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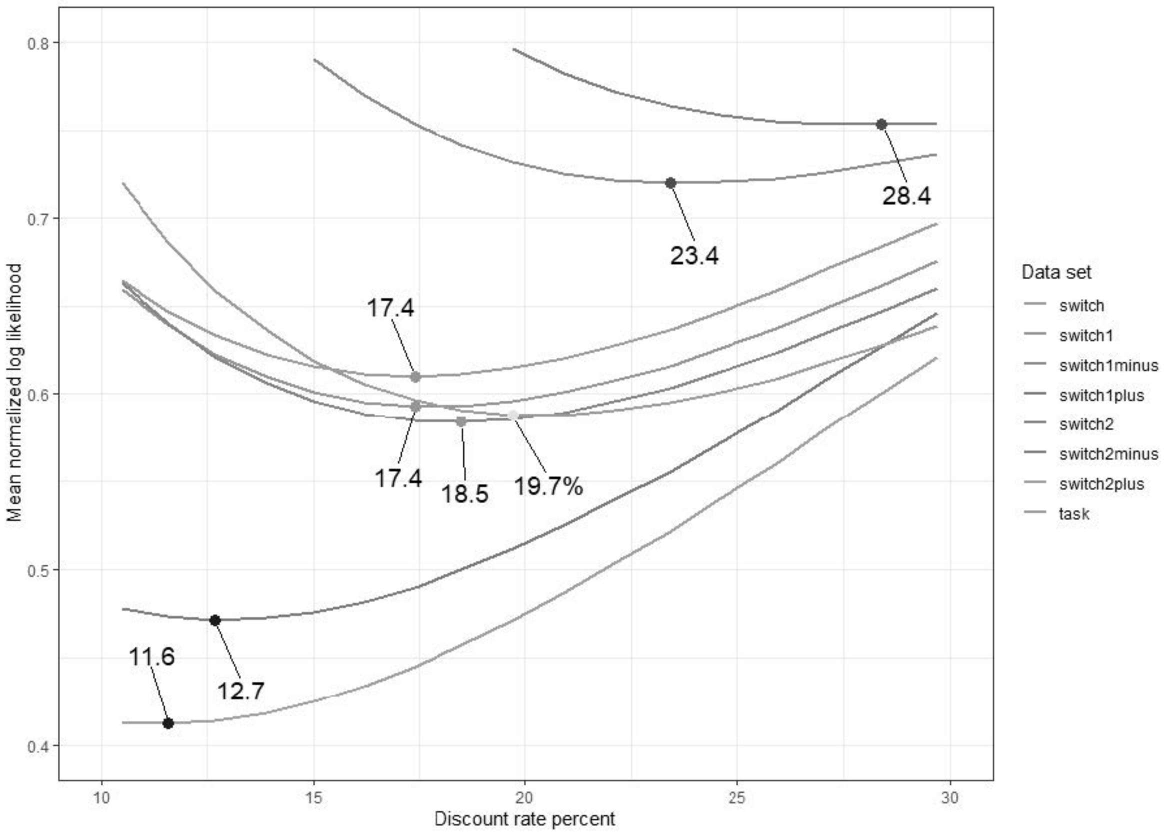

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Intertemporal Choice Lists and Maximal Likelihood Estimation of Discount Rates

Dag Einar Sommervoll[1], Stein T. Holden[2], and Mesfin Tilahun[3]

Abstract

The experiments designed to estimate real-life discount rates in intertemporal choice often rely on ordered choice lists, where the list by design aims to capture a switch point between near- and far-future alternatives. Structural models like a Samuelson discounted utility model are often fitted to the model using maximal likelihood estimation. We show that dominated tasks, that is, choices that do not define the switch point, may bias ML estimates profoundly and predictably. More (less) dominated near future tasks give higher (lower) discount rates. Simulation analysis indicates estimates may remain largely unbiased using switch point-defining tasks only.

Keywords: choice lists, time discounting, maximal likelihood estimation
JEL: C13, C81, C93, D91

1. Introduction

Time preferences are important for human choice, and until the 1980s, Samuelson's discounted utility model was the economists' main model tool. The last half century has seen rapid development in the extension of Samuelon's DU model as well as new model approaches (Cohen et al. (2020). On the empirical side, the major division is between experiments that seek to measure time preferences of consumption, in contrast to experiments concerning payouts, dubbed "Money Earlier or Later" (MELs). A critique of the latter is that monetary payouts may not mirror temporal consumption choices (Chabris et al. (2008) as payouts open for consumption smoothing.

We will not address this concern but focus on discount rates inferred from MEL experiments. In particular, we will follow the approach of Andersen et al. (2008). Their paper relies on double multiple-choice lists (DMPLs), one for risk and one

[1]School of Economics and Business, Norwegian University of Life Sciences and NTNU Trondheim Business School dag.einar.sommervoll@nmbu.no.
[2]School of Economics and Business, Norwegian University of Life Sciences, stein.holden@nmbu.no.
[3]Mekelle University and School of Economics and Business, Norwegian University of Life Sciences, mesfin.tilahun.gelaye@gmail.com.

for time preferences. A maximum likelihood estimation allows for joint estimates of concavity of the utility function (risk)[4] This approach has been a major influence on discount rate elicitation. Recent examples in development economics are Bonan et al. (2022), Ihli et al. (2022), and Cassar et al. (2017). Time preferences also play a key role in disaster economics. Three recent examples of Andersen et al. approach are Beine et al. (2020),Drichoutis and Nayga Jr (2022), and Gassmann et al. (2022). The latter two concern the COVID pandemic.

We will be largely concerned with the temporal MPLs. Such a list contains a number of tasks. The task concerns a near-future alternative, 100 dollars in a week, and a far-future alternative, 100 dollars in a month. Moreover, the list tends to be ordered in such a way that a far future (near future) alternative remains fixed, whereas the near future (far future) alternative gets progressively larger (or smaller). Such choice lists are designed to capture a switch point between a near and far future alternative. If the above-mentioned task was the first row on the list, the second row maybe 90 dollars in a week or 100 dollars in a month. The third row may be 80 in a week or 100 in a month. Suppose the respondent switches from the near future to the far future alternative between rows 2 and 3. In that case, that is, prefers 90 dollars in a week to 100 in a month but prefers 100 dollars in a month to 80 dollars in a week, we may estimate a discount rate interval (given some assumptions regarding the concavity of the utility function).[5]

Ordering task lists in this way is a natural way to explore intertemporal preferences. Moreover, as in Andersen et al. (2008) and subsequent academic contributions, these choices may be used to find maximum likelihood estimates for discount rate (and potentially the CRRA-risk parameter). Our point of departure is the realization that "all tasks are not created equal"; that is, tasks on a given choice list differ in informational content. The two tasks defining the switch point create (ideally) some discount rate bounds. The informational value of the other tasks, for example, the informational value of the insight that you prefer 100 dollars in a week to 100 dollars in a month when we know that you prefer 90 dollars in a week to 100 dollars. We dub the task, 100 dollars in a week or 100 dollars in a month, a *dominated* task. It is important to stress that this definition does not consider the actual question order, that is, whether or not previous responses could infer the respondent's choice. The definition relates to all choices that do not define the switch point. In this case, from an informational point of view, we can reconstruct the entire MPL if we know the switch point.

Our point of departure is that most tasks in temporal MPLs are dominated.

[4]They rely on a constant relative risk aversion utility model (CRRA-model): $U(M) = (w + M)^{1-r}/(1-r)$, where w is the background consumption and R the CRRA coefficient.

[5]Or as used in Cohen et al. (2020) an RRR (Required Rate of Return) interval.

To what extent do dominated tasks influence discount rate estimates (in ML estimations)? We find that the discount rate estimates are affected profoundly. This applies, in particular, to the case where the respondents make few or no mistakes. Estimates on MPLs on a large data set gathered in Ethiopia are highly influenced by the inclusion or exclusion of dominated tasks. The monthly discount rate varies from 11 to 28 percent, depending on the inclusion or exclusion of dominated tasks. As the actual discount rate in unknown, we have it is hard to assess the question of the size and direction of bias due to exclusion or inclusion of dominated tasks.

To address the question of bias we turn to synthetic data. We generate data using the model we estimated and study the impact of including or excluding dominated choices. In this case, we can assess potentially biased discount rates as the actual discount rate is known.

There are two main strategies for time preference elicitation. One is closely linked to the Andersen et al. (2008) paper. This is often referred to as the DMPL, the double multiple price list approach, as it relies on two multiple price lists, one for risk and another for time. These price lists allow for a joint maximum likelihood estimation of risk and time parameters. The other much-used approach is to rely on convex budget shares (CTB) Andreoni and Sprenger (2012). These two competing elicitation approaches have spurred a debate. It is interesting to note that at the heart of this debate is the informational content of corner solutions in the CTB approach (Harrison et al. (2013),(Andreoni et al. (2015)). A key point for us is that tasks' informational content is not, as often implicitly assumed, equal. Moreover, in the case of intertemporal MPLs, they tend to, by design, involve dominated tasks. The experimental design of the Ethiopian data set we here use as an illustration used rapid elicitation[6] to minimize respondent errors.

The remainder of the paper is organized as follows. Section 2 describes the experimental design and the data. Section 3 describes the basic Samuleson discounted utility model which parameters, hereunder the discount rate are to be estimated. The estimation method follows Andersen et al. (2008) closely. This is discussed in detail. Section 4 is divided into two parts. The first estimates model parameters given the Ethiopian data set, and study how the estimated discount rates varies with the inclusion or exclusion of dominated tasks. In the second part, we generate synthetic data based on estimated parameters from the first part. This data set, set of generated choice lists, are used to estimate the model parameters again. The discount rate estimates are then compared with the true discount rate, as this is know in this case. This allows us to address to what extent inclusion or exclusion of dominated tasks bias discount rates. Section 5 concludes.

[6]See Section 2

2. Experimental design and the data set

2.1. Experimental design and implementation

The data set used in the study is based on a large sample field experiment with young adults living in rural areas in Ethiopia. A within-subject $3 * 3 + 1$ multiple price list (MPL) design was used with a randomized order of the the treatment levels. Nine of 10 treatments had a one-week front-end delay, and the 10th treatment had no front-end delay and was included to test for potential present bias. It was combined with a small amount (100 ETB) and 12 months time horizon. The $3 * 3$ design included three far future point-in-time treatment levels, 3, 6, and 12 months, and three magnitude levels, 100, 500, and 1000 Ethiopian Birr (ETB). The daily wage rate in these rural areas at the time of the experiment was about 30 ETB.

The far future amount and the time horizon were kept constant in each PL, and only the near future amount varied within each PL. Rather than presenting the whole list to respondents, a random row for each PL was presented first. Depending on the response (preference for the smaller near future amount or the larger far future amount), the enumerator was instructed to the bottom or the top of the list. This is used to narrow the range of implied discount rates. With a switch between the near future and far future amounts at the bottom or top of the list, the enumerator was instructed to go to the middle row between the first row and bottom (top) row and continue to narrow in on a switch point in the list quickly. We will refer to this procedure as rapid elicitation. The advantage of this method is that it simplifies the choice alternatives for the respondent who only sees and makes one binary choice at a time. This is likely to mitigate order effects, reduce the time needed to identify a switch point in each PL, and lead to only one switch point in the list. The enumerator was instructed also to fill in the remaining tasks on the choice list. In other words, mistakes related to dominated tasks are eliminated.

If respondents preferred the near future amount at the bottom row in the PL, the enumerators were told to add one or more extra rows at the bottom of the table with even smaller amounts until a switch point is found (implying very high discount rates). The advantage of fixing the far future amount, varying the front-end amount, and adding rows when needed is that it avoids upward censoring of the identified discount rates. Such censoring is common when the near future amount is fixed (Halevy, 2015; Pender, 1996; Yesuf and Bluffstone, 2019). High discount rates are more frequently found in developing countries and may be associated with poverty and liquidity constraints (Holden et al., 1998; Pender, 1996; Yesuf and Bluffstone, 2019). [7]

[7]This approach is also likely to reduce bias towards the middle in each PL, which has been a concern (Andersen et al., 2006). Random choices in the lists may also be associated with biases

Like Andersen et al. (2008), we incentivized the experiment by including a 10 percent probability of winning. The respondents were informed about this before the start of the game. For delayed payouts, a guarantee was given by the local university (Mekelle University), and a reward card was given to the winners of future amounts, stating the time and amount to be paid out. The respondents were informed that they should collect their future payouts at the office of the local credit provider (DECSI). One of the authors was in charge of the fieldwork and arranged all payouts. Mekelle University is a trusted and long-term operator in the study areas. Table 2 in the appendix gives an example of a price list. Furthermore, Table 4 in the appendix gives an overview of the MPLs with variation in near and far future points in time and the far future amounts.

Table 1: The Experiment. The number of treatments in each treatment level in parenthesis

Treatment type	Treatment levels
Front end point in time	Current (1), 1 week delay (9)
Endpoint in time	3 months (3), 6 months (3), 12 months (4)
Future amount level	100 ETB (4), 500 ETB (3), 1000 ETB (3)

Note: ETB = Ethiopean Birr.

2.2. Sample

Our study uses data from a field experiment where the respondents are resource-poor young adults living in a risky environment where they combine individual and group business activities as sources of livelihood. Our sample differs systematically from the typical laboratory samples with university students as we have more variation in age and years of schooling. Young adults eligible for joining the youth business group program had to be land-poor, come from the municipality, and be interested in the program. We cannot, therefore, rule out sample selection bias, like for any student sample taking part in a lab experiment. One potential advantage is that we had a large sample of business groups and group members to sample from in the five districts where we implemented the experiment.

2.3. Rapid elicitation

The whole CL needs to be presented to the respondents. They are only given binary alternatives from one row on the list, starting from a randomly chosen row.

(Andersson et al., 2016). The randomly chosen starting point may be associated with bias if the first choice is erroneous.

Table 2: An example MPL

Time pref. Series no.	Start point	Task no.	Receive at far future period	Choice	Receive at near future period	Choice
8		1	1000		1000	
8		2	1000		900	
8		3	1000		800	
8		4	1000		700	
8		5	1000		600	
8		6	1000		500	
8		7	1000		400	
8		8	1000		300	
8		9	1000		200	
8		10	1000		100	
8		11	1000		50	

The list is only used for recording the responses and the sequence of rows the enumerator presents. A rapid elicitation approach was applied to reduce the number of questions needed to identify each CL's switch point. The interviewer starts at a random starting row (predetermined) and then proceeds to the top or the bottom of the list. If the respondent at the randomized starting point prefers the near future amount (far future amount), the enumerator goes to the bottom (top) of the list. Table 2 gives one MPL used in the Ethiopian experiments. If a switch is recorded, the enumerator is instructed to go to the middle row between the two and repeat this process until the switch point is identified.[8] Some respondents preferred the very small near-future amount, even for the bottom row in the list. In such cases, an additional row was added at the bottom, with the near future amount reduced to extend the CL. This procedure was repeated until the switch point was reached.

2.4. Data preparation

The raw data set consists of 109,385 observations, each a choice between two prospects. All choice lists should have precisely one switch point. Due to registration mistakes, some have 2 or more. All observations (rows) belonging to choice lists with nonunique switch points are excluded (2621 observations). This leaves 106,764 observations.

Switch points play a special role in the following ML estimation and analysis. Table 3 gives the median and the mode (the most frequent) switch point. It is interesting to note that switch points tend to be biased towards the end of the lists, and for three lists, the mode for the switch is below the original list. This means

[8]This approach is also likely to reduce bias towards the middle. However, the randomly chosen starting point may lead to bias if the respondent makes an erroneous choice.

that the contingency plan of adding more rows to the list became more than a safety measure for extreme temporal preferences. It proved to be the norm.

Table 3: Switch point in the 10 choice list, median and mode

	med	mode
1	8	8
2	9	9
3	10	11
4	8	8
5	9	8
6	10	10
7	7	7
8	9	9
9	10	11
10	10	11

3. Structural models

We will rely on a classical Samuelson discounted utility model as a benchmark model for comparing payouts at different times. The benchmark model is constructed in the following way.

Let time-dated utility be represented by a constant elasticity of marginal utility (CEMU) utility function;

$$u = (y^{1-\theta} - 1)/(1-\theta) \tag{1}$$

where θ is the constant elasticity of marginal utility, and the function is modified to accommodate $\theta = 1$.

Consider the standard choice problem where a respondent chooses between two payouts, M_A, and M_B, at time t_A and t_B, respectively. Furthermore, let $t_0 \leq t_A < t_B$, where t_0 denotes the present time.

In this case, the respondent must decide between:

$$U_A = e^{-\delta(t_A - t_0)} u(y_1 + M_A) + e^{-\delta(t_B - t_0)} u(y_2) \tag{2}$$

and

$$U_B = e^{-\delta(t_A - t_0)} u(y_1) + e^{-\delta(t_B - t_0)} u(y_2 + M_B) \tag{3}$$

where $u(\cdot)$ is the CEMU utility function given in 1, δ is the discount rate, and y_1 (y_2) is the amount (asset or background consumption integration) that the prospect amount is integrated with at time t_A (t_B).

We use the daily wage, $y_0 = w_0$, as a starting reference point for the asset integration base consumption level.[9]

All models we estimate and compare are generalizations of this Samuleson DU model.

3.1. Model estimation

We use the maximal likelihood estimation approach with the Luce error specification (Holt and Laury, 2002) to estimate the model parameters. The Luce specification allows respondents to make mistakes and choose the alternative with the lowest utility. The probability of choosing the lowest utility decreases as the difference in utility between alternatives increases. The mistake probability is parametrized by the parameter μ in the Luce specification. For a more thorough discussion, see Holt and Laury (2002). We use the μ-dependent utility differential:

$$\nabla EU = \frac{EU_A^{\frac{1}{\mu}}}{EU_A^{\frac{1}{\mu}} + EU_B^{\frac{1}{\mu}}} \tag{4}$$

This gives rise to the following likelihood function:

$$\begin{aligned} &\ln L(\delta(x_i), \mu(x_i); Choice_{ijk}) = \\ &\sum_i ((ln(\Phi(\nabla EU)|Choice_{ijk} = 1) + (ln(\Phi(1 - \nabla EU)|Choice_{ijk} = 0)) \end{aligned} \tag{5}$$

where i ranges over respondents, j choice lists, and k over choice list rows. $Choice_{ijk} = 1(-1)$ denotes the choice of alternative A (B), and the x_i's include the CL level treatments and other covariates.

4. Analysis

In this section we will first illustrate the estimated discount rate sensitivity to inclusion of dominated tasks using the Ethiopian data set described under the data section. We will then consider the question of bias due to inclusion of dominated tasks by looking at synthetic data.

4.1. A first illustration of the discount rate sensitivity to dominated tasks

We will fit the Samuel DU model described in Section 3 in this section. For transparency reasons, we will only estimate the discount rate δ and keep the curvature and Luce error fixed ($\theta = 0.1$ and $\mu = 0.3$).

[9]The daily wage is 30 Ethiopian birr.

We calculate the minus log-likelihood for δ for different subsets of tasks in choice lists. These subsets are:

1. The task dataset is the entire dataset.

2. The switch data set consists of only the two tasks defining the switch point in each MPL.

3. The switch1 data set consists of the switch point defining tasks plus the task directly above and below these two tasks.

4. The switch2 data set is defined similarly to switch1, but we include the two tasks directly above or directly below the switch point defining tasks.

In other words, if the respondent switches between the near future and far future choice between tasks 5 and 6, only these two tasks are present in the switch data set. In the switch1 data set, we have tasks 4, 5, 6, and 7, whereas the switch2 dataset has 3, 4, 5, 6, 7, and 8.

Figure 1 shows the minus log-likelihoods curves, with highlighted minima. We see that the curve corresponding to all tasks on all lists gives a monthly discount rate of 19.7 percent.

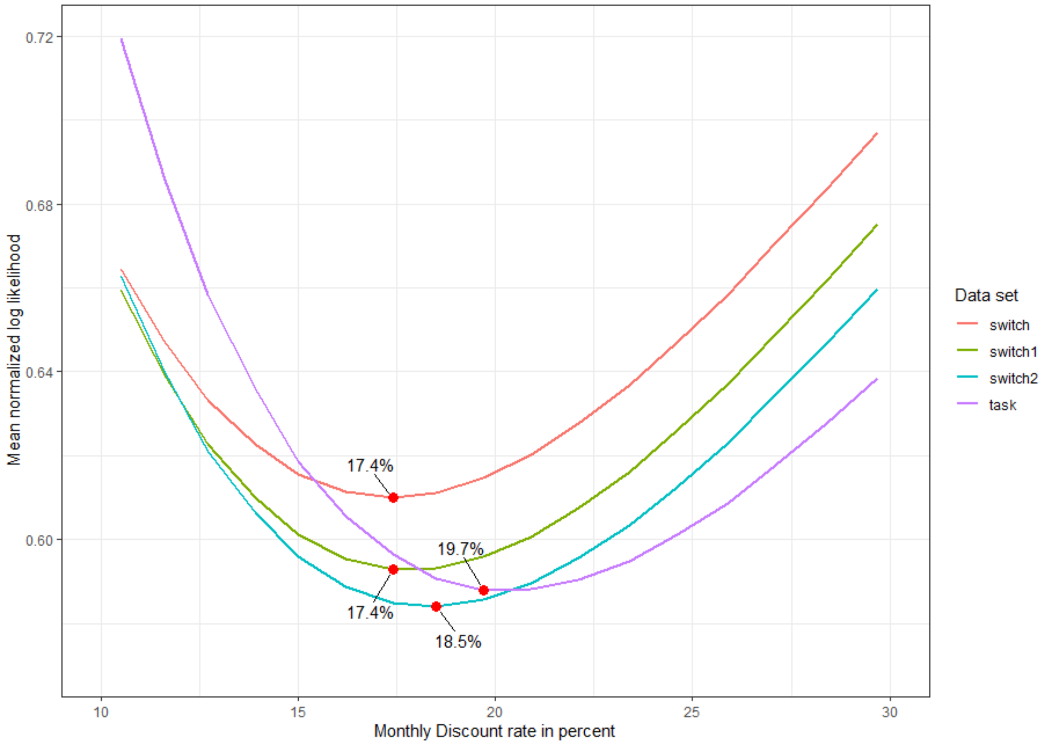
The main takeaway from Figure 1 is the discount rate sensitivity to the inclusion (or exclusion) of dominated tasks. Whereas an estimation using all tasks gives a discount rate of 19.7 percent, the estimate using only the switch point defining tasks gives a discount rate of 17.4 percent. Including one of the closest dominated tasks leaves the estimate unchanged at 17.4 percent. Including the two dominated tasks at both sides of the switch point defining tasks increases the estimate to 18.5 percent. These are significant economic differences. From an informational point of view, the ML estimates sensitivity to dominated choices is surprising. This sensitivity may also be problematic if complete task lists are used in the ML estimation.

Maximal likelihood estimation finds an estimate for a model parameter, here δ, which is most likely given the observations at hand. It is natural to assume that more near-future alternatives chosen make a high discount rate more likely. So, whether or not this also applies to dominated tasks. If it does, the observed discount rate sensitivity in Figure 1 should be even greater if we add a dominated task asymmetrically. To explore this, we define the data sets, where we add just the first (or the first and second) dominated tasks above (or below) the switch point defining tasks. We dub these data sets switch1minus and switch1plus for one added task. Likewise, we define the data sets switch2minus and switch2plus for two added tasks, either above (or below) the switch point defining tasks. Figure 2 shows that is indeed the case. The asymmetric inclusion of dominated tasks profoundly influences the discount rate. The monthly discount rate varies from 11.6 to 28.4 percent.

The central insight from this initial exploration is that the inclusion of dominated tasks profoundly influences ML's discount rate estimation. Moreover, estimates that

Figure 1: **Maximal Likelihood Estimates for Monthly Discount Rates. Symmetric Inclusion of Dominated Tasks**

The mean of (minus) log likelihood as a function of the monthly discount rate for the Samuleson DU model with $\theta = 0.1$ and Luce Error $\mu = 0.3$. Estimates for different cuts of the Ethiopian data set: the task, the switch, the switch1 and the switch2.



rely on balanced lists (switch, switch1, and switch2 in our first illustration) are less sensitive than the asymmetric ones. A first takeaway is that lists with switch points in the middle of the lists may, to some extent, balance out dominated tasks as the number at either side of the switch point is roughly equal. However, as our first figure shows, the estimates, even in the case of such balanced lists, are sensitive to the inclusion or exclusion of dominated tasks.

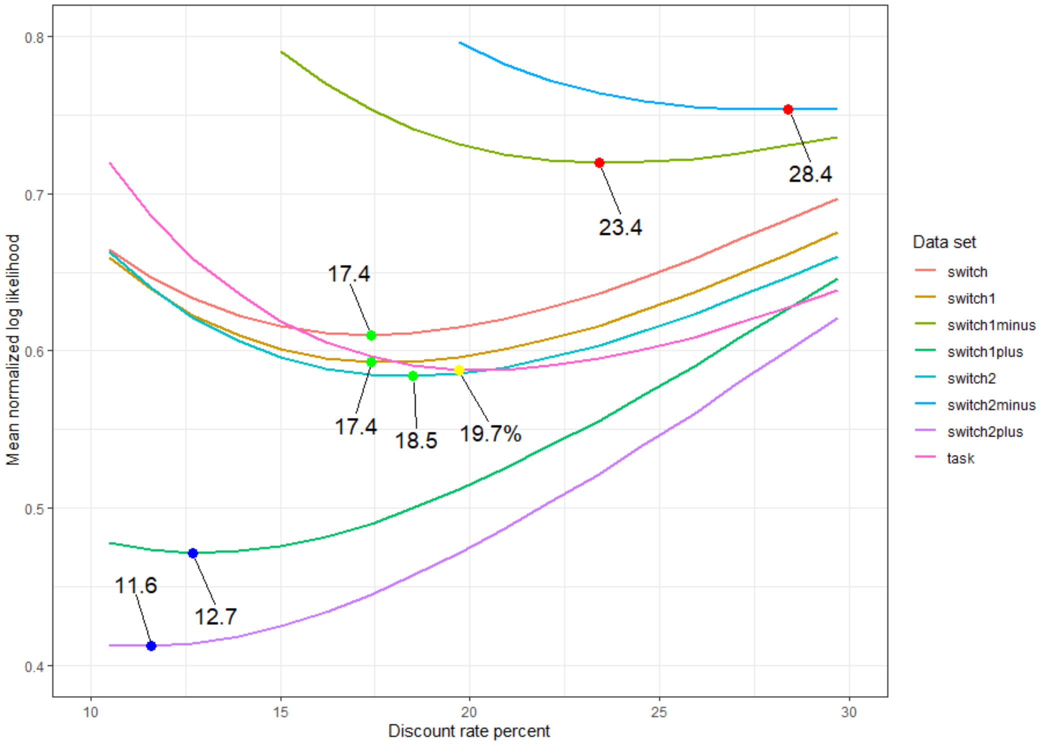
4.2. The Luce error

The Luce error in equation 4 is to allow for respondent mistakes. The probability of erring decreases as the difference in utility increases. In other words, if the actual switch point was between task 5 and task 6, the respondent may switch one row early or one row late, as the utility levels between alternatives may be close.

Figure 3 shows how the estimated monthly discount rate varies with μ, the Luce error. The sensitivity of the discount rate to the Luce error depends heavily on the inclusion or exclusion of dominated tasks. As the Luce error increases, the estimated discount rate spread increases dramatically. It must also be stressed that this fan-like spread dwarfs the discount rate spread for smaller μ values. This must not be taken as a convergence for small μ values. On the contrary, for low μ, the discount

Figure 2: **Maximal Likelihood Estimates for Monhly Discount Rates. Symmetric and Asymmetric Inclusion of Dominated Tasks**

The mean of (minus) log likelihood as a function of the monthly discount rate for the Samuleson DU model with $\theta = 0.1$ and Luce Error $\mu = 0.3$. Estimates for different cuts of the Ethiopian data set: the task, the switch, the switch1,the switch2, the switch1minus, the switch1plus, the switch2minus, and the switch2plus.



rates vary between 12 to 23 percent. The inclusion or exclusion of dominated tasks has a profound, economically significant impact on the estimated discount rates for all values of the Luce error. The fan shape of the plot is primarily driven by two datasets with the most asymmetric inclusion of dominated tasks (the switchplus2 and the switchminus2). These give very high and very low monthly discount rates, respectively.

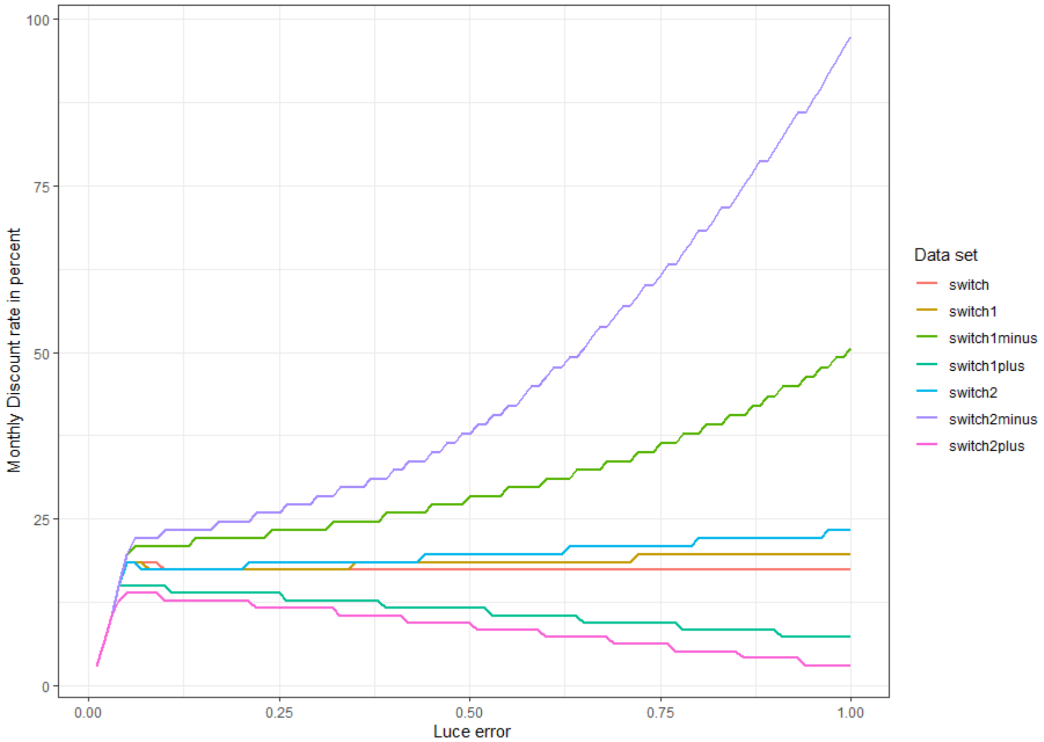
As these are estimates based on actual data, we cannot know the true (average) discount rate for the Ethiopian respondents. We will now turn to synthetic data. That is, we will generate data with known parameters for the discount rate, utility curvature, and Luce error and use maximal likelihood to estimate the discount rate. In such a controlled environment, we can address to what extent the maximal likelihood estimates are biased and, more importantly for our purpose, to what extent dominated tasks bias estimates.

4.3. Simulation analysis

ML estimates of the discount rate using real-life data, as above, showed a high sensitivity to the inclusion of dominated tasks. We may have some priors regarding

Figure 3: **Monthly Discount Rates as a function of the Luce Error**

The monthly discount rate for the Samuleson DU model with $\theta = 0.1$ and Luce Error $\mu = 0.3$ as a function of the Luce error. Estimates for different cuts of the Ethiopian data set: the task, the switch, the switch1,the switch2, the switch1minus, the switch1plus, the switch2minus, and the switch2plus.



a likely interval for monthly discount rates, but the analysis above offers little insight into which specifications that are closer to the "true" discount rates.

To address the question of bias, we turn to synthetic data. The model we use for data generation has a monthly discount rate $r = 0.07$[10] and $\theta = 0.1$. We stochastically generate the choices of using the same rows/observations as the Ethiopian data sets for different values of the Luce error, μ. We use a bootstrap method, draw 100 samples for a given μ[11], and calculate the ML estimate. Figure 4 shows the density distributions for the monthly discount rate for a range of μ values. A priori, we would expect that the variance of the discount rate estimate increases the Luce error. We see that this is indeed the case.

The most apparent feature is an increase in the discount rate estimate as the Luce error increases. It is well known that ML-estimators tend to be biased (Cox and Hinkley (1974)), and as this simulation analysis shows, it is biased in a surprisingly predictive way. Higher Luce error gives higher discount rate estimates—in concrete

[10] This corresponds to $\delta = \ln(1 + 0.07) = 0.06766$

[11] We use exactly the same lists as the original Ethiopian data set, that is each sample we have 106,764 observations/tasks

terms, lower (higher) Luce errors than 0.1 result in underestimates (overestimates). We should be careful to put much emphasis on the fact that $\mu = 0.1$ appears to be close to unbiased. The main takeaway is that there is a positive relationship between bias and the Luce error.

This finding is consistent with Figure 3 in the sense that there is a correlation between the Luce error and estimated discount rates. As Figure 3 concerns estimates on data gathered in the field, the true interest rate is unknown, and all we know is that most estimates must be (highly) biased. This simulation analysis points towards an intrinsic link between the Luce error and the discount rate. To what extent this link/bias is influenced by the inclusion or exclusion of dominant choices is unclear and will be investigated in the following.

Figure 4: **Density plot for the estimated discount rate for different choices of μ**

Bootstrap estimation for the Samuleson DU model with μ in the 0.05 to 0.50 range. Curvature parameter $\theta = 0.1$, monthly discount rate, $\delta = 0.07$. 100 simulations for each μ-value.

It must be stressed that these estimation results are for estimations of complete lists, including dominated choices. More importantly, these estimations rely on lists that may not include switch points or include several. These estimates are arguably informative concerning MLE performance on complete synthetic lists. They are, however, less relevant when it comes to comparisons with the real MPLs from Ethiopia, as the latter relied on rapid elicitation.

4.4. Synthetic data with one switch point only

This section follows the same bootstrap estimation strategy with 100 generated datasets for the Luce error ranging from 0.05 to 0.5, with one crucial difference. We use rapid elicitation to pin down the switch point with as few tasks as possible. Those lists where the rapid elicitation fails to find a switch point are discarded.[12]

[12]Some lists may not have a switch point. An example where we fail to find a switch point: We randomly pick row 4, and the choice this is near future, then rapid elicitation tells us to go to the

The most important feature of rapid elicitation is that a random mistake, a zero or one, may go undiscovered as the rapid elicitation algorithm does not use this task. Compared with generating one-switch lists by taking the expected outcome for every task, a strong suit of this approach is that rapid elicitation opens for that by chance a wrong switch point may be selected (this increases with μ, of course.)

Figure 4 shows the bootstrap density distribution of the monthly discount rate for mu's ranging from 0.05 to 0.5. One immediate takeaway is the positive relationship between the Luce error μ and the discount rate estimate.

A more direct way to address the primary research question of this paper, whether dominated tasks bias estimates, is to asymmetrically add dominated tasks and see to what extent the discount rate is biased. Figure 5 shows bootstrap simulations of models with different mu run on three datasets constructed using rapid elicitation.

We see that estimates using the switch points only are close to unbiased for small μs. Larger μs give a positive bias, which increases as μ increases. The data sets that include one dominated task either above (below), that is, one more near (far) future choice, give a positive (negative) bias. This bias grows fast with increasing μ.

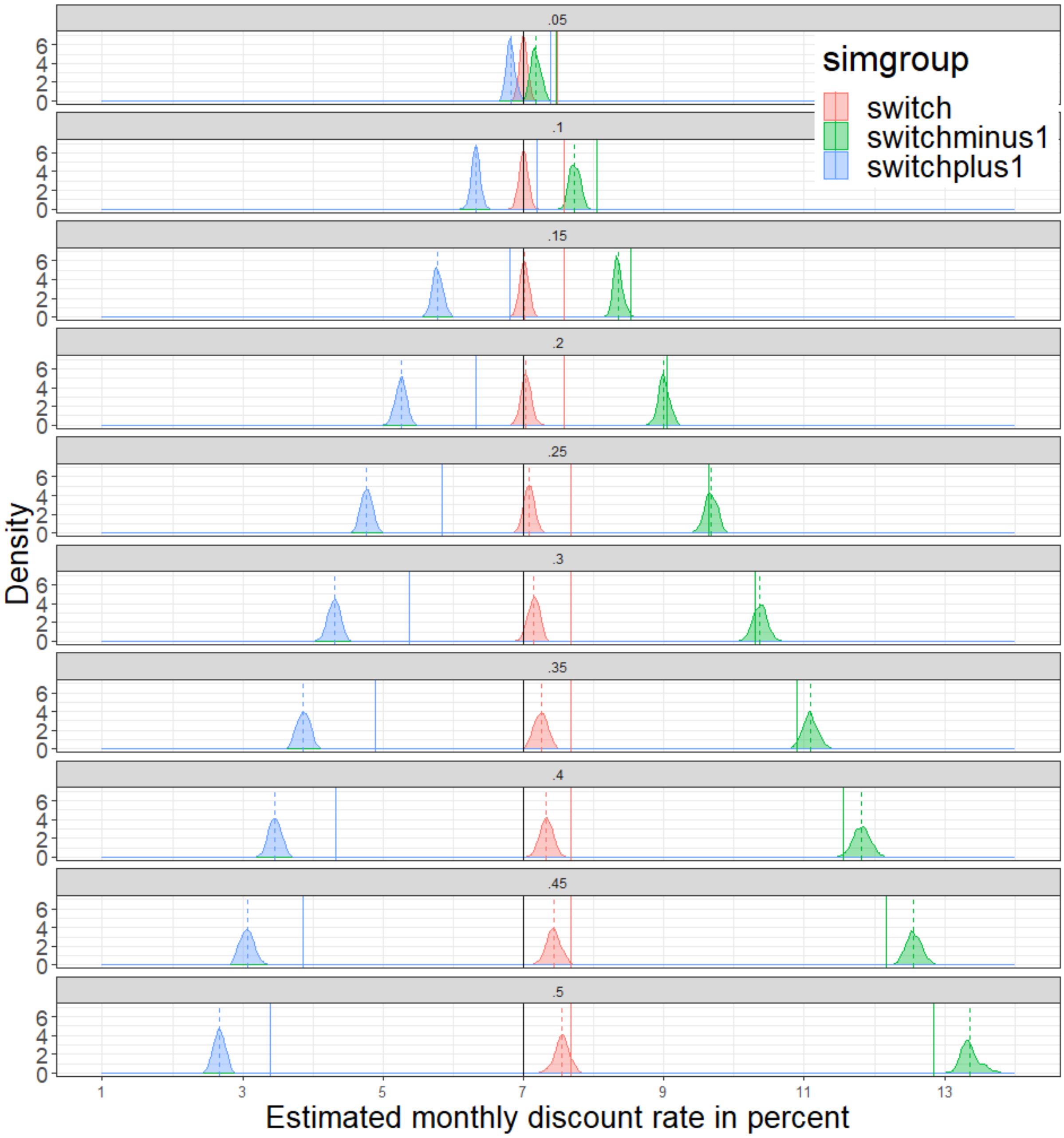
It is also interesting to note that estimates based on lists with no mistakes (solid lines) are also biased. Moreover, they are even biased for low μ.

A somewhat encouraging takeaway from this plot is that rapid elicitation for low μ is unbiased. An econometric recommendation is there for the use of rapid elicitation, and in the case of sufficiently low ($\mu \leq 0.2$ estimates are expected to be moderately biased at most.

bottom of the list. If the choice at the bottom of the list is near future again, then we do not find a switch point. Not that this does not rule out that the choice at task 9 was far future.

Figure 5: **Density plot for the estimated discount rate for different choices of μ. Switch point identified with rapid elicitation**

The bootstrap estimates are estimated on the two tasks defining the switch point (red), adding one dominated task above (one more near future choice, green), and adding one dominated task below (one more far future choice, blue). Dotted lines average estimate in indicated group, solid line with group color: Estimate in absence of mistakes, the expected choice chosen every time. Black solid line: the true discount rate. 100 simulations per μ



5. Conclusion

Ordered choice lists play a crucial role in many time and risk experiments. In this paper, we have considered time experiments only. By construction, such temporal choice lists have the majority of dominated tasks. That is a task in which the choice is known given the response of the two tasks defining the switch point in a choice list.[13]. We find that the inclusion or exclusion of dominated tasks affects discount rate estimates in a substantial and predictable way. More (less) dominated tasks where the near future alternative is preferred, gives higher (lower) discount rates. This appears to have gone unnoticed in the multiple-choice list literature.

Using a large data set from Ethiopa, we estimate monthly discount rates from 3 to 50 percent depending on which dominated tasks we include in addition to the tasks defining the switch point. This is disheartening. As we do not know the true discount rates, we cannot infer biases in a straight forward way.

In order to address bias from actual discount rates, we generate data, MPLs, from a structural model (Samuelson discounted utility model) and study to what extent inclusion/exclusion of dominated choices bias estimates. We find that in the absence of respondent mistakes, including dominated choices (complete choice lists), bias the estimate by about percent 1.3 percent (9.4 versus actual discount rate 7.1). In contrast, an estimation with switch points only gave an estimate close to the actual discount rate (7.3 versus 7.1)

A higher Luce error gives more noisy estimates of the discount rates, thus broader and lower density peaks. The positive relationship between the discount rate bias and the Luce error is more surprising and likely to be driven by the design of the choice lists. There is an inbuilt propensity for near-future choices for the chosen discount rate and utility curvature θ. Based on the insights from the preceding analysis based on actual Ethiopian data, this creates a bias towards higher discount rates. A bias that gets more accentuated for higher μ. One way to explore this is to search for discount rates that create a closer to 50/50 near future versus far future choices for the choices at hand. Table 3 may indicate a potential for following such a path.

An experimental design that aims for balanced choice lists may be beneficial in its own right as it makes switch points outside the list less likely. However, it only mitigates some of the bias related to dominated choices. The simulation analysis above points towards a targeted approach. This is to rely on rapid elicitation and use only the two tasks that identify the switch point in the ML estimation. A low Luce error (not much higher than 0.2 in our simulation) may give close to unbiased discount rate estimates. It must be stressed that the approach only seeks to minimize

[13] If we assume that the respondent does not make a mistake in one of the two switch point tasks.

a known bias of dominated choices, but biases have other origins. A misspecification of the model is known to bias estimates. Metaphorically speaking, we see the combo of rapid elicitation and using switch point defining tasks only as a cure for a known illness, bias induced by dominated choices, and acknowledge that other biases may be present.

References

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2006). Elicitation using multiple price list formats. *Experimental Economics*, 9(4):383–405.

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3):583–618.

Andersson, O., Holm, H. J., Tyran, J.-R., and Wengström, E. (2016). Risk aversion relates to cognitive ability: Preferences or noise? *Journal of the European Economic Association*, 14(5):1129–1154.

Andreoni, J., Kuhn, M. A., and Sprenger, C. (2015). Measuring time preferences: A comparison of experimental methods. *Journal of Economic Behavior & Organization*, 116:451–464.

Andreoni, J. and Sprenger, C. (2012). Estimating time preferences from convex budgets. *American Economic Review*, 102(7):3333–56.

Beine, M. A., Charness, G., Dupuy, A., and Joxhe, M. (2020). Shaking things up: on the stability of risk and time preferences.

Bonan, J., LeMay-Boucher, P., and Scott, D. (2022). Can hypothetical measures of time preference predict actual and incentivised behaviour? evidence from senegal. *World Development*, 159:106029.

Cassar, A., Healy, A., and Von Kessler, C. (2017). Trust, risk, and time preferences after a natural disaster: experimental evidence from thailand. *World Development*, 94:90–105.

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., and Taubinsky, D. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of risk and uncertainty*, 37:237–269.

Cohen, J., Ericson, K. M., Laibson, D., and White, J. M. (2020). Measuring time preferences. *Journal of Economic Literature*, 58(2):299–347.

Cox, D. and Hinkley, D. (1974). Theoretical statistics chapman and hall, london. *See Also*.

Drichoutis, A. C. and Nayga Jr, R. M. (2022). On the stability of risk and time preferences amid the covid-19 pandemic. *Experimental Economics*, 25(3):759–794.

Gassmann, X., Malézieux, A., Spiegelman, E., and Tisserand, J.-C. (2022). Preferences after pan (dem) ics: Time and risk in the shadow of covid-19. *Judgment and Decision Making*, 17(4):745–767.

Halevy, Y. (2015). Time consistency: Stationarity and time invariance. *Econometrica*, 83(1):335–352.

Harrison, G. W., Lau, M. I., and Rutström, E. E. (2013). Identifying time preferences with experiments: Comment. *Center for the Economic Analysis of Risk, Working Paper*, 9.

Holden, S. T., Shiferaw, B., and Wik, M. (1998). Poverty, market imperfections and time preferences: of relevance for environmental policy? *Environment and Development Economics*, pages 105–130.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5):1644–1655.

Ihli, H. J., Chiputwa, B., Winter, E., and Gassner, A. (2022). Risk and time preferences for participating in forest landscape restoration: The case of coffee farmers in uganda. *World Development*, 150:105713.

Pender, J. L. (1996). Discount rates and credit markets: Theory and evidence from rural india. *Journal of Development Economics*, 50(2):257–296.

Yesuf, M. and Bluffstone, R. (2019). Consumption discount rates, risk aversion and wealth in low-income countries: evidence from a field experiment in rural ethiopia. *Journal of African Economies*, 28(1):18–38.

6. Appendix

Table 4: Details regarding the Ethiopian Experiment.

Series	Initial time (weeks)	Future time (months)	Future Amount (ETB)	Task Row 10 Amount (ETB)
1	1	3	100	5
2	1	6	100	5
3	1	12	100	5
4	1	3	500	25
5	1	6	500	25
6	1	12	500	25
7	1	3	1000	50
8	1	6	1000	50
9	1	12	1000	50
10	0	12	100	5