal
`main_affliations`	Affiliations of the authors
Estimates	
`la`	Reported loss aversion coefficient λ
`la_type`	Type of reported λ
`la_aggmean`	= 1 if reported λ is aggregate-level
`la_indmean`	= 1 if reported λ is individual-level mean
`la_indmedian`	= 1 if reported λ is individual-level median
`both_stats`	= 1 if individual-level mean and median are reported
`se`	SE of λ (reported or calculated)
`se_imp`	SE of λ (reported, calculated, or imputed)
`se_type`	Type of SE (reported, calculated, or imputed)
`se_calc`	= 1 if SE is calculated from other information
`se_calc_method`	What information is used for SE calculation
Type of data	
`type_lab_exp`	= 1 if laboratory experiment
`type_field_exp`	= 1 if field experiment
`type_class_exp`	= 1 if classroom experiment
`type_online_exp`	= 1 if online experiment
`type_gameshow`	= 1 if TV game show
`type_field_other`	= 1 if other field data
Type of the experiment/survey	
`loc_lab`	= 1 if laboratory study
`loc_field`	= 1 if field study
`loc_online`	= 1 if online study
`loc_class`	= 1 if classroom study
Location of the experiment/survey	
`loc_country`	Country
`loc_state`	State
`loc_city`	City
`loc_<CONTINENT>`	Continent dummy

Variable	Description
Subject pool	
subject_children	= 1 if subjects are children
subject_uni	= 1 if subjects are university students/staffs
subject_elderly	= 1 if elderly population
subject_gen	= 1 if general population
subject_farmer	= 1 if subjects are farmers
subject_mixed	= 1 if mixed subject population
subject_unknown	= 1 if unknown population
subject_monkey	= 1 if subjects are Capuchin monkeys
Reward	
reward_real	= 1 if real reward
reward_money	= 1 if monetary reward
reward_food	= 1 if food reward
reward_cons_good	= 1 if consumption goods
reward_env_good	= 1 if environmental goods
reward_health	= 1 if health
reward_mixed	= 1 if mixed type
reward_other	= 1 if other type of reward
Method	
method_question	= 1 if questionnaire
method_seqbin	= 1 if sequential binary choice
method_mpl	= 1 if multiple price list
method_bdm	= 1 if BDM
method_matching	= 1 if matching
method_gp	= 1 if Gneezy-Potters
method_other	= 1 if other method
method_other_type	Description of the method (if method_other = 1)

Variable	Description
Utility specifications	
spec_u_est	= 1 if utility function is parametrically estimated
spec_u_crra	= 1 if CRRA is assumed
spec_u_crra_eq	= 1 if CRRA with common curvature is assumed
spec_u_crra_noneq	= 1 if CRRA with different curvatures is assumed
spec_u_cara	= 1 if CARA is assumed
spec_u_linear	= 1 if linear utility is assumed
spec_u_other	= 1 if other parametric form is assumed
spec_nonparametric	= 1 if U is nonparametrically recovered
Reference-point specifications	
spec_rp_zero	= 1 if reference point is 0
spec_rp_statusquo	= 1 if reference point is status quo
spec_rp_expectation	= 1 if reference point is expectation
spec_rp_other	= 1 if other type of reference point is assumed
Loss aversion	
loss_tversky_kahneman	= 1 if λ is defined as in Tversky and Kahneman
loss_koebberling_wakker	= 1 if λ is defined as in Köbberling and Wakker
loss_neilson	= 1 if λ is defined as in Neilson
loss_wakker_tversky	= 1 if λ is defined as in Wakker and Tversky
loss_bowman	= 1 if λ is defined as in Bowman, Minehart and Rabin
loss_koszegi_rabin	= 1 if λ is defined as in Kőszegi and Rabin
loss_other	= 1 if another definition of λ is used

Notes: See Online Appendix B for the definitions of loss aversion.

Variable	Description
Publication status	
pub_regular	= 1 if published in a peer-reviewed journal
pub_econtopfive	= 1 if published in a "Top 5" journal in economics
pub_unpub	= 1 if not published in a peer-reviewed journal
journal_if	Journal impact factor (in 2018)
journal_if_std	Standardized journal impact factor (in 2018)
Journal topic/discipline	
journal_category	Journal topic/discipline
cat_econ	= 1 if economics
cat_psych	= 1 if psychology
cat_neuro	= 1 if neuroscience
cat_agri	= 1 if agricultural sciences
cat_medical	= 1 if medical sciences
cat_mgt	= 1 if management
cat_transport	= 1 if transportation research
cat_multi	= 1 if multi-disciplinary

Notes: Journal categories are based on the classification provided by The Master Journal List (https://mjl.clarivate.com/home). Journal impact factors are downloaded from The Journal Citation Reports (https://clarivate.com/webofsciencegroup/solutions/journal-citation-reports/).

A.3 Approximation and Imputation of Missing Standard Errors

The dataset includes 192 estimates (out of 607) of loss aversion coefficient without corresponding standard errors (SEs). In order to keep these observations in our meta-analysis, we approximated and imputed missing SEs using other available information.

First, we calculated SEs of four observations from p-values of the two-sided test for the null hypothesis $H_0 : \lambda = 1$, from

$$se = \frac{|\lambda - 1|}{\Phi^{-1}(1 - p)},$$

where Φ^{-1} is the quantile function of the standard normal distribution.

Second, we approximated 64 SEs from the inter-quartile range (IQR) and sample size, using

$$se \approx \frac{1.35 \times \text{IQR}}{\sqrt{n}}.$$

Note that the use of this approximation formula is legitimate if the parameters are normally distributed in the population, which is a strong assumption in our dataset. Nevertheless, obtaining even an "approximated" SE seemed preferable to dropping the observation entirely, or to making other, even stronger, assumptions allowing us to keep the observation.

Finally, we imputed the remaining 124 missing SEs. The basic idea is to estimate the parameters characterizing their distribution in the data, $\log(se_o) \sim \mathcal{N}(\mu_{se}, \sigma_{se}^2)$. Using these distributional parameters, we can then estimate the missing values in SE by letting $\log(se_m) \sim \mathcal{N}(\widehat{\mu}_{se}, \widehat{\sigma}_{se}^2)$, where the subscripts o and m stand for *observed* and *missing*, respectively, and $(\widehat{\mu}_{se}, \widehat{\sigma}_{se})$ are estimated quantities.

Implementing this estimation, we will thus obtain values for the missing observations in SE that have the same mean and variance. We can, however, do much better than that if we can find other variables in our dataset that are significantly associated with SEs (McElreath, 2016). As it turns out, the single best predictor of the SE is the loss aversion estimate itself. Once it is controlled for, no other predictor—including the measurement type and the square root of the number of observations—is significant. The loss aversion coefficient explains 51% of the variance in SEs. By letting $\mu_{se} = \alpha_{se} + \beta_{se}\lambda$, we can thus get much better imputation results than by only using the distributional characteristics.

Figure A.4 shows the imputed standard errors juxtaposed with the observed standard errors, and plotted against the loss aversion coefficient. The solid line indicates the regression line of the SE on loss aversion in the subset of data for which we observe the SE. The estimates of loss aversion with and without SEs exhibit systematic difference ($p = 0.002$, Wilcoxon rank sum test; Figure A.3 and Figure A.4B) but, as we would expect, the imputed SEs are no different than the observed SEs on average ($p = 0.458$, Wilcoxon rank sum test; Figure A.4C).
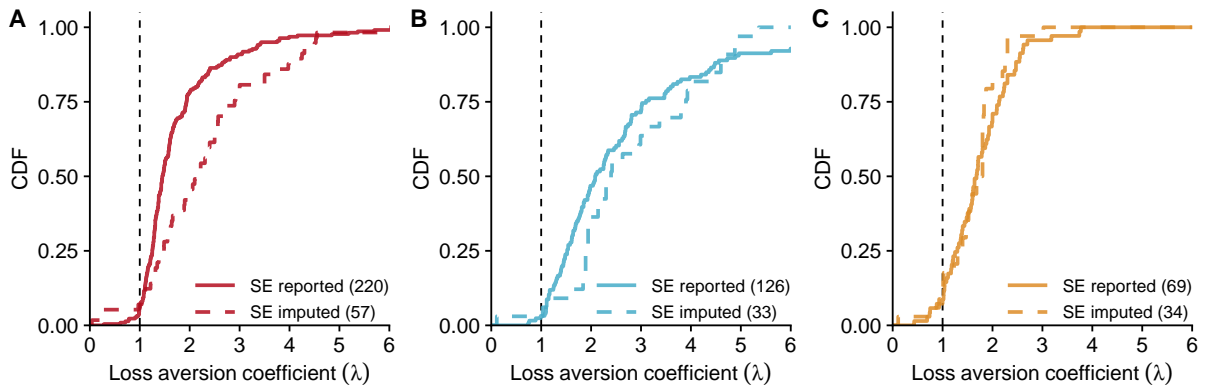
FIGURE A.3: Empirical CDF of reported loss aversion coefficient λ by the type of estimates and by the type of SE. *Notes*: Solid lines correspond to observations with reported SEs and dashed lines correspond to observations for which SEs are imputed.
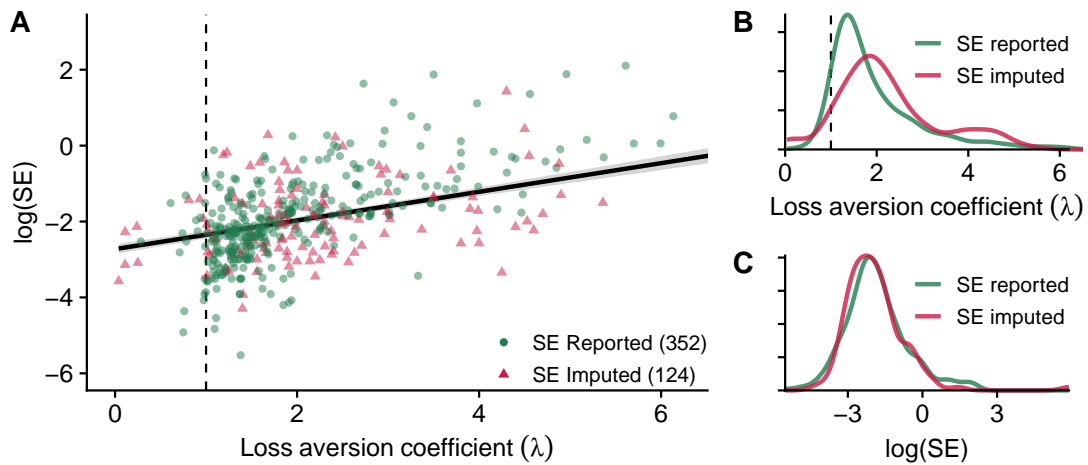

FIGURE A.4: Imputation of standard errors. *Notes*: The solid black line in panel A is the regression line of the standard errors on loss aversion in the data with observed standard errors. Panels B and C show Kernel density estimates of the distributions of λ and $\log(se)$. The Gaussian kernel with Silverman's rule of thumb for the bandwidth selection is applied. The x-axis in each panel is cut off at 6 for better visual rendering, but the density estimation keeps all the relevant observations.

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A.4 Journals

TABLE A.2: List of journals and disciplines.

	Journal	Category
1	Addiction	Substance Abuse
2	Addictive Behaviors	Psychology, Applied
3	American Economic Journal: Economic Policy	Economics
4	American Economic Journal: Microeconomics	Economics
5	American Economic Review	Economics
6	American Journal of Agricultural Economics	Agriculture/Agronomy
7	Behavioral Neuroscience	Neurosciences
8	Brain	Neurosciences
9	Cognition & Emotion	Psychology
10	Consciousness and Cognition	Psychology, Experimental
11	Current Biology	Cell Biology
12	Developmental Cognitive Neuroscience	Psychology, Development
13	Ecological Economics	Ecology
14	Economic Inquiry	Economics
15	Economics Letters	Economics & Business
16	Ekonomický časopis	Economics
17	Emotion	Psychology, Experimental
18	Environment and Development Economics	Economics
19	European Economic Review	Economics
20	European Journal of Operational Research	Operations Research & Management Science
21	European Journal of Transport and Infrastructure Research	Social Sciences, General
22	European Review of Agricultural Economics	Economics & Business
23	Experimental Economics	Economics
24	Frontiers in Human Neuroscience	Psychology
25	Frontiers in Psychology	Psychology, Multidisciplinary
26	Games and Economic Behavior	Economics
27	International Economic Review	Economics
28	International Journal of Applied Behavioral Economics	Economics & Business
29	International Journal of Research in Marketing	Economics & Business
30	Journal of African Economies	Agricultural Sciences
31	Journal of Banking & Finance	Business, Finance
32	Journal of Behavioral and Experimental Economics	Economics
33	Journal of Behavioral Decision Making	Psychology, Applied
34	Journal of Behavioral Finance	Business, Finance
35	Journal of Business & Economic Statistics	Business & Economics
36	Journal of Consumer Research	Economics
37	Journal of Development Economics	Economics
38	Journal of Development Studies	Social Sciences, General
39	Journal of Economic Behavior & Organization	Economics
40	Journal of Economic Dynamics and Control	Economics

	Journal	Category
41	Journal of Economic Psychology	Economics
42	Journal of Empirical Finance	Economics
43	Journal of Experimental Psychology: General	Psychology
44	Journal of Gambling Studies	Substance Abuse
45	Journal of Health Economics	Economics & Business
46	Journal of International Economics	Economics
47	Journal of Marketing Research	Economics
48	Journal of Mathematical Psychology	Psychology, Mathematical
49	Journal of Political Economy	Economics
50	Journal of Risk and Uncertainty	Business & Economics
51	Judgment and Decision Making	Psychiatry/Psychology
52	Management Science	Management
53	Marketing Science	Economics
54	Nature	Multidisciplinary Sciences
55	NeuroImage	Neurosciences
56	Neuron	Neurosciences
57	Neuropsychiatric Disease and Treatment	Psychiatry
58	Organizational Behavior and Human Decision Processes	Management
59	PLOS Computational Biology	Biochemical Research Methods
60	PLOS ONE	Multidisciplinary Sciences
61	PNAS	Multidisciplinary Sciences
62	Proceedings of the Royal Society B: Biological Sciences	Evolutionary Biology
63	Psicológica	Psychology, Experimental
64	Psychiatry Research	Psychiatry/Psychology
65	Psychological Science	Psychology
66	Psychology and Aging	Gerontology
67	Quantitative Finance	Economics
68	Quarterly Journal of Economics	Economics
69	Rationality and Society	Social Sciences, General
70	Review of Economics and Statistics	Economics
71	Review of Managerial Science	Management
72	Revista Espanola de Financiacion y Contabilidad	Business, Finance
73	Science	Multidisciplinary Sciences
74	Theory and Decision	Economics
75	Tourism Management	Hospitality, Leisure, Sport & Tourism
76	Transportation Research Part B: Methodological	Transportation Science & Technology
77	Transportation Research Record	Transportation Science & Technology
78	World Development	Economics

Notes: Journal categories are based on the classification provided by The Master Journal List (https://mjl.clarivate.com/home).

TABLE A.3: Disciplines.

	Frequency	Share (%)
Economics	62	47.7
Business/Management	21	16.2
Psychology	17	13.1
Multi-disciplinary	10	7.7
Psychiatry/Medicine	6	4.6
Neuroscience	4	3.1
Transportation/Tourism	3	2.3
Agriculture	2	1.5
Other	5	3.8
Total	130	100.0

B   Coefficient of Loss Aversion λ

We consider a situation where an agent makes a choice under risk between prospects with at most two distinct outcomes, as in Section 2. Let $(x, p; y)$ denote a *simple lottery*, which gives outcome x with probability p and outcome y with probability $1 - p$. For simplicity of exposition, we assume the reference point to be 0, so that the sign of the outcome indicates whether it is a gain or a loss. We call a lottery *non-mixed* if two outcomes have the same sign (i.e., either $x, y \geq 0$ or $x, y \leq 0$) and *mixed* if one of the outcomes is positive and the other outcome is negative. Without loss of generality, we assume that $x > 0 > y$ when we deal with a mixed lottery. In this setup, PT (Tversky and Kahneman, 1992) postulates that the agent evaluates non-mixed prospects $(x, p; y)$ with $x \geq y \geq 0$ or $x \leq y \leq 0$ by

$$w^s(p)U(x) + (1 - w^s(p)) U(y),$$

and mixed prospects $(x, p; y)$ with $x > 0 > y$ by

$$w^+(p)U(x) + w^-(1 - p)U(y),$$

where $w^s : [0, 1] \rightarrow [0, 1]$ is a probability weighting function for gains ($s = +$) or for losses ($s = -$), with $w^s(0) = 0$ and $w^s(1) = 1$, and $U : \mathbf{R} \rightarrow \mathbf{R}$ is a strictly increasing utility function satisfying $U(0) = 0$.

Several different definitions of loss aversion have been proposed and used in the literature. Below we summarize six definitions discussed in Abdellaoui, Bleichrodt and Paraschiv (2007).

- Kahneman and Tversky (1979) propose to define loss aversion by $-U(-x) > U(x)$ for all $x > 0$. One way to define a coefficient of loss aversion is to take the mean (or median) of

$$\frac{-U(-x)}{U(x)}$$

over the relevant values of x, such as the outcomes used in the experiment.

- Tversky and Kahneman (1992) implicitly use the ratio of the utility of a loss of one monetary unit and a gain of one monetary unit,

$$\frac{-U(-1)}{U(1)},$$

as a coefficient of loss aversion. This definition follows from a power utility specification (see equation (3) in Section 2).

- Wakker and Tversky (1993) propose to define loss aversion by $U'(-x) \geq U'(x)$ for all $x > 0$. One way to define a coefficient of loss aversion is to take the mean (or median)

of

$$\frac{U'(-x)}{U'(x)}$$

over the relevant values of x, such as the outcomes used in the experiment.

- Bowman, Minehart and Rabin (1999) propose to define loss aversion by $U'(-x) \geq U'(y)$ for all $x, y > 0$. A candidate for a coefficient of loss aversion is the ratio

$$\frac{\inf_{x>0} U'(-x)}{\sup_{y>0} U'(y)}.$$

- Neilson (2002) propose to define loss aversion by $U(-x)/(-x) \geq U(y)/y$ for all $x, y > 0$. A candidate for a coefficient of loss aversion is the ratio

$$\frac{\inf_{x>0} U(-x)/(-x)}{\sup_{y>0} U(y)/y}.$$

- Köbberling and Wakker (2005) propose a coefficient of loss aversion

$$\frac{\lim_{x\uparrow 0} U(x)}{\lim_{x\downarrow 0} U(x)}.$$

C Bayesian Hierarchical Model

C.1 Modeling Framework

The main goal of our meta-analysis is first to obtain the "best available" estimate of the loss aversion coefficient λ combining the available information in the literature and then to understand the heterogeneity of reported estimates across studies. To this end, we analyze the data using a *Bayesian hierarchical modeling* approach.

Meta-analysis is naturally hierarchical. The effect sizes reported in different studies are summary measures of individual-level behavior. We summarize these measures by estimating their mean and variation based on a given model. Additional hierarchical levels can be introduced, e.g., to deal with statistical dependence in estimates, such as when one and the same paper or study reports multiple estimates.

Hierarchical models, in turn, are naturally Bayesian (Gelman and Hill, 2006; McElreath, 2016). To see this, one can picture the estimated aggregate mean as an endogenous prior, that will then influence the estimates of the "true" study-level effect, depending on the uncertainty surrounding the estimate itself—a statistical procedure known as "shrinkage" or "pooling". One of the great advantages of the Bayesian approach is further that the estimate emerging from the meta-analysis—the posterior mean of our analysis—can serve as a prior for future empirical studies, and is easy to update with additional evidence. This is conducive to the systematic quantitative accumulation of knowledge—the prime objective of meta-analysis.

Consider the dataset $(\lambda_i, se_i^2)_{i=1}^m$, where λ_i is the *i*th *measurement* (or *observation*) of the loss aversion coefficient in the dataset and se_i is the associated standard error that captures the uncertainty surrounding the estimate. We assume that the *i*th reported estimate λ_i is normally distributed around the parameter $\overline{\lambda}_i$:

$$\lambda_i \mid \overline{\lambda}_i, se_i \sim \mathcal{N}(\overline{\lambda}_i, se_i^2), \tag{C.1}$$

where the variability is due to the sampling variation captured by the known standard error se_i.[1]

Sampling variation is part of the observed variation in the reported estimates $(\lambda_i)_{i=1}^m$, but it may not be all, since there is a possibility of "genuine" heterogeneity across measurements (due to different settings, for example). We model this by assuming that each $\overline{\lambda}_i$ is normally distributed, adding another level to the hierarchy:

$$\overline{\lambda}_i \mid \lambda_0, \tau \sim \mathcal{N}(\lambda_0, \tau^2), \tag{C.2}$$

where λ_0 is the *overall mean* of the estimated loss aversion parameters $\overline{\lambda}_i$, and τ is its standard

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[1]The parameter $\overline{\lambda}_i$ is often referred to as the "true effect size" in the random-effects meta-analysis.

deviation, capturing the variation between observations in the data. The overall variance in the data, therefore, consists of two parts, the between-observation variance, τ^2, and the individual sampling variation coming from measurement uncertainty, se^2. This can be clearly seen by combining expressions (C.1) and (C.2) into one:

$$\lambda_i \mid \lambda_0, \tau, se_i \sim \mathcal{N}(\lambda_0, \tau^2 + se_i^2).$$

Note that this formulation is mathematically equivalent to the classical formulation of random-effects meta-analysis (DerSimonian and Laird, 1986), which is typically expressed as

$$\lambda_i = \overline{\lambda}_i + \xi_i = \lambda_0 + \varepsilon_i + \xi_i,$$

where $\xi_i \sim \mathcal{N}(0, se_i^2)$ is a sampling error of λ_i as an estimate of $\overline{\lambda}_i$, and each observation-specific "true" effect $\overline{\lambda}_i$ is decomposed into λ_0 (the overall mean) and the sampling error ξ_j. It is further assumed that $\varepsilon_i \sim \mathcal{N}(0, \tau^2)$, where τ^2 is the between-observation heterogeneity, beyond the mere sampling variance. When $\tau = 0$, this model reduces to a fixed-effect meta-analysis. This highlights the central assumption underlying fixed-effect meta-analysis—that different estimates differ only based on random sampling variation—which clearly does not seem adequate for the diverse set of estimates included in our meta-analysis. We thus conduct a random-effects analysis, allowing for both random sampling variation and systematic differences between studies and estimates.

In this model, each observation λ_i in the data will be "pooled" towards the overall mean λ_0, with the extent of the pooling depending on two factors: (i) the standard error associated with the estimate; and (ii) how far the estimate lies from the estimated mean, λ_0. As we see above, the variance across observations is decomposed into two parts—variance due to error in estimation, and the genuine between-observation heterogeneity. The pooling equation for a specific observation i takes the following form

$$\overline{\lambda}_i = (1 - \omega_i)\lambda_i + \omega_i\lambda_0, \tag{C.3}$$

where ω_i is the "pooling factor" (Gelman and Pardoe, 2006), defined as

$$\omega_i = \frac{se_i^2}{\tau^2 + se_i^2}. \tag{C.4}$$

The equation makes it clear that the larger the SE *ceteris paribus*, the larger the pooling factor, and thus the closer the estimate will be drawn to the overall mean estimate of the population, indicated by λ_0. At the same time, the smaller the between-study variation captured by τ^2, the more pooling towards the population mean. This makes intuitive sense—estimates are pooled more to the extent that all estimates in the population are similar to each other, and to the

extent that they are characterized by a low degree of precision.

It is now straightforward to account for variation across estimates driven by observable characteristics—commonly referred to as meta-regression—by letting

$$\overline{\lambda}_i = \kappa_i + X_i\beta + \varepsilon_i, \tag{C.5}$$

where κ_i is the intercept of the regression, X_i a matrix of observable study characteristics for observation i, and β is a vector of regression coefficients. Notice that the residual is distributed as $\varepsilon_i \sim \mathcal{N}(0, \tau^2)$. By comparing the variance in this model to the variance estimated in a model empty of covariates, i.e., where X_i contains no entries, we will be able to assess what extent of the overall variance between observations is explained by the observation-level characteristics encoded in X_i. In particular, the variance explained is given by $1 - (\tau_1^2/\tau_0^2)$, where τ_0^2 is the estimated variance between observation in a model empty of covariates, and τ_1^2 is the equivalent variance term estimated in the meta-regression model.

While this normal-normal structure expressed in equations (C.1, C.2) is the benchmark setup we use, it will quickly become interesting to relax the modeling assumptions described here, e.g., by replacing the normal distribution with a robust student-t distribution or an asymmetric log-normal distribution, and by allowing for additional hierarchical levels to account for the lack of independence in the observations in our data.

We estimate the model in `Stan` (Carpenter et al., 2017) using the Hamiltonian Monte Carlo simulations, an algorithm for Markov Chain Monte Carlo, and launch it from `R` (https://www.r-project.org/) using `RStan` (Stan Development Team, 2020). Priors for the population-level parameters are chosen in such a way as to be mildly regularizing, i.e., they are informative but typically encompass ranges that are one order of magnitude larger than the estimated values we expect based on the range of the data (McElreath, 2016). Priors for lower-level parameters are then constituted by the endogenously estimated population-level parameters. The estimates we report are not sensitive to the choice of the particular priors we use (Section C.3.3 below).

C.2 Estimation

In Section 4.3, we started from fitting the benchmark model expressed as equations (C.1) and (C.2):

$$
\begin{aligned}
\lambda_i \mid \overline{\lambda}_i, se_i &\sim \mathcal{N}(\overline{\lambda}_i, se_i^2), \\
\overline{\lambda}_i \mid \lambda_0, \tau &\sim \mathcal{N}(\lambda_0, \tau^2), \\
\lambda_0 &\sim \text{half } \mathcal{N}(1, 5), \\
\tau &\sim \text{half } \mathcal{N}(0, 5).
\end{aligned}
\tag{M1a}
$$

(This model was called M1 in Section 4.3.) The estimated overall mean λ_0 is 1.809 with a 95% credible interval (CrI) of $[1.739, 1.878]$.

Pooling. Equations (C.3) and (C.4) describe the mechanism underlying the pooling. The amount of pooling applied to an observation—i.e., the extent to which an estimated parameter $\overline{\lambda}_i$ is drawn towards the overall mean λ_0 from its observed value λ_i—will depend on the SE associated with the observation, and its distance from the mean. This is illustrated in Figure C.1, which shows a scatter plot of the estimated loss aversion parameter, $\overline{\lambda}_i$, against the observed parameter, λ_i. For standard errors up to 0.4, almost no pooling is observed, even for values that fall relatively far from the mean. Pooling increases for larger SEs between 0.4 and 1, and becomes very strong for even larger SEs. The farther an observation falls from the mean, the more it is pooled, ceteris paribus. We further observe very strong pooling for large observations because the standard errors themselves tend to increase with loss aversion, as detailed above.
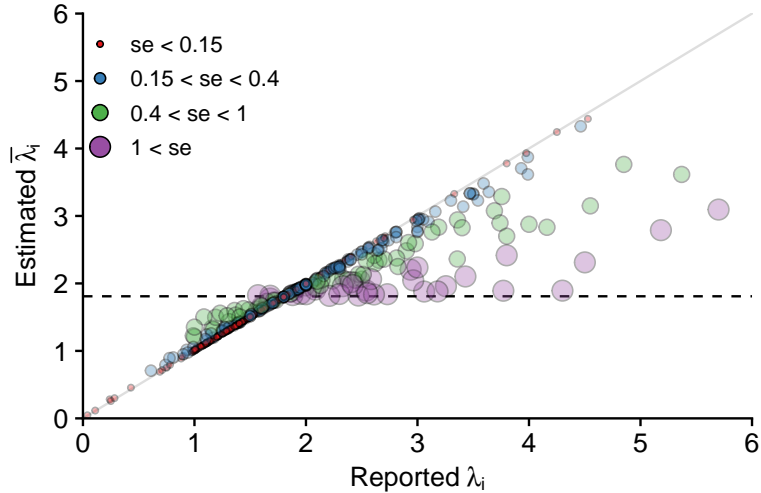

FIGURE C.1: Pooling of estimates by SE. *Notes*: The horizontal dashed line corresponds to the estimated overall mean $\lambda_0 = 1.809$. The axes are cut off at six for better visualization.

Additional models. In addition to models M1a and M2 discussed in Section 4.3, we esti-mated two additional "intermediate" models. The first alternative model is a straightforward extension of model M1a, replacing the normal distribution with a log-normal distribution:

$$
\begin{aligned}
\lambda_i \mid \bar{\lambda}_i, se_i &\sim \mathcal{N}(\bar{\lambda}_i, se_i^2), \\
\bar{\lambda}_i \mid \lambda_0^\ell, \tau_\ell &\sim \log \mathcal{N}(\lambda_0^\ell, \tau_\ell^2), \\
\lambda_0^\ell &\sim \mathcal{N}(1, 5), \\
\tau_\ell &\sim \text{half } \mathcal{N}(0, 5).
\end{aligned}
\tag{M1b}
$$

Note the super-/sub-scripts ℓ in the location and scale parameters $(\lambda_0^\ell, \tau_\ell^2)$ of the log-normal distribution. We can calculate the mean and the median of the distribution by $\exp(\lambda_0^\ell + \tau_\ell^2/2)$ and $\exp(\lambda_0^\ell)$, respectively, exploiting the properties of the log-normal distribution.

This leaves the assumption of independence in the observations to be addressed. Insofar as different research groups tend to use different theoretical approaches and measurement methodologies, such an independence assumption seems difficult to defend. This holds even more for multiple estimates contained in one and the same paper, some of which use the same data and use different estimation procedures or functional forms. Even if the data are different, the measurement setup and the methodology used for estimation are generally the same. This means that one paper containing a lot of estimates could potentially affect our global estimates, especially if, for whatever reason, some papers report a large number of particularly small or large estimates. Our 607 observations have been obtained from 150 distinct papers, the largest number of observations in a single paper being 53 (Rieger, Wang and Hens, 2017; Wang, Rieger and Hens, 2017), so the independence assumption seems rather heroic.

The second alternative model tries to address the non-independence of reported estimates by explicitly modeling the nesting of observations in papers. To do this, we introduce paper-level estimates as an additional hierarchical level. Let λ_{pi} be the ith estimate reported in paper p. We formulate a model as follows:

$$
\begin{aligned}
\lambda_{pi} \mid \bar{\lambda}_{pi}, se_{pi} &\sim \mathcal{N}(\bar{\lambda}_{pi}, se_{pi}^2), \\
\bar{\lambda}_{pi} \mid \bar{\lambda}_p, \sigma_p &\sim \mathcal{N}(\bar{\lambda}_p, \sigma_p^2), \\
\bar{\lambda}_p \mid \lambda_0^\ell, \tau_\ell &\sim \log \mathcal{N}(\lambda_0^\ell, \tau_\ell^2), \\
\lambda_0^\ell &\sim \mathcal{N}(1, 5), \\
\tau_\ell &\sim \text{half } \mathcal{N}(0, 5), \\
\sigma_p &\sim \text{half } \mathcal{N}(0, 5).
\end{aligned}
\tag{M1c}
$$

The system now explicitly models the nesting of the estimated observation-level param-eters, $\bar{\lambda}_{pi}$, in paper-level estimates, $\bar{\lambda}_p$. The latter are then modeled as following a log-normal distribution, just as previously. Figure C.2 illustrates the idea behind this formulation. Fig-

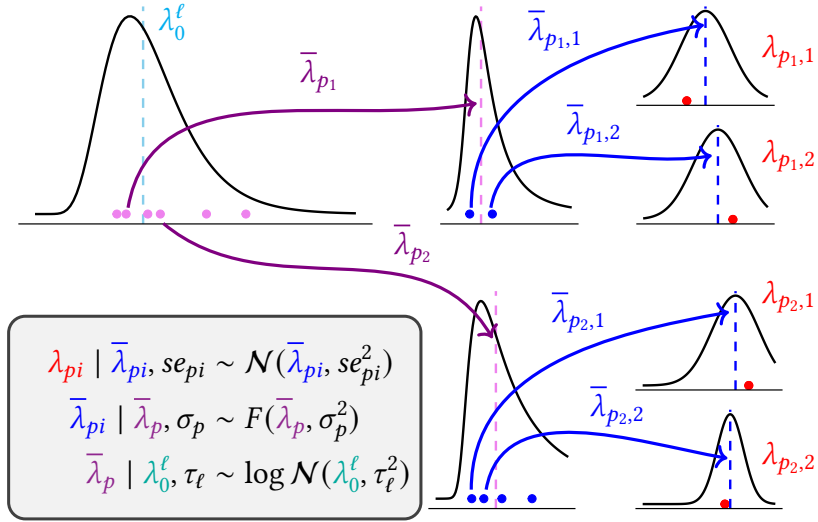FIGURE C.2: Illustration of the nesting structure in models M1c and M2. For the paper-level distribution F in the middle layer, model M1c assumes a normal distribution and model M2 assumes a student-t distribution with additional parameter df (degrees of freedom).

ure C.3 below summarizes all four models we estimated.

Estimating model M1b, we obtain a mean λ_0 of 1.826, with a 95% CrI of $[1.750, 1.910]$. Figure C.4 (top right panel) shows the posterior predictive distribution from the estimation of this model. The fit can be seen to be much better than that of the baseline normal-normal model shown above and to fit the actual observations closely. We thus conclude that a log-normal distribution provides a good fit for the data. The mean loss aversion λ_0 is 2.052 (95% CrI $[1.909, 2.208]$), under model M1c. The fit to the data, however, appears to be a little off, allowing room for improvement (Figure C.4, bottom left panel). The posterior predictive distribution puts a much larger likelihood on values between 1.8 and 3 while it puts a smaller likelihood on values below 1.5.

TABLE C.1: Summary of estimation results.

Model	Distributional assumption			Posterior of λ_0				Posterior of τ			
	Obs. level	Paper level	Pop. level	Mean	SD	2.5%	97.5%	Mean	SD	2.5%	97.5%
M1a	Normal		Normal	1.809	0.036	1.739	1.878	0.746	0.028	0.695	0.803
M1b	Normal		Log-normal	1.826	0.039	1.750	1.910	0.816	0.256	0.742	0.898
M1c	Normal	Normal	Log-normal	2.052	0.076	1.909	2.208	0.752	0.356	0.603	0.926
M2	Normal	Student-t	Log-normal	1.955	0.072	1.820	2.102	0.743	0.342	0.604	0.904

Notes: In Models M1c and M2, (λ_0, τ) are calculated from the log-normal parameters $(\lambda_0^\ell, \tau_\ell)$ by $\lambda_0 = \exp(\lambda_0^\ell + \tau_\ell^2/2)$ and $\tau^2 = [\exp(\tau_\ell^2) - 1] \exp(2\lambda_0^\ell + \tau_\ell^2)$.

Model M1a	Model M1b

Model M1a

$$\lambda_i \mid \overline{\lambda}_i, se_i \sim \mathcal{N}(\overline{\lambda}_i, se_i^2),$$
$$\overline{\lambda}_i \mid \lambda_0, \tau \sim \mathcal{N}(\lambda_0, \tau^2),$$
$$\lambda_0 \sim \text{half } \mathcal{N}(1, \nu),$$
$$\tau \sim \text{half } \mathcal{N}(0, \nu).$$

Model M1b

$$\lambda_i \mid \overline{\lambda}_i, se_i \sim \mathcal{N}(\overline{\lambda}_i, se_i^2),$$
$$\overline{\lambda}_i \mid \lambda_0^\ell, \tau_\ell \sim \log \mathcal{N}(\lambda_0^\ell, \tau_\ell^2),$$
$$\lambda_0^\ell \sim \mathcal{N}(1, \nu),$$
$$\tau_\ell \sim \text{half } \mathcal{N}(0, \nu).$$

Model M1c

$$\lambda_{pi} \mid \overline{\lambda}_{pi}, se_{pi} \sim \mathcal{N}(\overline{\lambda}_{pi}, se_{pi}^2),$$
$$\overline{\lambda}_{pi} \mid \overline{\lambda}_p, \sigma_p \sim \mathcal{N}(\overline{\lambda}_p, \sigma_p^2),$$
$$\overline{\lambda}_p \mid \lambda_0^\ell, \tau_\ell \sim \log \mathcal{N}(\lambda_0^\ell, \tau_\ell^2),$$
$$\lambda_0^\ell \sim \mathcal{N}(1, \nu),$$
$$\tau_\ell \sim \text{half } \mathcal{N}(0, \nu),$$
$$\sigma_p \sim \text{half } \mathcal{N}(0, \nu).$$

Model M2

$$\lambda_{pi} \mid \overline{\lambda}_{pi}, se_{pi} \sim \mathcal{N}(\overline{\lambda}_{pi}, se_{pi}^2),$$
$$\overline{\lambda}_{pi} \mid df, \overline{\lambda}_p, \sigma_p \sim t(df, \overline{\lambda}_p, \sigma_p^2),$$
$$\overline{\lambda}_p \mid \lambda_0^\ell, \tau_\ell \sim \log \mathcal{N}(\lambda_0^\ell, \tau_\ell^2),$$
$$\lambda_0^\ell \sim \mathcal{N}(1, \nu),$$
$$\tau_\ell \sim \text{half } \mathcal{N}(0, \nu),$$
$$df \sim \text{half } \mathcal{N}(0, \nu),$$
$$\sigma_p \sim \text{half } \mathcal{N}(0, \nu).$$
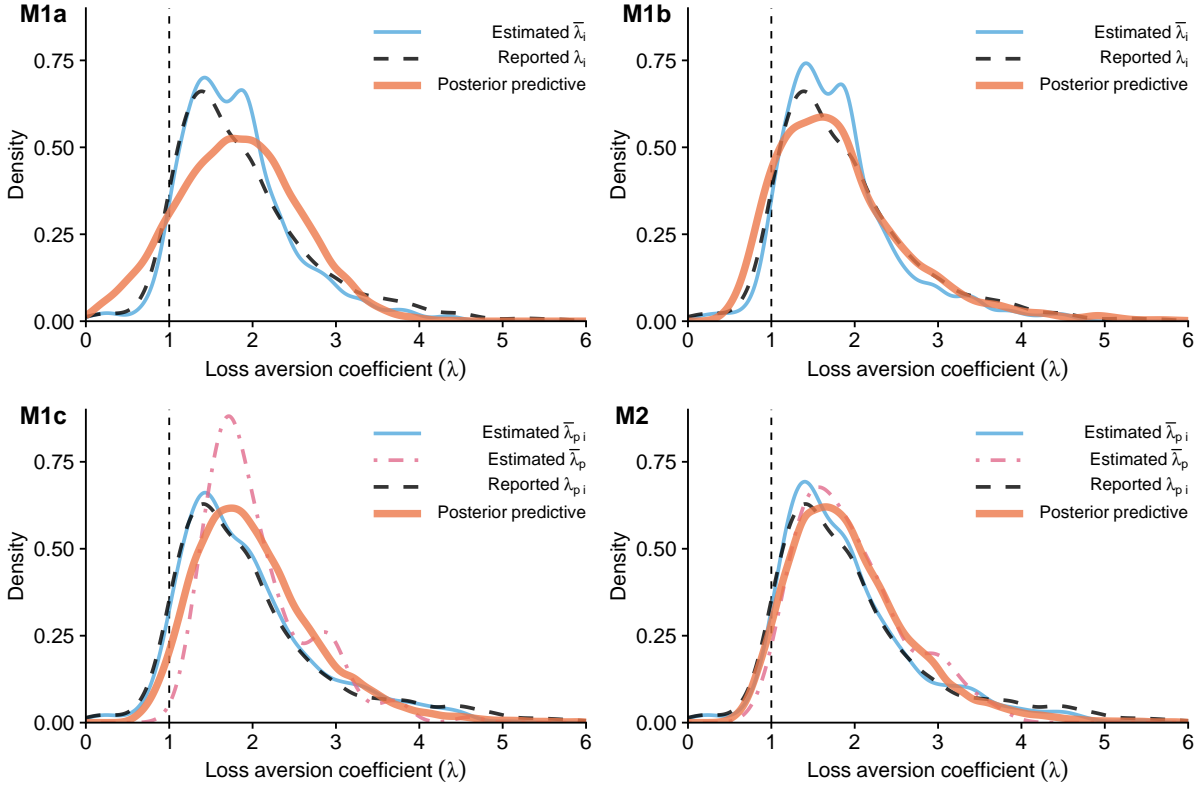
FIGURE C.3: Summary of models.

FIGURE C.4: Distributions of reported and estimated λ, and posterior predictive distribution of λ.

C.3 Robustness Checks

C.3.1 Estimation Using Subsets of the Dataset

TABLE C.2: Estimation result for each type of reported λ.

| Model | Type | Distributional assumption | | | Posterior of λ_0 | | | |
		Obs. level	Paper level	Pop. level	Mean	SD	2.5%	97.5%
M1a	Aggregate	Normal		Normal	1.700	0.046	1.613	1.789
	Individual mean	Normal		Normal	2.432	0.103	2.233	2.635
	Individual median	Normal		Normal	1.712	0.046	1.622	1.803
M2	Aggregate	Normal	Student-t	Log-normal	1.843	0.111	1.645	2.080
	Individual mean	Normal	Student-t	Log-normal	2.395	0.148	2.130	2.708
	Individual median	Normal	Student-t	Log-normal	1.728	0.085	1.574	1.903

Notes: In Model M2, λ_0 is calculated from the log-normal location parameter λ_0^ℓ by $\lambda_0 = \exp(\lambda_0^\ell + \tau_\ell^2/2)$.
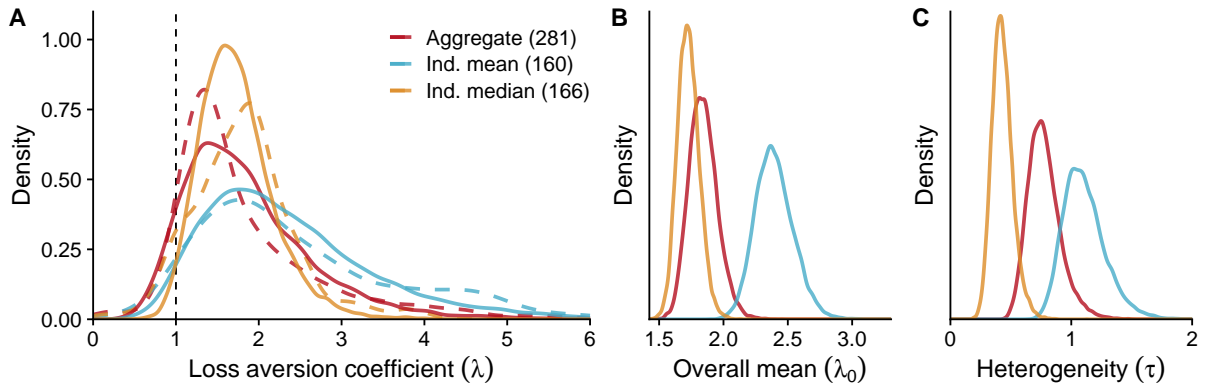

FIGURE C.5: Estimation of model M2 for each type of reported loss aversion coefficient separately. (A Distributions of reported λ_{pi} (dashed lines) and posterior predictive distributions (solid lines). (BC) Posterior distributions of λ_0 and τ. *Notes*: (λ_0, τ) are calculated from the log-normal parameters $(\lambda_0^\ell, \tau_\ell)$ are calculated by $\lambda_0 = \exp(\lambda_0^\ell + \tau_\ell^2/2)$ and $\tau^2 = [\exp(\tau_\ell^2) - 1] \exp(2\lambda_0^\ell + \tau_\ell^2)$.

C.3.2 Estimation Using the "Complete" Dataset

TABLE C.3: Sensitivity to SE imputation. (A) All data, including observations with imputed SEs (identical to Table 5). (C) Complete data, including only observations where associated SEs are available.

| Model | | Distributional assumption | | | Posterior of λ_0 | | | | Posterior of τ | | | |
		Obs. level	Paper level	Pop. level	Mean	SD	2.5%	97.5%	Mean	SD	2.5%	97.5%
M1a	A	Normal		Normal	1.809	0.036	1.739	1.878	0.746	0.028	0.695	0.803
	C	Normal		Normal	1.713	0.041	1.634	1.795	0.713	0.032	0.654	0.781
M1b	A	Normal		Log-normal	1.826	0.039	1.750	1.910	0.816	0.256	0.742	0.898
	C	Normal		Log-normal	1.710	0.040	1.634	1.794	0.672	0.229	0.600	0.751
M1c	A	Normal	Normal	Log-normal	2.052	0.076	1.909	2.208	0.752	0.356	0.603	0.926
	C	Normal	Normal	Log-normal	2.041	0.097	1.865	2.243	0.877	0.449	0.684	1.119
M2	A	Normal	Student-t	Log-normal	1.955	0.072	1.820	2.102	0.743	0.342	0.604	0.904
	C	Normal	Student-t	Log-normal	1.962	0.091	1.794	2.155	0.824	0.422	0.644	1.048

Notes: In Models M1c and M2, (λ_0, τ) are calculated from log-normal parameters $(\lambda_0^\ell, \tau_\ell)$ by $\lambda_0 = \exp(\lambda_0^\ell + \tau_\ell^2/2)$ and $\tau^2 = [\exp(\tau_\ell^2) - 1]\exp(2\lambda_0^\ell + \tau_\ell^2)$.

C.3.3 Sensitivity to the Choice of Priors

TABLE C.4: Sensitivity to prior specifications. The standard deviation for the half-normal distribution half $\mathcal{N}(0, \nu)$ is set at $\nu \in \{5, 10\}$.

| Model | ν | Distributional assumption | | | Posterior of λ_0 | | | | Posterior of τ | | | |
		Obs. level	Paper level	Pop. level	Mean	SD	2.5%	97.5%	Mean	SD	2.5%	97.5%
M1a	5	Normal		Normal	1.809	0.036	1.739	1.878	0.746	0.028	0.695	0.803
	10	Normal		Normal	1.809	0.035	1.740	1.880	0.747	0.027	0.696	0.802
M1b	5	Normal		Log-normal	1.826	0.039	1.750	1.910	0.816	0.256	0.742	0.898
	10	Normal		Log-normal	1.825	0.039	1.753	1.901	0.814	0.257	0.740	0.896
M1c	5	Normal	Normal	Log-normal	2.052	0.076	1.909	2.208	0.752	0.356	0.603	0.926
	10	Normal	Normal	Log-normal	2.051	0.076	1.909	2.204	0.749	0.357	0.601	0.925
M2	5	Normal	Student-t	Log-normal	1.955	0.072	1.820	2.102	0.743	0.342	0.604	0.904
	10	Normal	Student-t	Log-normal	1.955	0.072	1.819	2.100	0.742	0.340	0.602	0.904

Notes: In Models M1c and M2, (λ_0, τ) are calculated from log-normal parameters $(\lambda_0^\ell, \tau_\ell)$ by $\lambda_0 = \exp(\lambda_0^\ell + \tau_\ell^2/2)$ and $\tau^2 = [\exp(\tau_\ell^2) - 1]\exp(2\lambda_0^\ell + \tau_\ell^2)$.
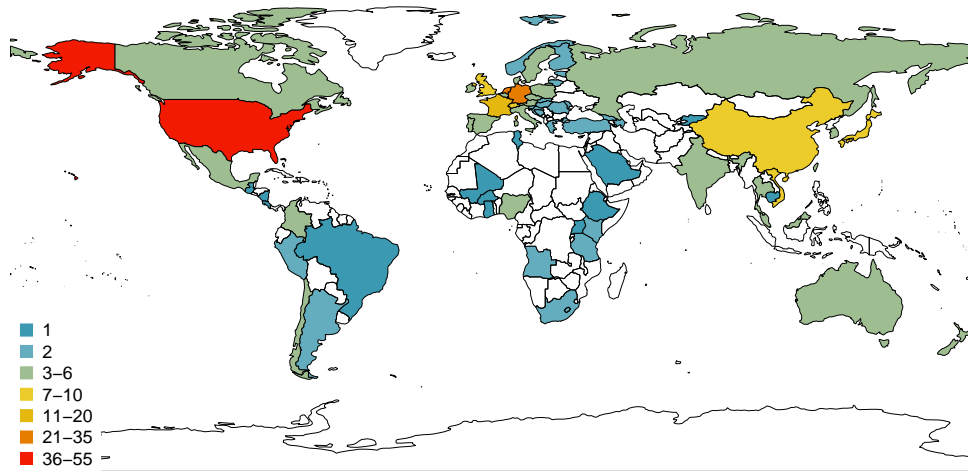
D Additional Figures and Tables

FIGURE D.1: Study location. *Notes*: It is possible that the same dataset was used in two or more papers (e.g., a cross-country dataset from Rieger, Wang and Hens (2017) and Wang, Rieger and Hens (2017) in Section 3.3) to estimate model parameters. In such a case, countries are counted multiple times. This map was created using R (`https://www.r-project.org/`) on a base world map obtained from Natural Earth (`https://www.naturalearthdata.com/`).
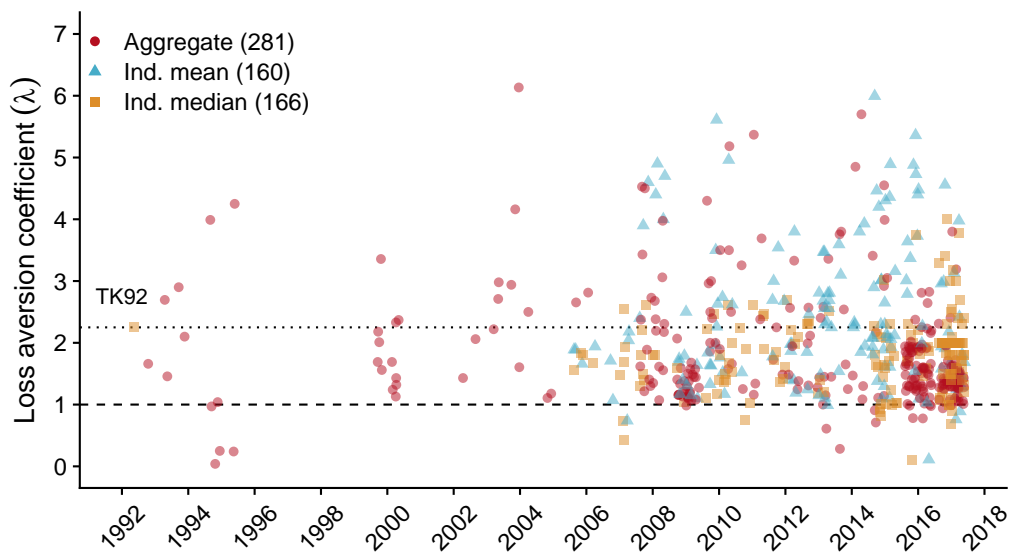
FIGURE D.2: Reported loss aversion coefficients (λ) over time. *Notes*: The y-axis is cut off at 7 for better visualization. The first observation, labeled "TK92", corresponds to the estimate 2.25 from Tversky and Kahneman (1992).

22
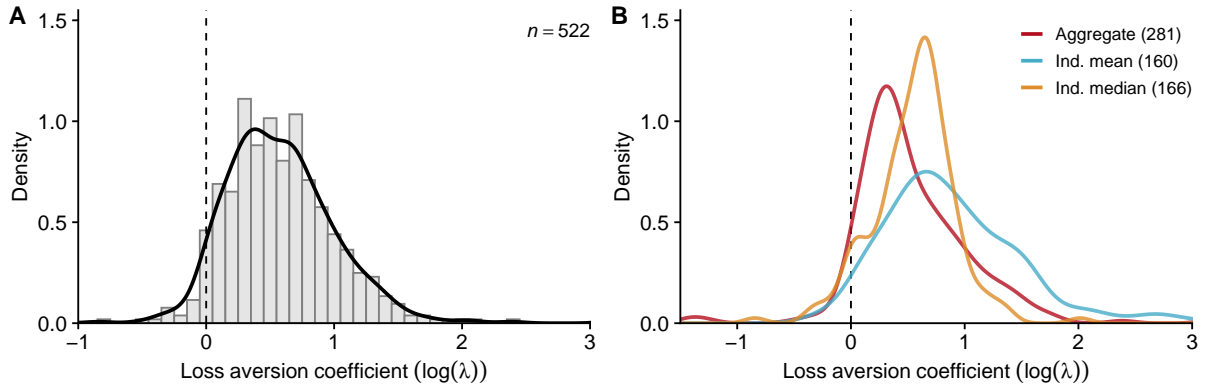
FIGURE D.3: Distribution of logged loss aversion coefficient $\log(\lambda)$. C.f. Figure 3. *Notes*: There are 85 cases that report both individual-level mean and median. We keep individual-level medians from these cases in panel A. Bins for the histogram are 0.1 wide. In panel B, the Kernel density estimate of the distribution $\log(\lambda)$ is plotted, using the Gaussian kernel with Silverman's rule of thumb for the bandwidth selection. All 607 estimates in the data are included.
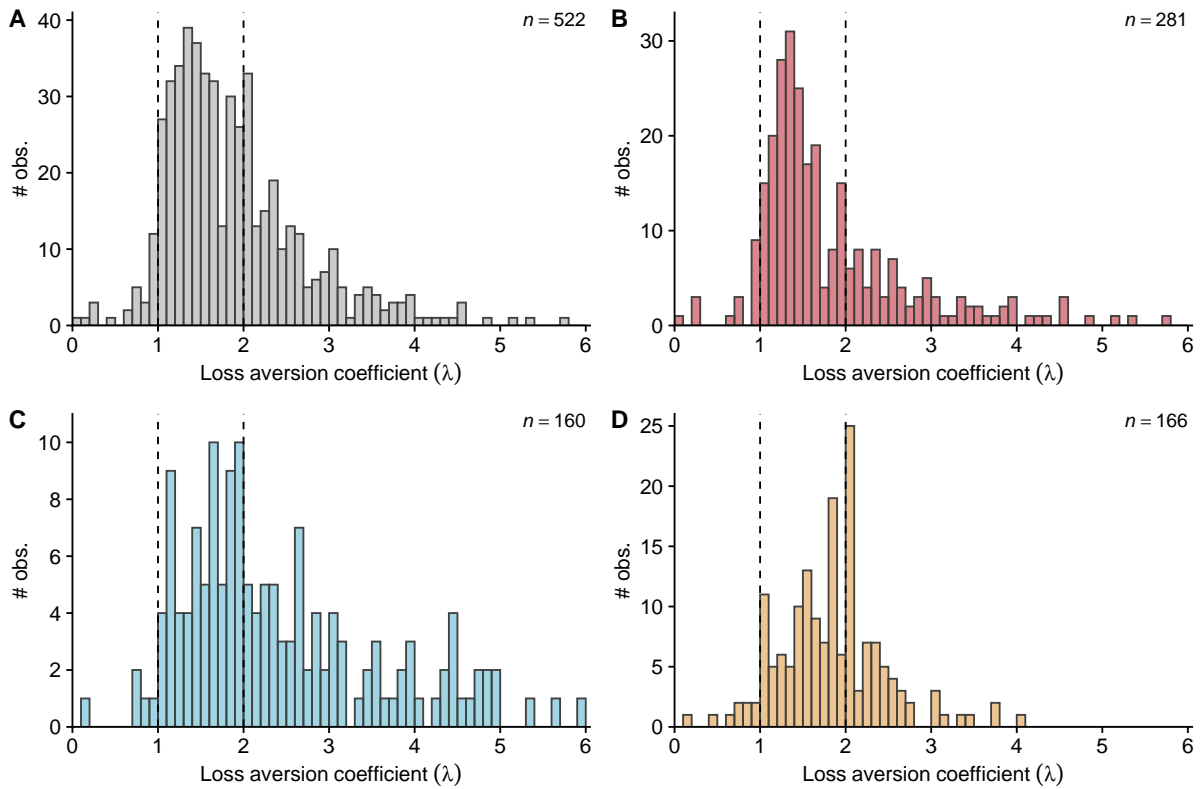

FIGURE D.4: Histogram of loss aversion coefficient λ. (A) All types of estimates combined. (B) Aggregate-level estimates. (C) Individual-level means. (D) Individual-level medians. *Notes*: There are 85 cases that report both individual-level mean and median. We keep individual-level medians from these cases in panel A. Bins for the histogram are 0.1 wide in each panel. The x-axis is cut off at 6 for better visual rendering.
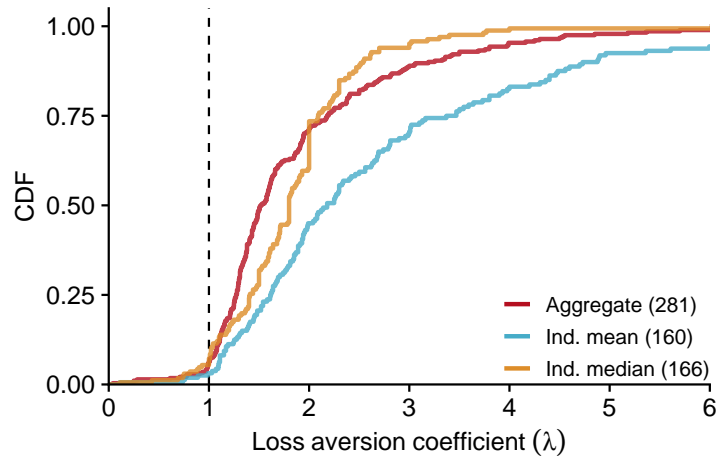
FIGURE D.5: Empirical CDF of reported loss aversion coefficient λ by the type of estimates. *Notes*: The *x*-axis is cut off at 6 for better visual rendering.
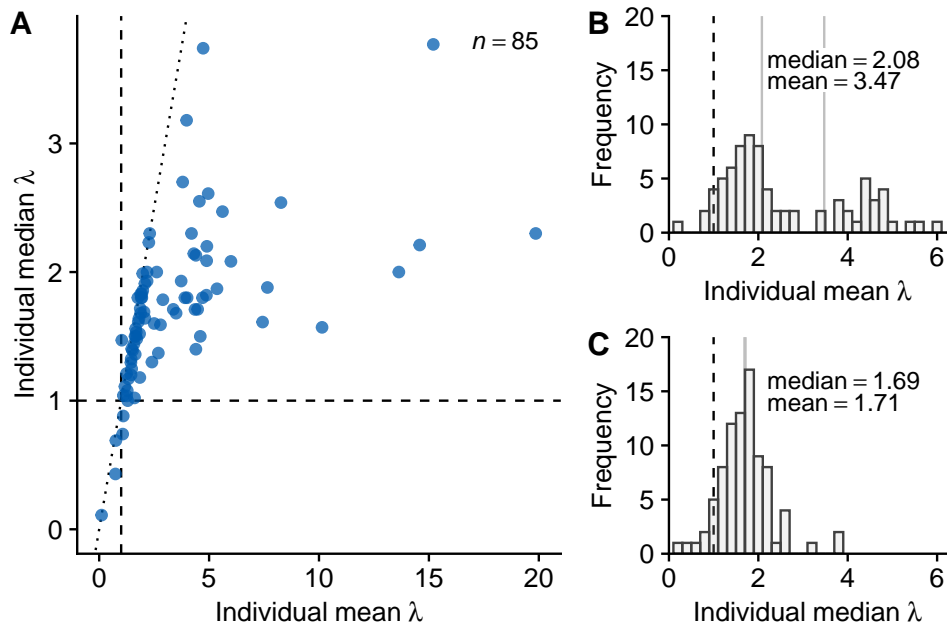

FIGURE D.6: Comparing 85 pairs of individual-level means and medians in 34 papers that report both. *Notes*: The mean is larger than the median in 94% (80 out of 85) of the pairs. Bins for the histogram are 0.2 wide in panels B and C.
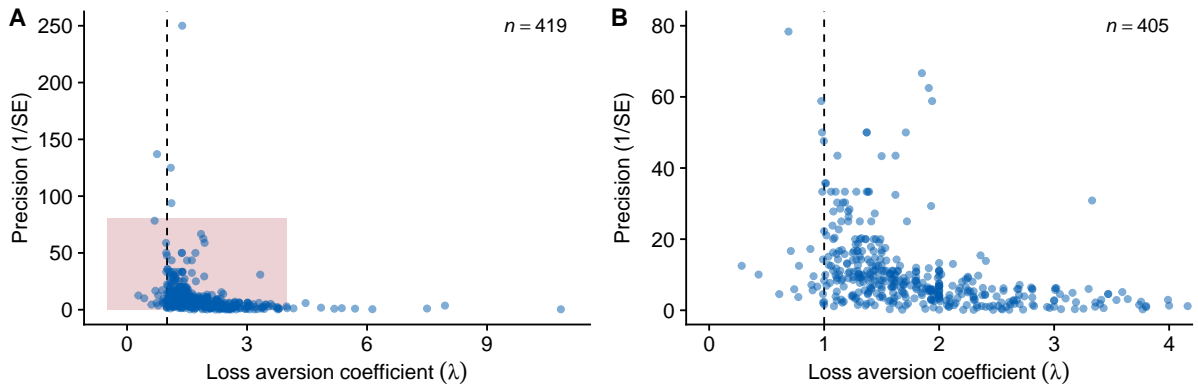
FIGURE D.7: Estimated λ and precision ($1/se$). (A) Complete dataset with reported SE. (B) A subset of the complete dataset (inside the red rectangle in panel A; $\lambda \leq 4$ and $1/se \leq 80$).
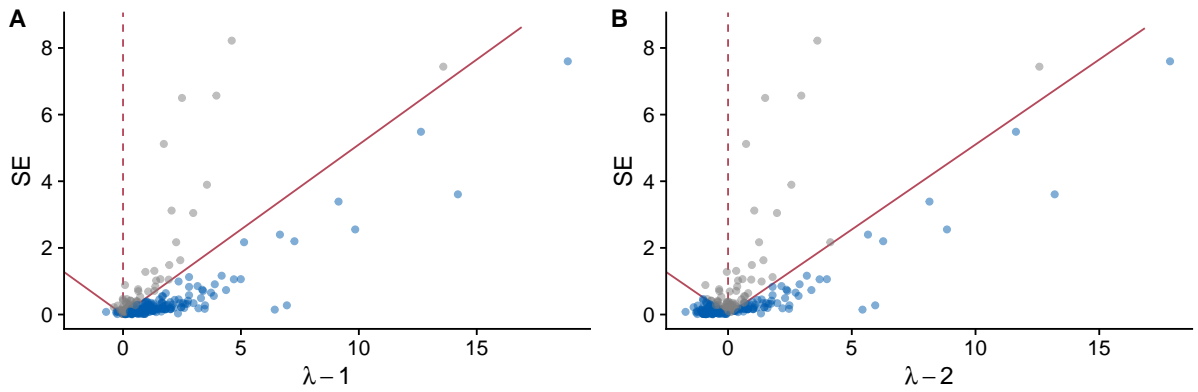

FIGURE D.8: Scatterplots of the estimated "effect size" against its standard error. (A) The effect size is $\lambda - 1$, corresponding to the null hypothesis of $H_0 : \lambda = 1$. (B) The effect size is $\lambda - 2$, corresponding to the null hypothesis of $H_0 : \lambda = 2$. C.f. Figure 10 panels BD. *Notes*: The plots show all 350 observations of aggregate-level and individual-level mean λ, which have associated standard errors reported in the paper.
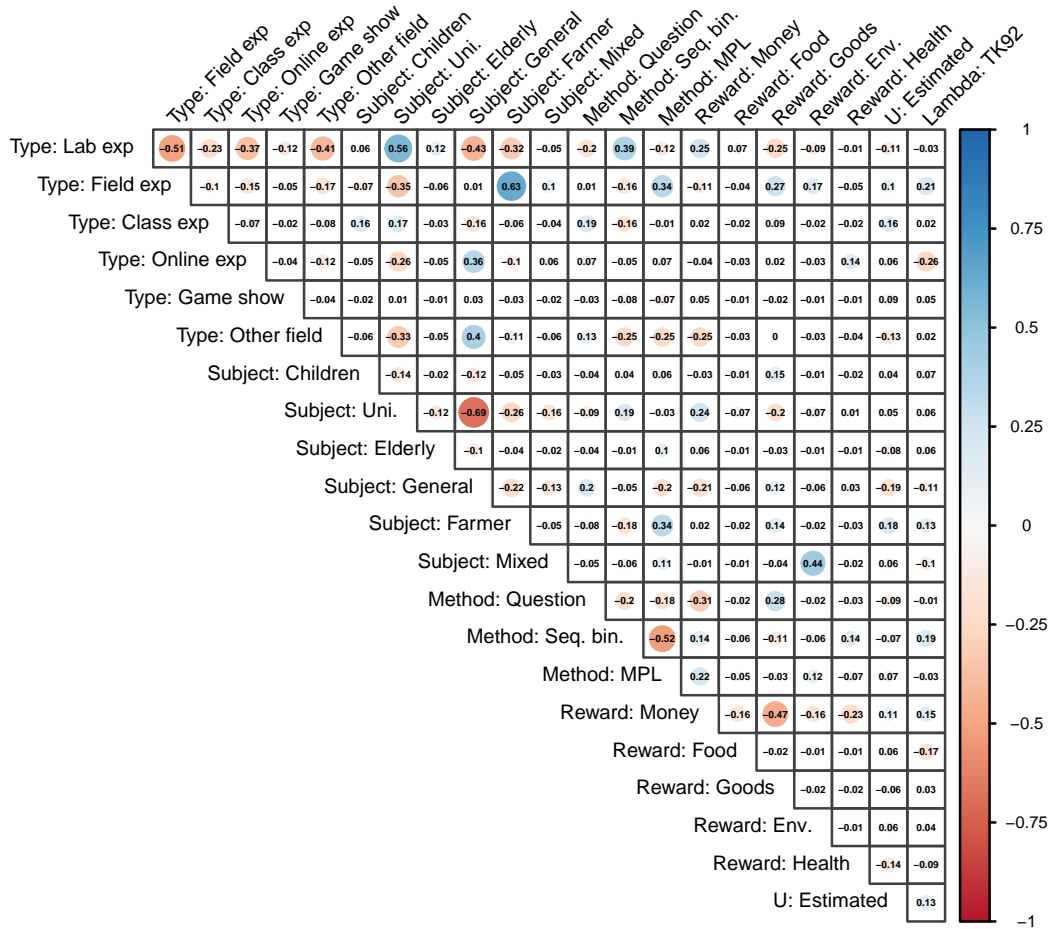
FIGURE D.9: Co-occurrences of design characteristics. *Notes*: Variables are all dichotomous, taking a value of 0 or 1. Numbers indicate correlation coefficients.
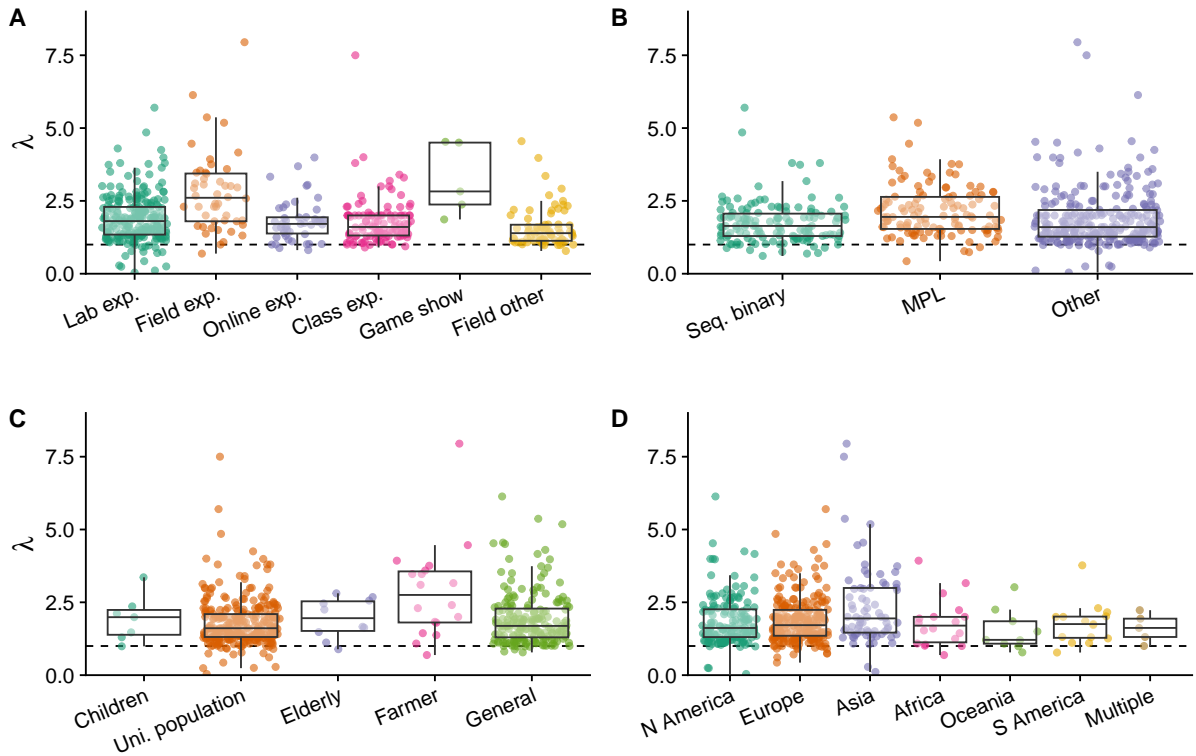
FIGURE D.10: Estimated loss aversion coefficient λ and study characteristics. (A) Type of data. (B) Elicitation method. (C) Subject population. (D) Location of data collection. *Notes*: The horizontal dashed line in each panel corresponds to $\lambda = 1$. The y-axis is cut off at 9 for visual clarity of lower numbers.

FIGURE D.11: Estimated loss aversion coefficient λ and study characteristics. (A) Definition of loss aversion coefficient. (B) Reference point. (C) Specification of u. (D) Reward type. (E) Publication status. (F) Journal discipline. *Notes*: The horizontal dashed line in each panel corresponds to $\lambda = 1$. The y-axis is cut off at 9 for visual clarity of lower numbers.
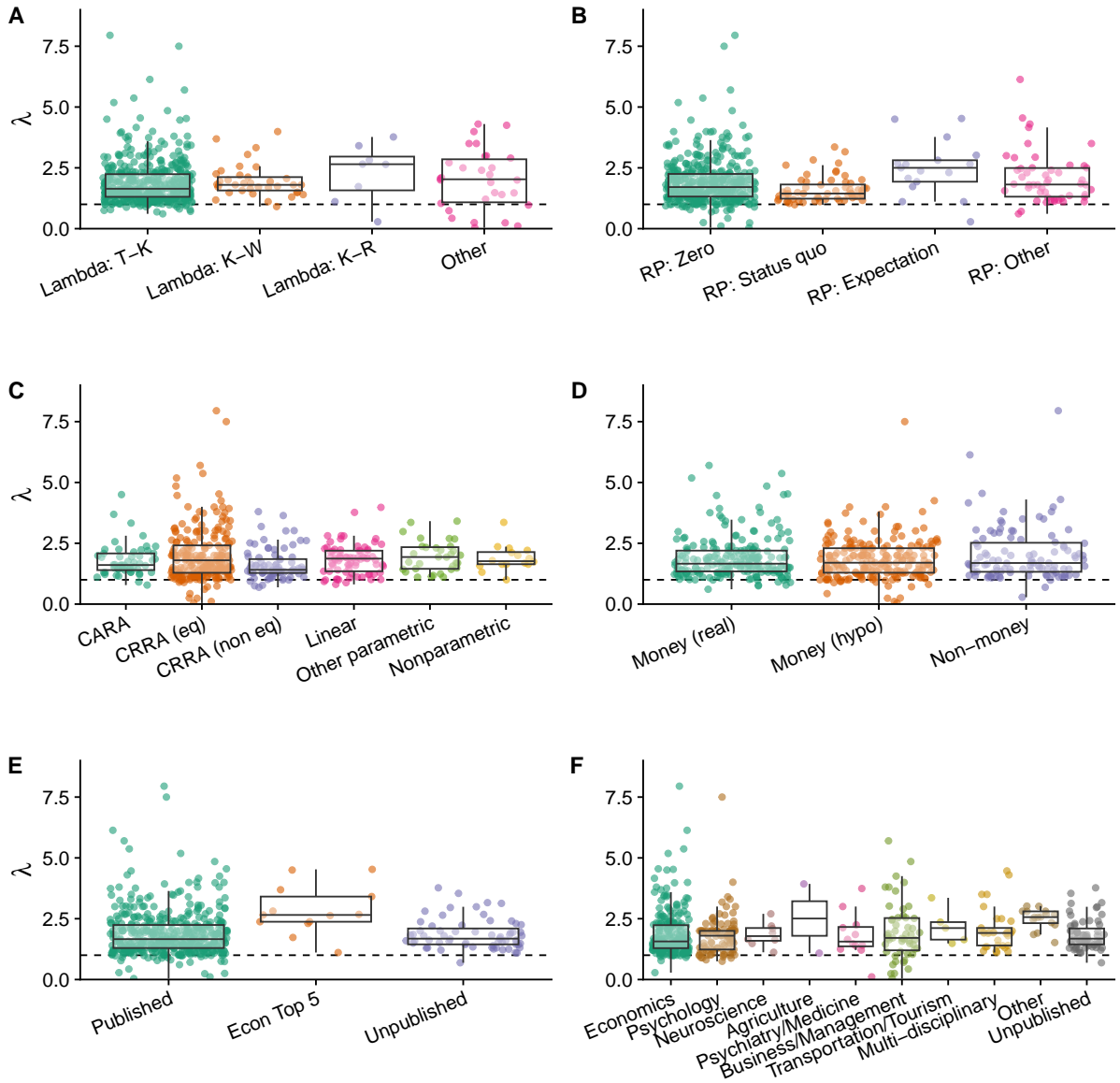
TABLE D.1: Meta-regression. Posterior distributions of coefficients (c.f. Figure 8).

Category	Variable	Median	2.5%	16.5%	83.5%	97.5%
Type of estimates	Individual-level mean			baseline		
	Individual-level median	−0.272	−0.382	−0.325	−0.222	−0.170
	Aggregate-level	−0.362	−0.602	−0.479	−0.249	−0.125
Type of data	Lab experiment			baseline		
	Field experiment	0.548	−0.014	0.284	0.802	1.072
	Classroom experiment	0.094	−0.486	−0.179	0.363	0.650
	Online experiment	−0.091	−0.623	−0.359	0.166	0.413
	Other field data	−0.225	−0.671	−0.444	−0.013	0.223
Subject pool	Univ. population			baseline		
	General	0.169	−0.135	0.025	0.314	0.475
	Farmer	0.400	−0.287	0.061	0.742	1.114
	Other	−0.075	−0.432	−0.251	0.097	0.284
Reward	Hypothetical money			baseline		
	Real money	−0.056	−0.337	−0.192	0.082	0.232
	Non-money	−0.125	−0.458	−0.287	0.035	0.205
Method	Binary choice			baseline		
	Survey	0.289	−0.284	0.018	0.550	0.818
	Matching	0.438	−0.864	−0.147	0.955	1.493
	Other	0.264	−0.012	0.129	0.399	0.541
Functional form of U	CRRA (same curvature)			baseline		
	CRRA (diff curvature)	−0.101	−0.392	−0.245	0.049	0.213
	CARA	0.100	−0.382	−0.135	0.328	0.544
	Linear	0.194	−0.180	0.021	0.362	0.535
	Other	−0.098	−0.481	−0.281	0.080	0.265
Reference point	Zero			baseline		
	Status quo	0.046	−0.311	−0.125	0.205	0.377
	Expectation	0.070	−0.730	−0.298	0.487	0.967
	Other	−0.054	−0.409	−0.224	0.107	0.276
Definition of λ	Tversky-Kahneman			baseline		
	Köbberling-Wakker	0.246	−0.226	0.025	0.451	0.660
	Kőszegi-Rabin	0.475	−0.661	−0.056	0.993	1.545
	Other	−1.068	−1.583	−1.313	−0.802	−0.483
	Unknown	−0.654	−1.385	−0.991	−0.335	−0.004
Continent	Europe			baseline		
	North America	−0.035	−0.197	−0.114	0.046	0.132
	Asia	−0.049	−0.152	−0.098	0.001	0.054
	South America	−0.046	−0.244	−0.143	0.058	0.179
	Africa	−0.190	−0.443	−0.313	−0.060	0.091
	Oceania	−0.403	−0.622	−0.504	−0.308	−0.205
	Multiple	0.039	−0.401	−0.136	0.217	0.479
	Unknown	−0.335	−1.053	−0.675	0.000	0.345
Publication status	Published (econ)			baseline		
	Published (non-econ)	0.000	−0.295	−0.143	0.143	0.292
	Unpublished	−0.248	−0.670	−0.453	−0.051	0.153

E   Frequentist Meta-Analysis

The random-effects meta-analysis (DerSimonian and Laird, 1986) assumes that

$$\lambda_i = \mu_i + \varepsilon_i = \lambda_0 + \xi_i + \varepsilon_i, \tag{E.1}$$

where $\varepsilon_i \sim \mathcal{N}(0, se_i^2)$ is a sampling variation of λ_i as an estimate of μ_i, and the observation-specific "true" effect μ_i is decomposed into λ_0 (the overall mean) and the sampling variation ξ_i. It is assumed that $\xi_i \sim \mathcal{N}(0, \tau^2)$, where τ^2 is the genuine heterogeneity, beyond the mere sampling variance, that must be estimated. Note that the random-effects model (E.1) reduces to the fixed-effect model when $\tau^2 = 0$. The random-effects estimate of λ_0 is calculated by the weighted average of individual estimates:

$$\lambda_0^{RE} = \frac{\sum_{i=1}^m g_i \lambda_i}{\sum_{i=1}^m g_i},$$

where the weight is given by $g_i = 1/(se_i^2 + \hat{\tau}^2)$ and $\hat{\tau}^2$ is the estimate of τ^2. As we explained in Section C.1 above, the model (E.1) is mathematically equivalent to model M1a. Note also that our dataset includes *statistically dependent* estimates. In order to account for such dependency, we use cluster-robust variance estimation to account for the correlation of estimates among each study (Hedges, Tipton and Johnson, 2010).

We also apply three-level modeling to handle statistically-dependent estimates. Let λ_{pi} denote the ith estimate of λ from paper p. The first level is $\lambda_{pi} = \mu_{pi} + \varepsilon_{pi}$, where μ_{pi} is the "true" loss aversion coefficient and $\varepsilon_{pi} \sim \mathcal{N}(0, se_{pi}^2)$ for the ith estimate in paper p. The second level is $\mu_{pi} = \overline{\lambda}_p + \xi_{pi}^{(2)}$, where $\overline{\lambda}_p$ is the average loss aversion in paper p and $\xi_{pi}^{(2)} \sim \mathcal{N}(0, \tau_{(2)}^2)$. Finally, the third level is $\overline{\lambda}_p = \lambda_0 + \xi_p^{(3)}$, where λ_0 is the population average of λ and $\xi_p^{(3)} \sim \mathcal{N}(0, \tau_{(3)}^2)$. These equations are combined into a single model:

$$\lambda_{pi} = \lambda_0 + \xi_{pi}^{(2)} + \xi_p^{(3)} + \varepsilon_{pi}. \tag{E.2}$$

We estimate a random-effects model (C.1) and a multi-level model (E.2). Results are presented in Table E.1: columns (1) and (2) use the subset of data where both λ and SE are reported (or reconstructed from other available information), and columns (3) and (4) use the full data where missing SEs are imputed as described above.

Random-effects estimate shows the average loss aversion coefficient between 1.7 and 1.8. The null hypothesis of no loss aversion (i.e., $H_0 : \lambda = 1$) is rejected at the conventional 5% significance level. We also look at the I^2 statistic (Higgins and Thompson, 2002), which measures the amount of heterogeneity relative to the total amount of variance in the observed effects.

TABLE E.1: Meta-analytic average of loss aversion coefficient.

	SE reported		All data	
	(1) Random-effects	(2) Multi-level	(3) Random-effects	(4) Multi-level
λ_0	1.7124	1.8854	1.8088	1.9373
	(0.0874)	(0.0811)	(0.0761)	(0.0669)
$\hat{\tau}^2$	0.5074		0.5562	
$se(\hat{\tau}^2)$	(0.0432)		(0.0386)	
I^2	99.5940		99.5408	
I^2 (within paper)		15.4056		34.0376
I^2 (between paper)		84.2991		65.5952
Observations	352	352	521	521
Clusters	114	114	150	150

Notes: Standard errors in parentheses are cluster-robust (Hedges, Tipton and Johnson, 2010). For observations which have both individual-level mean and median, we keep the median. Columns (1)-(2), "SE reported", use the complete dataset where SEs are reported in the paper. Columns (3)-(4), "All data", use the full dataset where missing SEs are approximated from available information or imputed. One observation with $\lambda = 23.46$ (the maximum value in the dataset) is excluded because the very large imputed SE produces an error in the estimation code.

Formally, the I^2 statistic is computed by

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

where $\hat{\tau}^2$ is the estimated value of τ^2 and

$$s^2 = \frac{(m-1) \sum g_i}{(\sum g_i)^2 + \sum g_i^2}$$

is the "typical" sampling variance of the observed effect sizes, where $g_i = 1/se_i^2$. We observe that 99% of the total variability in estimates is due to between-observation heterogeneity.

Taking into account the hierarchical structure of our dataset, the multi-level model provides an average loss aversion coefficient of about 1.9, which is slightly higher than the random-effect estimates discussed above. The heterogeneity measure I^2 adapted to the multi-level specification shows that 84% of the total variance is due to between-paper heterogeneity, 15% is due to within-paper heterogeneity, and the rest (less than 1%) is sampling variation (column (2)). The contribution of between-paper heterogeneity decreases to 66% when we use the full dataset with imputed standard errors (column (4)).

F Peer Prediction

During one of the early presentations of this paper at the Economic Science Association World Meeting in Vancouver in July 2019, we elicited guesses of our meta-analytic mean estimate of the loss aversion coefficient λ. We incentivized the audience to guess correctly with a CA\$50 dollar prize for the closest guess. See Figure F.2 for the entry form.

We collected 37 guesses from the audience, and 34 participants also reported their confidence levels (low, medium, or high). The summary statistics of guessed mean and median are presented in Table F.1. Of the 34 answers, 20 (58.8%) reported low confidence in their guesses, and only one reported high confidence. The distributions of guessed means and medians by their confidence level are shown in Figure F.1.

TABLE F.1: Summary statistics of guessed mean λ and median λ.

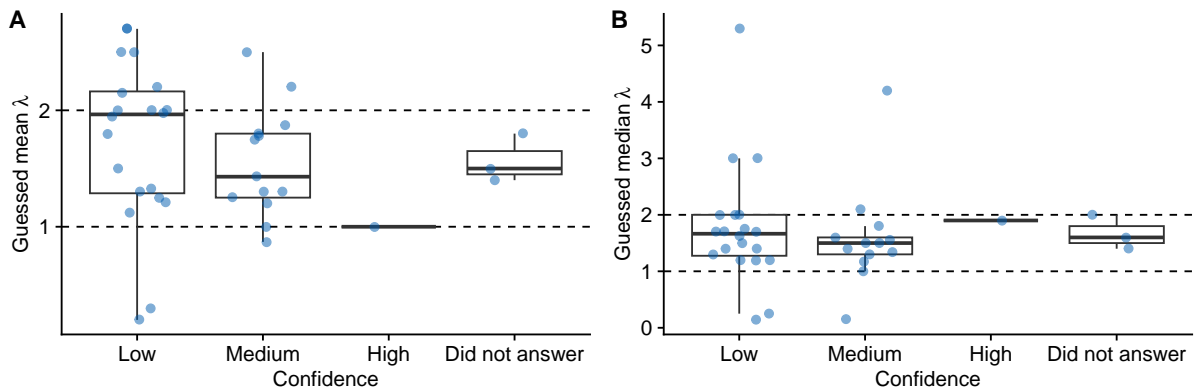| Guessed statistic	n	Mean	SD	Q1	Median	Q3	Min	Max
Mean λ	37	1.639	0.599	1.250	1.750	2.000	0.200	2.700
Median λ	37	1.700	0.952	1.300	1.560	1.900	0.140	5.300

FIGURE F.1: Boxplots of guessed mean λ (A) and median λ (B) by confidence level.

World ESA Vancouver
5 July 2019
Colin F Camerer talk

Meta-analysis prediction:
$50 CAD
each for most accurate mean and median guesses

What is the best *aggregate* estimate of the mean and median of loss aversion coefficient λ (will come from multiple estimates from 79 studies with reported standard errors and 52 with inferred standard errors)? No correction for publication bias or Hierarchical Bayes.

Mean ⎯⎯⎯⎯⎯⎯⎯   **Median** ⎯⎯⎯⎯⎯⎯⎯

Confidence (circle one)
Low   Medium   High

Name ⎯⎯⎯⎯⎯⎯⎯⎯⎯⎯⎯⎯
(can be anonymous; **name is needed if you want to get paid if you are most accurate**)

FIGURE F.2: Prediction entry form.

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