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Individual Discount Rates: A Meta-Analysis of the Experimental Evidence

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Abstract:

We examine 434 estimates of the individual discount rate reported in 27 published studies. The estimates vary substantially across studies with reported mean at the value of 0.4. We detect presence of selective reporting in the discounting literature using a meta-analytical methods. Our results suggest that relevant discounting literature overestimates the discount rate approximately twofold. We apply Bayesian model averaging to explain heterogeneity in the estimates. Discount rate estimates are influenced mainly by the experimental design used for its elicitation. We confirm domain independence and the effect of time horizon presented within the discounting task. Our results support the external validity of experiments conducted on student samples and the utilisation of hypothetical rewards in experiments.

JEL Classification: D01, C83, C90

Keywords: Discount rate, Discounting, Experiment, Publication bias, Meta-Analysis, Bayesian Model Averaging

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1 Introduction

Most important decisions on the private as well as public level often involve intertemporal choices and tradeoffs as decisions of today influence the future. Correct evaluation of future impacts of those choices on our well-being is crucial. Economic decisions intervene into various individual domains such as health, education, savings or business, but also into public domains such as government interventions, policies and social projects. Welfare analyses often involve non-monetary aspects for which a social discount rate is more applicable than a standard financial market discount rate. Climate change policies such as the ones over the social cost of carbon are one of the typical examples of long-term issues where benefits from policy-induced improvements can be considered as future impacts and where discounting of future costs and benefits plays a crucial role (Tol, 1999; Goulder and Stavins, 2002; Fujii and Karp, 2008; Anthoff et al., 2009).

Intertemporal preferences can be either observed empirically from the data set such as in (Lawrance, 1991; Warner and Pleeter, 2001; Dreyfus and Viscusi, 1995) or measured experimentally (Benzion et al., 1989; Chapman and Elstein, 1995; Coller and Williams, 1999; Harrison et al., 2010). Controlled economic experiments provide a natural framework to study time discounting in both laboratory and field conditions by enabling researchers to systematically vary the parameters to infer decision makers' preferences. Researchers of both economics and psychology fields have therefore devised various methods to experimentally measure intertemporal preferences described by the discounted-utility model (Samuelson, 1937). Despite different experimental methods available for eliciting time preferences there is no consensus on how to best measure discounting (Andreoni et al., 2015). Moreover, the discount rate is subjective to individual time preferences and its estimates vary greatly throughout the literature (Frederick et al., 2002; Coller and Williams, 1999).

We therefore collect 434 experimental estimates of the discount rate reported in 27 primary studies and review the literature quantitatively by a meta-analytical methods. Using a combined conditional estimator according to Stanley and Doucouliagos (2014) We explore the data for the presence of selective reporting, a phenomenon found to be widespread also in economics (Doucouliagos and Stanley, 2013). Furthermore, we focus on explaining the heterogeneity in discount rate estimates. Concentrating on aspects related to study design, methodology or subject pool characteristics we collect a set of 20 additional explanatory variables out of the primary studies and employ techniques of Bayesian model averaging (BMA, Raftery et al., 1997). By employing the BMA we address the model uncertainty inherent in meta-analysis and attempt

to establish whether these aspects systematically affect the reported estimates of the discount rate.

Our results suggest that a selective reporting is present within the relevant subsample of discounting literature. Published studies report only small estimates of the discount rate with high statistical precision, overestimating the discount rate parameter approximately twofold. Variation in estimates seem to be caused primarily by the experimental design of discounting tasks. We especially find the domain independence (Loewenstein et al., 2003), confirming the decisions made within domains of health or vacation being independent among each other, and also find that the time horizon of the task presented to subjects has an impact on resulting discount rate estimates.

Interestingly, we do not confirm several potential problems typically pointed out with respect to economic experiments. First, student subject pools tested in laboratories for discounting yield similar results as general population in large field experiments, disproving the rejection of external validity of experiments conducted on student samples. Second, real rewards do not significantly change discount rate estimates suggesting that hypothetical rewards are sufficient for collection of discount rate data.

The remainder of the paper is structured as follows. Section 2 reviews basic concepts of discounted-utility model and discusses the methods of discount rate elicitation. Section 3 describes our approach to data collection and presents the overview of our data set. Section 4 examines the selective reporting using meta-regressions. Section 5 investigates the sources of heterogeneity in the estimated discount rate parameters. Section 6 concludes. There are supplementary statistics and diagnostics of both meta regressions and BMA as well as various robustness checks to the analyses available in the appendices.

2 Estimating Discount Rate

Theory on intertemporal choice and discounting dates back to Irving Fisher's *Theory of Interest* (Fisher, 1930) and Paul Samuelson's article *Note on Measurement of Utility* where he postulated the discounted-utility model (Samuelson, 1937). His model was widely accepted with its central idea that concentrates various decisions about intertemporal choices into single parameter—the discount rate. Several modifications to the original discount functions was introduced since its origin to capture various irregularities such as hyperbolic (Ainslie, 1975; Mazur, 1984) or quasi-hyperbolic (Phelps and Polak, 1968; Laibson, 1997) discounting functions. The central idea however remains unchanged.

This study does not provide a complete and critical review of neither the basic model nor further proposed modifications, we merely briefly mention its basic concepts that are used in vast literature related to our study. For more detailed regard we refer an interested reader to standard economics textbooks or other survey literature, especially to Andersen et al. (2014) or Frederick et al. (2002) and Cheung (2016).

Discounted utility model captures the time preferences of an individual, more specifically the preference of an individual for immediate utility over delayed utility, represented by her intertemporal utility function $U^t(c_t, \dots, c_T)$ that can be described by functional form in equation 1:

$$U^t(c_t, \dots, c_T) = \sum_{k=0}^{T-t} D(k) \cdot u(c_{t+k}), \quad (1)$$

where $D(k)$ is the discount function and $u(c_{t+k})$ is cardinal instantaneous utility function ¹ that can be interpreted as individual's well-being in period $t + k$. The discount function $D(k)$ represents the relative weight that an individual places in period t on her well-being in period $t + k$ and encompasses parameter δ that represents individual's *pure rate of time preference*, i.e. her discount rate. This discount function can have different functional forms.

The standard exponential model, a well-known simple functional form used in majority of practical applications, is captured by following equation 2:

$$D(k) = \frac{1}{(1 + \delta)^k} \quad , k \geq 0 \quad (2)$$

where the discount rate d is simply $d^E(k) = \delta$. The key feature of this model is that the discount rate d is constant over time, i.e. the rate at which an individual discounts future well-being between today and tomorrow is identical to the rate that discounts future well-being between today and tomorrow in one month. Widely documented situation in which an individual has declining rate of time preference, not constant, is described as hyperbolic discounting. This generally means that the implicit discount rate over longer time horizons is lower than the implicit discount rate over shorter time horizons. A typical case out of the family of hyperbolic discounting functions proposed by Mazur (1984) is described by equation 3:

$$D(k) = \frac{1}{1 + \delta k} \quad (3)$$

whith hyperbolic discount rate $d^H(k) = (1 + \delta k)^{\frac{1}{k}} - 1$ (Andersen et al., 2014).

¹Standard assumptions on instantaneous utility function are: $u(0) = 0$, $u'(c) > 0$, $u''(c) \leq 0$.

Phelps and Pollak (1968) further introduced a quasi-hyperbolic specification of the discount function for use in a social planner problem. This specification is described by equation 4:

$$D(k) = \begin{cases} 1, & \text{if } k = 0 \\ \frac{\beta}{(1+\delta)^k}, & \text{if } k \geq 1 \end{cases} \quad (4)$$

where $\beta \leq 1$ and quasi-hyperbolic discount rate $d^{QH}(k) = \left(\frac{\beta}{(1+\delta)^k}\right)^{-\frac{1}{k}} - 1$. Characteristic feature of the quasi-hyperbolic specification is the discontinuity at time $t = 0$. This specification was furthermore applied to model individual agent behavior by Laibson (1997).

Several experimental methods are available for eliciting time preferences in both laboratory and field settings such as lotteries, choice lists, or bidding, and yet there is no consensus how to best measure discounting (Andreoni et al., 2015). Basic method for eliciting individual discount rates is however fairly simple in its essence—asking subjects questions whether they prefer some sure amount of money today (option A) or the same amount + X\$ tomorrow (option B), where X\$ is some positive amount.² By variation of X a researcher can infer bounds of an interval in which lies the subject’s individual discount rate.³ Experiments therefore involve series of questions aligned in lists such as in the classical choice list design of (Coller and Williams, 1999) or (Harrison et al., 2002). Modifications to this basic method are further used to elicit preferences more precisely, such as variations in delay between options A and B, domain in which are the preferences revealed (money, health etc.), magnitude of the domain or nature of the rewards (hypothetical or real).

There are several types of elicitation methods according to Frederick et al. (2002) that are commonly used in the experimental literature: i) choice; ii) matching; iii) rating; iv) pricing. Most common type of elicitation is choice method where subjects are presented alternative options and are asked to simply choose between them. This method provides discount rate intervals pre-generated by the experimenter rather than precise estimates of the discount rate of specific individuals. Matching method, on contrary, provides an exact inference of individual’s discount rate since she reveals her true indifference point by filling the blank field to “*equate two intertemporal options*” (Frederick et al., 2002, p.387). In rating tasks the subjects evaluate individual options by rating their attractiveness on predefined scale while in pricing tasks subjects specify their willingness to pay for individual options in which they either obtain or avoid par-

²We use the domain of money in dollar units for this simple illustrative example.

³The point of first switch to option B gives a measure of upper bound of her discount rate. We assume linear utility here for simplicity and discuss the relax of this assumption later.

ticular outcome. Rating and pricing tasks allow to manipulate time variable between subjects since immediate and delayed options are evaluated separately in contrast to choice and matching tasks.

Each method briefly described above has its further strong points and limitations. When subjects are asked to choose or evaluate multiple options at once in a standard choice list, the first or earlier choices inevitably influence choices that are made later. This procedural limitation—an anchoring effect—can be partially dealt with by employing titration procedures—exposing subjects to a sequence of different opposing anchors (Frederick et al., 2002). Timing of an outcome was found to have much lower effect when evaluating single option compared to a situation when two options occurring in different times are evaluated at once against each other (Loewenstein, 1987). Timing of two evaluating options is further argued to cause more general problem of additional risk or transaction cost imposed on the future option. Recent literature such as Harrison et al. (2005); Andersen et al. (2014) and others deal with this risk by employing a front end delay, shifting thus the immediate option to some nearer future and imposing some transaction costs also on the instant payoff.

Harrison et al. (2005) argues that standard choice tasks often executed through Multiple Price Lists (MPL) devised originally⁴ by Holt and Laury (2002) has three possible disadvantages: i) eliciting only interval responses; ii) allowing subjects to switch back and forth while moving down the list; and iii) MPL can be subject to framing effects. They therefore introduce an *iterative Multiple Price List* (iMPL) that allows the subjects to specify iteratively their choices through refined options within an interval chosen in the last option.

Inference of the discount rates out of the experimental task is dependent on the utility function presented in discounted-utility model 1. This function is however unobserved and therefore usually assumed to be linear, generating biased estimates for individuals with non-linear utility functions (Cheung, 2016). Recent literature of Andersen et al. (2008, 2014) measure time preferences controlling for non-linear utility by employment of *joint elicitation strategy*. Using the equivalence of utility for risk and time they use series of binary choices to infer the discount function conditional upon utility function elicited through Holt and Laury (2002) risk preference task. Further modifications of the design to measure time preferences controlling for non-linear utility includes e.g. work of Laury et al. (2012) who interact risk with time by using a lottery to be paid out with probability p_t in time t and with probability p_{t+k} in time $t + k$, where $p_t \leq p_{t+k}$ and p_{t+k} is varying through the choice list.⁵ Further ex-

⁴The MPL was originally devised for measuring risk aversion, but used for measuring intertemporal preferences by Collier and Williams (1999) or Harrison et al. (2002)

⁵They assume expected utility under risk.

periments measuring time preferences under control for non-linear utility were done e.g. by Takeuchi (2011) who employs separate choices under risk and over time using matched pairs of payoffs; Andreoni and Sprenger (2012b,a); Andreoni et al. (2015) who examine risk and time preferences through individual elicitation methods—convex time budgets and double multiple price list tasks; or Attema et al. (2016) who introduces a *direct method* of measuring discounting that is not dependent on knowledge or measurement of utility.

An alternative method for inferring the discount rates was devised by Chabris et al. (2008b) who infer the intertemporal preferences not only from standard choice tasks but also adopt an approach of inferring preferences using response times from these choices, i.e. how long it actually takes subjects to choose between option A and option B. They assume that “*subjects should take longest to decide when the two options are most similar in their discounted values*” and therefore argue that the inference from response times should, in principle, work (Chabris et al., 2008b, p.7). Results of Chabris et al. (2008b) suggest⁶ that choice-based and response-time-based estimates are nearly identical in their setting.

3 Data Set

We combine two sources of primary studies into our dataset—we search google scholar⁷ for experimental discounting literature and furthermore go through references of retrieved studies for additional discounting studies that do not get into top search results. We do not include all studies from each source exclusively. We apply two basic inclusion criteria. Each study included into our dataset must be of experimental nature, either lab or field, and need to report estimate of discount parameter—rate or factor—or contain information allowing for its calculation. We do not explicitly require the study to report a measure of uncertainty but we always search for it and code it since it is crucial for our analysis, i.e. for measuring publication bias. Furthermore, we include only published studies since they are peer-reviewed and therefore assumed to be of better quality. We add the last study on October 11, 2018, and terminate the data collection. Our final dataset covers 27 studies comprising 434 estimates of the discounting parameter.⁸ The oldest study was published in 1989, the newest

⁶This paper was published in form of a working paper in NBER working paper series only.

⁷Google Scholar searches full text of studies in addition to the title, abstract, and keywords; search query: discount method experiment field “discount rate” OR “discount factor”

⁸We assembled 404 estimates of discount rate, either directly or calculated out of available data (e.g. regressions) and 30 estimates of discount factors from 1 study (Read and Read, 2004) that we recoded to rates according to corresponding discounting formulas. We use the term *discount rate* for all these

one in 2017, representing almost three decades of research in the area. Overview of reviewed studies is presented in Table 1.

Table 1: Studies included into dataset

Andersen et al. (2006)	Coller and Williams (1999)
Andersen et al. (2008)	Deck and Jahedi (2015a)
Andersen et al. (2014)	Deck and Jahedi (2015b)
Andreoni et al. (2015)	Dolan and Gudex (1995)
Bauer and Chytilová (2013)	Hardisty et al. (2013)
Benzion et al. (1989)	Harrison et al. (2002)
Cairns and der Pol (1997)	Harrison et al. (2010)
Cassar et al. (2017)	Duquette et al. (2012)
Chabris et al. (2008a)	McClure et al. (2007)
Chapman and Elstein (1995)	Newell and Siikamäki (2015)
Chapman (1996)	Read and Read (2004)
Chapman and Winqvist (1998)	Tanaka et al. (2010)
Chapman et al. (1999)	Zauberman et al. (2009)
Chesson and Viscusi (2000)	

Apart from collection of estimates of our cardinal variable—the discount rate and available measures of statistical uncertainty—we code additional explanatory variables to control for sources of variation in our data sample. We control for the type of the discounting estimate, that is whether the estimate was reported as discount rate or factor. We include the length of time horizon presented to the subjects in the experimental task or questionnaire.⁹ In order to be able to classify discount rate estimates to different types of discounting we include categorical variable describing whether the reported estimate is of hyperbolic or exponential discounting.¹⁰ We further control whether the study is done in the lab or in the field; if payoffs used in the study are only hypothetical or real, i.e. paid out to the subjects; which elicitation method (choice, matching, rating) and domain (money, health, etc.) is used for eliciting of specific estimate; and whether the framing of the task is positive (giving), negative (loosing) or neutral. We also control for standard essentials of subject pool by includ-

estimate types in the following text.

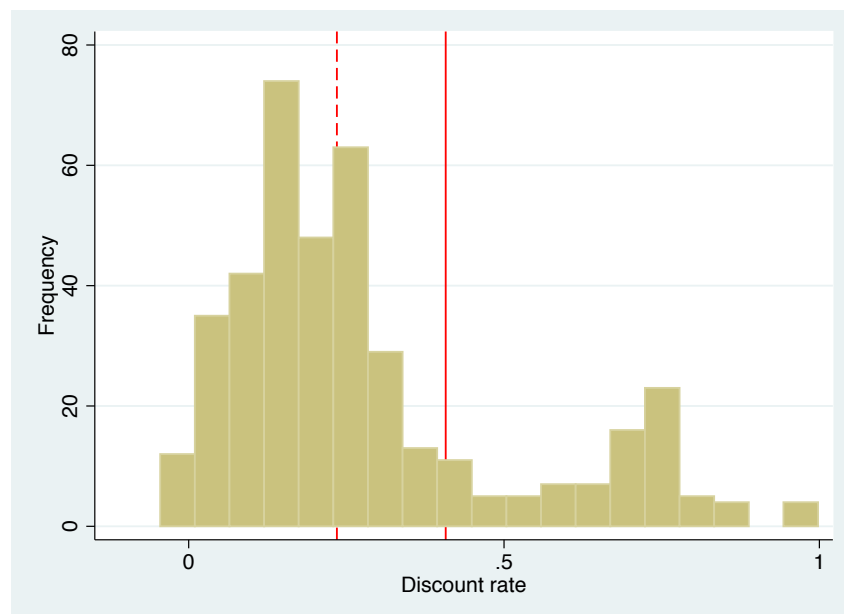
⁹Some studies vary time horizon holding the payoff constant. Such studies do not separate different time horizons into different treatments and therefore do not report exact time point in which the subjects made the switch. We therefore code the maximum horizon presented in the task and include dummy variable to control for this effect.

¹⁰We can not code discounting type in 59 observations due to lack of information. We further recognize exponential mixture share (1 case), quasi-hyperbolic discounting (3 cases) and mixed general model (1 case) in the dataset. We respectively recode these due to low rate of incidence as: exponential, hyperbolic, na.

ing the dummy variables for whether it contains students or professionals; gender of subjects it includes (m/f/both); and continent and country where the subject pool was hired. Additionally we look up publication information for each study that comprises of impact factor¹¹ and the number of Google citations that we weight by number of years since first version of the study. We describe and further use these additional variables in Section 5.

Discount rates in our dataset ranges from -0.035 to 8.930 , with mean value of 0.408 and standard deviation 0.659 . Histogram of the variable *discrate* with upper bound imposed on the 99th percentile of the date is presented in Figure 1. The distribution is highly left-skewed, with median value of 0.235 . Negative values of discount rate estimates are very rare, even though present, and exclusively a matter of health domain. The distribution thus have several outliers on both sides. We overcome potential influence of these outliers in our analysis by winsorization of discount rate¹² at 0.025 percentile level from each tail.

Figure 1: fig: Histogram of discount rate estimates



Notes: The figure depicts histogram of the discount rate estimates reported by individual studies. Extreme values are omitted from the graph ($\delta < 1$), but are accounted for in all regressions. Solid vertical line denotes the sample mean, dashed vertical line denotes the sample median.

¹¹We use Discounted recursive REPEC impact factor that can be retrieved at <https://ideas.repec.org/top/top.series.rdiscount.html>

¹²Together with combined standard errors of discount rate described farther in this paragraph.

Standard errors¹³ of the discount rate estimates are reported only in 252 observations out of 434 in our dataset. Researchers often claim that their true effect is indeed large and robust even though they do not support such claims by providing the standard errors of their estimates. We do not exclude such studies that do not report any statistical measure of uncertainty of the estimates; we apply Bootstrap resampling technique¹⁴ to those studies rather than exclude them to approximate estimates of standard errors at least on the study-level. We then combine data of standard errors from primary studies with bootstrapped standard errors on study-level into variable *discrate_se_comb* that is used in our subsequent analysis.¹⁵ Our results prove robust when we control for the effect of resampling. The subset of discount rates without reported uncertainty measures has the mean of 0.326 and standard deviation of 0.336. There is total of 197 observations out of 10 studies that does not provide any statistical measure of uncertainty of reported estimates in our dataset, which makes 45.39% of the standard errors being bootstrapped on study level. Summary statistics of selected variables are presented in Table 2. Study-level and country-level heterogeneity of discount rate estimates can be observed in Figures 2 and 3, respectively.

Table 2: Summary statistics of selected variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
discrate	434	0.408	0.659	-0.035	0.137	0.430	8.930
discrate_se	252	0.025	0.039	0.0001	0.008	0.026	0.390
discrate_se_comb	434	0.063	0.132	0.000	0.009	0.040	1.505

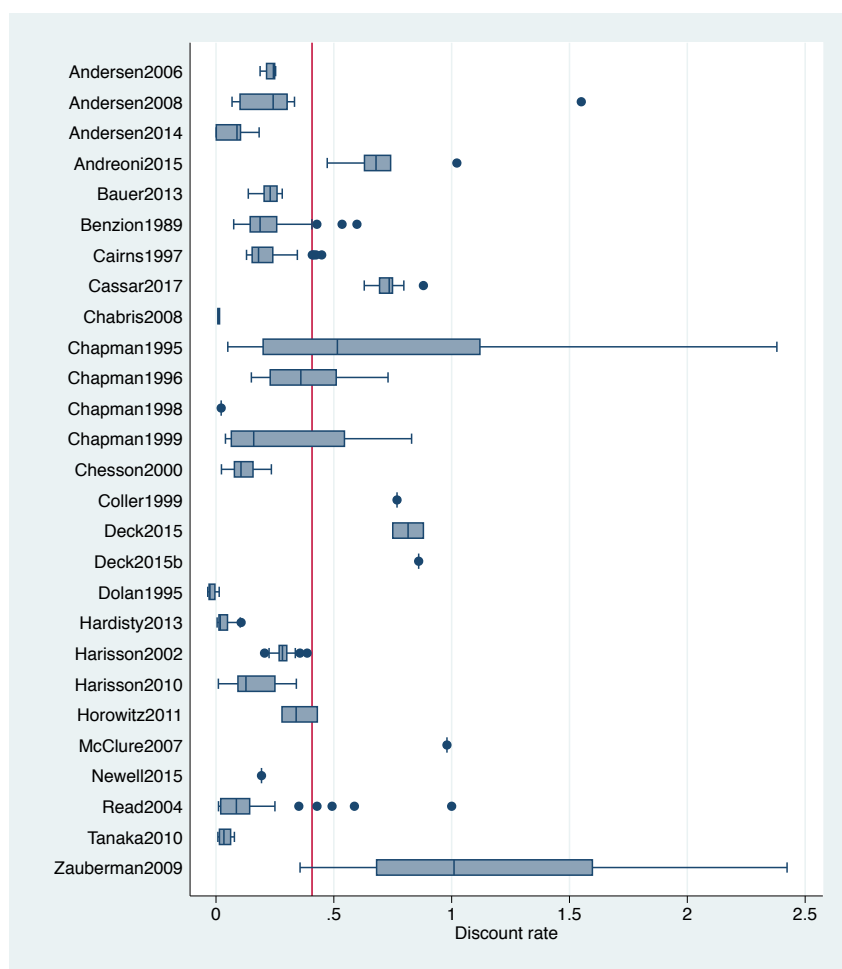
Notes: Following abbreviations stand for: *discrate* = discount rate; *win* = winsorized at $p = 0.025$; *comb* = combined with resampled std. errors.

¹³We recalculated other reported statistical measures of uncertainty to standard errors.

¹⁴We use *bootstrap* command in Stata 14.0, which we apply to discount rate data of each study separately, storing bootstrapped mean.

¹⁵There are two studies in our dataset that do not report any measure of statistical uncertainty and do not provide more than one observation per study. Resampling can be used for approximation of standard errors only if there are multiple observations per study, otherwise SE of resampled estimate is zero. For Coller and Williams (1999); Deck and Jahedi (2015b) we therefore obtain zero standard error approximations and consequently can not calculate precision of the estimates as $1/SE$. Further parts of our analysis that use weighting by precision of the estimate are therefore based on 25 studies only. This applies especially for Funnel plot of discount rate in Figure 4 and Funnel asymmetry tests in Table 3.

Figure 2: Study-level variation of discount rate estimates



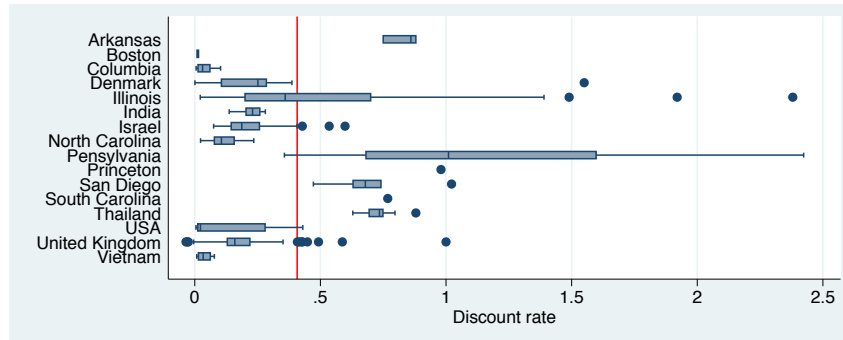
Notes: The figure shows a box plot of estimates of discount rate reported in individual primary studies (observations above the 99th percentile omitted). Red solid line represents sample mean.

4 Detection of Publication Bias

Selective reporting has been identified as serious threat to scientific validity.¹⁶ Researchers thrive for scientific publications and therefore tend to have strong preference for reporting statistically significant or “positive” results. Selective reporting was found to be widespread also in economics (Doucouliagos and Stanley, 2013). We hypothesize that discounting literature is no exception. Selective reporting is a general term for publication selection or bias, a special case that limit its essence to published studies only. We are more prone to the term publication bias since we include only

¹⁶See for example Stanley and Doucouliagos (2014); Havranek et al. (2018b) and others for lists of references that address to selective reporting.

Figure 3: fig: Country-level variation of discount rate estimates



Notes: The figure shows a box plot of estimates of discount rate reported in primary studies executed in individual countries (observations above the 99th percentile omitted).. Red solid line represents sample mean.

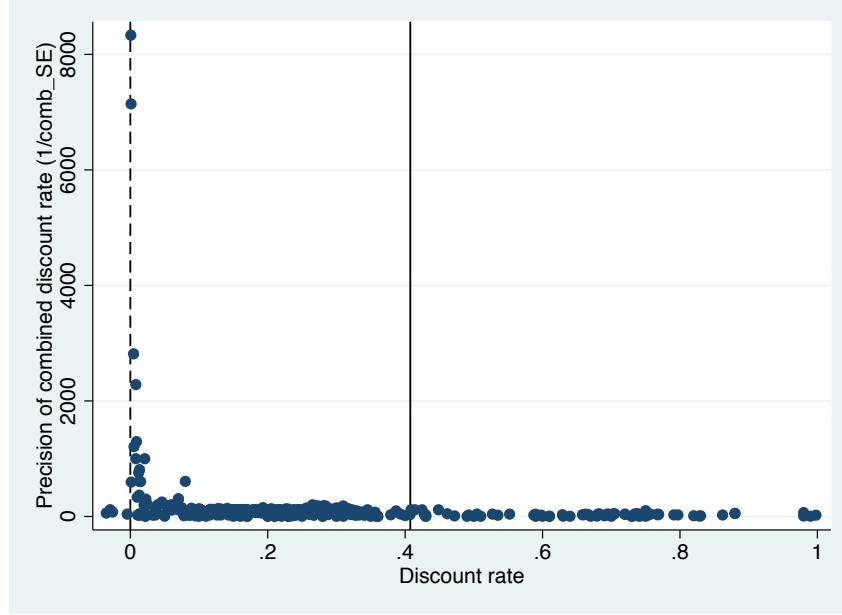
published studies into our dataset and therefore use this term thenceforth.

Discount rate express intertemporal preferences of an individual—the lower the discount rate, the more patient one is and vice versa. General belief among economists and psychologists is that the discount rate estimates should be positive¹⁷ between zero and one, with a tendency to impatience. Estimates outside this range together with statistically insignificant estimates are therefore reported rarely in the literature. Our sample mean of 0.408 indeed implies such expectations. One would further expect that there would be certain portion of estimates reported with appropriate statistical precision in an empirical literature, which the discounting one certainly is. Figure 4 however shows different pattern. It is a so-called funnel plot that commonly serves as a visual representation of publication bias (Egger et al., 1997; Stanley and Doucouliagos, 2010). This simple scatter plot with the effect’s magnitude on the horizontal axis and the inverse of the standard error—its precision—on the vertical axis, shows that researchers report precise data of discount rate almost exclusively for small effect sizes only and that high effect sizes of discount rate are associated with low statistical precision. This fact certainly suggest presence of publication bias in our sample of discounting data (Stanley, 2005; Stanley and Doucouliagos, 2014).

Next, we examine correlation between the discount rate estimates and their standard errors quantitatively to test for presence of publication bias. Following Stan-

¹⁷Sign of discount rate estimate depends highly on the framing of experimental task—gains having generally positive sign while losses related specifically to health domain tend to report negative sign of the estimate. Negative estimates are, however, rare in our sample, the funnel plot is asymmetric denoting only positive side of the graph since the majority of experimental tasks are offering monetary gains (77, 19%).

Figure 4: Funnel of discrete



Notes: The figure depicts funnel plot of the discount rate estimates. Extreme values are omitted from the graph ($\delta < 1$), but are accounted for in all regressions. Solid vertical line denotes the sample mean. Based only on 25 studies due to inability of calculation of precision for Collier and Williams (1999); Deck and Jahedi (2015b), more information in footnote 15.

ley and Doucouliagos (2014) we apply a combined conditional estimator *PET-PEESE*. First, we test $H_0 : \hat{\delta}_1 = 0$ by a simple meta-regression model used by Egger et al. (1997)—the *Egger* or *precision-effect* test in equation 5:

$$\hat{\delta}_{ij} = \delta_1 + \gamma_1 \cdot SE(\hat{\delta}_{ij}) + u_{ij}, \quad (5)$$

where $\hat{\delta}_{ij}$ is the i -th estimate of the discount rate and $SE(\hat{\delta}_{ij})$ is its corresponding standard error of the j -th study; u_{ij} is the disturbance term. The precision-effect test (PET) “provides a valid basis for determining whether there is a genuine empirical effect beyond publication selection bias” (Stanley and Doucouliagos, 2014, p.64) and is known to give biased estimates of the underlying true effect when this is non-zero (Stanley, 2008). First part of Table 3 shows results of PET test for various model specifications; we cluster standard errors at the study level in all of them. We obtain positive and statistically significant estimate of γ_1 —the coefficient that represents publication bias—in all specifications. The underlying discount rate corrected for the bias represented by the coefficient δ_1 is 0.258 in OLS specification, which is about 62% of original mean

of our sample (0.408). Such result is consistent with the rule of thumb suggested by Ioannidis et al. (2017) and indicates strong publication bias. We do not obtain statistically significant underlying effect when controlling for study-specific characteristics by study-level fixed effects.

Table 3: Funnel asymmetry tests

PET tests	OLS	FE	Precision	Study
<i>SE</i> (publication bias)	1.923** (0.569)	5.046*** (0.836)	4.958** (1.718)	1.661*** (0.491)
Constant (corrected effect)	0.258*** (0.0615)	0.0790 (0.0479)	0.0796* (0.0352)	0.313*** (0.0703)
Observations	434	434	432	434
PEESE tests	OLS	FE	Precision	Study
SE^2 (publication bias)	5.173** (1.845)	15.17* (6.189)	10.36** (3.487)	4.821** (1.564)
Constant (corrected effect)	0.310*** (0.0724)	0.198** (0.0694)	0.114** (0.0415)	0.350*** (0.0672)
Observations	434	434	432	434

Notes: The table reports results of the regressions 5 (PET test) and 6 (PEESE test). All variables winsorized at $p = 0.025$. The standard errors of the regression parameters are clustered at the study level and shown in parentheses. OLS = ordinary least squares, FE = study-level fixed effects. Precision = weighted by the inverse of the standard error. Study = weighted by the inverse of the number of estimates reported per study. Weighting by the precision of the study based only on 25 studies due to inability of calculation of precision for Coller and Williams (1999); Deck and Jahedi (2015b), more information in footnote 15. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$.

Since the equation 5 contains heteroskedasticity,¹⁸ we further use weights in order to estimate the meta-regression model in line with Stanley and Doucouliagos (2014). First, we use *precision* of the estimate, i.e. $1/SE$, as weights. This approach gives more weight to more precise results, but there is an important caveat in this weighting scheme. Estimation of standard errors is in economics often an important feature of the model and weighting by precision can create bias by itself in case the study underestimates the standard error. We therefore use also the inverse of the number of estimates reported per study as second weight (*study*). This approach equalizes the impact that each study has on the results. Both weighting schemes yield positive and significant results for both publication bias as well as corrected effect. Weighting by

¹⁸There is apparent heteroskedasticity in the baseline regression, since the standard error of the discount rate estimate, i.e. the independent variable, is a measure of the dispersion of the magnitude of the estimate of the discount rate, i.e. dependent variable.

the inverse per study estimates gives milder effect on the corrected discount rate resulting in about 76% of the original mean of our sample.

Regardless of insignificances described above, Table 3 implies rejection of the PET hypothesis and indicate that the true effect in the equation 5 is indeed non-zero. Since the true model of the selective reporting is an undisclosed complex function of the standard errors, Stanley and Doucouliagos (2014) examines a quadratic approximation that yields very good results. We therefore apply a second step in line with Stanley and Doucouliagos (2014) in our analysis of discounting literature—a conditional, weighted quadratic estimator of precision-effect estimate with standard errors (PEESE), described in equation 6:

$$\hat{\delta}_{ij} = \delta_2 + \gamma_2 \cdot SE^2(\hat{\delta}_{ij}) + u_{ij}, \quad (6)$$

where δ_1 from equation 5 is constrained to zero.

Second part of the Table 3 reports results of equation 6 in different specifications. We again cluster standard errors of all regressions on the study-level since estimates reported in the same study are unlikely to be independent. All model specifications yield positive and significant results of publication bias as well as underlying corrected effect. Numerically are our results consistent with the true effect of the discount rate between 0.11 and 0.35 compared to the original mean of the data being 0.408. Relevant discounting literature therefore overestimates the discount rate parameter due to the publication bias approximately twofold.¹⁹ This degree suggests a strong publication bias according to the rule of thumb presented by Ioannidis et al. (2017). Our results prove to be robust when controlling for resampling of missing standard errors. Table 6 in the appendix provides results of meta-regressions performed on observations with reported uncertainty measures.

5 Heterogeneity in Estimates

Heterogeneity in estimates of the discount rate was described by previous studies (Frederick et al., 2002; Andersen et al., 2014; Cheung, 2016). Frederick et al. (2002, p.352) claims that: *"While the DU model assumes that people are characterized by a single discount rate, this literature reveals spectacular variation across (and even within) studies."* Our dataset is no exception—Figures 2 and 3 show that we observe strong heterogeneity on both study-level as well as country-level. In this section we try to tackle the problem and explain high variation in estimates by analysing discount rates and their

¹⁹Average true effect resulting from different specifications is $0.11 + \frac{0.35-0.11}{2} = 0.23$, being approximately one half of the reported mean estimate of the discount rate.

standard errors together with additional 20 explanatory variables we have coded out of the examined studies.

Common approach would be to estimate model with all explanatory variables by some standard regression technique (OLS) and eliminate potential redundant variables in a step-wise fashion. This method would however not prove its usefulness in our case since standard errors of many coefficients in such regression would be exaggerated and therefore would not provide good-enough basis for elimination. Furthermore, even though there are some theoretical predictions stemming from the discounting literature regarding the decisions about variables that could be included in the model, we gathered a lot of information that would be hard to classify. It would be hard to identify a proper set of variables, since we face extensive model uncertainty. We therefore search for some technique that can address this uncertainty inherent in a meta-analysis—we estimate the heterogeneity of our dataset by Bayesian model averaging (Raftery et al., 1997).

Bayesian model averaging (BMA) tackles the problem of uncertainty by estimating models for all possible combinations of explanatory variables in the dataset²⁰ and constructing a weighted average over estimated coefficients (posterior means) across all these models. Weights used for averaging stem from posterior model probabilities arising from Bayes' theorem and are analogous to information criteria in frequentist econometrics. Posterior model probabilities (PMP) measure how well the particular model fits the data conditional on model size. BMA produces posterior inclusion probability (PIP) for each variable, which is the sum of the posterior model probabilities for the models in which the variable is included. Recent application of Bayesian model averaging in meta-analyses in economics and finance comprise of e.g. Havranek et al. (2015b, 2017); Havranek and Irsova (2017); Havranek et al. (2018a,b). More details on BMA can be found e.g. in Raftery et al. (1997) or Eicher et al. (2011).

Application of BMA is however not straightforward since estimating all possible combinations of models with standard available technology becomes infeasible starting from already a few number of variables. Typical approach is to approximate the whole model space by applying the Markov chain Monte Carlo Model Composition algorithm that walks only through the models with high posterior model probabilities (Madigan et al., 1995). This approximation can be done relatively simply by using the BMA R package developed by Zeugner and Feldkircher (2015). We take advantage of this package and estimate the model space using $2 \cdot 10^6$ iterations and $1 \cdot 10^6$

²⁰If matrix of explanatory variables X contains K potential variables, this means estimating 2^K variable combinations, i.e. 2^K models. This result in $2^{21} = 2097152$ models in our case, since we coded the discount rate, its standard errors (1) and 20 additional variables.

burn-ins to ensure convergence.²¹ Bayesian model averaging is sensitive to estimation framework, especially to the use of *priors* representing researcher’s prior beliefs on probability of each model (the model prior) and regression coefficients (Zellner’s g-prior). In the baseline specification we decide to follow Eicher et al. (2011) who show that these intuitive priors yield the best predictive performance: we use the unit information prior (“UIP”) for Zellner’s g-prior that assigns the prior weight of one data observation; and the uniform model prior that gives each model the same prior probability.²²

5.1 Variables Explaining Heterogeneity

We have coded 20 additional explanatory variables that should help us to explain the heterogeneity in discount rate estimates. The explanatory variables are listed in Table 4; we report description of each variable, its mean, standard deviation, and mean weighted by the inverse of the number of estimates reported per study, which effectively equalizes the impact of small and large study samples. We divide the explanatory variables into 4 categories: Estimation characteristics, Experimental characteristics, Subject pool characteristics, and Publication characteristics.

5.1.1 Estimation Characteristics

Variation of discount rate estimates can in the first instance stem from theoretical assumptions of intertemporal choice model used in the experimental task presented to subjects. That is mainly from type of discounting model and time horizon that subjects face in their decision. We provide survey of discounting models in Section 2. Research studies included in our dataset report hyperbolic discounting model most frequently (281; 65%), followed by exponential discounting model (89; 20%). Special cases of discounting models such as exponential mixture share, quasi-hyperbolic discounting or mixed general model occur rarely in our dataset (5 cases in total). We could not identify discounting model in non-negligible 14% of the data (59) and use it as the reference category. Time horizon of the decisions presented to the subjects spans from one day to 50 years, while its mean value is 5.01 years. We therefore apply logarithm value to this variable in order to dispose of scale effect. Some studies, however, vary time hori-

²¹Regarding iterations (I) and burn-ins (B) of BMA we compared three scenarios: i) $I = 10 \cdot 10^5$, $B = 5 \cdot 10^5$; ii) settings indicated above and finally used in the analysis; and iii) $I = 10 \cdot 10^6$, $B = 5 \cdot 10^6$. All scenarios yielded very similar results.

²²Robustness check using benchmark g-prior for parameters suggested by Fernández et al. (2001) and the beta-binomial model prior for the model space according to Ley and Steel (2009) can be found in the appendix C

Table 4: Summary of explanatory variables

Variable	Description	Mean	SD	WM
discrate	Discount rate estimate.	0.407	0.659	0.072
discrate_se_comb	Standard error of the discount rate estimates combined with resampled standard errors.	0.063	0.132	2.789
<i>Estimation characteristics</i>				
disc_factor	= 1 if reported variable is discount factor instead of rate.	0.069	0.254	0.033
hyperbolic	= 1 if discounting type estimated is hyperbolic.	0.654	0.476	0.046
exponential	= 1 if discounting type estimated is exponential.	0.207	0.406	0.071
ln_timelength	Logarithm of time horizon of the task.	0.721	1.529	-0.022
idtimehorizon	= 1 if only maximum time horizon of the task could be coded for observation.	0.357	0.480	0.083
method_exp	= 1 if controlled laboratory experiment was used instead of a field experiment.	0.764	0.425	0.056
<i>Experimental characteristics</i>				
reward_real	= 1 if the reward subjects received was real.	0.384	0.487	0.109
elicmethod_match	= 1 if matching was used as a method of elicitation.	0.495	0.501	0.029
domain_health	= 1 if experiment was conducted over the domain of health.	0.105	0.308	0.062
domain_other	= 1 if experiment was conducted over other domain (vacation, liquid or certificate).	0.096	0.296	0.057
framing_negative	= 1 if framing of the experimental task was presented as negative, i.e. losing.	0.041	0.200	0.122
framing_neutral	= 1 if framing of the experimental task was presented as neutral.	0.027	0.164	0.062
<i>Subject pool characteristics</i>				
ln_samplesize	Logarithm of the sample size used for the experiment.	4.796	0.752	0.062
students	= 1 if subject pool consisted of students.	0.375	0.485	0.069
male	= 1 if subject pool contained male subjects only.	0.025	0.157	0.051
female	= 1 if subject pool contained female subjects only.	0.029	0.171	0.061
continent_namerica	= 1 if experiment was conducted in North America.	0.306	0.462	0.112
continent_asia	= 1 if experiment was conducted in Asia.	0.110	0.314	0.062
<i>Publication characteristics</i>				
ln_google_per_year	Logarithm of the number of citations the study received in Google Scholar.	2.739	1.340	0.058
std_pubyear	Standardized publication year of the study.	0.000	1.001	NA

Notes: SD = standard deviation, WM = mean weighted by the inverse of the number of estimates reported per study.

zon holding the payoff constant and therefore do not separate different time horizons into different treatments. Since such studies do not report exact time point in which the subjects made the switch, we cannot always distinguish the exact time horizon corresponding to the estimate. We therefore code at least the maximum time horizon presented to subjects in the task and include dummy variable to control for the effect of this inconsistency in the data. Last but not least we control for an experimental method of estimation—i.e. if controlled laboratory experiment or a field experiment was used in the certain study.

5.1.2 Experimental Characteristics

Any experiment can be affected by procedural subtleties. Second set of explanatory variables therefore comprise of experimental and behavioral characteristics of the task presented to the subject pool. Psychological research suggest that there should be no systematic difference observed between real and hypothetical payoffs in discounting experiments (Johnson and Bickel, 2002; Kühberger et al., 2002; Locey et al., 2011). Most recent literature provide more ambivalent results stating that hypothetical conditions yield patterns of discounting that mirror those for real effort tasks but these may change with repeated exposure to the decisions—nature of the payoffs provided together with repetition of those tasks therefore need to be taken into account when designing discounting studies (Hinvest and Anderson, 2010; Malesza, 2018). We therefore control for this payoff effect by extracting the information on the nature of the reward from primary studies. 62% of our observations is reported with only hypothetical payoffs. This information can furthermore serve as a proxy for the size of the payoffs presented to subjects, since large payoffs are often associated with hypothetical decisions and comparatively small payoffs with real decisions (Kühberger et al., 2002).²³

Following Frederick et al. (2002) and others we control for the variation in estimates caused by the elicitation method used in the experiment. We include dummy variables for matching tasks into our set of explanatory variables, taking choice tasks as reference category present in 49% of cases. Important behavioral aspect of the task is represented by the domain over which is the intertemporal decision made. The majority of observations utilize monetary payoffs (82%); we therefore take it as natural reference category in this regard. We code the remaining domains in dummy variables, distinguishing between health domain (10.5%) and others (vacation, liquid or

²³We could not code the magnitude of the payoffs out of the primary studies and therefore use only proxy instead.

certificate—9.6%).²⁴

The design of any experiment is seldom immune to issues of framing effects that refer to the finding that subjects often respond differently to different descriptions of the same problem (Tversky and Kahneman, 1981). The majority of discounting tasks are presented (framed) as positive monetary decision, i.e. choice between some sure amount of money today or some greater amount tomorrow (93%). There are however also negative framing of the tasks present in our dataset (4%), where Chapman and Winqvist (1998) and Hardisty et al. (2013) used monetary losses in their experiments. Other studies with negative framing operate with health domain (Dolan and Gudex, 1995; Read and Read, 2004). We coded neutral framing for only 2% of observations.²⁵

5.1.3 Subject Pool Characteristics

We describe subject pool characteristics of an individual study by several variables. First, we control for the size of the subject pool by coding the number of subjects used for deriving the respective observation. We use logarithmic scale to reduce its size effect on estimation, true mean value is equal to 160.7. Second, we control for composition of subject pool by incorporating dummy variables stating whether it consists of male and female subjects. The majority of studies however uses non-exclusive subject pools consisting of both males and females (94.5%). General concern of any experimental study is its external validity, i.e. the extent to which its results can be generalized to other situations. Economic experiments are often criticized for using university students of (mainly) economics as experimental subjects—a pool of specific characteristics not always generalizable to the whole population (Marwell and Ames, 1981; Carter and Irons, 1991; Frank et al., 1993). Behavior of decision makers recruited from natural markets has been examined in variety of contexts and it has, on the other hand, typically not differed from that exhibited by more standard (and far less costly) student subject pools (Davis and Holt, 1993, p.17).²⁶ We therefore control for the effect of student subject pool in our analysis. Last but not least we hypothesize that the heterogeneity in estimates may be caused by different socio-economic areas and therefore

²⁴Total of domain percentages do not sum to 100% since some experiments used more domains at once. Money was used together with health in 8 observations (Chapman and Elstein, 1995; Chapman, 1996) and triad money, health and vacation was used in 3 observations (Chapman, 1996).

²⁵Neutral framing occur only for Chapman (1996). In this study participants made decisions that traded money for health and vice versa in both positive and negative framing. Since we could not distinguish individual treatments within reported results, we coded framing as neutral.

²⁶See (Davis and Holt, 1993) for examples of this evidence. More recent literature on non-significant differences between student and non-student samples represent e.g. (Depositario et al., 2009).

control for continents out of which the subject pool was recruited.²⁷

5.1.4 Publication Characteristics

Furthermore, we include several publication characteristics, such as in Havranek et al. (2018a) or Havranek et al. (2018b), in order to control for systemic variation of discount rate estimates with respect to year of publication or quality of the study. Controlling whether there is a systemic difference between old and new studies can be easily done by including the year of publication into the analysis. We include only published studies into our dataset and use standardize their publication year.²⁸ Addressing quality of the study is of higher difficulty. We derive information about the quality of the study from Discounted recursive REPEC impact factor²⁹ which is not available for studies outside the field of economics. We therefore gather the number of Google Scholar citations for each study and the year of first version of the study reported by Google Scholar. Then we construct the proxy for quality by weighting the number of citations by number of years since first version of the study. We again use logarithmic scale to reduce its size effect on estimation.

5.2 Results of BMA

The results of the BMA estimation are visualized in Figure 5. The variables are displayed on the vertical axis sorted by posterior inclusion probability from top to bottom. PIP can be thought of as a Bayesian analogy of statistical significance—we therefore see the most significant variables on top of the figure. Columns on the horizontal axis denote individual regression models sorted cumulatively according to the posterior model probability (PMP) from left to right. The PMP represents how well the model fits the data relative to its size; the width of the columns is proportional to the PMP. The colors of individual cells represent signs of corresponding regression coefficients. Blue color (darker in greyscale) depicts included variables with positive estimated sign while the red color (lighter in greyscale) depicts included variables with negative estimated sign. Variables with no colors are not included in given model.

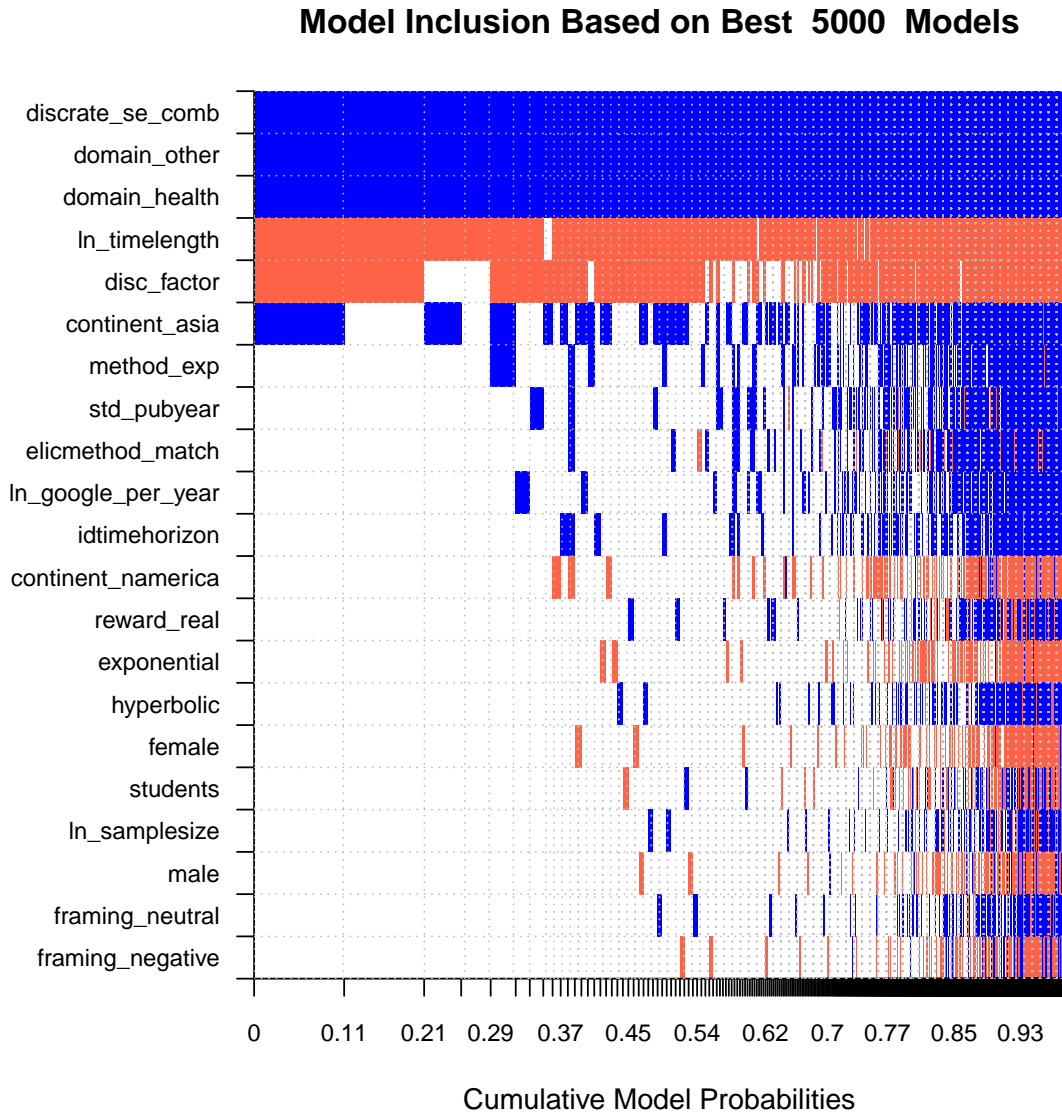
The numerical results of BMA are reported in the left-hand panel of Table 5, which

²⁷The majority of studies however recruit subjects from European countries (58.3% obs.), and North American area (30.6% obs.). Only 11.1% observations originate from Asian continent. Ethnic and cultural diversity is therefore not large.

²⁸We standardize by subtracting mean and dividing by standard deviation. We originally used logarithm of the publication year but this specification caused severe deflections of intercepts since due to strongly positive nature of publication year. We therefore use standardization instead.

²⁹Discounted recursive REPEC impact factor can be retrieved at <https://ideas.repec.org/top/top.series.rdiscount.html>

Figure 5: Model inclusion in BMA (based on "UIP" g-prior)



Notes: Notes: The response variable is the estimate of discount rate. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities; only the 5,000 best models are depicted. Estimation based on "UIP" Zellner's *g-prior* and "uniform" model probability prior recommended by Eicher et al. (2011). Blue color (darker in greyscale) depicts included variables with positive estimated sign. Red color (lighter in greyscale) depicts included variables with negative estimated sign. Variable with no color is not included in the model. Numerical results of BMA exercise are reported in Table 5.

reports posterior mean and standard deviation for each variable together with posterior inclusion probability. We follow the rule of thumb presented in Kass and Raftery (1995), according which there is a decisive evidence that three of our regressors have an effect on the discount rate estimate with PIP higher than 0.99.³⁰ The most important variables explaining heterogeneity in discount rate estimates seem to be the domain over which subjects of the experiments are making particular decisions and the length of the delay or time horizon presented in those decisions.

Values of all future outcomes should be discounted at a constant rate according to the discounted utility theory (Frederick et al., 2002). Constant rate of discounting is violated e.g. by hyperbolic discounting (Mazur, 1984) or more recently Tsukayama and Duckworth (2010) found that subjects discounted rewards more steeply when they found the domain particularly tempting. The second part of this statement, the equivalence of all future outcomes, refer particularly to the domain over which is discounted. Several studies found that discount rates are not well correlated across different domains such as money and health, which is called domain independence. The signs of the effects however differ. Cairns (1992) for example estimated discount rates significantly lower for future health as compared to future wealth states; Chapman and Elstein (1995) on the other hand demonstrated on two experiments that decision makers use different discount rates for health-related decisions and money-related decisions, but with higher rates for health domain.³¹ Our results confirm domain independence. Both health and "other" domains, specified in our dataset as vacation, special certificates or even liquids, have positive effect on individual discount rate estimate suggesting that individuals tend to be more impatient when making decisions over their health states or holiday preferences then over money.

Second important factor influencing the heterogeneity in discount rate estimates is the length of the delay over which is the decision made. This factor is inherently embedded as the parameter k in the discounted utility model presented in equation 1. We again repeat that the discounted utility theory states that values of all future outcomes should be discounted at a constant rate (Frederick et al., 2002) and that this property is violated by several anomalies such as hyperbolic discounting. Our results confirm that the discount is indeed not constant. There is a small negative effect of the length of the delay on discount rate apparent in our dataset, therefore the longer the time horizon the lower the estimated discount rate. We hypothesized that this result would be influenced by our inability to code exact time horizon with which the par-

³⁰Furthermore, one variable has the evidence strong ($PIP \in (0.95;0.99)$) and two variables weak ($PIP \in (0.5;0.75)$).

³¹Follow e.g. Loewenstein et al. (2003) for more examples of domain independence.

Table 5: Explaining heterogeneity in discount rate estimates

Variable	Bayesian Model Averaging			Frequentist Check (OLS)		
	Post. Mean	Post. SD	PIP	Coeff.	SE	p-val.
Intercept	0.192	NA	1.000	0.263	0.045	0.000
Standard error	1.446	0.230	1.000	1.254	0.096	0.000
<i>Estimation characteristics</i>						
disc_factor	-0.218	0.165	0.716			
hyperbolic	0.003	0.022	0.063			
exponential	-0.005	0.029	0.068			
ln_timelength	-0.074	0.028	0.957	-0.082	0.022	0.000
idtimehorizon	0.013	0.049	0.117			
method_exp	0.036	0.095	0.182			
<i>Experimental characteristics</i>						
reward_real	0.005	0.040	0.072			
elicmethod_match	0.036	0.124	0.142			
domain_health	0.369	0.100	0.993	0.183	0.166	0.270
domain_other	0.772	0.105	1.000	0.533	0.205	0.009
framing_negative	-0.001	0.032	0.045			
framing_neutral	0.003	0.040	0.046			
<i>Subject pool characteristics</i>						
ln_samplesize	0.000	0.009	0.047			
students	-0.000	0.021	0.055			
male	-0.002	0.039	0.046			
female	-0.006	0.046	0.057			
continent_namerica	-0.021	0.079	0.114			
continent_asia	0.130	0.151	0.501	-0.061	0.188	0.745
<i>Publication characteristics</i>						
ln_google_per_year	0.005	0.016	0.131			
std_pubyear	0.023	0.070	0.172			

Notes: The frequentist check (OLS) includes variables recognized by the (BMA) as comprising the best model. Standard errors are clustered at the study level. We do not include variable disc_factor into OLS estimation since discount factor was reported only in one study and we would therefore not be able to cluster the estimation on the study level. SD = standard deviation, PIP = Posterior inclusion probability, SE = standard error.

ticular discount rate estimate was observed for all observations³². This however does not seem to prove as right expectation. The dummy variable identifying that the study reports only maximum time horizon of the task is not included in many BMA models. There is therefore not a significant difference between observations from different time ranges of the discounting tasks, or more specifically there is not a significant difference between experimental treatments varying payoffs and time horizon.

Further results suggest that it matters whether the researcher implies the discounting parameter as rate or factor. Even though we do not consider this result as robust since we examined only one study that uses factors (Read and Read, 2004).³³ A weak significance is also obtained within a dummy variable for estimates obtained on Asian continent. The benchmark demographic area—Europe—together with North America seems to report very similar pattern of discounting. Even though not considerably, Asian perception of intertemporal preferences seem to differ according to our analysis. Wang et al. (2016, p. 9) refers to the typically high long term orientation score in East Asian countries, especially Confucian cultures, who tend to put higher value on the future and are more likely to be patient.

Last but not least a measure of statistical uncertainty of the estimate—the standard error—has significant impact on the estimate of discount rate. We are well aware that our combined standard errors are artificially constructed to quite large extent.³⁴ We therefore provide a robustness check by estimating the BMA on dataset with non-combined standard errors, i.e. only with observations coded out of studies that provide a measure of statistical precision by itself, without the necessity of resampling. Results of this partial analysis that can be found in the appendix C are slightly different to those obtained by our original dataset but generally confirms the baseline.

Analysis of regressors without having an effect on discount rate estimates (i.e. with posterior inclusion probability lower than 0.5, (Kass and Raftery, 1995)) brings additional valuable insights. In Section 5.1.1 we referred to the literature suggesting there should be no difference whether real or hypothetical payoffs are used in discounting experiments.³⁵ Our results confirm that it indeed does not matter whether the decision is made in the laboratory with fictive payoffs only. Real rewards does not significantly change estimates of discount rate. Researchers can thus use hypothetical questions and rewards that have even some advantages in the domain of time preferences since they allow to ask questions involving a long time horizons and large payoffs (Wang

³²We could not code exact horizon in 35% of observations. Detail reported in Table 4.

³³We also did not include the variable `disc.factor` into the frequentist check regression described in the following text, for details see below.

³⁴For 45.39% of observations, for more details see Table 2.

³⁵For further supporting literature see e.g. Wang et al. (2016).

et al., 2016). Neither negative nor neutral framing of decisions presented to subjects does result with high posterior inclusion probabilities. We hypothesize that this fact is caused by insufficient number of observations with these types of framing yielding low statistical power.³⁶

Our data suggest that subject pools consisting of students yield in discounting tasks similar results as general population. The rejection of external validity of studies conducted on student samples therefore does not apply in our case. Neither solely male nor female pools report significantly different results of discount rates in our sample.³⁷

5.2.1 Robustness Checks

In order to check whether our results are robust we perform several different re-estimations. First, we combine the reduction of model uncertainty from BMA estimation and traditional frequentist econometrics. Best BMA model includes six explanatory variables (plus intercept) with posterior inclusion probability higher than 0.5 that should according to Kass and Raftery (1995) have non-negligible impact on our response variable. We re-estimate this best BMA model with standard OLS technique, clustering standard errors at the study level and weighting the regression by inverse number of estimates per study to reduce the impact of large studies. Results of this estimation are provided in the right hand panel of Table 5, labelled as Frequentist Check. Eventually we did not include the variable `disc_factor` into estimation. The estimated covariance matrix of moment conditions was not of full rank within this model since discount factor dummy variable was equal to one just and only for one study (Read and Read, 2004) and therefore caused problems within clustering at the study level.

Next, we perform a robustness check using an alternative set of BMA priors, employing the benchmark parameter `g`-prior suggested by Fernández et al. (2001) together with the beta-binomial model prior for the model space, which gives each model size equal prior probability (Ley and Steel, 2009).³⁸ The results of this robustness check are reported in Table 8 in the appendix, being very similar to the baseline specification.

Finally, we also perform a robustness check by estimating the BMA on dataset with non-combined standard errors already described in section 5.2. Its results are quite similar to the baseline specification but includes slightly different set of explanatory

³⁶Negative framing - 4%; neutral framing - 2%.

³⁷Even though we may not have enough data for obtaining a strong estimates with observations only slightly below 3% of the dataset.

³⁸We label this estimation according to the `g`-prior parameter as "BRIC."

variables. Main difference lies in inclusion of exponential model specification together with average number of Google citations obtained per year as significant in explaining heterogeneity in discount rate estimates. Interestingly, health domain disappears from variables with important impact on discount rate. Numerical as well as graphical results can be found in the appendix C.

6 Concluding Remarks

We quantitatively survey a sample of literature experimentally estimating discount rates of individual economic agents. We examine 434 estimates of the discount rate reported in 27 primary studies. By meta-regression methods commonly used in economics, medicine and other fields we detect presence of selective reporting in this literature. Mean value of reported discount rate estimates is 0.408 in our sample. We find that this value drops to about one half when we correct for publication bias, suggesting that individuals are on average more patient than indicated by examined primary studies.

Estimates of the discount rate are furthermore very disperse. We try to explain this heterogeneity by employing Bayesian model averaging, a method accounting for model uncertainty inherent in meta-analysis caused by high number of explanatory variables. We find that a crucial factor influencing the variation in discount rate estimates is the domain over which individuals make the decisions and confirm thus domain independence found by previous literature on discounting. The heterogeneity is further caused by the time horizon the individual subjects face during the decision.

The results of our study may apply in various contexts. One of the crucial dimensions over which the utility functions are defined is the time preference. Understanding individual time preferences and their synthesis to more general level is therefore a critical element of much of economic analyses. Discount rate, the parameter expressing time preferences, has an important implications in decisions regarding savings, educational investments, smoking, exercise and other real-world behaviors (e.g. Chabris et al., 2008a; Meier and Sprenger, 2010). Accurate measures of discounting parameters can provide helpful guidance in welfare analyses on the potential impacts of policies and provide useful diagnostics for effective policy targeting (Andreoni et al., 2015) or can be furthermore applicable to model political campaigns, advertisement or R&D Investments (Deck and Jahedi, 2015b). Interesting examples provide behavioural applications examined e.g. by Deck and Jahedi (2015a) and Deck and Jahedi (2015b) who examine discounting in strategic settings such as auctions or experimental contests in which it is often critical to accurately predict behavior of counterparts to act opti-

mally. Such real-time decisions involve correct appraisal of the discount rate that can be provided by our results.

The climate change policies in which an individual pure rate of time preference or social discount rate is needed for evaluation of long term effects of those policies can serve as an example of welfare analysis application. Pure rate of time preference together with growth rate of per capita consumption and elasticity of marginal utility of consumption creates basis for calculation of Ramsay discount rate consisting of *time* and *growth* discounting elements Fearnside (2002); Anthoff et al. (2009); Foley et al. (2013). Our discount rate synthesis together with results of Havranek et al. (2015a) who synthesise the elasticity of marginal utility of consumption can be utilized for calculation of the pure rate of time preference out of the Ramsay discount rate.

We point out three possible caveats that may apply to results of our analysis. First, our results are based only on sub-sample of all available studies eliciting intertemporal preferences of individuals. The economic and psychological literature on discounting is vast. We believe that we have collected representative sample of experimental literature published with time span of almost thirty years of research. Next, only about a half of collected estimates are reported with a measure of uncertainty from which we can compute approximate standard errors. We overcome this caveat by resampling standard errors on study level for observations with missing data. Last but not least, even though we control for variation in major design aspects of experiments used for elicitation of discount rate estimates, those experiments have many unique methodological as well as procedural details that makes them different from each other. Such details are however not collectable out of primary studies and therefore unobserved by our analysis.

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Appendices

A PAT-PEESE Robustness Check

Table 6: Funnel asymmetry tests for observations with reported SE

PET tests	OLS	FE	Precision	Study
<i>SE</i> (publication bias)	7.993** (2.427)	7.865** (2.166)	14.18*** (3.028)	5.640*** (1.360)
Constant (corrected effect)	0.148* (0.0584)	0.151** (0.0471)	0.0178 (0.0192)	0.192* (0.0754)
Observations	252	252	252	252
PEESE tests	OLS	FE	Precision	Study
SE^2 (publication bias)	67.65* (24.57)	88.99** (29.63)	157.1** (56.50)	47.95*** (13.26)
Constant (corrected effect)	0.258** (0.0704)	0.238*** (0.0280)	0.0792* (0.0358)	0.260*** (0.0755)
Observations	252	252	252	252

Notes: The table reports results of the regressions 5 (PET test) and 6 (PEESE test) for observations with reported SE. All variables winsorized at $p = 0.025$. The standard errors of the regression parameters are clustered at the study level and shown in parentheses. OLS = ordinary least squares, FE = study-level fixed effects. Precision = weighted by the inverse of the standard error. Study = weighted by the inverse of the number of estimates reported per study. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Supplementary Diagnostics of BMA

Table 7: Summary of BMA estimation

Mean no. regressors 6.5881	Draws 2e+06	Burn-ins 1e+06	Time 4.447921 minutes
No. models visited 524963	Modelspace 2097152	Visited 25%	Topmodels 98%
Corr PMP 0.9999	No. Obs 434	Model Prior uniform / 10.5	g-Prior UIP
Shrinkage-Stats Av=0.9977			

Notes: In this specification we employ the priors suggested by Eicher et al. (2011) based on the predictive performance: the uniform model prior (each model has the same prior probability) and the unit information prior (the prior provides the same amount of information as one observation of the data).

Figure 6: Correlation matrix of BMA variables

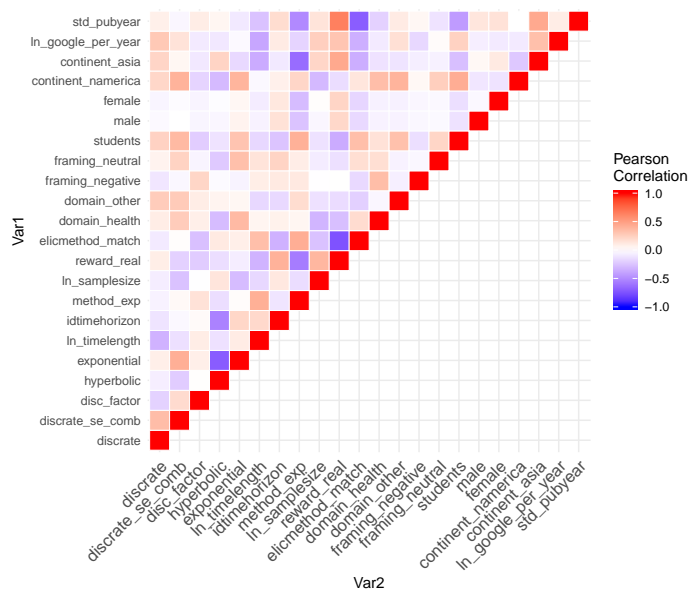
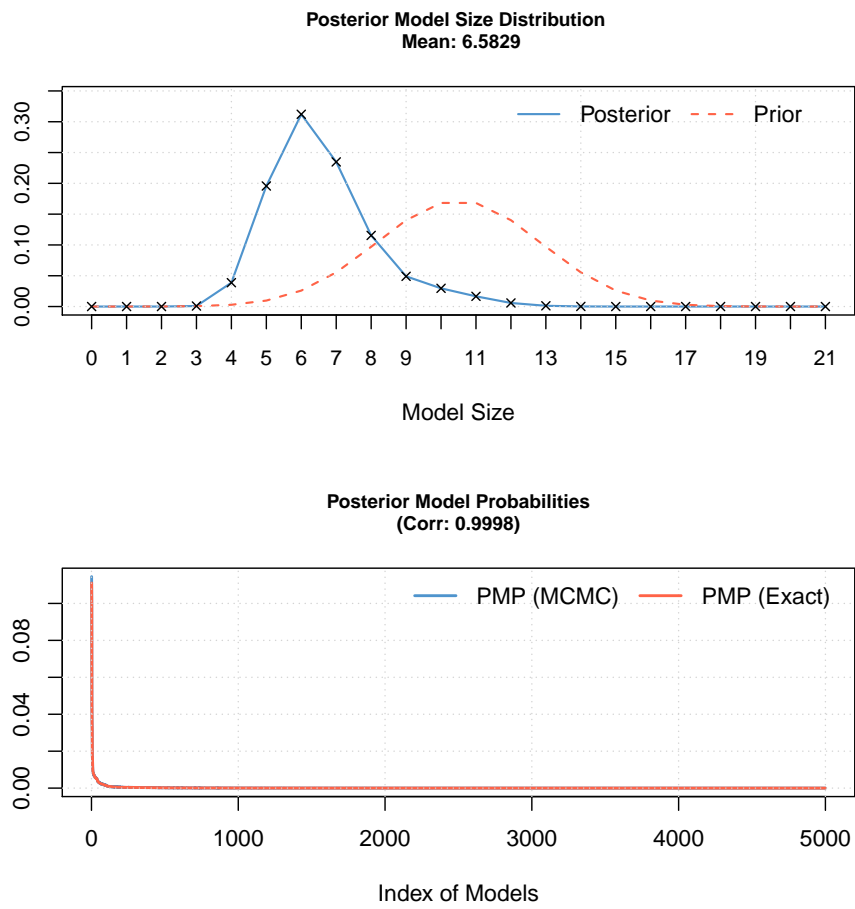


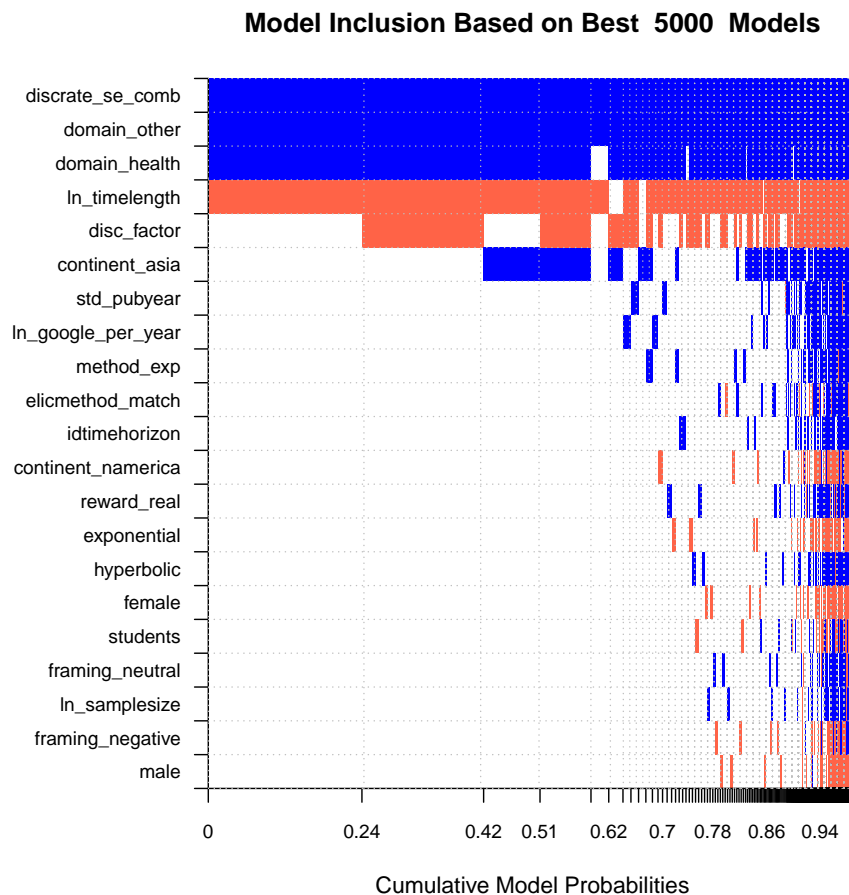
Figure 7: Model size and convergence for UIP prior



Notes: Notes: The figure shows Model size and convergence for UIP prior.

C Robustness Checks of BMA

Figure 8: Model inclusion in BMA (based on "BRIC" g-prior)



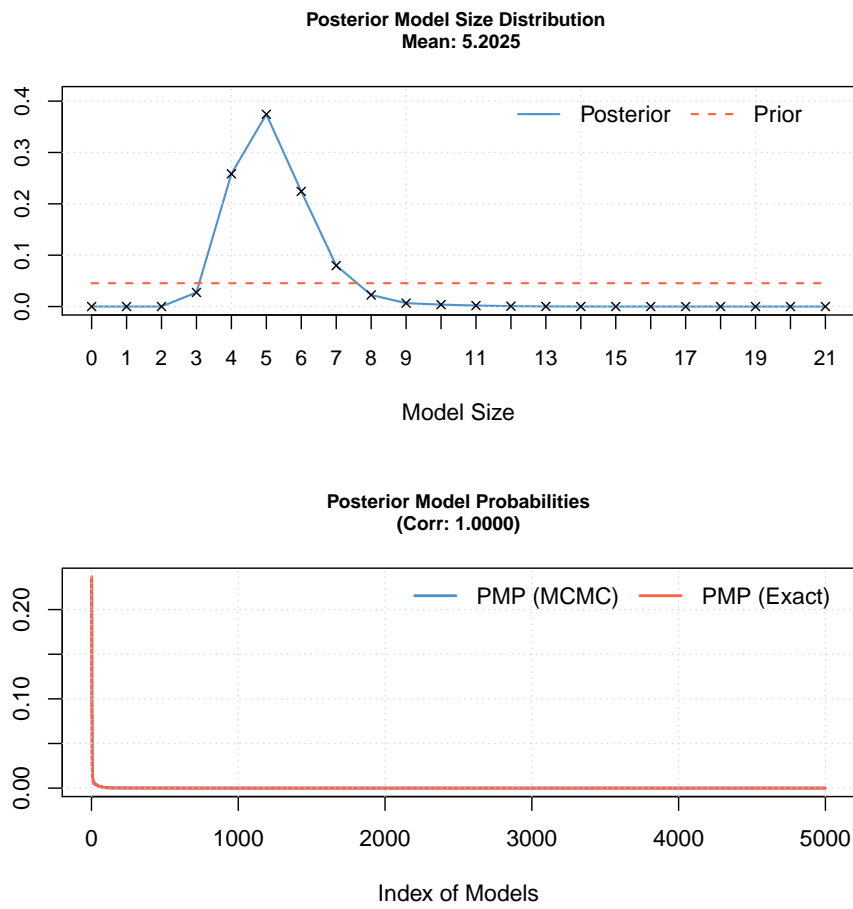
Notes: Notes: The response variable is the estimate of discount rate. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities; only the 5,000 best models are depicted. Estimation based on "BRIC" Zellner's *g-prior* according to Fernández et al. (2001) and "random" model probability prior suggested by Ley and Steel (2009). Blue color (darker in greyscale) depicts included variables with positive estimated sign. Red color (lighter in greyscale) depicts included variables with negative estimated sign. Variable with no color is not included in the model. Numerical results of BMA exercise are reported in Table 5.

Table 8: Robustness checks to heterogeneity in discount rate estimates

Variable	BRIC g-prior			Without resampling		
	Post. Mean	Post. SD	PIP	Post. Mean	Post. SD	PIP
Intercept	0.248	NA	1.000	0.084	NA	1.000
Standard error combined	1.443	0.219	1.000	NA	NA	NA
Standard error	NA	NA	NA	3.530	0.386	1.000
<i>Estimation characteristics</i>						
disc_factor	-0.143	0.166	0.478	NA	NA	NA
hyperbolic	0.001	0.013	0.025	-0.002	0.015	0.092
exponential	-0.002	0.019	0.029	-0.105	0.074	0.753
ln_timelength	-0.076	0.027	0.945	-0.043	0.012	0.991
idtimehorizon	0.002	0.021	0.034	-0.000	0.011	0.072
method_exp	0.006	0.041	0.046	0.004	0.019	0.098
<i>Experimental characteristics</i>						
reward_real	0.002	0.023	0.031	0.031	0.051	0.361
elicmethod_match	0.006	0.048	0.040	-0.003	0.025	0.128
domain_health	0.333	0.116	0.952	-0.000	0.017	0.063
domain_other	0.751	0.102	1.000	0.684	0.085	1.000
framing_negative	-0.000	0.021	0.019	-0.002	0.024	0.071
framing_neutral	0.001	0.026	0.019	NA	NA	NA
<i>Subject pool characteristics</i>						
ln_samplesize	0.000	0.006	0.019	0.000	0.006	0.067
students	-0.000	0.012	0.022	-0.002	0.016	0.089
male	-0.001	0.025	0.019	0.002	0.020	0.064
female	-0.002	0.029	0.023	0.002	0.021	0.067
continent_namerica	-0.003	0.030	0.031	-0.016	0.040	0.203
continent_asia	0.084	0.137	0.320	0.241	0.072	0.977
<i>Publication characteristics</i>						
ln_google_per_year	0.001	0.009	0.052	0.026	0.019	0.731
std_pubyear	0.004	0.027	0.053	0.004	0.020	0.200
N	434			252		

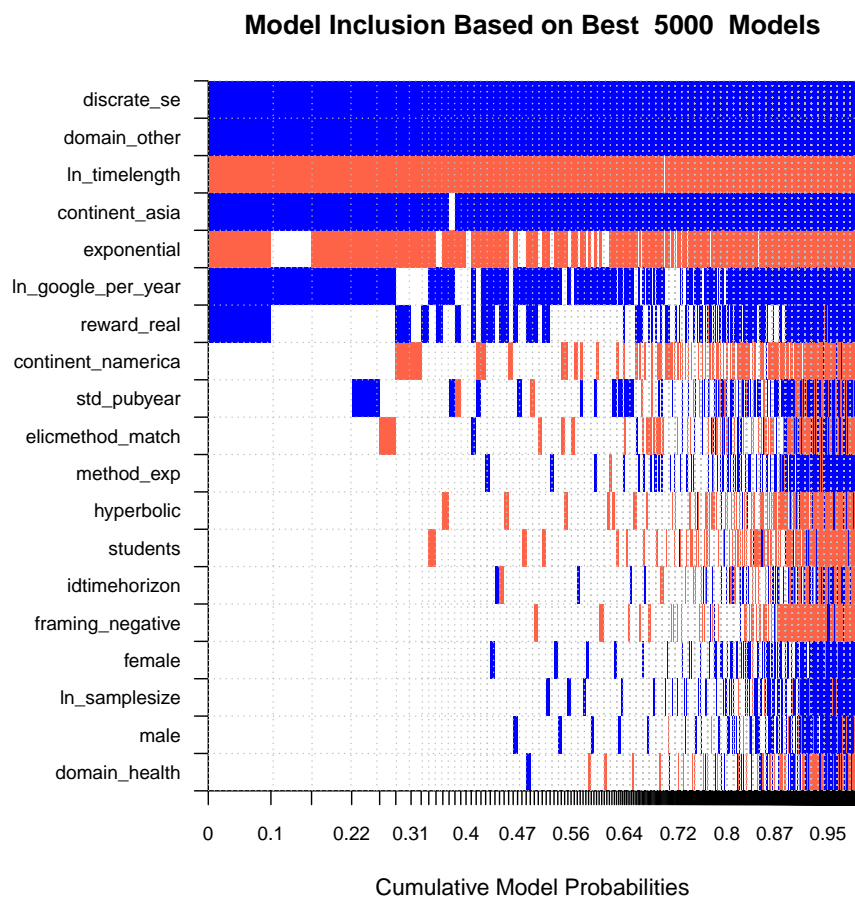
Notes: We do not include variables disc_factor and framing_neutral into the BMA analysis without resampling of missing standard errors since these variables are not present in reduced dataset. SD = standard deviation, PIP = Posterior inclusion probability, SE = standard error.

Figure 9: Model size and convergence for BRIC prior



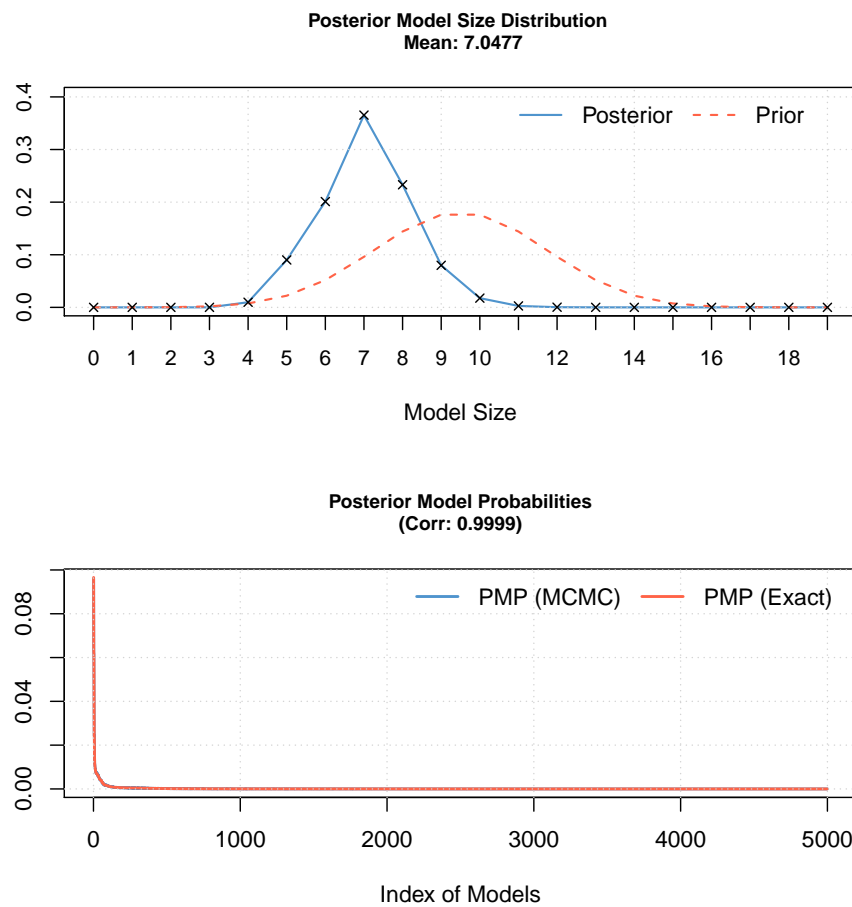
Notes: Notes: The figure shows Model size and convergence for BRIC prior.

Figure 10: Model inclusion in BMA with non-combined SE (based on "UIP" g-prior)



Notes: Notes: Robustness check includes observations with reported measure of statistical precision, i.e. with obtainable standard errors. The response variable is the estimate of discount rate. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities; only the 5,000 best models are depicted. Estimation based on "UIP" Zellner's *g-prior* according to Fernández et al. (2001) and "random" model probability prior suggested by Ley and Steel (2009). Blue color (darker in greyscale) depicts included variables with positive estimated sign. Red color (lighter in greyscale) depicts included variables with negative estimated sign. Variable with no color is not included in the model. Numerical results of BMA exercise are reported in Table 5.

Figure 11: Model size and convergence for non-combined SE (based on "UIP" g-prior)



Notes: Notes: The figure shows Model size and convergence for UIP prior. Robustness check includes observations with reported measure of statistical precision, i.e. with obtainable standard errors.

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