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Mental Zooming as Variable Asset Integration in Inter-Temporal Choice

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ABSTRACT

Our time preferences deviate systematically from that of Homo economicus. They seem to be driven by a form of mental zooming, where higher and more distant amounts induce a more holistic perspective in contrast to smaller and near future amounts. The authors model zooming as variable asset integration and ask whether this can explain the observed variation in discount rates in experiments. It can. Equally important, the zooming for both time and magnitude is similar across two countries (Ethiopia and Malawi) and within a country (Ethiopia).

KEYWORDS

Asset Integration, Magnitude Effects, Time Discounting, Zooming Theory

INTRODUCTION

Loewenstein and Prelec (1992) were the first to give a good overview of anomalies in inter-temporal choice. Anomalies are defined to be violations of the discounted utility (DU) model of Samuelson (1937). While Samuelson's ambitions were very modest for this model, it gained widespread popularity as it represented rational inter-temporal choice equivalent to Expected Utility Theory (EUT) in risky decisions. To this day, it serves as a valuable benchmark. The anomalies in intertemporal choice include hyperbolic discounting (discount rates fall with the length of the time horizon), magnitude effects (small outcomes discounted more than large outcomes), the sign effect (gains are discounted more than losses), preference for improving sequences, and the delay-speedup asymmetry (Loewenstein and Prelec, 1992).

This paper aims to contribute to the literature on hyperbolic discounting and magnitude effects and their possible explanations. Hyperbolic discounting differs from exponential discounting (DU-model) in two ways. It puts higher weight on the present, and it involves a higher degree of patience for more distant prospects than the DU-model dictates. This paper refers to the latter as general hyperbolic discounting in contrast to the former, which is impatience in the form of present bias. The focus here is on general hyperbolic discounting. In particular, the study investigates to what extent the zooming theory, proposed by Holden and Quiggin (2017), is consistent with the empirical regularities found in incentivized lab-in-the-field experiments. The rationale behind the zooming theory and model is

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that larger and more distant amounts pave the way for a broader financial assessment compared to smaller near future amounts. In other words, the lower discount rates observed for larger and more distant amounts arises because the respondents take a more long-term and holistic view of their financial situation for such decisions. This means that they, to a larger extent, integrate the amount with other assets and consumption plans. In contrast, smaller and near future amounts call for narrower framing and thereby less asset integration. At a technical level, the zooming in the zooming models works through variable asset integration, where small near future amounts involve close to zero asset integration whereas larger amounts and longtime horizons call for considerable asset integration. Section 3 gives the algebraic formulation of the model and how it is applied to experimental data.

Different theories have been proposed to explain hyperbolic discounting. First, the most well-known and documented is the present bias associated with immediate pleasure, addiction, self-control problems and commitment devices, and liquidity constraints. Present bias is associated with quasi-hyperbolic discounting (Loewenstein and Prelec, 1992; Augenblick et al., 2015; Augenblick and Rabin, 2019; Balakrishnan et al., 2020) - also defined as the (β, δ)-formulation and originated from Phelps and Pollak (1968). Second, risk or uncertainty about future payments versus immediate payments is another potential reason for apparent time-inconsistent choices, and that has been studied (Halevy, 2008, 2015; Epper et al., 2011). To control for such differences in risk between immediate and future payments, some studies include delayed up-front points in time, such as introducing a one-week delay. A recent study in Kenya revealed that even very short delays in initial payment eliminated present bias (Balakrishnan et al., 2020). Other studies have provided guarantees related to future amounts. Grijalva et al. (2014) provided such guarantees and found diminishing impatience in a Multiple Choice List (MCL) experiment with time horizons of 5, 10, and up to 20 years into the future.[1] Moreover, a Convex Time Budget (CTB) experiment[2] with similar long time horizons and guaranteed future payments (Grijalva et al., 2018), also found diminishing impatience associated with longer time horizons. Their estimated discount rates were an order of magnitude lower than rates found with the CTB approach over much shorter time horizons of 5-14 weeks by Andreoni and Sprenger (2012), who found high discount rates and no present bias. The discount rate gap across these studies may be due to general hyperbolic effects but requires more variation in time horizon treatments to be detected within one study. Both studies used relatively small university student samples from universities in the US. It is natural to ask to what extent their results carry over to less select respondent groups. In particular, we ask whether general hyperbolic effects are found in broader respondent groups in other parts of the world? Our study provides evidence of that.

In the seminal paper on magnitude effects (Thaler, 1981), Thaler found that discount rates decline with higher magnitudes. This magnitude effect has, over the years, been confirmed by many researchers, e.g., (Benzion et al., 1989; Green et al., 1997; Kirby and Maraković, 1995). The lion's share of these contributions is in Thaler's original paper's spirit and relied on the ranking of hypothetical prospects and offered no real payouts. However, magnitude effects are also confirmed in several more recent incentivized experiments. Andersen et al. (2013) is one example. They studied magnitude effects based on incentivized experiments with adult Danes and found small but statistically significant magnitude effects. However, the variation in magnitude levels was limited in their study, with the largest amounts (DKK 3000[3]) being only double the smallest amounts (DKK 1500). Halevy (2015) used magnitude levels of 10 USD and 100 USD with a week delay in a student sample in Canada and found highly significant magnitude effects. Holden and Quiggin (2017) also found highly significant magnitude effects in their rural sample in Malawi, where the largest magnitude levels were up to 20 times larger than the smallest amount. Similar magnitude effects are reported in Sun and Potters (2019).

Some intertemporal choice models open for the contingency that a choice between prospects A and B is not evaluated in isolation, but the potential amounts, say M_A and M_B, are integrated with other assets, for instance, a daily wage, w. In other words, the respondent utility-ranks the time discounted potential amount pairs $(M_A + w, w)$ and $(w, M_B + w)$, where the first amount is at t_A and the second is at t_B. Such limited asset integration models have gained some popularity in risk experiments and may explain small stakes risk aversion (Binswanger, 1981; Wik et al., 2004; Andersen et al., 2018). Limited and variable asset integration in risk may also help explain the Rabin paradox (Rabin, 2000).[4]

The role of asset integration is less studied in the context of intertemporal choice. Andersen et al. (2008) included constant asset integration with a daily wage rate as base consumption when estimating discount rates for adult Danes to ensure positive discount rates. Andreoni and Sprenger (2012) estimated asset integration or base consumption integration with a Stone-Geary utility function based on the CTB data and revealed that the estimated discount rates and utility curvature were sensitive to base consumption levels. They suggested that future research should address the issue of asset integration.

Holden and Quiggin (2017) show that within-subject variation in time horizon and magnitude levels from a field experiment with a sample of adults from Malawi is consistent with their zooming theory. This study relies on the same zooming framework and uses population-averaged mental zooming theory models. These models are estimated on an large Ethiopian data set and compare them with similar estimations for the original Malawian data used by Holden and Quiggin (2017). A unique within-subject 3*3+1 design is used to separately estimate the magnitude, general hyperbolic, and present bias effects at the population level. Next, the zooming theory's external validity is tested by a country comparison (Malawi and Ethiopia) and a district comparison (Ethiopia). Finally, unit-free zooming parameters are derived for time horizon and magnitude to assess their similarity across samples.

These time horizon and magnitude treatments are considered as objective factors with reference to Böhm-Bawerk's distinction between objective and subjective factors (Böhm-Bawerk, 1889). Though the analysis rests on the zooming framework of Holden and Quiggin (2017), this study differs in one important way. It does not estimate individual risk aversion to determine individual utility curvature.[5] In contrast, it assumes that a log utility function with variable asset integration is appropriate for the estimation of population-averaged discount rates.

The estimation results demonstrate strong and consistent population-averaged general hyperbolic and magnitude effects in the Ethiopian data as a whole and by district, with discount rates falling with the length of time horizon and magnitude levels of future amounts. Moreover, the estimated zooming parameters are similar across the countries (Ethiopia and Malawi) and the Ethiopian districts. It must be stressed that this zooming behavior is not present bias in disguise. By including some choice lists comparing present and future amounts, a test for present bias is implemented in the zooming models, and present bias is highly significant both statistically and economically. However, it does not explain the general diminishing impatience in the data. In other words, the respondents are present biased zoomers, and zooming behavior is the most salient population-averaged characteristic for all the independent population samples.

This paper has four contributions to the literature. First, it tests the external validity of the zooming theory of Holden and Quiggin (2017), using a large new data set from Ethiopia that allows for district-wise testing.[6] To the best of the authors' knowledge, this paper is the first to check external validity in this way. A requirement for such a test on two data sets (from two countries) is that the experiments themselves are essentially the same in terms of the design of choice lists. In this study, the Ethiopian experimental design and data allow both a between-country and a within-country comparison.

Second, it provides evidence of widespread strong general hyperbolic preferences based on incentivized field experiments. Third, it provides evidence of widespread strong magnitude effects in the same data based on the unique within-subject time horizon times magnitude level treatments. Furthermore, the unit-free zooming parameters in time and magnitude are astonishingly consistent across samples. The zooming parameter in time is about double in size of that for magnitude. The mental zooming telescope is therefore adjusting more strongly in time than in money.

The remainder of the paper is organized as follows. Section 2 gives a description of experimental designs and summary statistics regarding the experiments. Section 3 briefly presents the zooming theory and its implementation for the experimental data at hand. Section 4 provides the results of the base model without zooming as well as the zooming model. Section 5 concludes.

EXPERIMENTAL DESIGN AND DATA

The data sets used in the comparative zooming-analysis originate from two different field studies, one in Malawi (2012) and one in Ethiopia (2017). Both rely on a within-subject multiple-choice list (MCL) design. Both field experiments were incentivized by the respondents having a 10% chance of winning.[7] A random draw after the completion of all price lists determined whether or not the respondent was a winner. The local university guaranteed future payments. In Ethiopia, the lucky winners received a reward card with name, date, and amount to be paid out and could collect the money at the local savings and credit institution (DECSI). In contrast, in Malawi, the local university (LUANAR) also administered the actual payouts. The respondents in both countries had reason to trust the local university as it had operated in the study areas for several years and lived up to its obligations.

The field experiments were carried out through interviews by carefully trained experimental enumerators as the respondents were computer illiterate. Classrooms in schools or farm training centers were used for the field experiments. Typically, each corner in the classroom had one enumerator and one respondent facing the corner. Standardized explanations were translated to the local language, Tigrinya in Ethiopia, and Chichewa in Malawi, to minimize enumerator bias.[8]

In each CL, the endpoints in time and magnitude level are fixed. The near future point in time is also fixed, and it is only the near future amount that varies within each CL, with the highest amount at the top and the lowest amount at the bottom. Only the near future amount is varied in each list. This design allowed identifying very high discount rates, which is difficult and potentially costly for designs with the near future amount fixed. Future amounts and time horizons varied across CLs in the within-subject design. These future amounts and time horizons are the within-subject exogenous treatments in our analysis. The order of the CLs, and thereby the within-subject treatments, was randomized for each respondent, and the order was recorded, allowing testing for order bias in the analysis.

The whole CL is not presented to the respondents. They are only given binary alternatives from one row on the list, starting from a randomly chosen row. The list is only used for recording the responses and the sequence of rows presented by the enumerator. We use a rapid elicitation approach 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 either to the top or the bottom of the list. This choice, up or down, is done in the direction that is most likely to lead to a switch. 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 (see example list 10 in the Appendix). 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.[9] 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.

We first describe the large Ethiopian field study. The description of the Malawi study that follows covers only the treatments that are identical to those in the Ethiopian experiment as only those are used in the following analysis.

The Ethiopian Experimental Design and Implementation

The treatments used included two front end timing treatments (present time and one-week delay), three endpoint timing treatments (3, 6, and 12 months), and three endpoint magnitude treatments (100, 500, and 1,000 ETB[10]), in a 3*3+1 design. There was only one treatment with no front-end delay that included the lowest amount (100 ETB) and the longest time horizon (12 months) to test for the importance of present bias. Table 1 summarizes the experimental design.

The Malawian Experimental Design and Implementation

The Malawian design was more complicated[11] but in our comparative study here, we only included equivalent treatments of those in our Ethiopian experiment. However, the factorial combination of treatments was somewhat different; see Table 1 for the combination of front-end, time horizon, and magnitude treatments.[12] The front end or near future timing treatments included present (no delay) and one week delay. The far future timing treatments included 3-months, 6-months, and 12-months from the present time.[13] The magnitude levels, which were fixed for the endpoints, were MK 1,000, MK 5,000, and MK 10,000.[14] The largest far future amount is, therefore, 10 times the smallest far future amount. The smallest amount represents 3.3 times the daily wage rate.[15]

This comparative study's treatment variations for both countries are presented in Table 1. The numbers in parentheses in Table 1 indicate the number of repetitions of each treatment level in the total set of treatments. Unlike in the Ethiopian experiment, the treatments were randomized across households. Each respondent was exposed to 9 of 27 CLs. The randomization was done so that all 27 series were randomized across three respondents within a village. In this comparative study, as only 17 of 27 treatments are used, there is some variation in the number of CLs per respondent. Holden and Quiggin (2017) provide further information about the Malawian experiments and data.

Table 10 in the Appendix gives an example of a CL. Furthermore, Table 9 in the Appendix gives an overview of the treatments in the whole MCL.

Table 1. Treatments in the Ethiopian and Malawian experiments

Country	Treatment type	Treatment levels
Ethiopia	Front end point in time	Current (1), 1 week delay (9)
	Endpoint in time	3 months (3), 6 months (3), 12 months (4)
	Far Future amount level	100 ETB (4), 500 ETB (3), 1000 ETB (3)
Malawi	Front end point in time	Current (5), 1 week delay (12)
	Endpoint in time	3 months (8), 6 months (5), 12 months (4)
	Far Future amount level	1 KMK (4), 5 KMK (5), 10 KMK (8)

Note: ETB = Ethiopian Birr. KMK= Thousand Malawian Kwacha. The number of treatments at each treatment level in parenthesis.

Magnitude Levels in the Ethiopian and Malawian Experiments

To compare mental zooming through asset integration across countries, we need to measure time and magnitudes comparably. The universal measurement of time in days, months, and years is natural for comparison across the two countries. Amounts do not have the same widely recognized scale of measurement. We adopt the much-used local daily wage as a unit for comparison. Table 2 gives the conversion to daily wage units for the CLs used in the subsequent analysis.

Table 2. A comparison of the Ethiopian and Malawian experiments

Ethiopia		Malawi	
Amount Ethiopian Birr	Daily wage units	Amount Malawian Kwacha	Daily wage units
1000	33.3	10000	33.3
500	16.7	5000	16.7
100	3.33	1000	3.33

Note: Calculations based on a daily wage rate of 300 MK in Malawi in 2012 and 30 ETB in Ethiopia in 2017.

Table 2 displays the closely matched magnitude treatment levels across the two countries (measured by the number of daily wage units). We see that the Malawian experiment contained more treatments without front-end delay.

Overview of the Data

Table 3 gives an overview of the data in terms of the number of subjects, the total number of observations, observations per subject, and for Ethiopia, a breakdown of these per district sample. The number of observations per subject was lower in Malawi as only the CLs that matched the CLs in the Ethiopia experiment were included. The standard CLs in Ethiopia resulted in 110 observations per subject. However, as rows were added at the bottom of some CLs for some subjects to reach a switch point, the average number of observations per subject is 112. Each subject in Malawi responded to 9 CLs, but on average, about half of these fitted the Ethiopian CLs and were therefore included in the estimation.

Table 3. Treatments in the Ethiopian and Malawian experiments

	Ethiopia	Malawi
No. of respondents	978	350
CLs per respondent	10	4
Rows per CL[a]	≥ 11	≥ 11
No. of observations	109,384	15,214
Percentage male	68.5	56.8
Mean age (sd)	28.3 (9.9)	51.9 (16.6)
Ethiopian Districts	**No. of respondents**	**No. of observations**
Raya Azebo	186	20,983
Degua Tembien	233	25,861
Seharte Samre	115	12,688
Klite Awlalo	133	15,043
Adwa	311	34809

[a]The CL is longer if not a switch point is reached in a standard list of 11 rows, as more rows are added until a switch point is reached.

The Zooming Theory in Brief

The zooming theory's fundamental idea is that decisions involving longer time horizons and larger amounts get a more holistic assessment and consideration than decisions that involve shorter time horizons and smaller amounts. Therefore, mental zooming involves a higher degree of asset integration for prospects with longer time horizons and larger amounts than prospects involving shorter time horizons and smaller amounts. Rather than thinking about asset integration as something that takes place or not, the theory assumes that mental zooming acts through a varying degree of asset integration.[16]

In order to give this theory an algebraic formulation, consider that a respondent faces the choice between two amounts, M_A and M_B at time t_A and t_B, respectively. Furthermore, let $t_0 \leq t_A < t_B$, where t0 denotes the present time.

In this case, the respondent must decide between:

$$U_A = e^{-\delta(t_A - t_0)} u(y_A + M_A) + e^{-\delta(t_B - t_0)} u(y_B)$$

and:

$$U_A = e^{-\delta(t_A - t_0)} u(y_A) + e^{-\delta(t_B - t_0)} u(y_B + M_B)$$

where $u(\bullet)$ is the utility function, δ is the discount rate, and y_A (y_B) is the amount (asset or background consumption integration) that the prospect amount is integrated with at time t_A (t_B).

The model uses the daily wage, $y_0 = w_0$, as a starting reference point for the asset integration base consumption level. Moreover, the zoom adjusted base consumption is modeled the following way:

$$y_A = y_B = w_0 f(t_B - t_A, M_B)$$

where w_0 is the daily wage rate and $f(t,M)$ is a differentiable function with $f'_t > 0$ and $f'_M > 0$.

Note that the monotonicity property (in both arguments) ensures a higher degree of asset integration for higher and more distant amounts. Moreover, asset integration is only driven by the highest and most distant prospective amount (M_B), which is the future reference amount in each CL. As the same level of asset integration is assumed for both alternatives A and B in each CL, the notation can be simplified and the two utility alternatives Equation 1 and Equation 2 can be rewritten as (by using Equation 3):

$$U_A = e^{-\delta(t_A - t_0)} u\left(w_0 f(t_B - t_A, M_B) + M_A\right) + e^{-\delta(t_B - t_0)} u\left(w_0 f(t_B - t_A, M_B)\right)$$
$$U_B = e^{-\delta(t_A - t_0)} u\left(w_0 f(t_B - t_A, M_B)\right) + e^{-\delta(t_B - t_0)} u\left(w_0 f(t_B - t_A, M_B) + M_B\right)$$

In the following, relying on a log-utility function[17]:

$$U_A = e^{-\delta(t_A - t_0)} \log(w + M_A) + e^{-\delta(t_B - t_0)} \log(w)$$
$$U_B = e^{-\delta(t_A - t_0)} \log(w) + e^{-\delta(t_B - t_0)} \log(w + M_B)$$

where w is the asset integration (measured in daily wage rate units). Note that this is a CRRA-utility function with $r = 1$.[18]

In the zoom models, the asset integration, $w = w_0 f(t_B - t_A, M_B)$, is allowed to vary across treatments in the within-subject design but not across individuals within the same sample as the study focuses on population-averaged treatment effects.

Model Estimation

To estimate the model parameters, the maximal likelihood estimation approach with the Luce error (μ) specification is used (Holt and Laury, 2002).[19] The μ-dependent utility differential is estimated as a binary choice model:

$$\nabla U = \frac{U_A^{1/\mu}}{U_A^{1/\mu} + U_B^{1/\mu}}$$

This gives rise to the following likelihood function:

$$\ln L\left(\delta\left(x_i \right), \mu\left(x_i \right); Choice_{ijk} \right)$$
$$= \sum_i \left(\left(\ln\left(\Phi(\nabla U) \mid Choice_{ijk} = 1 \right) + \ln\left(\Phi(1 - \nabla U) \mid Choice_{ijk} = 0 \right) \right) \right)$$

where *i* represents respondents, *j* choice lists, and *k* choice list rows. $Choice_{ijk} = 1(0)$ denotes the choice of alternative A (B) in each row, and the x_i include the CL level treatments and other covariates.[20]

ANALYSIS

In this section, the base models for the annualized discount rates are estimated first, where the asset integration is fixed, followed by the zooming models where the asset integration is allowed to vary.

Base Models With Fixed Asset Integration

In the base model, the annualized discount rate is allowed to depend on both the magnitude of future amounts and the time horizon (measured by the time difference between the two points in time for alternative dated amounts and present bias). The explicit base model for the log annualized discount rate is a linear function:

$$\log \delta = C + \alpha \log W + \beta \log T + \gamma PB + \sum_{j=1}^{10} \zeta_j ST_j$$

where C is a constant, W is far future amount measured in daily wage units, T is the time difference in months between amount A and amount B, PB is the present bias variable[21], and ST_j represent the starting row dummies for the CL in question.

The utility models are of the form given by Equations 6 and 7, and it is a partial asset integration model in the sense that $f(t_B - t_A, M_B) = 1$ in Equation 3, such that the base consumption integrated asset level is $w = w_0$, i.e. one daily wage across all CLs. With this specification, eventual hyperbolic and magnitude effects should show up in the parameters on the time, magnitude, and present bias treatment variables.

The prime focus in this paper is the time and magnitude treatment effects in the annualized discount rate. Tables 4 and 5 give the estimation results for Ethiopia and Malawi, respectively, with an increasing number of controls introduced. An important, perhaps surprising finding is that controlling for present bias does leave the log time-difference coefficient virtually unchanged.[22] This implies that the quasi-hyperbolic model can immediately be rejected for both countries. It must be noted that present bias also contributed to significantly higher discount rates in both countries in the range of 13 to 16 percentage points higher annual discount rates than for CLs with delayed initial points in time. In short, the respondents, in addition to being present biased, show a very strong tendency of having lower discount rates for more distant time horizons.

Table 4. The Ethiopian base models. Asset integration: 1 daily wage [a]

	Dependent variable: log δ			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Logdwr	-0.352*** (0.006)	-0.335*** (0.006)	-0.334*** (0.006)	-0.329*** (0.006)
Logtimediff	-0.588*** (0.009)	-0.609*** (0.009)	-0.610*** (0.009)	-0.605*** (0.009)
presentdummy		0.164*** (0.015)	0.163*** (0.015)	0.154*** (0.015)
Constant	2.147*** (0.030)	2.131*** (0.031)	2.130*** (0.030)	2.136*** (0.031)
μ	0.044*** (0.001)	0.044*** (0.001)	0.044*** (0.001)	0.064*** (0.006)
Starting row FE	No	No	Yes	Yes
μ-Enumerator FE	No	No	No	Yes
Observations	109,384	109,384	109,384	109,384
Respondents	978	978	978	978

Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

Table 5. The Malawian base models. Asset integration: 1 daily wage [a]

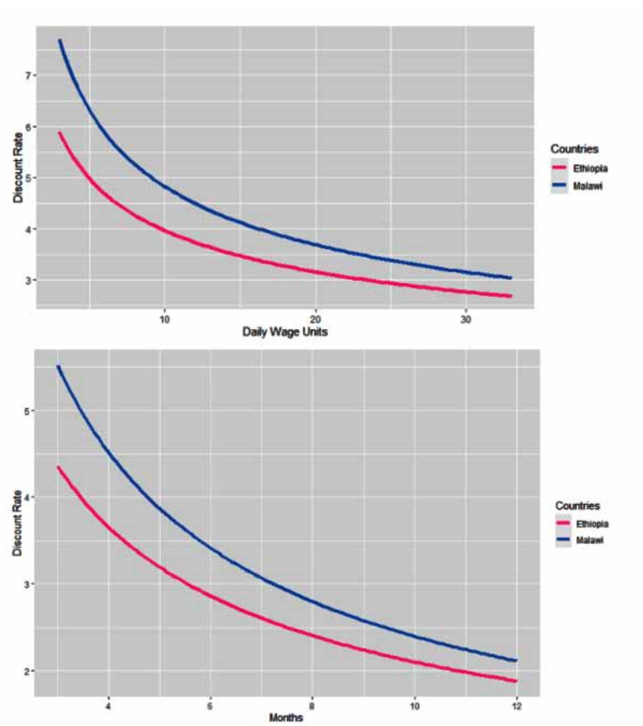
	Dependent variable: log δ			
	Model 1	**Model 2**	**Model 3**	**Model 4**
logdwr	-0.392*** (0.033)	-0.385*** (0.032)	-0.384*** (0.033)	-0.388*** (0.032)
logtimediff	-0.694*** (0.063)	-0.696*** (0.061)	-0.695*** (0.062)	-0.692*** (0.062)
presentdummy		0.140*** (0.046)	0.137*** (0.047)	0.127*** (0.048)
Constant	2.516*** (0.133)	2.437*** (0.138)	2.456*** (0.140)	2.468*** (0.148)
μ	0.061*** (0.004)	0.061*** (0.004)	0.062*** (0.004)	0.058*** (0.007)
Starting row FE	No	No	Yes	Yes
μ-Enumerator FE	No	No	No	Yes
Observations	15,214	15,214	15,214	15,214
Respondents	350	350	350	350

Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

The additional controls possibly associated with measurement errors had minimal effects on the population-averaged time and magnitude parameters in both countries. The main conclusion is that the estimated time and magnitude effects remain robust to the inclusion of additional controls.[23]

More importantly, the across-country point estimates of the most refined models (model 4) for the time and magnitude coefficients are not significantly different. This is comforting, as it tells us that the population-averaged marginal effects of more distant time horizons or larger future amounts are essentially the same across the two country samples. However, the constant terms, the starting point of the annualized (log) discount rates are significantly different across countries.[24] Figure 1 illustrates this point for the magnitude and time horizon.

Figure 1. Discount rate as a function of magnitude and discount rate as a function of time. Ethiopia and Malawi



Another way to shed light on the difference across countries is to compare across country variation to within-country variation. The much larger sample size for Ethiopia is utilized to make separate population-averaged estimates for five district samples. The results are given in Table 6.

Table 6 shows that there is striking stability across districts for the magnitude coefficient. Only one pair, the lowest (Degua Tembien), and the highest (Adwa), are not within two standard deviations of each other.[25] The Malawi sample has a slightly higher coefficient than the district of Degua Tembien in Ethiopia but within two standard deviations of this point estimate.

In the case of the time horizon coefficient, there is a clear and statistically significant division between the three first districts (Raya Azebo, Degua Tembien, Seharti Samre), which are in the −0.54 to −0.59 range, compared to the two last districts (Kilite Awlalo, Adwa), which are in the −0.64 to −0.69 range. The latter two districts are on par with Malawi (−0.69). For the time horizon coefficient, the cross-country variation, therefore, is within the district variation in Ethiopia.

There is a significant variation in the constant term estimates across Ethiopian districts in Table 5. These represent treatment levels outside the specified treatment ranges (one-month time horizon and future amount of one daily wage), which also explain the large size of these coefficients, which

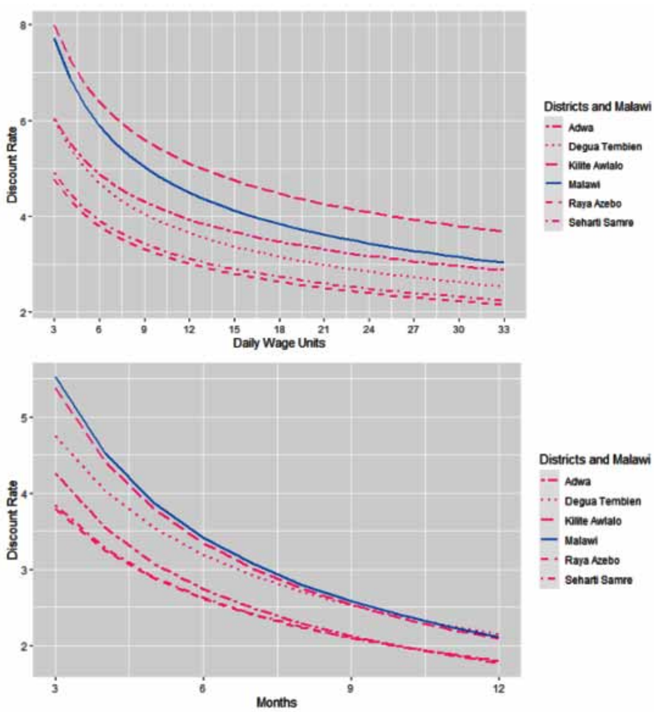
Table 6. Base models estimation for Ethiopian districts [a]

	Dependent variable: log δ				
	Raya Azebo	Degua Tembien	Seharti Samre	Kilite Awlalo	Adwa
logdwr	-0.330*** (0.012)	-0.360*** (0.014)	-0.326*** (0.018)	-0.323*** (0.018)	-0.310*** (0.012)
logtimediff	-0.539*** (0.020)	-0.575*** (0.019)	-0.550*** (0.027)	-0.684*** (0.023)	-0.632*** (0.015)
presentdummy	0.150*** (0.031)	0.147*** (0.028)	0.153*** (0.047)	0.137*** (0.051)	0.163*** (0.026)
Constant	1.925*** (0.066)	2.190*** (0.069)	1.950*** (0.082)	2.433*** (0.070)	2.141*** (0.055)
μ-Constant	0.058*** (0.012)	0.067*** (0.013)	0.059*** (0.020)	0.078*** (0.016)	0.064*** (0.012)
Observations	20,983	25,861	12,688	15,043	34,809
Respondents	186	233	115	133	311

Model 4 specification (Table 3) with present bias, enumerator and starting row FE. Asset integration= 1 daily wage. Cluster robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

Figure 2. Discount rate as a function of magnitude (daily wage units) and as a function of time horizon (months) for Ethiopian districts and Malawi.



are measured as 100% units of annualized discount rates. For the districts, the range is 1.9 to 2.43, and for Malawi it is at the high end of this range (2.45). Malawi resembles Kilite Awlalo for the constant term and timing coefficients and Degua Tembien for the magnitude coefficients. At the higher level, the coefficients for Malawi are within the district variation of Ethiopia. However, no district is a close match when all three parameter estimates (constant, time, and magnitude) are simultaneously compared.

A third way to illustrate the difference in point estimates of the constant term, time, and magnitude coefficients is to plot the discount rate as a function of time and magnitude. Figure 2 plots the Ethiopian district estimates together with the Malawi sample estimates.

Zoom Models

In this section, the zoom models for Malawi, Ethiopia, and the five Ethiopian districts are presented to explore to what extent the zooming appears to be robust across countries and districts.

For the base models, the degree of asset integration was constant $f(t_A - t_o, M_B) = 1$ (all prospects were combined with one daily wage unit). In the zooming models, a function of the following form is fit:

$$f\left(t_B - t_A, M_B\right) = c \cdot \left(\frac{t_B - t_A}{6}\right)^a \left(\frac{M_B}{16.7w_0}\right)^b$$

Table 7. Zoom model estimation by country with present bias FE and start row FE [a]

	Dependent variable: log δ	
	Ethiopia	**Malawi**
Zoom parameters:		
a	1.96	1.84
b	0.96	0.67
Base asset parameter		
c	1	3
logdwr	0.000 (0.007)	-0.001 (0.029)
logtimediff	0.001 (0.009)	-0.000 (0.071)
presentdummy	0.138*** (0.015)	0.106** (0.041)
Constant	0.190*** (0.029)	0.074 (0.144)
μ-const	0.080*** (0.008)	0.081*** (0.011)
Observations	109,384	15,214
Respondents	978	350

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

[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months. This model corresponds to Model 4 inTable 4 and Table 5.

where $t_B - t_A$ is the time difference between the far future and near future points in time for alternative potential amounts, measured in months. M_B is the future amount measured in daily wage units, w_0, the daily wage, and where a, b, and c are parameters to be determined.

The zoom parameters of interest are a and b. They represent the marginal time and magnitude zooming coefficients. The parameter c, in contrast, is the base point asset integration and is set just high enough to ensure that all discount rates are positive.[26] Table 7 displays the zoom parameters for the Ethiopia and Malawi models.

The zoom parameters for the time horizon are similar. One way to get a feeling for the difference is to look at a doubling of the time difference from 6 months to 12 months. The doubling results in a $2^{1.96} = 3.89$-fold increase in the asset level integrated with the prospect in contrast to $2^{1.84} = 3.58$ fold increase for Malawi. The zoom effect of doubling magnitude from the median magnitude ($16.7w_0$) gives a $2^{0.96} = 1.95$-fold increase in the integrated asset level for Ethiopia. The corresponding number for Malawi is 1.59. In other words, there is some cross-country variation in the time and magnitude zooming parameters. More striking is the difference between the zooming degree for time and magnitude. A doubling of the time horizon leads to close to a four-fold increase in the level of asset integration. In contrast, a doubling of the amount has only half the effect, a (close to) two-fold effect on the level of asset integration. This indicates that time effects (hyperbolic) are relatively stronger than magnitude effects. This comparison is dimensionless and hence independent of how time and money are measured. It is an intriguing possibility that this asymmetry between time and magnitude is a robust characteristic of human nature, just like loss aversion is.

The zooming models by district in Ethiopia are presented in Table 7. The estimates of the zoom parameters appear to be robust across districts. All the district-wise time horizon zoom parameters

Table 8. Zoom models by district for Ethiopia [a]

	Dependent variable: log δ				
	Raya Azebo	**Degua Tembien**	**Seharti Samre**	**Kilite Awlalo**	**Adwa**
Zoom parameters:					
a	1.76	1.80	1.86	2.21	2.11
b	1.01	1.06	1.02	0.91	0.90
Base asset parameter					
c	1	1	1	1	1
logdwr	-0.002 (0.012)	-0.001 (0.014)	0.001 (0.019)	0.000 (0.018)	0.000 (0.012)
logtimediff	0.001 (0.019)	0.001 (0.019)	-0.000 (0.027)	-0.000 (0.026)	-0.001 (0.015)
presentdummy	0.126*** (0.031)	0.116*** (0.028)	0.143*** (0.046)	0.141*** (0.050)	0.164*** (0.025)
Constant	0.116* (0.064)	0.296*** (0.064)	0.141* (0.080)	0.337*** (0.068)	0.150*** (0.050)
μ-Constant	0.069*** (0.015)	0.077*** (0.015)	0.069*** (0.024)	0.104*** (0.021)	0.081*** (0.015)
Observations	20,983	25,861	12,688	15,043	34,809
Respondents	186	233	115	133	311

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

[a]All models have starting row FE and enumerator FE for the Luce error. logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

are in the 2 ± 0.25 interval. Likewise, the district-wise magnitude zoom parameters are all in the 1 ± 0.1 interval. This implies that the district-wise spread is around 10 percent for time horizon and magnitude. Moreover, the asymmetry mentioned above between time and magnitude also applies to the district zooming estimates.

CONCLUSION

This study has used experimental field data from two countries (Ethiopia and Malawi) to assess the external validity of the zooming theory of Holden and Quiggin (2017). The zooming theory argues that general hyperbolic and magnitude effects in time preference experiments are explained by variable asset integration. A more holistic evaluation takes place for prospects with longer time horizons and larger amounts. This implies that such prospects are, to a larger extent, integrated with the current wealth, income, or consumption level of the respondents than prospects with a shorter horizon and smaller amounts.

A large data set from five districts in Ethiopia is used and compared with the original data set of Holden and Quiggin (2017) from Malawi. The analysis shows a highly consistent pattern of population-averaged hyperbolic time horizon and magnitude effects across locations. Moreover, the pattern appears to be consistent with the zooming theory. The time horizon and magnitude effects imply that discount rates fall as time horizons and amounts increase. It must be stressed that the strong general hyperbolic pattern persists after controlling for the present bias in the data.

The results are promising in the sense that an introduction of two zooming parameters, one for the time horizon (a) and one for the magnitude (b), was enough to capture a large share of the within-subject treatment effects across all experimental samples. Equally important, the actual population-averaged zooming appears to be roughly at the same level across districts and countries.

The study found that the behavioral responses in the time preference experiments were consistent with the zooming theory and variable asset integration. While evidence of partial or no asset integration has been observed in risk preference experiments, asset integration has received less attention with respect to time preferences. We show that mental zooming or narrow bracketing not only may explain small stakes risk aversion but also hyperbolic and magnitude effects in time preferences.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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ENDNOTES

1 A Multiple Choice List (MCL) experiment, also sometimes called a Multiple Price List (MPL) is an experiment where the respondent faces a list of binary choices between prospects.

2 A Convex Time Budget design requires that the respondent solves a max problem of the type $\max_{c_t, c_{t+k}} U(c_t, c_{t+k})$, such that $1 \, r \, c_t + c_{t+k} = m$. That is, it allows the respondent to choose a convex combination of amounts. For further details, see Andreoni and Sprenger (2015).

3 About 540 USD with the 2013 exchange rate.

4 Rabin has shown that a risk-averse, expected-utility-maximizing individual who, from any initial wealth level, turns down gambles where she loses 100 or gains 110, each with 50 percent probability, will turn down 50–50 bets of losing 1,000 or gaining any sum of money. This is commonly referred to as Rabin's paradox.

5 The estimation of individual utility curvature relied on the assumption that the utility under risk is the same as the utility over time. Some recent studies have questioned this assumption (Abdellaoui et al., 2013; Andreoni and Sprenger, 2012, 2015; Cheung, 2016, 2019).

6 The Malawian and Ethiopian data sets consist of 350 and 978 respondents, respectively. This gives a total of 1328 respondents.

7 Andersen et al. (2014) tested the effect of paying only a subset of the participants by varying the probability of payment for discounting tasks from 10% to 100% and found that the effect of probabilistic discounting to be insignificant in their sample of adult Danes. A review of alternative payment regimes Charness et al. (2016) indicated that in most comparisons of paying all or a subset, the loss of motivation is small, much smaller than the implied reduction in actual payment. This finding is also in line with non-linear probability weighting and over valuation of low probabilities. An obvious benefit of payouts to only a fraction of respondents is the possibility to run more experiments for a given funding. It also reduces the administrative costs of future payments to the spatially dispersed respondents.

8 In the analysis, we introduce enumerator fixed effects to control for enumerator bias.

9 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. We test for such potential bias.

10 ETB is Ethiopian Birr.

11 We refer to Holden and Quiggin (2017) for a description of the full design.

12 In all experiments, subjects have to choose between M_A at t_A and M_B at t_B, where $t_A < t_B$. A front-end timing treatment means that t_A varies and t_B remains fixed. Likewise, an endpoint timing treatment means that t_B varies while t_A remains fixed.

13 To keep things simple for the respondents, we did not adjust the far future time horizons for the near future time delay but adjusted the one-week difference in time horizon, e.g., 9 months - 1 week, in the mathematical calculation of discount rates during estimation.

14 MK is Malawian Kwacha.

15 See next section for a comparison of the monetary values across countries.

16 Holden and Quiggin (2017) proposed this theory and found empirical support for zooming relying on data from Malawi. Moreover, they claimed zooming accounted for the lion's share of the hyperbolic discounting and magnitude effects present in the data. We follow their formulation (with some minor notational changes) closely.

17 20We use Equation 3 to write the utilities in a more condensed form.

18 The family of constant relative risk aversion utility (CRRA) functions, $u(c) = [1/(1-r)]c^{1-r}$ has ln(c) as a limiting case corresponding to r = 1. In the analysis we only consider population-averaged zooming, and assume that CRRA=1 is appropriate for population averages.

19 The Luce specification allows for 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).

20 The CL treatments are specified differently across models. Other covariates also vary from model to model; see equation 10. A respondent's probability of picking the alternative with the lowest utility may depend on the enumerator skill. We allow for enumerator bias in the error rate (μ). In other words, the frequency of respondent mistakes depends on enumerator skill. We do not allow for enumerator fixed effects in (log)δ for the following reason. Enumerator fixed effects tend to give a downward bias of the constant (log)δ term, as some of this "reference" point annualized discount rate is wrongly attributed to enumerators. The effect varies with the irrelevant default enumerator, which is a smoking gun for the unintended modeling cost of enumerator fixed effects in this class of models. We have neither found papers that use enumerator fixed effects nor found papers that comment on the potential enumerator bias in models of this type. We believe this is due to this challenge of "an arbitrary partition" of the reference point annualized discount rate.

21 This variable is equal to 1 if the amount is at once, 0 otherwise.

22 -0.588 versus -0.609 for Ethiopia, and -0.694 versus -0.696 for Malawi. We control for present bias by a dummy variable equal to 1 for choices involving an immediate amount. An alternative is to exclude all choices that involve immediate amounts. In the appendix, Tables 11 and 12 provide the estimates, where we consider only choices between future amounts. Note that in this case, Model 1 and Model 2 are equal as there are no immediate amounts. The estimate is unchanged for Ethiopia (-0.609) and slightly lower (-0.710) for Malawi. We will, in the following, rely on the full sample and models with present bias dummy.

23 Due to the smaller sample in the Malawi case, the standard errors are considerably higher (roughly 3 times higher), which raises the bar regarding finding statistically different point estimates. We also note that the parameter for the error rate, μ, is similar across countries.

24 The point estimate for the Ethiopian constant is 2.136, which is just outside two standard deviations of the Malawian point estimate (2.468 − 2 x 0.148 = 2.17).

25 It must be noted that the probability of the max draw and min draw being more than two standard deviations apart is more than 60 percent in the case of 5 draws from a normal distribution. In other words, we cannot reject the hypothesis that all districts have an equal magnitude coefficient.

26 The base (point) asset integration corresponds *to* $t_B - t_A = 6$ (months) and MB = 16.7 (daily wages). The model's actual fitting relies on an iterative procedure. The stopping criterion is when time and magnitude coefficients get close to zero (and insignificant), and c is high enough to ensure positive discount rates. Though the zooming parameters are given by the strict criterion, the lower limit that leaves all discount rates positive, the other estimates sensitivity to the actual a and b is of interest. Table 13 and Table 14 in the appendix gives the estimates corresponding to Table 7 for a plus-minus 10 percent change in a and b.

APPENDIX: ADDITIONAL INFORMATION

Table 9. 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

Table 10. The Ethiopian Experiment

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	

Table 11. The Ethiopian base models. Only prospects with future amounts. Asset integration: 1 daily wage [a]

	Dependent variable: log δ			
	Model 1	**Model 2**	**Model 3**	**Model 4**
logdwr	-0.335*** (0.006)	-0.335*** (0.006)	-0.334*** (0.006)	-0.329*** (0.006)
logtimedifm	-0.609*** (0.009)	-0.609*** (0.009)	-0.609*** (0.009)	-0.604*** (0.009)
Constant	2.134*** (0.031)	2.134*** (0.031)	2.133*** (0.031)	2.139*** (0.032)
μ	0.044*** (0.001)	0.044*** (0.001)	0.044*** (0.001)	0.066*** (0.007)
Observations	98,316	98,316	98,316	98,316
Respondents	978	978	978	978

Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

Table 12. The Malawian base models. Only prospects with future amounts. Asset integration: 1*daily wage* [a]

	Dependent variable: log δ			
	Model 1	**Model 2**	**Model 3**	**Model 4**
logdwr	-0.391*** (0.041)	-0.391*** (0.041)	-0.389*** (0.041)	-0.388*** (0.041)
logtimedifm	-0.710*** (0.087)	-0.710*** (0.087)	-0.706*** (0.087)	-0.680*** (0.086)
Constant	2.469*** (0.155)	2.469*** (0.155)	2.490*** (0.158)	2.437*** (0.168)
μ	0.060*** (0.004)	0.060*** (0.004)	0.062*** (0.005)	0.056*** (0.008)
Starting row FE	No	No	Yes	Yes
μ-Enumerator FE	No	No	No	Yes
Observations	8,811	8,811	8,811	8,811
Respondents	350	350	350	350

Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

Table 13. Sensitivity to zoom parameters illustrated by ±10 percent variation in a and b.The Ethiopian zoom model [a]

	Dependent variable: log δ				
	(a,b)	**(0.9a,b)**	**(1.1a,b)**	**(a,0.9b)**	**(a,1.1b)**
logdwr	0.000 (0.007)	0.001 (0.007)	-0.000 (0.007)	-0.026*** (0.007)	0.029*** (0.007)
logtimedifm	0.001 (0.009)	-0.061*** (0.009)	0.063*** (0.009)	-0.020** (0.009)	0.022** (0.009)
presentdummy	0.138*** (0.015)	0.137*** (0.014)	0.143*** (0.015)	0.150*** (0.014)	0.125*** (0.015)
Constant	0.190*** (0.029)	0.292*** (0.029)	0.089*** (0.029)	0.218*** (0.029)	0.161*** (0.029)
μ	0.080*** (0.008)	0.081*** (0.008)	0.080*** (0.008)	0.086*** (0.009)	0.074*** (0.007)

Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months.

Table 14. Sensitivity to zoom parameters illustrated by ±10 percent variation in a and b.The Malawian zoom model [a]

	Dependent variable: log δ				
	(a,b)	$(\mathbf{0.9}a,b)$	$(\mathbf{1.1}a,b)$	$(a,\mathbf{0.9}b)$	$(a,\mathbf{1.1}b)$
logdwr	-0.001 (0.029)	-0.005 (0.029)	0.004 (0.029)	-0.018 (0.030)	0.020 (0.029)
logtimedifm	-0.000 (0.071)	-0.073 (0.070)	0.074 (0.073)	-0.055 (0.069)	0.064 (0.075)
presentdummy	0.106** (0.041)	0.106** (0.041)	0.106*** (0.041)	0.104** (0.042)	0.108*** (0.040)
Constant	0.074 (0.144)	0.202 (0.143)	-0.057 (0.145)	0.109 (0.146)	0.021 (0.143)
μ	0.081*** (0.011)	0.081*** (0.011)	0.082*** (0.012)	0.086*** (0.012)	0.076*** (0.011)

Cluster robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
[a]logdwr= log daily wage rate units, logtimediff= log time difference between alt. A and alt. B in months

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