



Norwegian University of Life Sciences  
School of Economics and Business



# **Bounded awareness and anomalies in intertemporal choice: Google Earth as metaphor and model**

**Stein T. Holden and John Quiggin**

**Working Papers No. 13 / 2015**

ISSN: 2464-1561

# Bounded awareness and anomalies in intertemporal choice: Google Earth as metaphor and model

By

Stein T. Holden<sup>1</sup> and John Quiggin<sup>2</sup>

**Abstract** This paper draws on recent developments in the theory of choice under uncertainty to model anomalies in intertemporal choice. Cognitive limitations leading to hyperbolic discounting and magnitude effects in intertemporal choice may be described in terms of bounded awareness, and represented by phenomena familiar from visualization software such as Google Earth. Cognitive limits on visualization impose constraints on both the area being viewed and the level of detail of the view, with a trade-off between the two. Increasing detail at the expense of limiting the area viewed may be described as zooming.

Data from a field experiment were used to assess the theory with an incentive-compatible multiple price list approach involving magnitude levels of 5x, 10x and 20x the basic magnitude level with time horizons of one, three, six and 12 months. Without zooming adjustments in base consumption, very strong hyperbolic and magnitude effects were found, and present bias could not explain the hyperbolic effects. The zooming model provides an explanation of what appear to be significant intertemporal anomalies in the data.

<sup>1</sup> School of Economics and Business, Norwegian University of Life Sciences, P.O. Box 5003, 1432 Ås, Norway, Email: stein.holden@nmbu.no

<sup>2</sup> School of Economics, University of Queensland, Brisbane, QLD, Australia.

**Key words:** Intertemporal choice, hyperbolic discounting, magnitude effects, zooming, limited asset integration, field experiment, calibration test.

**JEL codes:** D03, D91, C93.

---

## 1 Introduction

Anomalies in inter-temporal choice include hyperbolic discounting, quasi-hyperbolic discounting (present bias), and magnitude effects (Chung and Herrnstein 1967; Thaler 1981; Ainslie 1991; Loewenstein and Prelec 1992; Laibson 1997) and represent deviations from the well-known discounted utility model (Samuelson 1937).

Likewise, magnitude effects in inter-temporal choices in form of systematically lower discount rates associated with prospects with larger monetary amounts appears as an accepted empirical regularity<sup>3</sup> with few convincing explanations. It may not be explained by the functional form of the utility function and is named as the “increasing proportional sensitivity property” (Prelec and Loewenstein 1991).

Hyperbolic discounting has been a popular way to model anomalies in intertemporal choice associated with inter-temporal inconsistent behavior with potential negative externality effects. While hyperbolic discounting has been accepted as a widespread behavioral characteristic there is no generally accepted account of its sources or its relationship to other aspects of choice, notably including choice under uncertainty.

The aim of this paper is threefold. First, we link anomalies in intertemporal choice to the literature on unawareness that has arisen mainly in the context of

<sup>3</sup> See Frederick, Loewenstein and O'Donoghue (2002) for a review of early studies and Andersen et al. (2010) for a more recent review.

choice under uncertainty. Second, we introduce a visual metaphor for bounded awareness as ‘zooming’, derived from visualization software such as Google Earth. Third, we present the results of experimental studies designed to test the zooming hypothesis.

The approach used in the present paper draws on recent developments in the theory of choice under uncertainty, in which the standard assumption that decisionmakers are aware of all possible states of nature is relaxed. Models incorporating various forms of ‘unawareness’ have been developed by Grant and Quiggin, 2013, Halpern and Rego (2006), and Heifetz, Meier and Schipper (2006) among others. Schipper (2015) provides a bibliography.

The standard assumption of full awareness may be violated in two ways. First, decisionmakers may limit the set of contingencies they consider, effectively imputing zero probability to some possible states of nature. Quiggin (2015) refers to this as ‘reduction’. Alternatively, decisionmakers may lump together contingencies which are, in reality, distinct, as in Heifetz, Meier and Schipper (2006). Quiggin (2015) refers to this as coalescence.

Given bounded cognitive resources, decisionmakers must engage in both reduction and coalescence if they are to reduce even relatively simple decision problems to a manageable scale. Moreover, there is a trade-off between the two processes: the fewer possibilities are excluded from consideration, the coarser must be the aggregation of those that remain.

Visualization software inspired by Google Earth provides a metaphor that is familiar to many. With use of such tools one chooses an area to ‘zoom in’ on as well as the degree of zooming in. As one zooms in new details appear but the frame becomes much narrower. Zooming permits more focus on the details within a narrow frame but causes the user to lose sight of the larger landscape.

In many situations the brain works as a mental zooming device and narrows in the focus on some specific issues or aspects of prospects that are compared and

does not evaluate these holistically. Narrow framing (Barberis, Huang and Thaler 2006) or choice bracketing (Read, Loewenstein and Rabin 1999) in some contexts are more specific outcomes of the zooming behavior of the brain. This is therefore a more general theory to attempt to explain what appears as specific patterns of systematic inconsistent intertemporal choices which have been captured with hyperbolic discount functions or as magnitude effects with higher patience for larger prospects.

In the present paper, we apply the ‘zooming’ metaphor in relation decisions involving intertemporal choice. The main focus of the paper is the relationship between ‘zooming out’ and asset integration. We argue that higher stakes are likely to contribute to ‘zooming out’ which in turn leads to higher levels of asset integration.

Section one of the paper reviews the literature on hyperbolic discounting and magnitude effects in intertemporal choice including the attempts that have been made at explaining the phenomena. Section three outlines the interpretation of zooming in relation hidden framing and partial asset integration. Section four describes field experiments used to obtain data for testing the consistency of the theory with the data. Section five uses standard along with the zooming model of bounded awareness to demonstrate and discuss the predictive power of the model. The final section concludes.

## **2 Literature Review**

Research has revealed that both animals and humans behave as if their discount functions are approximately hyperbolic (Chung and Herrnstein 1967; Loewenstein and Prelec 1992; Ainslie 1991; Laibson 1997), with quasi-hyperbolic discounting explained by present bias and liquidity constraints.

Magnitude effects in discounting arise when a proportional increase in the magnitude of both current and future consumption possibilities leads to reduced discounting, that is, to an increase in the likelihood of choosing higher consumption in the future, rather than a smaller increase in present consumption.

Thaler (1981), who finds strong magnitude effects, hypothesizes that these effects are explained by self-control problems. He also observes that both hyperbolic and magnitude effects can be explained by a fixed cost of waiting. However, the experiments that he conducts do not include such fixed costs, which must therefore be psychic.

Andersen et al. (2010), in their review of the literature on magnitude effects, emphasize that most studies that identify magnitude effects use hypothetical questions and do not satisfy the quality standards of experimental economics. Loewenstein and Prelec (1992) state that the magnitude effect cannot be due to the curvature of the utility function because the effect tends to be stronger for small amounts. However, Andersen et al. (2010) question this argument.

Another explanation could be that there is a fixed cost or minimum amount that is needed before a delay in receiving a given amount becomes salient (Benhabib, Bisin and Schotter 2010). This threshold would result in a decreasing magnitude effect as amounts increase. Such threshold effects may naturally be considered in the light of the literature on bounded awareness which has mainly focused on choice under uncertainty.

Two notions of unawareness are considered in the literature. In the first, characterized by Grant and Quiggin (2013), agents have access to a proper subset of the true state space. This form of unawareness is referred to as restriction. In the second form of unawareness, characterized by Heifetz, Meier, and Schipper (2006), agents have access to a representation of the state space derived as a projection of the true state space. This form of unawareness is referred to as coalescence.

In terms of the Google Earth metaphor, zooming in leads to reduction, since the range of possibilities and time periods under consideration is restricted. Zooming out leads to coalescence, since distinctions between possibilities are disregarded.

Zooming may be either beneficial or harmful, depending on whether the possibilities and distinctions excluded from consideration are in fact relevant. For example, to the extent that coalescence elides irrelevant aspects of framing, it yields superior decisions.

In the present context, it will be argued that zooming out promotes asset integration and, by reducing the prevalence of hyperbolic discounting, tends to generate more dynamically consistent decisions.

### 3 A Model with Zooming

We begin with an additively time-separable intertemporal utility function with exponential discounting as the benchmark model. We assume that respondents have concave utility functions within given time periods (Andersen et al. 2008). We focus exclusively on “gains only” situations so that we can ignore “gain-loss” asymmetries. The hyperbolic and magnitude anomalies that we seek to explain are evident in experiments with gains only and therefore are not a direct effect of gain-loss asymmetries.

Respondents are given the choice between two prospects<sup>4</sup>,  $M_A$  at time  $t_1$  and  $M_B$  at time  $t_2$ , where  $t_1 > t_0 = 0$  and  $t_1 < t_2$ . Decision-makers must choose between  $U_A$  and  $U_B$ :

<sup>4</sup> A prospect is a good or amount of money received at a specific point in time. The individual is assumed to integrate this good or additional budget item into its utility function. However, this integration is partial and more partial the smaller or less significant the amount or good is.

$$\begin{aligned}
U_A &= \left( \left( e^{-\delta(t_1-t_0)} u(y_1 + M_A) \right) + \left( e^{-\delta(t_2-t_0)} u(y_2) \right) \right) \\
U_B &= \left( \left( e^{-\delta(t_1-t_0)} u(y_1) \right) + \left( e^{-\delta(t_2-t_0)} u(y_2 + M_B) \right) \right)
\end{aligned}
\tag{1}$$

where  $\delta$  is the continuous time discount rate and where  $y$  is background consumption.

The zooming theory with limited asset integration assumes that the prospects offered at two different points in time are integrated to varying degrees with decisions regarding other endowments of the decision-maker. This concept can be illustrated as follows:

$$u(c(P^*) + x) - u(c(P^*)) = (u(c(P^*) + y) - u(c(P^*))) \delta^{t'-t}
\tag{2}$$

where base consumption is assumed to be a function of the prospect characteristics  $P^*$ . Using a daily wage rate ( $y$ ) as the “starting reference point” for short-term prospects makes it possible to model zoom-adjusted base consumption as follows<sup>5</sup>:

$$c(P^*) = y(P^*) = yf(t_2 - t_1, M_B); \text{ with } \frac{\partial f}{\partial (t_2 - t_1)} > 0; \frac{\partial f}{\partial M_B} > 0
\tag{3}$$

The degree of this type of asset integration depends on the length of the time horizon and the magnitude of the prospects. A higher level of asset integration, “zooming out”, occurs over longer time horizons and for larger amounts, whereas for shorter time intervals and smaller amounts, a lower level of asset integration is needed. Thus, in the latter case, the decision is “zoomed in”, becoming more myopic and less holistic because the problem may be more trivial or of a more short-term nature. The novel contribution of this theory is therefore the notion that

<sup>5</sup> The functional form for zooming adjustment may be explored empirically through calibration. We cannot rule out that respondents consciously also adjust their discount rate if alternative borrowing and lending opportunities are there for alternative prospects. Our experimental data come from an area where such opportunities are very poorly developed possibly explaining high shadow discount rates.



the decision-maker automatically adjusts the framing of the decision problem to the most relevant scale to simplify the decision-making process.

In zooming in on a narrower set of factors and excluding other issues, the individual faces a simplified problem that can be evaluated more quickly, which, in turn, will expedite decision-making. The adjustment involves no adjustment of the discount rate, which is assumed to be constant for an individual at that specific point in time. If this theory is correct, zoom-adjustment of the base consumption level should eliminate or reduce hyperbolic and magnitude effects in time preference experiments, and decisions should appear rational in the zoom-framing perspective, as in other theories of reference-dependent preferences (Kőszegi and Rabin 2006; 2007).

Given that reference consumption levels are unobservable, we assume that for the period in question, a base consumption level and investment levels that are similar in magnitude to those upon which the decisions are based are appropriate starting points. This is similar to assumptions made by other researchers, e.g., Andersen et al. (2008; 2011). The structural model may therefore simply be reformulated as follows to capture zooming adjustment with partial asset integration:

(4)

$$U_A = \left( \left( e^{-\delta(t_1-t_0)} u(y_1 f(t_2-t_1, M_B) + M_A) \right) + \left( e^{-\delta(t_2-t_0)} u(y_2 f(t_2-t_1, M_B)) \right) \right)$$

$$U_B = \left( \left( e^{-\delta(t_1-t_0)} u(y_1 f(t_2-t_1, M_B)) \right) + \left( e^{-\delta(t_2-t_0)} u(y_2 f(t_2-t_1, M_B) + M_B) \right) \right)$$

where base consumption at each point in time represents the unobservable zooming level, which, according to the proposed model, is a function of the length of the time interval and the magnitude of the amount at the far end that is under consideration in each choice set. Larger amounts and longer time horizons imply wider framing and zooming out because these decisions are more momentous and

therefore “require” a more holistic treatment that implies a higher level of asset integration.

Another aspect of equation (4) is that it focuses on the utilities of prospects, where utility is a function of incomes received under alternative prospects. Following Andersen et al. (2008), respondents are risk-averse and have utility functions with diminishing marginal utility. Neglect of this property could lead to the overestimation of discount rates. Diminishing marginal utility is also relevant in more narrow framing perspectives, as diminishing marginal utility also affects short-term consumption. Indeed, we argue that it is narrow framing that leads to diminishing marginal utility in short-term decision-making, which tends to be consumption-oriented. More long-term and larger decisions tend to be investment-oriented and are associated with consumption over longer periods of time. For the sake of simplicity, in testing the potential explanatory power of the zooming model, we have used utility functions with constant elasticity of marginal utility. In addition, we vary this elasticity to assess the sensitivity of the results of such variations.

In testing whether the model potentially can explain hyperbolic discounting and magnitude effects, these phenomena should as a minimum be reduced and ultimately become very small when zooming adjustment of base consumption is included in the analysis of experimental data with time horizon and magnitude effects included among the (randomized) experimental treatments. We therefore use such data to test the potential explanatory power of the model.

There are, however, three important unobservable components that require attention in relation to such a calibration test: a) the determinants of the appropriate initial base consumption; b) the determinants of the functional form of the zooming adjustment to the length of the time horizon; and c) the determinants of the functional form of the zooming adjustment to the magnitude effect. The zooming model implies that the base consumption level is an increasing function of both the

length of the time horizon and the magnitude of the far end monetary payment (with less narrow framing for larger, longer-term decisions).

Andersen et al. (2008) chose the daily wage rate as the base consumption level in their time preference experiments in Denmark. We have used the same daily wage rate as a starting point for decisions with a short time horizon (one month).

If mental zooming is similar to visual zooming and if the observable area adjusts similarly to the mentally observed “area”, it may be relevant to test this adjustment to the mental “area” as if the brain translates the visual area using the same scale as the mental “area”. For example, when one visually zooms in using Google Earth, reducing the distance from the earth to half the initial distance reduces the visually observable area to one quarter if the angle of vision is constant and the radius of the observable area is reduced by half.

When base consumption is included in a non-linear utility function, the same non-linear adjustment to time and magnitude frames occurs if these frames are included in linear form. We therefore start with this type of linear adjustment in the consumption/income space to time and magnitude frames in a logarithmic utility function, assessing the effects of deviating from it. Because we do not have a theory that indicates clearly which functional form is more appropriate, we resort to testing alternative functional forms empirically. Because the unobservable base consumption level and degree of zooming may vary across individuals, we test for the general tendency in the data. Some individuals may be more prone to high levels of asset integration; thus, they may make more holistic decisions and exhibit greater “rationality.” In contrast, others may zoom in more narrowly and may thus exhibit greater myopia and “irrationality” in their decisions. We use experimental data to “calibrate” different base consumption levels and the functional form of the zoom adjustment in the two dimensions of time and magnitude.

The model may explain quasi-hyperbolic discounting or present bias as an instance of extremely narrow framing of base consumption that, in the limit,

reduces to a purely static decision that ignores future outcomes. This may occur as a break or a switch from the more continuous framing adjustment that is implied by the mental zooming hypothesis to a purely static/myopic corner solution.

#### **4 Experimental Design and Implementation**

Using a multiple price list (MPL) design, field experimental data from representatives gathered from a random sample of rural households in Malawi were used to examine anomalies in intertemporal choice and to test whether the hidden zooming hypothesis has the potential to explain these phenomena. The treatments used included three front-end timing treatments, four endpoint timing treatments and four magnitude level treatments. The front-end timing treatment included present timing, a one-week delay and a one-month delay, specifications that allowed for separate testing of quasi-hyperbolic versus hyperbolic discounting. The end-point timing treatments included one-month, three-month, six-month and 12-month delays. The magnitude levels, which were fixed for the end points, were 1,000 MK<sup>6</sup>, 5,000 MK, 10,000 MK and 20,000 MK. Although other researchers have used MPLs where the near future amounts are fixed and varying the more distant amounts (Pender 1996; Andersen et al. 2011), such a design can lead to substantial censoring in developing country settings (Pender 1996; Yesuf and Bluffstone 2009). We therefore chose to fix the more distant future amount and identified a switching point through offering alternative near future or current amounts.

A possible limitation of the Andersen et al. (2011) study is that they use only two magnitude levels, DKr 1500 and DKr 3000, which implies only a doubling of the magnitude. The experiments include magnitudes that are five, 10 and 20 times

<sup>6</sup> MK=Malawi Kwacha, 1 US\$= 284 MK at the time of the experiments (August 2012).

the smallest magnitude, with varying delays in the initial point in time and with real payments. We can therefore test whether fixed transaction costs related to delayed payments can eliminate the magnitude effect, as suggested by the findings of Andersen et al. (2011), and can test the model in the magnitude dimension.

This strategy allows for much higher discount rates without any censoring problems. Even given this design, however, we encountered individuals with extremely high discount rates that were outside the range of our standardized lists. For these individuals, we extended the lists on an individual basis until a switch point was identified. Fixing the future amount of each prospect is also a convenient way to test the model. The simple design of the intertemporal choice prospects in the MPLs is presented (example of the prospects) in the Appendix. The basic treatment variations are presented in Table 1.

**< Table 1 Treatments In Time Preference Experiments >**

There are 44 unique possible combinations, as the 1 month-1 month combination is irrelevant. We further reduced the number of treatments to 27 but retained the “middle ground” treatments that were considered most relevant to the analysis of farm input demand decisions, which the experiments were designed to illuminate, and which are typically made 3-6 months before a crop is harvested. The amounts that smallholder farm households typically spend on farm inputs are also in the range of 5,000 to 20,000 MK. We preferred to compare two future points in time in most treatments (20) but included a sufficient number of treatments (7) involving the comparison of the present time with a future point in time to test for present bias. The numbers in parentheses in Table 1 indicate how many of the treatments contained each treatment level.

The treatments were randomized across households. Each household was confronted with 9 of the 27 series, so that all 27 series were distributed across three household representatives in each village.

The time preference experiments were run jointly with risk preference and input demand experiments. The order of these experiments was randomized, which enabled us to test for the order effects of the experiments.

In each series, using ten cards from a card deck, the starting point was randomized by the experimental enumerator to minimize starting point bias. After receiving an answer for this random task, the enumerator was told to go to the end point of the series in the direction in which a switch point was expected, where the direction depended on whether the respondent chose the near future (current) amount or the far future amount. If the respondent chose the near future amount, the bottom task in the series would be chosen. If the respondent then switched to the far future amount, the enumerator would move to the series in the middle between the two previously tested series and then continue to quickly narrow in on the switch point.

There were cases in which a switch point was not identified before the bottom of the series was reached. The enumerator then added rows by offering even smaller near future (current) amounts until a switch point was detected. In analyzing the data, we tested for starting point bias by creating a variable that interacted the starting point dummy with the row number that had been randomly chosen as the starting point in that series.

Four well-trained Malawian MSc-graduates in economics were recruited as experimental enumerators. They were first trained by the author in the classroom for one day and then tested the experimental formats on one another after being introduced to the designs. Next, they were involved in the field testing of the designs in an out of the sample location, also with close follow-up by the author.

After some modifications to the design and refinements of the method of conducting the interviews, an implementation plan was established. Within each district, several villages (typically four per district) were sampled. The experiments required one day in each village, and one district was completed in one week.

A suitable school within the village (in most cases) or in close proximity was identified as the field laboratory. A classroom was typically chosen, and tables and chairs were organized in each corner of the room so that each enumerator could interview a respondent without being disturbed by the others. The respondents sat with their backs to the center of the classroom. Those who had not yet participated in the experiments waited at sufficient distances outside the classroom and were unable to observe the activities taking place inside. Those who had completed all experiments received their payments (in cash and in kind) and were asked to return to their homes and avoid speaking with anyone outside the classroom who had not yet participated in the experiment. The enumerators conducted all three types of experiments while randomizing their order and rotating the respondents among themselves.

Due to the limited literacy and numeracy of the respondents, the enumerators had to spend time explaining the details to them and teaching them the concepts of probability and random choice that were required for them to participate in the more cognitively challenging risk preference experiments. We decided not to provide the respondents with information about the implied annual discount rates in the intertemporal choice tasks, as most of the respondents were unfamiliar with the concept of an annual discount rate.

All of the respondents received pay-outs in the risk preference and input demand experiments, whereas each respondent had a 10 percent probability of receiving a pay-out in the time preference experiments based on a random draw of a card from ten cards. For a winner, a new card would be drawn to identify one of the nine series he or she had completed, and another card would be drawn to determine the task in that series. Their choice during that task determined whether they would receive the near future payment or the far future payment.

The organizers of the survey, who were from the University of Malawi, took responsibility for ensuring that proper payments were made on the appropriate

dates. The fact that the households belonged to a panel that had been visited and interviewed many times during the preceding six years gave the respondents reason to trust that they would in fact receive the future payments.

## 5 Methods and Data Analysis

The Utility differential from equation (4) is specified as

$$(5) \quad \nabla U = U_A / (U_A + U_B)$$

capturing the probability that prospect A is chosen. A further extension of the estimation of the above models includes stochastic errors. More specifically, we applied the Luce specification, which was also used by Holt and Laury (2002) in estimates of risk preferences and by Laury et al. (2012) in estimates of time preferences:

$$(6) \quad \nabla U = U_A^{1/\mu} / (U_A^{1/\mu} + U_B^{1/\mu})$$

where  $\mu$  is the stochastic (Luce) error. We use the simple logarithmic constant relative risk aversion (CRRA) utility function with relative risk aversion  $r = 1$  as the base model, which leads to lower estimates of discount rates than when risk aversion is ignored (Andersen et al. 2008).

The logarithmic function is conservative in that it implies a higher degree of risk aversion than that observed by Holt and Laury (2002) in their estimates of risk aversion among students in the US and that observed by Andersen et al. (2008) in their joint estimations of risk and time preferences in Denmark. Although some findings indicate that poor people tend to be more risk averse than others –such that they exhibit decreasing relative risk aversion (DRRA) relative to wealth and increasing partial risk aversion (IPRA) relative to game levels (Wik et al. 2004; Yesuf 2004) – Binswanger (1980) and Mosley and Verschoor (2005) find no significant association between risk aversion and wealth.



Based on the prospects presented and the utility function, a log-likelihood function is constructed for the maximum likelihood estimation of relevant parameters such as the discount rate ( $\delta$ ), the noise parameter ( $\mu$ ), treatment (prospect) characteristics ( $Z_i$ ) and respondent characteristics ( $X_j$ ):

(7)

$$\ln L(\delta, \mu; Choice_{ij}, Z_i, X_j) = \sum_j ((\ln \Phi(\nabla U) | Choice_{ij} = 1) + (\ln \Phi(1 - \nabla U) | Choice_{ij} = 0))$$

The choice of exponential discounting enables us to test for deviations from this specification with our randomized treatments and makes it possible to assess whether the zooming hypothesis potentially can explain hyperbolic discounting and magnitude effects. Significant time horizon and magnitude treatment effects in the baseline estimates without zooming adjustments in base consumption serve as a starting point for the test of the zooming hypothesis.

Constant base consumption in the baseline models is set at the average daily wage rate, i.e., 300 MK. This may be an appropriate base consumption level for decisions pertaining to relatively short periods of time (for example, less than one month) but may provide too narrow a frame for longer-term decisions or decisions involving larger amounts than are consumed over short periods.

The sensitivity analyses of zooming calibration adjustment in this study included varying the elasticity of marginal utility (functional form of the utility function), the functional form of the magnitude adjustment and the functional form of the time horizon adjustment. Risk preference experiments were conducted on the same households using the Holt and Laury (2002) MPL under two approaches.

The first approach involved hypothetical real-world framing of the choice between different varieties of the main staple crop (maize) given alternative states of nature (drought or no drought). The second approach employed the same design structure but included monetary outcomes and real payouts.

These experiments yielded average rates of relative risk aversion of 1.3 in the hypothetical experiments involving crop varieties and 0.8 in the experiments involving real monetary payouts using a CRRA utility function. Accordingly, the time preference experiments used utility functions with elasticities of marginal utility of -0.8, -1.0, and -1.3, with the logarithmic utility function as a reasonable base model.

The elasticity of adjustment of base consumption to the time horizon and the magnitude of future payments varied from 0.5 to 2.0 in consumption/income space, and the results were compared with those for models that employ the usual approach, i.e., with constant base consumption and where the discount function is adjusted instead (e.g., Loewenstein and Prelec 1992).

Table 2 presents the results of tests of alternative zooming adjustments of base consumption. In the first test, zooming adjustment is just made for the length of the time horizon by multiplying base consumption by the length (number of months) of the time horizon (linear zooming in the time horizon). The second and third zooming adjustments combined linear adjustment for the length of the time horizon with linear adjustment for the magnitudes of the fixed future amounts normalized, alternatively, by the lowest and second lowest future amounts.

Additional zooming adjustments were used to assess nonlinear (concave) magnitude adjustments. A concave adjustment for magnitude and a convex adjustment for time horizon in consumption space within the logarithmic utility function were found to provide a reasonably good fit. The stability of such nonlinear zooming adjustments across sites or sample populations is, however, a question that requires further investigation.

< **Table 2** - Models With Alternative Base Consumption Zooming For Time Horizon And Magnitude Of Future Offers >

## 6 Results and Discussion

We start by examining the estimation results using a standard continuous time exponential discounting utility function with constant base consumption set at the average local daily wage rate (the baseline model). The elasticity of marginal utility is set to unity (with a logarithmic utility function). The results for this structural model are presented in Table 3, and the predicted discount rate distributions by time horizon are shown in Figure 1.

The model demonstrates very strong hyperbolicity and magnitude effects. The discount rate varies from 150 percent for a one-month time horizon to implausible negative values for a 12-month time horizon. Such conscious discount rate adjustments seem very implausible and seems to lend support for an alternative explanation where varying the degree of asset integration systematically with prospect characteristics may be a reasonable alternative route.

As a first step towards testing the zooming hypothesis, to adjust base consumption to the time frame of the prospects, we have made base consumption a linear function of the number of months of the time horizon in the second model in Table 3, assuming that respondents zoom out and integrate their prospect decisions into a larger base consumption level when the prospects are more long-term. The predicted discount rate distributions by length of time horizon are presented in Figure 2. We observe that the variation in discount rates across time periods is reduced and that most of the distribution of the discount rates for the 12-month horizon has non-negative values.

Figure 3 shows the predicted magnitude effects for the same model with linear adjustments in base consumption to the time horizon only. Although the size difference in discount rates between the time horizon treatments was reduced by more than 60 percent, as seen in Table 3, the size difference in the magnitude effects increased by approximately 20 percent.

**Table 3** - Time Preference Models Without And With Zooming Adjusted (For Time Horizon) Base Consumption

**Fig. 1** Predicted Discount Rate Distributions For 10000 MK Series With 1, 3, 6 And 12 Months Future Horizons And Delayed Initial Period With Constant Base Consumption=MK300

**Fig. 2** Predicted Discount Rate Distributions for 10000 MK Series with 1, 3, 6 and 12 Months Future Horizons with Zooming Model 1

**Fig. 3** Predicted Discount Rates for Alternative Future Amounts (Magnitude Effects), with 3 months horizon, Zooming Model 1 (Base Consumption only Adjusted for Time Horizon)

The zooming hypothesis also states that the base consumption level or degree of asset integration implies the zooming of base consumption to the amounts in the prospects under consideration. A set of models was run that tested the joint zooming of base consumption in time horizons and magnitudes of prospects. The first two models are linear in time horizon and magnitude in consumption space but differ with respect to the normalization of the magnitude effect, where the first model is normalized by the smallest amount (1,000 MK) and the second model is normalized by the second smallest amount (5,000 MK).

Under the first model, the magnitude effect was reversed, as it was for longer time horizons. The second model, which gives less weight to the magnitude adjustment, yielded discount rates that were close to each other in the treatments with three-, six- and 12-month horizons and with magnitudes of 5,000, 10,000 and 20,000 MK, whereas the smallest amounts and time horizons were associated with significantly higher discount rates. A similar result was found in the third model in Table 4, where base consumption was adjusted to the square root of the magnitude in combination with linear adjustment in the time horizon, implying a weaker adjustment to magnitudes than to the time horizon.

Figures 4 and 5 show the discount rate distributions predicted by the zooming model for the time horizon and magnitude treatments. The model appears to perform well in both dimensions with respect to eliminating time horizon and magnitude effects, except for the smallest magnitudes and shortest time horizons, which may be associated with a discontinuous shift towards very narrow framing.

**Table 4** - Models With Alternative Zooming Adjustment Of Base Consumption

**Fig. 4** Predicted Discount Rates for Alternative Time Horizons with Zooming Adjustment Model 4, with MK10000 Series

**Fig. 5** Predicted Discount Rates for Alternative Future Amounts with Zooming Adjustment Model 4

The experiments included treatments with the initial point either delayed or current to test for present bias (quasi-hyperbolic discounting). Tables 3 and 4 reveal significant present bias in the form of higher discount rates when the near point in time is the present.

Figures 6 and 7 show the model's prediction of discount rates when the initial point is the present and when the initial point is delayed for larger amounts (10,000 MK) and three- and 12-month horizons (Figure 6) as well as for smaller amounts (1,000 MK) and three- and six-month horizons (Figure 7). The extent of the present bias appears to be larger for smaller amounts and does not become insignificant after the zooming adjustment in base consumption.

**Fig. 6** Predicted Discount Rates with and without Initial Time Delay (Present Bias) with Zooming Adjustment Model 4, MK 10000 series with 3 and 12 Months Horizon

**Fig. 7** Zooming Adjustment and Present Bias for Small Amounts (1000 MK), Zooming Adjustment Model 4 with 3 and 6 Months Horizon with and without Initial Delay (Present Bias)

A final set of models with quadratic zooming in the time horizon and square-root zooming in the magnitude in the consumption space for three different elasticities of marginal utility (EMU) is presented in Table 5. The least concave utility function has an EMU that equals -0.8, and the most concave utility function has an EMU that equals -1.3, in addition to the standard logarithmic utility function used in the earlier model specifications. The zooming adjustment in base consumption is held constant in the consumption space in the three models to illustrate how variations in the curvature of the utility function affect the estimated average discount rates and zooming adjustment through the utility function.

**Table 5** - Sensitivity To Alternative Utility Functions (Elasticities Of Marginal Utility)

**Table 6** - Predicted Average Discount Rates For Models With Varying Elasticity Of Marginal Utility

The average predicted rates by time horizon and magnitude are presented in Table 6, where the time horizon rates are for 10,000 MK treatments with delayed initial payment and where the discount rates for alternative magnitudes are for all time horizons with delayed initial payment. Tables 5 and 6 demonstrate that zooming adjustments in base consumption may well explain both “hyperbolic discounting” and magnitude effects. Figures 8 and 9 illustrate the predicted discount rate distributions for the model with logarithmic utility in Tables 5 and 6.

Table 6 also clearly shows how sensitive the discount rate estimates are to variations in assumptions about the curvature of the utility function, whereas the zooming model appears to be quite robust to variations in the curvature of the utility function. Adjusting base consumption may therefore be theoretically more appropriate than adjusting the discount function to the time horizon or the

magnitudes of decision prospects if we want a model that is closer to how people actually behave and handle the alternative prospects in these experiments. However, this supposition should be further tested with alternative data sets.

**Fig. 8** Predicted Discount Rates for Alternative Time Horizons for Zooming Model 5 (Quadratic Adjustment in Time Horizon and Square Root Adjustment in Magnitude and Logarithmic Utility)

**Fig. 9** Predicted Discount Rates for Alternative Future Amounts, Zooming Adjustment Model 5 with Logarithmic Utility

## 7 Conclusion

As stated by Loewenstein and Prelec (1992), no simple theory can hope to account for all motives that influence a particular decision. In this paper, we have proposed a ‘zooming’ model based on the idea of bounded awareness. We hope that the model will contribute to a deeper understanding of certain anomalies in intertemporal choice: hyperbolic discounting and magnitude effects.

Doubt about the existence of these phenomena has arisen because they have been mostly identified in hypothetical experiments that do not meet the quality standards of experimental economics (Andersen et al. 2011). Based on an incentive-compatible field experiment with prospects characterized by alternative time horizons and magnitudes, we demonstrate that these phenomena are highly significant and cannot be explained by present bias/quasi-hyperbolic discounting. They are, however, consistent with the zooming model proposed here.

Future research should aim to further test the model by examining more explicit questions about how respondents integrate their decisions with their background consumption and/or by more explicitly framing the background consumption that respondents should consider when making their decisions. Furthermore, it will be important to test the model in different environments to assess the conditions for its

dominance versus more holistic modes of framing intertemporal prospects to which respondents may switch.

## References

- Ainslie, G. (1991). Derivation of Rational Economic Behavior from Hyperbolic Discount Curves. *American Economic Review* 81 (2): 334-340.
- Andersen, S., Harrison, G.W., Lau, M. I., & Rutström E. E. (2008). Eliciting Risk and Time Preferences. *Econometrica* 76 (3): 583–618.
- Andersen, S., Harrison, G.W., Lau, M. I., & Rutström E. E. (2010). Discounting Behavior and the Magnitude Effect. Unpublished.
- Andersen, S., Harrison, G.W., Lau, M. I., & Rutström E. E. (2011). Discounting Behavior: A Reconsideration. Unpublished.
- Azfar, O. (1999). Rationalizing Hyperbolic Discounting. *Journal of Economic Behavior & Organization* 38 (2): 245-252.
- Barberis, N., Huang, M., & Thaler, R. H. (2006). Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing. *American Economic Review* 96 (4): 1069-1090.
- Benhabib, J., Bisin, A., & Schotter, A. (2010). Present-Bias, Quasi-Hyperbolic Discounting, and Fixed Costs. *Games and Economic Behavior* 69 (2): 205-223.

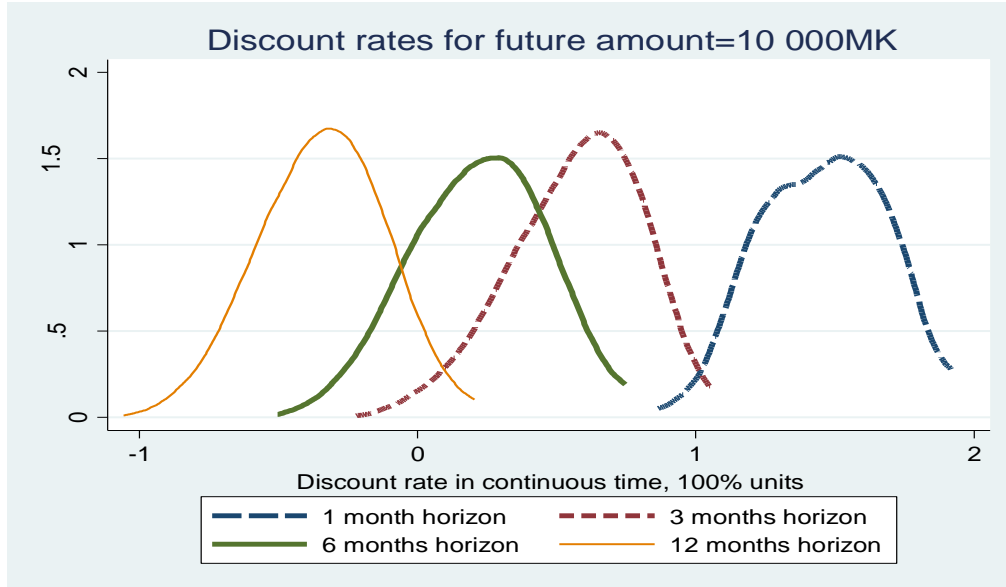


- Binswanger, H. P. (1980). Attitudes toward risk: experimental measurement in rural India. *American Journal of Agricultural Economics* 62 (3): 395–407.
- Chung, S. H., & Herrnstein, R.J. (1967). Choice and Delay of Reinforcement. *Journal of the Experimental Analysis of Behavior* 10 (1): 67-74.
- Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature* 40 (2): 351-401.
- Grant, S. & Quiggin, J. (2013). Inductive reasoning about unawareness. *Economic Theory* 54(3): 717-55.
- Halpern, J. & Rego, L. (2006), 'Extensive games with possibly unaware players', Proceedings of Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems, Hakodate, Japan, May 8-12.
- Heifetz, A., Meier, M. & Schipper, B. (2006). Interactive Unawareness. *Journal of Economic Theory* 130(1): 78-94
- Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review* 92 (5): 1644-1655.
- Kőszegi, B., & Rabin, M. (2006). A Model of Reference-Dependent Preferences. *Quarterly Journal of Economics* 121 (4): 1133-1165.
- Kőszegi, B., & Rabin, M. (2007). Reference-dependent Risk Attitudes. *American Economic Review* 97 (4): 1047-1073.

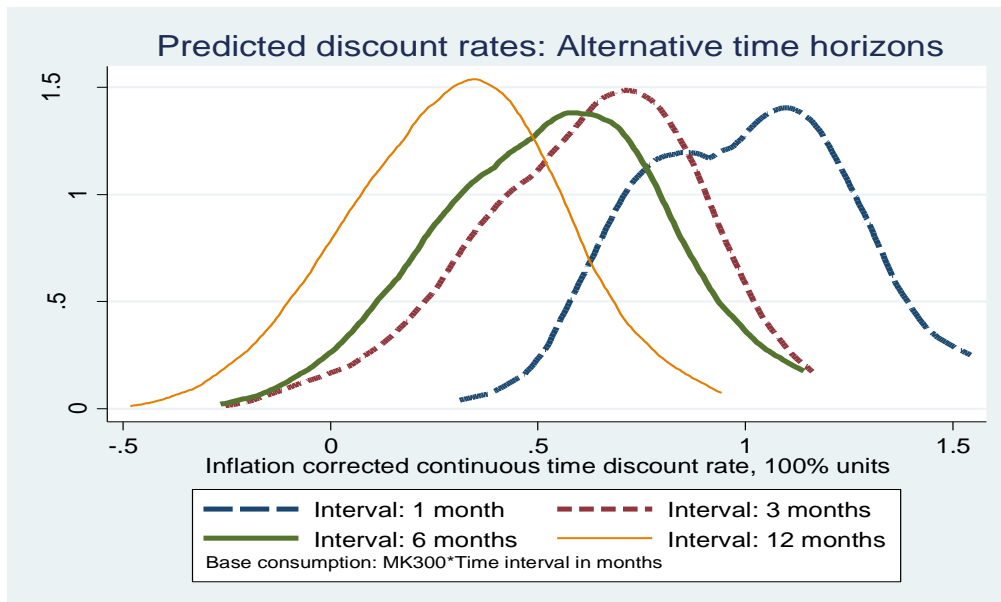
- Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *Quarterly Journal of Economics* 112 (2): 443-478.
- Laury, S. K., McInnes, M. M., & Swarthout J. T. (2012). Avoiding the curves: Direct elicitation of time preferences. *Journal of Risk and Uncertainty* 44 (3): 181-217.
- Loewenstein, G., & Prelec, D. (1992). Anomalies in Intertemporal Choice: Evidence and an Interpretation. *Quarterly Journal of Economics* 107 (2): 573-597.
- Mosley, P., & Verschoor, A. (2005). Risk attitudes and the ‘vicious circle of poverty’. *The European Journal of Development Research* 17 (1): 59-88.
- Pender, J. L. (1996). Discount rates and credit markets: Theory and evidence from rural India. *Journal of Development Economics* 50 (2): 257-296.
- Prelec, D., & Loewenstein, G. (1991). Decision Making over Time and under Uncertainty: A Common Approach. *Management Science*, 37 (7): 770-786.
- Quiggin, J. (2015), The value of information and the value of awareness, *Theory and Decision*, forthcoming
- Read, D., Loewenstein, G., & Rabin, M. (1991). Choice Bracketing. *Journal of Risk and Uncertainty* 19: 171-197.
- Samuelson, P. A. (1937). A note on measurement of utility. *The Review of Economic Studies* 4 (2): 155-161.

- Schipper, B. (2015), 'The Unawareness Bibliography',  
<http://www.econ.ucdavis.edu/faculty/schipper/unaw.htm>
- Thaler, R. (1981). Some Empirical Evidence on Dynamic Inconsistency.  
*Economics Letters* 8 (3): 201-207.
- Wik, M., Kebede, T. A., Bergland, O., & Holden S. T. (2004). On the measurement  
of risk aversion from experimental data. *Applied Economics* 36 (21): 2443-  
2451.
- Yesuf, M. (2004). *Risk, time and land management under market imperfections:  
Applications to Ethiopia*. Unpublished PhD-dissertation, Gotenburg  
University, Gotenburg.
- Yesuf, M., & Bluffstone, R. A. (2009). Poverty, risk aversion, and path dependence  
in low-income countries: Experimental evidence from Ethiopia. *American  
Journal of Agricultural Economics* 91(4): 1022-1037.

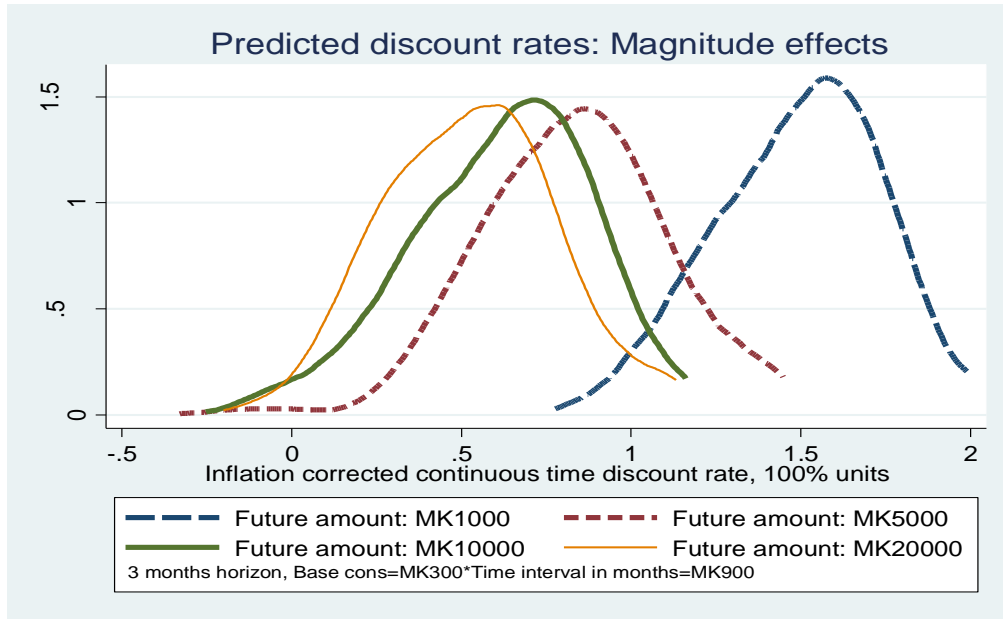
## Figures



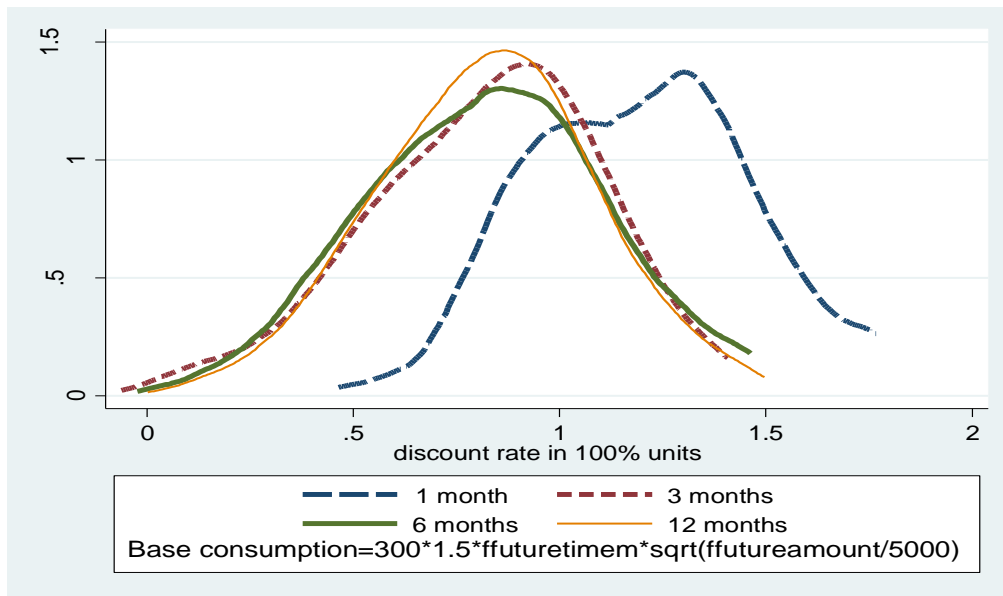
**Fig. 1** Predicted Discount Rate Distributions For 10000 MK Series With 1, 3, 6 And 12 Months Future Horizons And Delayed Initial Period With Constant Base Consumption=MK300



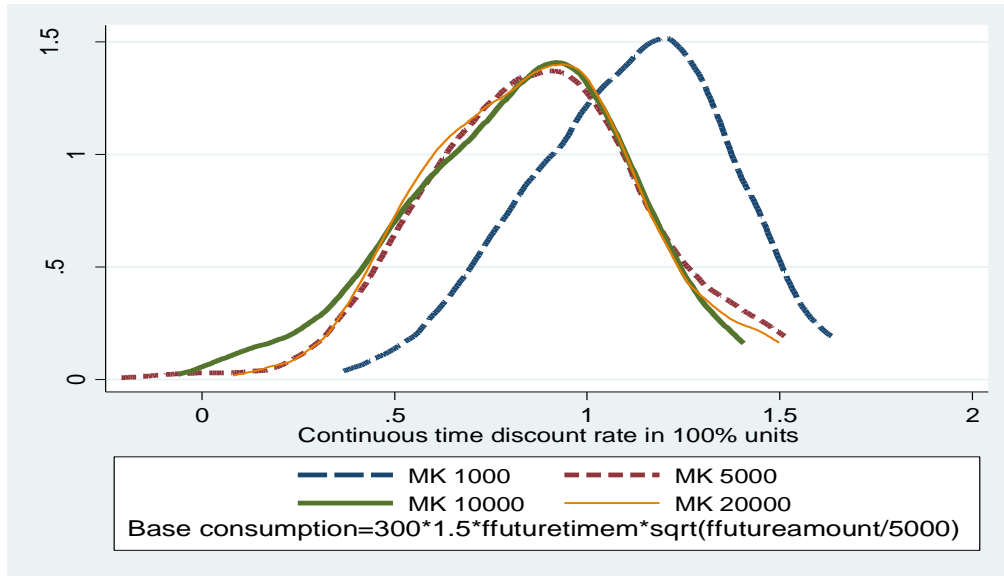
**Fig. 2** Predicted Discount Rate Distributions for 10000 MK Series with 1, 3, 6 and 12 Months Future Horizons with Zooming Model 1



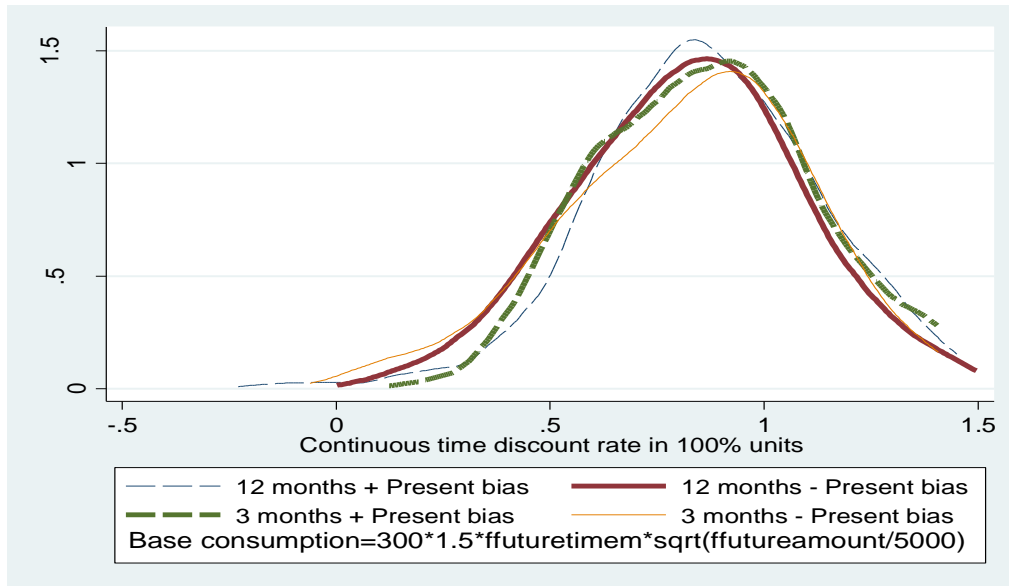
**Fig. 3** Predicted Discount Rates for Alternative Future Amounts (Magnitude Effects), with 3 months horizon, Zooming Model 1 (Base Consumption only Adjusted for Time Horizon)



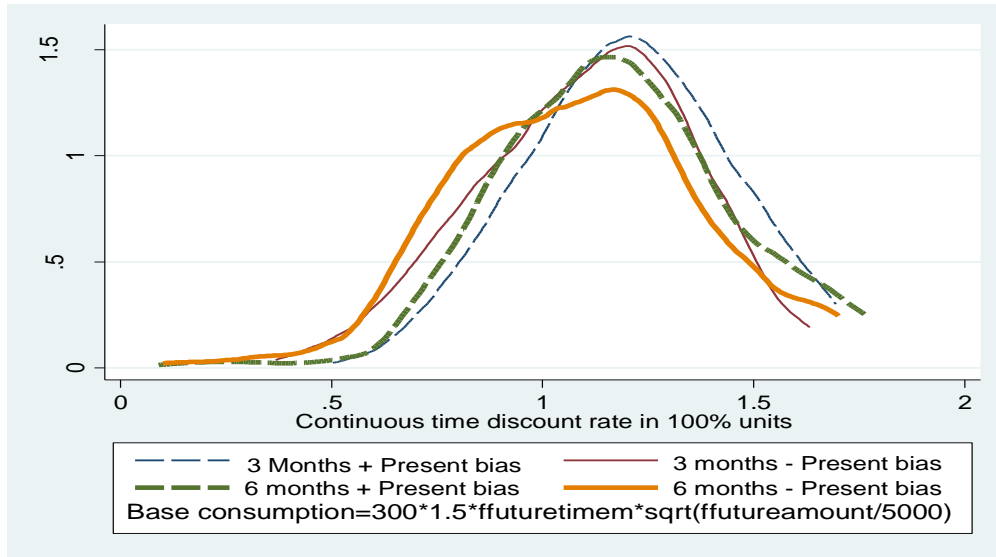
**Fig. 4** Predicted Discount Rates for Alternative Time Horizons with Zooming Adjustment Model 4, with MK10000 Series



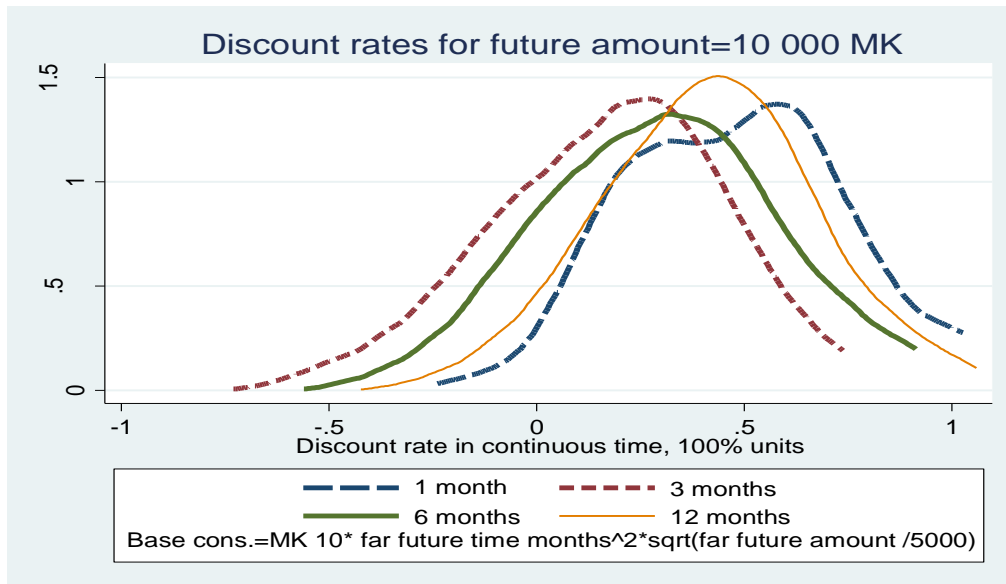
**Fig. 5** Predicted Discount Rates for Alternative Future Amounts with Zooming Adjustment Model 4



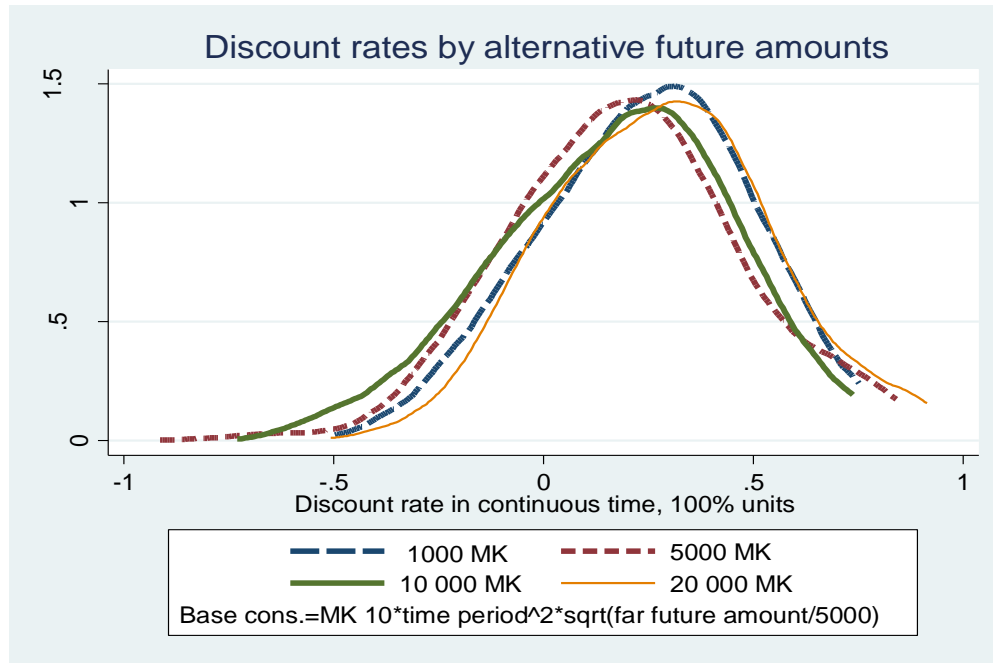
**Fig. 6** Predicted Discount Rates with and without Initial Time Delay (Present Bias) with Zooming Adjustment Model 4, MK 10000 series with 3 and 12 Months Horizon



**Fig. 7** Zooming Adjustment and Present Bias for Small Amounts (1000 MK), Zooming Adjustment Model 4 with 3 and 6 Months Horizon with and without Initial Delay (Present Bias)



**Fig. 8** Predicted Discount Rates for Alternative Time Horizons for Zooming Model 5 (Quadratic Adjustment in Time Horizon and Square Root Adjustment in Magnitude and Logarithmic Utility)



**Fig. 9** Predicted Discount Rates for Alternative Future Amounts, Zooming Adjustment Model 5 with Logarithmic Utility



## Tables

**Table 1** Treatments In Time Preference Experiments

Treatment type	Treatment levels
Front end point in time	Current(7), 1 week delay(13), 1 month delay(7)
End point in time	1 month(5), 3 months(11), 6 months(6), 12 months(5)
Future amount level	1000MK(6), 5000MK(6), 10000MK(9), 20000MK(6)
<i>Note:</i> MK=Malawian Kwacha	

**Table 2** - Models With Alternative Base Consumption Zooming For Time Horizon And Magnitude Of Future Offers

Zooming model	Base consumption adjustment
1	MK 300*far future time months
2	MK 300*far future time months*far future amount/1000
3	MK 300* far future time months*far future amount /5000)
4	MK 300*1.5* far future time months*sqrt(far future amount /5000)
5	MK 10*(far future time months)^2*sqrt(far future amount/5000)

**Table 3** - Time Preference Models Without And With Zooming Adjusted (For Time Horizon) Base Consumption

	Baseline model without zooming adjustment	Zooming adjustment model 1
Future amount: Baseline=1000MK		
Future amount: 5000MK	-0.569****	-0.666****
Future amount: 10000MK	-0.773****	-0.908****
Future amount: 20000MK	-0.819****	-1.023****
Far future point in time: Baseline=1 month		
3 months	-0.995****	-0.423****
6 months	-1.398****	-0.514****
12 months	-2.096****	-0.728****
Dummy for front end point=current	0.122***	0.083**
Dummy for front end point=1 month	0.111**	0.079*
Experienced drought shock in 2011/12, dummy	0.259*	0.261*
Random starting point dummy*Task number	-0.029****	-0.021****
Constant	1.825****	1.603****
Luce error constant	0.061****	0.037****
Prob. > F	0.000	0.000
Number of observations	31631	31631

*Note:* Maximum likelihood models with logarithmic utility functions with Luce error. Baseline model where the base consumption level=MK300. Zooming adjustment model 1, where the base consumption level=MK300\*Months time delay.

Models were corrected for inflation (20 percent continuous time discount rate).

\*\*\*\* Significant at the 0.1 percent level.

\*\*\* Significant at the 1 percent level.

\*\* Significant at the 5 percent level.

\* Significant at the 10 percent level.

**Table 4** - Models With Alternative Zooming Adjustment Of Base Consumption

	Zooming adjustment models		
	2	3	4
Future amount: Baseline=1000MK			
Future amount: 5000MK	0.127	-0.214***	-0.249***
Future amount: 10000MK	0.292****	-0.294****	-0.323****
Future amount: 20000MK	0.424****	-0.268****	-0.310****
Far future point in time: Baseline=1 month			
3 months	-0.387****	-0.461****	-0.423****
6 months	-0.255***	-0.499****	-0.434****
12 months	0.907	-0.594****	-0.413***
Dummy for front end point=current	0.174***	0.179***	0.172***
Experienced drought shock in 2011/12, dummy	0.268*	0.285*	0.286*
Present bias*Shock interaction	-0.121*	-0.114	-0.111
Dummy for front end point=1 month	0.090*	0.099**	0.096*
Random starting point dummy*Task number	-0.009*	-0.019****	-0.018****
Constant	0.948****	1.101****	1.194****
Luce error constant	0.014****	0.035****	0.030****
Prob. > F	0.000	0.000	0.000
Number of observations	31631	31631	31631

*Notes:* Maximum likelihood models with logarithmic utility functions with Luce error. Models where the base consumption level is adjusted as shown in Table II.

\*\*\*\* Significant at the 0.1 percent level.

\*\*\* Significant at the 1 percent level.

\*\* Significant at the 5 percent level.

\* Significant at the 10 percent level.

**Table 5** - Sensitivity To Alternative Utility Functions (Elasticities Of Marginal Utility)

	Utility function		
	$u=y^{0.2}$	$u=\ln(y)$	$u=y^{(-0.3)}$
Future amount: Baseline=1000MK			
Future amount: 5000MK	-0.146*	-0.067	-0.228**
Future amount: 10000MK	-0.213****	-0.116*	-0.392****
Future amount: 20000MK	-0.152**	-0.024	-0.368****
Far future point in time: Baseline=1 month			
3 months	-0.602****	-0.364****	-0.516****
6 months	-0.653****	-0.244***	-0.379****
12 months	-0.695****	-0.106	-0.360***
Dummy for front end point=current	0.096**	0.099***	0.128***
Dummy for front end point=1 month	0.103**	0.101**	0.100*
Random starting point dummy*Task number	-0.022****	-0.025****	-0.031****
Experienced drought shock in 2011/12, dummy	0.241*	0.241	0.277
Tool endowment index	-0.014	-0.012	-0.013
Farm size in ha, gps measured	-0.056*	-0.057*	-0.057
Enumerator dummies	Yes	Yes	Yes
District dummies	Yes	Yes	Yes
Constant	0.940****	0.271	0.102
Luce error constant	0.095****	0.061****	-0.085****
Prob. > F	0.000	0.000	0.000
Number of observations	31631	31631	31631

*Note:* Base consumption adjustment =  $10 * (\text{far future time months})^2 * \sqrt{\text{far future amount}/5000}$ . Maximum likelihood models with alternative utility functions with Luce error. Inflation corrected models, adjusted with 20 percent (continuous time discount rate).

\*\*\*\* Significant at the 0.1 percent level.

\*\*\* Significant at the 1 percent level.

\*\* Significant at the 5 percent level.

\* Significant at the 10 percent level.

**Table 6** - Predicted Average Discount Rates For Models With Varying Elasticity Of Marginal Utility

		Utility function		
Length of time period, months		$u=y^{0.2}$	$u=\ln(y)$	$u=y^{(-0.3)}$
	1	1.035	0.541	0.074
	3	0.484	0.212	-0.392
	6	0.441	0.344	-0.249
	12	0.379	0.442	-0.251
All		0.514	0.364	-0.248
Future amount, MK				
	1000	0.823	0.434	0.166
	5000	0.624	0.379	-0.079
	10000	0.514	0.364	-0.248
	20000	0.640	0.420	-0.201
All		0.619	0.392	-0.133

*Notes:* The table shows predicted discount rates in 100 percent units for models in Table 5. The discount rates for alternative time horizons are for 10000 MK treatments with delayed initial payment and the discount rates for alternative magnitudes are for all time horizons with delayed initial payment.

## **Appendix**

### **Time preference experiments**

**Instructions to experimental enumerators:** In these experiments there is no risk. The choices are between amounts of money to be received with certainty at different points in the future. In each case the respondent chooses between two options and indicates the one he/she prefers. You tick the preferred choice in each task. You will introduce several series of choices between more distant future and more near future (or current) money options (in MK). In each series we keep the future option constant while we vary the more near future (or current) option till we identify the switch point for the respondents. Also here we expect only one switch point per series for responses to be consistent in that specific series. Make sure that you in each series make it very clear to the respondents when the two points in time are as compared to the date of the interview. Remind the respondent about this as you move down each series till you identify the switch point. They should make choices that are most preferred given their current living conditions and need for money at the different points in time that are indicated in each series.

**Randomized series:** There will also be a variation in the time preference survey instrument from household to household (randomized variation of treatments). You have to be careful to put household numbers on all pages to ensure that we do not get a mix-up. You should also put your name on every questionnaire.

**Starting point bias.** There may be a problem of starting point bias and respondents to continue to give the same answer as you move through a series. To reduce such bias: Randomize the starting point in each series (pull card for yourself). Afterwards move to the corner where you expect a switch compared to the first response to the random starting point. When (if) you get a switch select the

task in the middle between the two earlier responses that resulted in a switch to quickly narrow in the switch point.

**Inconsistent responses across series:** If inconsistencies are observed across series, confront respondents with those to get explanations or corrections of such inconsistencies.

**Instructions to players:** *“You will be asked to respond to a series of money payment options at different points of time in the future. The distance into the future as well as the amounts will vary from task to task and you shall always in each case indicate which of the two options you prefer, given your current situation and future anticipated needs. Make sure you make careful decisions as you do not know which of these may become subject to real payout after you have answered all the questions. This will be determined through a lottery afterwards.”*

**Example of format:**

<b>Time preference series 19</b>				
Task	Receive at far future point in time	Choice	Receive at near future point in time	Choice
	<b>1 year from now, MK</b>		<b>1 week from now, MK</b>	
<b>391</b>	10000		10000	
<b>392</b>	10000		9500	
<b>393</b>	10000		9000	
<b>394</b>	10000		8000	
<b>395</b>	10000		7000	
<b>396</b>	10000		6000	
<b>397</b>	10000		5000	
<b>398</b>	10000		4000	
<b>399</b>	10000		3000	
<b>400</b>	10000		2000	
<b>401</b>	10000		1000	

**Identification whether there will be a real payout on one of the time preference questions:** Use cards 1(A) to 10 from a card deck. Allow households to randomly sample one card. If they are lucky to draw the 1(A) they win. If they win, use the cards again to identify which of the series that they played to be used for payout and then the task within that series that should be used. Their choice in that task determines their payout and the timing of payout.

The household Won /Did not Win

Series selected if they Won:\_\_\_\_\_

Task chosen if they Won:\_\_\_\_\_

Payout amount:\_\_\_\_\_

Signature if the household Won:\_\_\_\_\_