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Abstract The appropriate way to empirically estimate time-dated utility and time preferences based on experimental data has been subject to controversy. Our study assesses whether within-subject magnitude treatments are more appropriately modeled through utility curvature, variable asset integration or as magnitude effects in the discounting function. We find that modeling magnitude effects through utility curvature at the same time as allowing for variable asset integration gives theoretically more consistent parameter ranges than including magnitude effects directly in the discounting function. Models with constant discount rates and limited and constant asset integration are rejected. More restricted but variable asset integration gives close to linear utility functions but such models are less robust than a matching fund model which gives a better fit and is robust and stable across multiple samples.

Keywords Discounting · Time-dated utility · Utility curvature · Asset integration · field experiment · Ethiopia

JEL Classifications C93 . D91

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1 Introduction

Utilities under risk and over time have been subject to recent controversy and intensive research with many important contributions triggered in particular by the paper by Andersen et al. (2008). Using a double Multiple Choice List (MCL) approach they estimated utility under risk and assumed time-dated utility in time preference experiments to have the same functional form. This resulted in a substantial reduction in the estimated discount rates when the time-dated utility curvature was determined by the Constant Relative Risk Aversion (CRRA) coefficient from the risk MCL.

A number of studies have later questioned whether utility under risk and over time are the same and have used alternative methods to test this (Abdellaoui et al., 2013; Andreoni and Sprenger, 2012a,b; Andreoni et al., 2015; Cheung, 2019). Cheung (2016) provides a good review of most of these studies. The methods used to elicit utility under risk and over time differ across these studies. However, one finding in common is that they find utility under risk and over time to be different and not to be closely correlated. Another finding in common is that utility under risk is found to be more concave than utility over time.

Our study aims to contribute to this literature by assessing whether time-dated utility can be estimated and be associated with magnitude effects in discounting behavior. Many studies have found that discount rates decline with the magnitudes of the prospects offered. Chapman (1996) found that magnitude effects in discount rates were much smaller after correcting for utility function curvature. Loewenstein and Prelec (1992) also explained magnitude effects as resulting from utility function curvature.

Another unsettled area in the estimation of utility under risk and over time is the degree of integration with background consumption or wealth (often called degree of asset integration). This issue has received more attention in relation to decisions under risk and empirical studies indicate a limited level of asset integration in an instantaneous utility function. Andersen et al. (2008) used a daily wage as the background level of consumption both in the risk and time preference estimation. Full asset integration would imply risk neutral behavior in small gambles and constant discount rates over varying time horizons in time preference experiments. This implies that limited asset integration can explain small stakes risk aversion which has been perceived as a puzzle (Rabin, 2000), and hyperbolic discounting (Holden and Quiggin, 2017). Andreoni and Sprenger (2012a) used a Stone-Geary utility function to estimate background consumption parameters in their estimation of time preferences. An important lesson from their study was that both the discount rate and the utility curvature parameters were sensitive to background consumption. They found that the discount rate declined and the concavity of the utility function increased with increasing background consumption and it was challenging to jointly estimate background consumption, utility curvature and discount rates given the high share of corner solutions in their data.

Holden and Quiggin (2017) found substantial magnitude and time horizon effects in an experiment where they assumed utility under risk and over time were the same and estimated under risk. They attributed hyperbolic and magnitude effects to variable asset integration based on a ”mental zooming” theory with larger amounts and longer time horizons resulting in higher degrees of asset integration. They used a separate risk experiment to elicit utility under risk that was used to handle utility in time as well. We question whether this may explain persistent magnitude effects in the discounting functions.

We propose a new theory for time-dated utility without assuming that utility under risk and over time are the same. It focuses on population-averaged behavior. We test the theory using data from an incentivized large sample lab-in-the-field experiment with substantial within-subject treatment variation in magnitude levels and time horizons that facilitate simultaneous estimation of discount functions and time-dated utility curvature while varying the assumptions about the degree of asset integration.

We ask the question whether so-called magnitude effects in time preference experiments, where larger amounts are associated with lower discount rates than for smaller amounts, can be explained by concavity in time-dated utility, captured by constant elasticity of marginal utility (CEMU) utility functions, and/or variable degrees of asset integration, similar to the zooming theory of Holden and Quiggin (2017). Theoretical assumptions are relaxed in a step-wise approach while critically examining the plausibility of parameter estimates as a method to choose among specifications. Constant discounting is tested towards more flexible discounting functions to assess hyperbolic effects, while explicitly testing for present bias. We study population averaged effects with our within-subject design. The large sample allows testing of the robustness of the results by splitting into district-wise samples.

The results indicate that models with variable asset integration give parameters more in line with theoretical assumptions (positive discount rates for all within-subject treatments and non-convex time-dated utility). The model with "matching fund" asset integration gave the most robust results (high consistency across the district-wise samples in utility and discounting parameters, and with low Luce error estimates) and time-dated utility with substantial concavity. The discounting functions retained strong general hyperbolic patterns as well as present bias.

We outline the theory for time-dated utility in part 2 of the paper. The experimental design, sampling and data are described in part 3. The estimation and identification strategy is presented in part 4 and the results in part 5, including robustness checks. The findings are discussed and related to the literature in part 6 before we conclude.

2 Model framework

In the following we will give a modeling framework for population averaged behavior that aims to explain certain systematic anomalies observed in inter-temporal choice. We will start from a classical Samuelson discounted utility model, where discount rate, utility curvature and asset integration is constant across within subject treatments. From this classical baseline, we introduce more flexible models where discount rates, utility curvature and asset integration vary systematically at the population level across within-subject treatments.

2.1 Base model

Consider the standard binary choice problem, where the respondent has to choose between two prospects, M_A at time t_A, or M_B at time t_B, where $t_0 \leq t_A < t_B$ (t_0 is the present time):

$$U_A = e^{-\delta(t_A - t_0)} u(y_1 + M_A) + e^{-\delta(t_B - t_0)} u(y_2) \tag{1}$$

and

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

where $u(\cdot)$ is the time-dated utility function, δ is the continuous time discount rate, and y_1 (y_2) is the time-dated base consumption that is integrated with the prospects at time t_A (t_B).

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

$$u = ((y)^{1-\theta} - 1)/(1-\theta) \tag{3}$$

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

Our baseline model is the basic Samuelson (1937) discounted utility (DU) model applied to our binary choice data and is given by equations 1, 2 and 3, where the asset integration is fixed to one daily wage ($y_1 = y_2 = w$).[1] In this baseline, the discount rate, δ, and the CEMU-parameter, θ, are endogenously determined as population-averaged and treatment-averaged variables based on the treatment variation in time horizons and magnitude levels[2]. A growing number of studies have questioned whether utility under risk can be used to represent time-dated utility curvature in inter-temporal choice (Andreoni and Sprenger, 2012b,a, 2015; Abdellaoui et al., 2013; Cheung, 2015, 2016, 2019). It is based on this literature that we use this alternative approach and estimate θ from the substantial variation in magnitude levels included in our unique experimental design.

2.2 Model extensions and theoretical foundations

The base model described in the preceding subsection does not allow for present bias nor for more general hyperbolic behavior and magnitude effects that have been identified in many studies of inter-temporal choice. We explore three dimensions for model extensions from the basic DU model to get better population-averaged fit with respondent data. These three dimensions include δ variation (Dimension 1=non-constant discounting), θ variation (Dimension 2=utility curvature), and asset integration variation (Dimension 3=variable asset integration).

[1] In other words, we assume limited asset integration in line with Andersen et al. (2008, 2018).

[2] We elaborate on the experimental design and treatments in part 3.

Earlier research on discounting behavior for long primarily explored Dimension 1 in form of assessing present bias (quasi-hyperbolic) and to some extent general hyperbolic discounting (discount rates falling with length of time horizon after controlling for present bias), and magnitude effects in discounting. The theoretical foundations for present bias are well documented and related to phenomena such as procrastination, addiction, immediate pleasure, and liquidity constraints (Loewenstein and Prelec, 1992; Laibson, 1997). The theoretical foundations for general hyperbolic and magnitude effects are more controversial and have to a less extent been tested. The hyperbolic model was proposed by psychologists while the quasi-hyperbolic model has dominated in economics and there have been few attempts to rigorously compare these (O'Donoghue and Rabin, 2015). Our approach is a more comprehensive approach as it nests these models by retaining exponential discounting while testing for present bias and time horizon effects by including dummy variables for MCLs with present versus future amounts and for each time horizon length. We use delayed front-end points in time as the base to avoid the confound with uncertainty associated with delayed payoffs when assessing the time horizon effect. Our β is therefore the inverse of that in the (δ, β)-model (Phelps and Pollak, 1968; Laibson, 1997).

Dimensions 1 and 2 have been explored in many of the recent studies where a growing number of studies have assessed whether utility under risk can be used to represent time-dated utility. We are not aware that any other study has assessed these two dimension jointly like we do in model Extension 1, see Table 1. In Extension 1 we test for hyperbolic discounting, including present bias. This approach begs for the question whether magnitude effects should be solely assumed into the utility curvature (Dimension 2) or whether it should also be brought into or retained in dimension 1 (magnitude effects in discounting) (Chapman, 1996; Loewenstein and Prelec, 1992). Extension 2 in addition allows for magnitude effects in the discounting dimension. Like in the baseline model, both these extensions allow CEMU-θ to be endogenously determined but constant across treatments and sample while asset integration is exogenous and constant at the daily wage rate level. Table 1 sums up all the extensions we test.

Table 1 Model variants.[a]

Dimension Model	1 Discount rate (δ)	2 Utility curvature (θ)	3 Asset integration (y)
Baseline model	$\delta(.)$	$\theta(M_B;.)$	w
Extension 1	$\delta(t_B,\beta;.)$	$\theta(M_B;.)$	w
Extension 2	$\delta(t_B,\beta,M_B;.)$	$\theta(M_B;.)$	w
Extension 3	$\delta(t_B,\beta,M_B;.)$	$\theta(t_B,M_B;.)$	w
Extension 4	$\delta(t_B,\beta;.)$	$\theta(t_B,M_B;.)$	M_B
Extension 5	$\delta(t_B,\beta;.)$	$\theta(t_B,M_B;.)$	$w(M_B/\text{mean}(M_B))$
Extension 6	$\delta(t_B,\beta;.)$	$\theta(t_B,M_B;.)$	$w(M_B/\text{mean}(M_B))(t_B/\text{mean}(t_B))$

[a] β is present bias dummy parameter.

In Dimension 2, the time-dated utility is captured. We choose a simple one-parameter CEMU utility function with an endogenous but constant population-averaged CEMU-θ for this in the first three models. These models assume that every point in time has the same shape of the time-dated utility function. Next, we want to test the hypothesis that the CEMU-θ parameter is constant and implying that the time-dated utility curvature is constant across time horizons. In Extension 3 the CEMU-parameter, θ, is therefore allowed to vary with time horizon t_B by making it a function of the time horizon dummy variables. Our hypothesis is that the time-dated utility function is less concave for longer time horizons.

In dimension 3 the degree of asset integration is captured. While Expected Utility Theory initially assumed full asset integration with wealth, research especially of risk preferences has revealed small gamble risk aversion and thereby limited asset integration (Rabin and Thaler, 2001; Binswanger, 1981).

We propose that the time-dated utility function will be more quickly saturated, and thereby more concave, if the amount received is consumed/utilized in a short period of time. However, the logical response to the receipt of larger amounts is to spread the utilization of this money over a longer time interval and thereby integrate the use of this windfall money with the background consumption over a longer time period. This is the fundamental theoretical argument for our proposition that higher magnitude levels are associated with higher degree of asset/consumption integration. To assess this, our next step is to allow the asset integration (y) to vary with magnitude. We apply two alternative approaches to this in Extensions 4 and 5 in Table 1. The first approach allows the windfall future time-dated amounts to be integrated with the same size background consumption. While this may sound arbitrary, it is not more arbitrary than the previous choice of a daily wage as the time-dated background consumption level used by Andersen et al. (2008) in risk as well as time preference estimation or the use of zero asset integration used in many studies. For comparison we include two additional variants for asset integration. In Extension 5 we normalize the variation in asset integration around the mean future amount multiplied by the daily wage, see Table 1. Finally, in Extension 6, we allow the degree of asset integration also to vary with time horizon by multiplying with the normalized time horizon length. This is inspired by the zooming theory of Holden and Quiggin (2017) which states that asset integration increases with time horizon and magnitude levels because longer horizons and larger amounts involve "bigger" decisions that stimulate subjects to zoom out and think more holistically.

To highlight the importance of Dimension 3 we illustrate in Figure 1 that a higher degree of asset integration implies a comparison of near future and far future prospects further out to the right where the utility function is flatter. This implies less diminishing utility associated with larger amounts compared smaller amounts and to models with zero or small and fixed degree of asset integration. Likewise, if a longer time horizon implies a higher degree of asset integration this also results in comparison of prospects in a region of the time-dated utility function with less curvature.

Overall, we are therefore assessing three alternative theoretical routes or dimensions for handling inter-temporal choice. All three routes have theoretical merit. The assessment of magnitude effects and the three alternative routes for capturing them

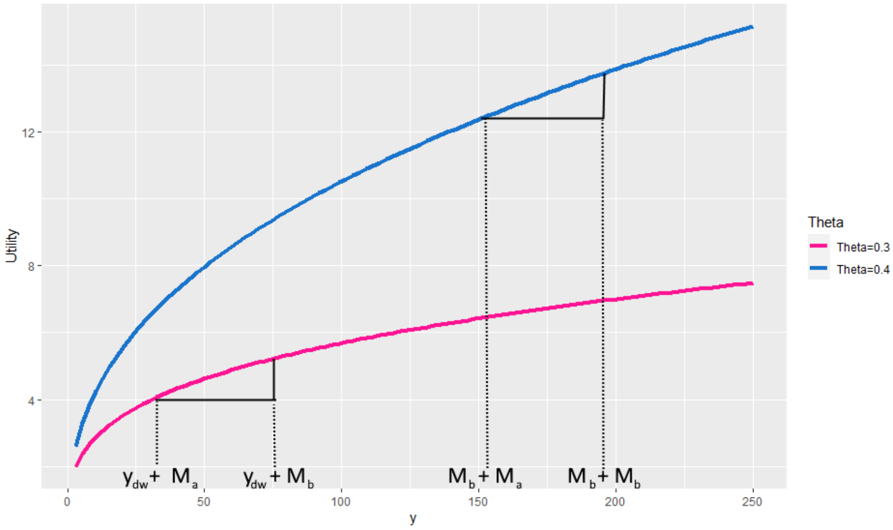

Fig. 1 Two different θ-asset integration pairs that give the same utility difference.

have, however, not been analyzed comprehensively before. This is the major novel contribution of our paper.

The theoretical merit of the alternative model specifications is assessed by judging the theoretical plausibility of estimated parameters and thereby functional forms of the discounting and utility functions. In general, discount rates for all time horizons and magnitudes are expected to be non-negative and utility functions to be non-convex as we operate in the gains domain only. We also expect the results for reliable specifications to be robust and reasonably consistent across sub-samples. For Dimension 2 the H_0 hypothesis is that θ does not vary with time horizon, or in other words, the time-dated utility function is stable and unaffected by the time horizon. We return to how we in more detail assess the alternative models against each other in part 4 of the paper where the size of the Luce error is considered as an additional indicator.

3 Description of experiments, sampling and data

3.1 Experimental design and field implementation

The data set used in the study is based on a large sample ”lab-in-the-field” experiment with young adults living in rural areas in Ethiopia. A within-subject $3*3+1$ Multiple Choice List (MCL) design was used with 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 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 CL and only the near future amount varied within each CL. Rather than presenting the whole list to respondents, a random row for each CL was presented first as a binary choice. Depending on the response (preference for the smaller near future amount or the larger far future amount), the enumerator was instructed to go to the bottom or the top of the list. This is used to narrow in 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 quickly narrow in on a switch point in the list. One advantage of this method is that it simplifies the choice alternatives for the respondent who does not see the whole price list and only makes one binary choice at the time without being distracted by information from all the other rows in the same CL. This should also reduce the risk of order effects, reduce the time needed to identify a switch point in each CL, and lead to only one switch point in the list. If respondents preferred the near future amount also at the bottom row in the CL, the enumerators were told to add one or more extra rows at the bottom of the table with even smaller amounts till a switch point is found (implying extremely high discount rates). Another advantage of fixing the far future amount and varying the front end amount, and with 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). [3]

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 for all payouts. Mekelle University is a trusted and long-term operator in the study areas. Table **??** in the appendix gives an example of a Choice List. Furthermore, Table **??** in the Appendix gives an overview of the MCLs with variation in near and far future points in time, and the far future amounts.

3.2 Sampling and data

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

[3] 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 (Andersson et al., 2016). The randomly chosen starting point may be associated with some bias if the first choice is erroneous. We tested for such potential bias (test results available from the authors upon request). Controlling for such bias had minimal effects on the issues we study in this paper.

Table 2 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.

business activities as sources of livelihood. Our sample differs systematically from the typical laboratory samples with university students by our sample having substantially lower level of average education and larger variation in the number of years of completed education. We also have a larger age variation. Young adults eligible for joining the youth business group program had to be land-poor and 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 we have 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.

The total sample of groups was 742 and the average number of youth members per group was 19.5, giving a total sample of close to 15,000 members. We randomly sampled groups and for sampled groups we sampled 12 members. Some groups had less than 12 members and then we tried to include all members that were available at the time of the experiment. We analyze data from 978 subjects in 119 youth business groups in five districts where we have 109,384 observations based on the 10 CLs.

Decisions under risk and over time are of central importance in their livelihood choices and understanding the logic of their decisions as revealed through experiments can be important for policy-making and interventions to create more sustainable livelihoods.

4 Model Estimation, Validation and Robustness Checks

The models are estimated using the maximum likelihood approach based on the binary choice data and the switch points identified in each CL in the within-subject design. We use the Luce error specification to handle decision errors. [4]

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

This gives rise to the following likelihood function:

[4] Blavatskyy and Maafi (2018) found that models with non-constant discount rates were better fitted with choice-based models with Luce (1959) errors than models with Fechner (1860) errors or Wilcox (2008) contextual errors.

$$\ln L(\delta, \theta, \mu; Choice_{ij}, M_A, |t_B, M_B, \beta|W_D) = \sum_i ((ln(\Phi(\nabla U)|Choice_{ij} = 1) + (ln(\Phi(1 - \nabla U)|Choice_{ij} = 0)) \tag{5}$$

where $Choice_{ij} = 1(-1)$ denotes the choice of alternative A (B). Alternative model specifications are estimated relating the population-averaged endogenous parameters (discount rate (δ), utility-θ and Luce error(μ) to the within-subject treatments to test alternative functional forms (exponential versus (quasi)-hyperbolic discounting functions (dimension 1), concavity of the time-dated utility (dimension 2), and constant and variable asset integration (dimension 3). We estimate population-averaged parameters for the full sample and per district (W_D).

In addition to assessing parameter signs and sizes versus theoretical expectations, we use the Luce error as an indicator of the model fit. A lower Luce error indicates a better fit of the model specification.

To assess the external validity and robustness of model results for the different specifications, we split our sample to run models of sub-populations across districts. We estimated district-wise models for the following model specifications that are included in Appendix 2:

a) Table 3, Baseline Samuelson DU model.

b) Table 3, Extension 3: Model with constant asset integration and hyperbolic discounting and magnitude effects.

c) Table 4, Extension 4: Matching fund models.

d) Table 4, Extension 5: Low but variable asset integration in magnitude.

e) Table 4, Extension 6: Low but variable asset integration in magnitude and time horizon.

5 Results

The first set of model results are presented in Table 3. The discount rates in all tables are measured as annualized inflation-corrected continuous time discount rates in 100% units. The models in Table 3 are specified with a low and constant base consumption (asset integration) level of one daily wage. The Baseline model is the DU model with exponential discounting with endogenous population-averaged discount rate and CEMU utility function with endogenous constant population-averaged Utility-θ across all the within-subject treatments. Table 3 shows that the continuous time discount rate in the DU model is 63.4 % and the $\theta = 0.349$, indicating quite concave time-dated utility with θ being highly significant and larger than zero.

In Model E1 in Table 3, we test for non-constant discount rates by including dummies to test for present bias and time horizon effects, i.e. population-averaged general hyperbolic and quasi-hyperbolic discounting. The base for the discount rate in Model E1 is 3 months horizon, while the parameters for the dummies for 6 and 12 months horizons have to be added to the base (constant) parameter to get the discount rate for each time horizon treatment. The present bias treatment was for the 12 months horizon and the discount rate for 12 months horizon without a delayed near future point in time has to be calculated by adding the parameter for the present bias to that for 12 months horizon and the constant parameter. We see that the base parameter for 3 months horizon is 188.6% while for 12 months horizon it is $(188.6 - 96.4)\% = 92.2\%$ with one week delayed initial point in time. Without delayed initial point in time, the discount rate is 14% higher, equal to 106.2%.Furthermore, Model E1 in Table 3 shows that the $\theta = -0.68$ which implies that the utility function is highly convex. The convex utility function contributes to the very high discount rates compared to the Baseline model.

Model Extension 2 (E2) deviates from E1 by including magnitude effects in the discounting function. This results in a dramatic change in the Utility-θ which changes from -0.68 to 1.08, that is from highly convex to highly concave. The model fit appears to be better as the Luce error reduces dramatically compared to the Baseline and E1 models. The magnitude effects in the discounting function are highly significant and in line with earlier findings, i.e. larger amounts are associated with lower discount rates even when utility curvature is modeled on magnitude levels. The time horizon and present bias variables remain significant and in the same direction as in model E2 while the constant term in the discount rate model is dramatically reduced after magnitude effects are included, causing a substantial reduction in all discount rates. They even move into the negative range for long horizons and large amounts.

Model Extension 3 (E3) expands from E2 by allowing Utility-θ to vary with time horizon. Table 3 shows that the concavity increases with time horizon but not much from the very high constant term for the shortest horizon. The Luce error reduces slighly compared to model E2 but the discount rates remain in the negative area for long horizons and large amounts.

The models that allow variable asset integration (dimension 3) are presented in Table 4. Extension 4 (E4) uses matching fund asset integration. The model gives quite concave utility that is increasing slightly for long horizons (12 months). It gives discount rates that decline with time horizon and increase by about 21% when there is no delay in initial point in time. The discount rate remains in the non-negative range for all time horizon treatments. The Luce error is small, indicating good model fit.

Model Extension 5 (E5) restricts asset integration around a daily wage by multiplying the daily wage with the relative magnitude of the future amount (normalized to average future amount). Table 4 shows that this model gives a utility function that is only slightly concave while concavity increases with the length of the time horizon, slightly more than in model E4. The discount rates are all in the reasonable range and with significant time horizon and present bias treatment effects. However, the Luce error is substantially higher than for the E4 model, indicating a poorer fit.

Model Extension 6 (E6) expands on E5 by also allowing asset integration to vary with time horizon (normalized to average horizon length). Like model E5, this specification also gives close to linear utility but in this case with Utility-θ being lower for longer time horizons. The discount rate parameters are quite similar in size to in the E5 specification and the Luce error is slightly higher and almost ten times as high as for models E2-E4.

Table 3 Discounting models with time-dated utility and constant asset integration

EQUATION	VARIABLES	(Baseline)	(E1)	(E2)	(E3)
Discount rate	Present bias		0.140***	0.146***	0.162***
			(0.017)	(0.015)	(0.015)
	6 Months		-0.468***	-0.426***	-0.431***
			(0.009)	(0.010)	(0.009)
	12 Months		-0.964***	-0.876***	-0.876***
			(0.011)	(0.013)	(0.012)
	500 Future amount			-0.609***	-0.624***
				(0.016)	(0.016)
	1000 Future amount			-0.808***	-0.832***
				(0.019)	(0.018)
	Constant	0.634***	1.886***	1.062***	1.044***
		(0.064)	(0.034)	(0.027)	(0.027)
Utility θ	6 Months				0.040***
					(0.005)
	12 Months				0.095***
					(0.008)
	Constant	0.349***	-0.677***	1.079***	1.070***
		(0.089)	(0.056)	(0.019)	(0.019)
Luce error	Constant	0.220***	0.498***	0.035***	0.031***
		(0.032)	(0.024)	(0.002)	(0.002)
	Observations	109,384	109,384	109,384	109,384
	Log likelihood	-44385	-38769	-37923	-37741

Discount rates are measured in 100% units.
Cluster-robust standard errors in parentheses, clustered at subject level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.1 Robustness checks

To further inspect the robustness and validity of these models we next run district-wise models for five districts. The results are presented in Tables A2.1-A2.5 in Appendix 2 and are briefly summarized here.

Table A2.1 presents the DU Baseline models for each district. We observe substantial variation in Utility-θ across districts, varying from -0.36 but insignificantly different from 0 in Degua Tembien district to 0.60 in Adwa district. The Degua Tembien model also suffers from large standard errors and larger Luce error than for the other districts.

Table A2.2, based on Extension 3, with magnitude effects in the discounting function, gives very similar results and with small Luce errors in all districts. The fit is therefore very good. The main problem with these models is that they all result in implausible negative discount rates for large amounts and long time horizons. The time-dated utility function is strongly concave and increasing in concavity with the length of time horizon for all districts.

Table A2.3, based on Extension 4 (Matching fund asset integration), gives consistent results across four out of five districts. District Klite Awlalo (model 4) gives junk results. For the remaining four districts the Luce errors are low and the utility curva-

Table 4 Discounting models with variable asset integration

EQUATION	VARIABLES	(E4)	(E5)	(E6)
Discount rate	Present bias	0.206***	0.175***	0.178***
		(0.015)	(0.012)	(0.013)
	6 Months	-0.445***	-0.490***	-0.423***
		(0.009)	(0.011)	(0.013)
	12 Months	-0.909***	-1.041***	-0.872***
		(0.012)	(0.016)	(0.022)
	Constant	1.256***	1.465***	1.419***
		(0.021)	(0.042)	(0.055)
Utility θ	6 Months	0.011	0.046***	-0.050***
		(0.008)	(0.014)	(0.015)
	12 Months	0.070***	0.158***	-0.121***
		(0.013)	(0.021)	(0.025)
	Constant	0.582***	0.029	0.105*
		(0.049)	(0.054)	(0.058)
Luce error	Constant	0.033***	0.296***	0.320***
		(0.003)	(0.018)	(0.023)
	Observations	109,384	109,384	109,384
	Log likelihood	-37174	-37325	-37456

Discount rates are measured in 100% units.
Cluster-robust standard errors in parentheses, clustered at subject level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

tures were similar and concave with concavity increasing slightly for the longest time horizon. [5]

Table A2.4, based on Extension 5, gives quite similar results across four out of five districts. The utility curvature is less well determined in Samre district (model 3). Utility is closer to linear for short horizons (3 months) and concavity increases slightly for longer time horizons. The Luce errors are substantially higher than for the Matching fund models.

Table A2.5, based on Extension 6, gives close to linear utility but with some variation in utility curvatures across districts. Unlike for Extension 5, the curvature is lower for long horizons (12 months). Like for Extension 5, utility curvature is less well established (high standard errors) for Samre district.

6 Discussion

We will discuss the results for our time-dated utility theory with variable asset integration in comparison with the dominant theories in the field, based on the estimated models.

[5] A noteworthy finding is that when a present bias dummy is included in the time-dated utility function, the model for Klite Awlalo performs very similar to the models for all other districts and gives an equally low Luce error. This is the case even though the present bias dummy is insignificant in the utility model for all districts. The results are available from the authors upon request.

The baseline Samuelson DU model with constant (population-averaged and treatment averaged) discount rate and endogenous utility-θ can be rejected as all the alternative models provide strong evidence of non-constant discount rates. The district-wise models with constant discount rates gave variable results for Utility-θ.

Extension 1 (E1), which introduces controls for present bias and time horizon. These effects are highly significant but this model fails in the sense that it generates strongly convex time-dated utility. When magnitude effects are allowed to affect discount rates directly as well as indirectly through the utility function in Extension 2, concave utility reemerges and the magnitude effects in the discounting function are strong and highly significant and with negative sign for longer time horizons. This result indicates that magnitude effects in discounting cannot be explained by utility curvature alone Chapman (1996); Loewenstein and Prelec (1992). And this basic result does not change when allowing time-dated utility curvature to vary with the length of time horizon in Extension 3. While models E2 and E3 apparently provides a good fit as demonstrated by the low Luce errors, their fundamental weakness is that they generate negative discount rates for long time horizons and large amounts. We therefore also reject these specifications as they give theoretically implausible parameter estimates.

Models E1, E2, and E3 demonstrate highly significant present bias in the data with the present bias contributing to discount rates being 14-16.2% *ceteris paribus*. These models also demonstrate strong and highly significant diminishing impatience after controlling for present bias. We cannot therefore reject the two hypotheses regarding there being hyperbolic effects in the data and we have to reject the Samuelson DU model. We also have to reject the hypothesis that hyperbolic discounting is only due to present bias. When it comes to magnitude effects in the discounting function, models E2 and E3 indicate that these cannot be explained solely as utility curvature effects. Overall, none of the models with constant asset integration inspected so far are fully satisfactory from a theoretical perspective based on the inspection of the estimated parameters.

Our time-dated utility theory suggested that larger amounts are to a larger extent integrated with background consumption and this may imply a fundamental error in models that impose constant or no asset integration. It is thus of interest whether the models with variable asset integration are better able to overcome the observed limitations of the models with limited and constant asset integration and produce more plausible parameter estimates. We present three models with variable asset integration for the full sample in Table 4.

Model E4 with matching fund asset integration, is based on our time dated utility theory that asset integration increases (linearly) with amounts allocated for utilization over a longer time interval. It produces more plausible parameter estimates with discount rates varying from 34.7% for 12 months horizon to 125.6% for 3 months horizon. The model yields quite concave utility-θ in the fairly narrow range 0.582-0.652, similar to the DU model but much lower than in the E2 and E3 specifications. There is a weak tendency that concavity increases with longer time horizon. In our theory we proposed that time-dated utility will be less concave when focusing at more distant points in time and this is not consistent with the finding in this specification. We also notice that the Luce error is low and at about the same size as in the E2 and

E3 models, indicating its good fit. We note that the concavity of the utility is quite strong in this model compared to some other recent studies estimating utility curvature through other means than behavior in risk experiments Andreoni and Sprenger (2012a); Abdellaoui et al. (2013); Cheung (2019). The inclusion of quite high magnitude levels in our experiment may be a reason for this. Less variation in magnitude levels may give closer to linear and less accurate estimates.

Model E5 allows variable asset integration but at a more restricted level, allowing it to vary with magnitude around a daily wage level. This model also yields reasonable discount rates in the range from 42.4-146.5%. These higher discount rates than in the previous model are explained by less concave utility with θ in the range 0.029-0.187. In this model the concavity increases somewhat more as the time horizon is extended compared to model E4. The Luce error is much larger than for the matching fund model. Overall, these two models with variable asset integration give parameter estimates that are more plausible for all treatments and treatment levels compared to the models with constant and limited asset integration.

Model E6 expands asset integration by also allowing it to vary with time horizon. This specification is inspired by the Holden and Quiggin (2017) zooming theory which allows asset integration to vary both in time horizon and magnitude while deriving utility curvature from a risk experiment. Unlike that study, we use magnitude effects also to estimate utility curvature and we do not aim to use variable asset integration to eliminate time horizon and magnitude effects. We test only how a linear adjustment for time horizon in the asset integration function affects the utility and discount function parameter estimates. We find that this model yields reasonable and slightly higher discount rates than the previous models and utility curvature that is close to linear but slightly concave for shorter time horizons. This specification therefore gives utility curvature estimates that are close to other recent studies (Abdellaoui et al., 2013; Andreoni and Sprenger, 2012a; Cheung, 2019) in terms of being close to linear but concave. The finding of utility curvature declining slightly with time horizon is also consistent with our time-dated utility theory. However, the Luce error in the model is slightly higher than for model E5 and much higher than for model E4, indicating that it gives a poorer fit to the data.

To further scrutinize the alternative models against each other, we assess the robustness of the results by estimating the models separately in five district-wise samples, see tables in Appendix 2.

Assessing jointly the variants of asset integration models across districts, the matching model E4 gives very robust and similar results across districts (except one) and with very low Luce errors. Discount rates are all within reasonable ranges and utility-θ does not vary much across districts or across time horizon treatments but is quite strongly concave in all models, within the range 0.515-0.751 across four districts and time horizon treatments. This compares to utility-θ variation from -0.014-0.273 for the E5 model when leaving one district out, and to -0.186-0.248 for the E6 model across four districts. The Luce errors are 8-10 times higher for models E5 and E6 than for model E4. This finding gives some cracks in the finding of apparent nice aggregate parameter estimates for the E5 and E6 models compared to the matching fund model (E4).

Overall, the models with variable asset integration give more plausible discount rates and utility curvature estimates than models with fixed and limited asset integration. The findings lend support to our theory about time-dated utility stating that larger amounts are integrated with larger consumption or asset values, based on the idea that larger amounts are perceived to be used over a longer time period.

7 Conclusion

We have used data from a large field experiment with within-subject magnitude and time horizon treatments to jointly estimate population-averaged time-dated utility and discounting functions. The experimental data are used to test the appropriateness of different theoretical models and hypotheses. In particular, we wanted to test our new time-dated utility theory stating that the level of asset integration is increasing in magnitude by larger amounts being distributed and combined with larger background consumption over longer time-intervals for time-dated utility. The theory also opens for additional asset integration for more far future prospects based on the zooming theory of Holden and Quiggin (2017) as well.

We assessed three dimensions for incorporating magnitude effects in inter-temporal discounting. The most common way has been to include it as magnitude effects directly in the discounting function. The second dimension is to incorporate magnitude effects through the time-dated utility function and use variation in magnitude treatments to identify the curvature of the time-dated utility function. The third dimension is through variable asset integration that increases with magnitude levels. Our study revealed that the first two, alone or in combination, were insufficient to give plausible parameter estimates in discounting and utility. However, using dimension two and three to incorporate magnitude effects gave models with parameters within reasonable ranges. A model with "matching fund" asset integration gave more robust and stable results and better fit (low Luce errors) than models with more restricted but variable asset integration. The latter types of models gave utility functions that were closer to linear than the matching fund model that gave quite concave utility functions. Our assessment is based on the requirement that discount rates should be non-negative for all time horizon and magnitude levels and have non-convex utility functions in the gains domain of the experimental payoffs that our experiment investigates.

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8 Appendix 1. Experimental tool

Overview of the Multiple Choice List design is presented in Table A1.1.

Table A1.1. Overview of Multiple Choice Lists

Choice List	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

Example of Choice List in the field experiment is presented in Table A1.2:

9 Appendix 2. Sensitivity Analyses

District-wise model results are presented below for selected structural model formulations.

Table A1.2. Example of Choice List

Time pref. Series no.	Start point	Task no.	Recive 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	

Table A2.1. Baseline DU model, by district

				District		
		(1)	(2)	(3)	(4)	(5)
EQUATION	VARIABLES	Raya	D. Tembien	S. Samre	K. Awlalo	Adwa
Discount rate	Constant	0.758***	1.107***	0.550***	0.628***	0.451***
		(0.137)	(0.207)	(0.117)	(0.133)	(0.070)
Utility θ	Constant	0.039	-0.355	0.355**	0.571***	0.603***
		(0.222)	(0.392)	(0.164)	(0.133)	(0.077)
Luce error	Constant	0.287***	0.522***	0.173***	0.182***	0.140***
		(0.081)	(0.172)	(0.049)	(0.053)	(0.023)
	Observations	20,983	25,861	12,688	15,043	34,809
	Log likelihood	-8054	-10896	-4596	-6433	-14070

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.2. Extension 3: Hyperbolic models with magnitude effects and constant asset integration, by district

EQUATION	VARIABLES	(1) Raya	(2) D. Tembien	(3) S. Samre	(4) K. Awlalo	(5) Adwa
Discount rate	Present bias	0.181***	0.145***	0.189***	0.152***	0.162***
		(0.031)	(0.027)	(0.048)	(0.052)	(0.028)
	6 Months	-0.345***	-0.411***	-0.409***	-0.507***	-0.478***
		(0.020)	(0.018)	(0.030)	(0.028)	(0.017)
	12 Months	-0.784***	-0.838***	-0.835***	-0.994***	-0.930***
		(0.027)	(0.025)	(0.038)	(0.033)	(0.020)
	500 Future amount	-0.650***	-0.684***	-0.607***	-0.589***	-0.595***
		(0.030)	(0.035)	(0.043)	(0.041)	(0.029)
	1000 Future amount	-0.850***	-0.899***	-0.820***	-0.826***	-0.791***
		(0.036)	(0.040)	(0.045)	(0.042)	(0.034)
	Constant	0.864***	1.088***	0.913***	1.262***	1.070***
		(0.048)	(0.061)	(0.061)	(0.087)	(0.048)
Utility θ	6 Months	0.060***	0.023*	0.056***	0.025*	0.055***
		(0.011)	(0.012)	(0.018)	(0.013)	(0.009)
	12 Months	0.126***	0.078***	0.134***	0.071***	0.104***
		(0.017)	(0.018)	(0.019)	(0.020)	(0.012)
	Constant	1.072***	1.068***	1.054***	1.080***	1.071***
		(0.034)	(0.041)	(0.046)	(0.053)	(0.034)
Luce error	Constant	0.025***	0.035***	0.025***	0.037***	0.030***
		(0.003)	(0.006)	(0.003)	(0.008)	(0.004)
	Observations	20,983	25,861	12,688	15,043	34,809
	Log likelihood	-6864	-9444	-3821	-5414	-11820

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.3. Extension 4: Discount rate models with time-dated utility with Matching fund asset integration, by district

EQUATION	VARIABLES	(1) Raya	(2) D. Tembien	(3) S. Samre	(4) K. Awlalo	(5) Adwa
Discount rate	Present bias	0.231***	0.223***	0.222***	0.088***	0.182***
		(0.030)	(0.030)	(0.041)	(0.023)	(0.027)
	6 Months	-0.354***	-0.430***	-0.412***	-0.554***	-0.491***
		(0.020)	(0.018)	(0.029)	(0.040)	(0.017)
	12 Months	-0.815***	-0.870***	-0.866***	-1.216***	-0.965***
		(0.026)	(0.025)	(0.036)	(0.067)	(0.019)
	Constant	1.113***	1.217***	1.183***	3.549***	1.323***
		(0.044)	(0.044)	(0.057)	(0.056)	(0.039)
Utility θ	6 Months	0.035*	-0.006	0.020	-1.039	0.030**
		(0.019)	(0.013)	(0.031)	(0.724)	(0.014)
	12 Months	0.097***	0.050**	0.087**	0.317	0.085***
		(0.035)	(0.024)	(0.042)	(1.323)	(0.023)
	Constant	0.531***	0.701***	0.505***	-18.571***	0.515***
		(0.115)	(0.084)	(0.131)	(1.204)	(0.108)
Luce error	Constant	0.032***	0.028***	0.031***	2.086***	0.036***
		(0.007)	(0.006)	(0.007)	(0.165)	(0.007)
	Observations	20,983	25,861	12,688	15,043	34,809
	Log likelihood	-6899	-9237	-3854	-5290	-11632

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.4. Extension 5: Discount rate models with time-dated utility with wage and magnitude calibrated asset integration. by district

EQUATION	VARIABLES	(1) Raya	(2) D. Tembien	(3) S. Samre	(4) K. Awlalo	(5) Adwa
Discount rate	Present bias	0.199***	0.194***	0.181***	0.147***	0.152***
		(0.025)	(0.025)	(0.031)	(0.036)	(0.023)
	6 Months	-0.431***	-0.450***	-0.510***	-0.554***	-0.551***
		(0.027)	(0.019)	(0.050)	(0.028)	(0.018)
	12.ffuturetimem	-0.981***	-0.980***	-1.086***	-1.143***	-1.104***
		(0.041)	(0.029)	(0.077)	(0.042)	(0.026)
	Constant	1.336***	1.361***	1.746***	1.675***	1.541***
		(0.123)	(0.078)	(0.342)	(0.105)	(0.075)
Utility θ	6 Months	0.096***	0.001	0.140	0.026	0.081***
		(0.034)	(0.026)	(0.100)	(0.031)	(0.024)
	12 Months	0.219***	0.113***	0.329**	0.138***	0.184***
		(0.055)	(0.040)	(0.153)	(0.052)	(0.035)
	Constant	-0.014	0.160*	-0.555	0.010	-0.010
		(0.170)	(0.094)	(0.587)	(0.124)	(0.100)
Luce error	Constant	0.266***	0.283***	0.386**	0.351***	0.299***
		(0.049)	(0.037)	(0.154)	(0.050)	(0.032)
	Observations	20,983	25,861	12,688	15,043	34,809
	Log likelihood	-6837	-9350	-3815	-5336	-11663

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.5. Extension 6: Discount rate models with time-dated utility with wage, magnitude and time horizon calibrated asset integration, by district

EQUATION	VARIABLES	(1) Raya	(2) D. Tembien	(3) S. Samre	(4) K. Awlalo	(5) Adwa
Discount rate	Present bias	0.196***	0.201***	0.164**	0.153***	0.154***
		(0.028)	(0.026)	(0.069)	(0.037)	(0.023)
	6 Months	-0.401***	-0.364***	-0.511***	-0.474***	-0.492***
		(0.056)	(0.022)	(0.087)	(0.032)	(0.025)
	12 Months	-0.872***	-0.785***	-1.050***	-0.954***	-0.945***
		(0.108)	(0.038)	(0.272)	(0.052)	(0.039)
	Constant	1.465***	1.285***	2.136	1.561***	1.517***
		(0.339)	(0.104)	(2.149)	(0.116)	(0.103)
Utility θ	6 Months	0.021	-0.096***	0.083	-0.080**	-0.014
		(0.046)	(0.034)	(0.232)	(0.032)	(0.025)
	12 Months	-0.039	-0.157***	0.019	-0.159***	-0.099**
		(0.063)	(0.054)	(0.205)	(0.059)	(0.041)
	Constant	-0.147	0.248**	-1.194	0.170	0.046
		(0.437)	(0.098)	(4.749)	(0.104)	(0.114)
Luce error	Constant	0.347**	0.303***	0.608	0.350***	0.330***
		(0.136)	(0.047)	(1.330)	(0.053)	(0.042)
	Observations	20,983	25,861	12,688	15,043	34,809
	Log likelihood	-6860	-9385	-3821	-5354	-11701

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1