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High Discount Rates: - An Artifact Caused by Poorly Framed Experiments or a Result of People Being Poor and Vulnerable?

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By

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Abstract

This study revisits the issue whether poverty and shocks are associated with high discount rates by using an incentive compatible Multiple Price List approach in a poor rural population in Africa where a substantial share of the population had been affected by drought in the recent rainy season. Randomized treatments included tests for present bias, magnitude effects and time horizon effects. While the study revealed significant present bias, magnitude and time horizon effects, exposure to drought increased the average rates of time preference by 24-26% and present bias increased discount rates by 9-12% compared to one week delay.

JEL: C93, Q54, D91

Key words: Time preferences, poverty, climatic shocks, risk aversion, artifactual field experiment, Multiple Price List approach, Malawi.

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1. Introduction

Holden, Shiferaw and Wik (1998) developed a theoretical model and implemented time preference experiments in three countries (Indonesia, Ethiopia and Zambia) to test whether poverty and cash constraints explain why poor people have high discount rates and therefore have limited ability and motivation to invest in environmental conservation. A natural experiment also allowed them to establish a causal relationship from wealth to the discount rate. The study used a one year horizon in the experiments and compared amounts of money (or food) at present with fixed future amounts and found high discount rates that appeared to be driven up by poverty and liquidity constraints. On the other side, Moseley (2001) argues that the poor may have lower discount rates because they are often willing to sacrifice current consumption in order to save assets for the future as an important survival strategy. People living in risky environments will not survive if they are too myopic and do not plan carefully their survival strategies. However, Moseley did not carry out any study of the time preferences of such poor people. A review by Cardenas and Carpenter (2008) concludes that there is little evidence that poor people are more risk averse than people in the developed world while the evidence is mixed for time preferences. They also conclude that there is insufficient evidence to verify whether poor people behave as if they are using hyperbolic discounting. Pender (1996) found discount rates to be higher in a seven months experiment than in experiments with 12, 19 and 24 months time span but there were not significant differences between the latter three horizons.

Another unresolved issue is whether and to what extent time preferences and risk preferences respond to background variables such as shocks and are correlated with wealth and other characteristics of individuals such as vulnerability. Binswanger (1980) and Wik et al. (2004) found that luck in earlier experimental rounds reduced the degree of risk aversion (or improved expectations through a change in subjective probabilities). A growing literature has investigated how risk preferences respond to background risk and wealth characteristics but such a literature using more credible experimental methods is still scant for time preferences and especially so in a developing country setting.

Andersen et al. (2008) state that discount rates calculated based on a comparison of the choice between receiving an amount today and another amount at some future date tend to give very high discount rates. Furthermore, they state that discount rates calculated based on a comparison between two future dates are relatively low and constant with respect to time delays. Holden et al. (1998) used a comparison between today and one year into the future and this could then be one reason for their finding of very high discount rates. A second weakness of the Holden et al. (1998) study was that it used hypothetical questions while the standard in the new experimental economics literature is to ensure incentive compatibility (Cummings et al. 1995; 1997; Harrison and Rutström 2008). The third potential important weakness is that most studies of time preferences have assumed that the respondents are risk neutral and therefore have not adjusted for risk aversion. As many studies have shown, the large majority of people, and particularly poor people, are risk averse (Binswanger 1980; Binswanger and Sillers 1983; Wik et al. 2004; Harrison et al. 2007).

New standards have been established for elicitation of risk preferences since the seminal study by Holt and Laury (2002) which used multiple price lists (MPL). More recently, Andersen et al. (2008) used double multiple price lists (DMPL) to jointly estimate risk and time preferences. Tanaka, Camerer and Nguyen (2010) used a similar approach (DMPL) to elicit loss aversion and time preferences.

Risk aversion is also found to be the dominant characteristic in more wealthy societies. Holt and Laury (2002) estimated that students in their experiments had constant relative risk aversion coefficients between 0.68 and 0.97. Andersen et al. (2008) show in a study of the Danish adult population that estimated discount rates are reduced from 25.2% to 10.1% when adjusting for the concavity of the utility function. They jointly estimate risk and time preferences and find average relative risk aversion to be about 0.74 for the sample of Danish adults.

Could therefore these weaknesses in the methodology in earlier studies invalidate the findings in the experiments of Holden et al. (1998) in terms of their average high discount rates that were correlated with poverty and increased by shocks and liquidity constraints? Meier and Sprenger (2010) found that objectively measured credit constraints taken from individual credit reports are not correlated with MPL responses in the US. Present bias may be explained by psychological models of temptation and self-control (Laibson 1997; O'Donoghue and Rabin 1999) and may therefore be about consumption utility rather than liquidity. We propose that consumption smoothing problems of poor households living in settings with multiple market imperfections that are related to hard liquidity and credit constraints affect their time preferences. Such households may even lack access to modest amounts of cash.

Our study contributes to the literature on time preferences by assessing the existence and relative importance of present bias, magnitude effects, hyperbolic discounting and shock impacts on time preferences of a poor rural African population by using a credible and incentive-compatible Multiple Price List (MPL) artifactual field experiment in the context of a natural experiment (drought) that part of the sample had been exposed to. Experimental treatments test and control for present bias (quasi-hyperbolic discounting), magnitude effects, time horizon effects and drought shock effects on individual discount rates

We are building on the approaches of Holt and Laury (2002) and Andersen et al. (2008) in our estimation of time preferences in Malawi to assess whether correction of present bias and concavity of the utility function bring utility discount rates down towards market rates of interest. We test for magnitude effects and hyperbolism after controlling for present bias.

2. Literature review

Holden, Shiferaw and Wik (1998) was one of the first studies on the relationship between poverty and time preferences. They applied hypothetical questions to poor resettlement households in

Sumatra (Indonesia), central highlands of Ethiopia, and in northern Zambia. Benefiting from a natural experiment in Sumatra they were able to establish the causal relationship from poverty to high discount rates rather than the other way around. They found much higher discount rates for households from Java that had relatively recently settled in a poorer location with poor market access than in a settlement population with same origin with better market access. Similarly they also established a strong negative correlation between livestock wealth and discount rates in Ethiopia. They found a strong negative correlation between household size and discount rates after controlling for total income per consumer unit. Based on an argument of economies of scale in consumption they interpreted this as evidence of a causal effect of income on the discount rate after having ruled out other explanations for this correlation. They also found significant negative correlations between cash liquidity and savings in the studies in Indonesia and Zambia. They used a theoretical model to demonstrate how liquidity constraints may affect time preference rates when credit markets are imperfect or missing. The shadow price on the liquidity constraint drives up the discount rate. Shocks would have a similar effect when they create a need for consumption smoothing. Vulnerable households living in risky environments are therefore prone to have high discount rates. The estimated time preferences would be equal to the market rate of interest when credit markets are perfect but will be a function of the preferences, market characteristics and constraints that each household faces when credit markets are missing. Shocks and vulnerability can therefore lead to desperate strategies of asset depletion in order to meet urgent consumption needs. Provision of insurance or safety nets may be important public interventions to reduce the likelihood of such negative inter-temporal externalities, prevent poverty traps and stimulate investment, environmental conservation and long-term growth (ibid.).

Another earlier study by Pender and Walker (1990) using experiments with real payoffs in India also found an inverse relationship between wealth and discount rates. Their methodology did not allow them to estimate discount rates higher than 100% and they found that one third of the sample had discount rates above 100%. Yesuf and Bluffstone (2008) found a similar negative correlation between wealth and discount rates in Ethiopia using incentivized experiments without delayed initial period. They found high average discount rates but did not correct for risk aversion. Di Falco et al. (2011), using hypothetical time preference experiments in Ethiopia found that climatic shocks increase discount rates and that this had a negative effect on soil conservation investments, using climate shock as an instrument to predict the endogenous discount rates. Haushofer et al. (2013) used a lab experiment to test whether income shocks increase discount rates and found significant evidence of this.

Several studies have shown that discount rates are a decreasing function of the time delay over which they are estimated (Thaler 1981; Benzion et al. 1989; Horowitz 1988) and they become particularly high when the time delays are short (Anderssen et al. 2008). Several studies have also shown that the elicited discount rates tend to decline with the magnitude of the amounts offered (Thaler 1981; Benzion et al. 1989; Loewenstein 1988).

Andersen et al. (2008) estimate jointly the risk and time preferences for a sample of adults in Denmark and find that joint elicitation results in significantly lower discount rates than if these were estimated separately and based on the assumption that individuals are risk neutral. With this approach they estimated annual discount rates at 10.1% against 25.2% when risk neutrality is assumed.

Rabin (2000) has demonstrated that with full asset integration individuals should be risk neutral in gambles with small stakes. Risk aversion in small stakes will otherwise lead to extreme and implausible levels of risk aversion in large stakes games, something that is not observed. However, empirical studies have shown that individuals only partially integrate their decisions with their wealth (Binswanger 1980; Wik et al. 2004). It is therefore also plausible that the curvature of the utility function matters when assessing alternative prospects over time where larger far future stakes are compared with smaller more near future stakes.

Credit rationing is common in formal credit markets and is caused by moral hazard and adverse selection (Stiglitz and Weiss 1981) and by the riskiness, covariate risk, spatial nature of agriculture, poor infrastructure, and asymmetric information leading to pervasive high transaction costs in rural areas in developing countries (Binswanger and Rosenzweig 1986).

To our knowledge there exist no study that has compared the relative importance of present bias, time horizon, magnitude and curvature of the utility function versus shocks in explaining the often observed high discount rates among poor people in low income countries. This study contributes in this direction.

3. The setting

Our artifactual field experiments were carried out in six districts in Central and Southern Malawi. The total sample size was 350 persons representing rural households that had been randomly drawn and were part of a household panel survey that had been repeated in 2006, 2007, 2009 and 2012. They were therefore familiar with visits by researchers and students from Norwegian University of Life Sciences/University of Malawi that were responsible for these surveys. They were also used to be compensated for the time spent in the surveys and have had some exposure to experiments before related for farm inputs (Holden and Lunduka 2012).

The sample consists of smallholder agricultural households with small farm sizes, depending primarily on rain-fed agriculture, growing maize as their primary staple crop in combination with other crops. A large share of them is net buyers of food (deficit producers) and is partly engaged in off-farm income generating activities. Droughts are quite common, particularly in the southern part of Malawi. A large share of the households had experienced drought in 2011/12 in form of a dry spell during the rainy season that negatively affected their crop production. Exposure to this shock is therefore a natural experiment our experiments can utilize. The rainy season lasts from November till March/April followed by a long dry season (uni-modal rainfall pattern). The experiments took place in August-September in 2012, a week after the survey had been carried out in each community collecting a wide range of data from the households.

Malawi has since 2005 had a large-scale targeted Farm Input Subsidy Program, distributing free coupons to smallholder households that then benefit through getting highly subsidized fertilizers and seeds. A large share of the rural population had benefited from this program after 2005 and it has contributed to national and household food security although there have been problems with corruption and targeting errors under the program (Holden and Lunduka 2013). Financial constraints and shortage of foreign currency caused a cut-back of the subsidy program in 2011/12 season by about 40%. This cut-back may also have affected the sample households and contributed to their financial stress and food insecurity that may have affected their elicited discount rates.

Tables 1, 2 and 3 provide basic information about sample households disaggregated by districts based on the 2012 survey that took place immediately before the experiments. Table 1 provides information about farm sizes, farm values (MK), gross sales values (MK), exposure to drought (shock exposure) in 2011/12, and whether households have access to formal employment, and whether they are having a non-agricultural business.

The first four districts; Thyolo, Zomba, Chiradzulu, and Machinga; are located in the Southern Region of Malawi, while Kasungu and Lilongwe are located in the Central Region. Population densities are highest and farm sizes smallest in the Southern Region and poverty is also more severe there. Lilongwe district is located closer to the capital and the land market is more active and this may explain the higher farm values. Sale revenues are higher in Kasungu where more tobacco is produced and farm sizes are larger. The dry spell drought in 2011/12 hit large parts of Malawi. We see that all districts were affected but Kasungu a bit less than other districts. About 15% of the sample has household members with formal employment while about 45% of the sample has some form of non-agricultural business.

Table 2 provides information about access to credit, informal employment and fertilizer subsidies over the last three years. We see that 29% of the households had applied for loan during the last 12 months and of these 84% had obtained a loan. About 54% of the households have had informal employment during the last year. It is likely that missing responses in this variable means no informal employment but we are not quite sure. 73-75% of the households had accessed subsidized fertilizer through the subsidy program during the last three years so in terms of access if has not been reduced by the cut-back of the program by 40% in 2011/12. Our data reveals, however, that the amounts given to each household had been reduced by households receiving one coupon rather than two coupons and more often having to share a coupon[2] (Holden and Mangisoni, 2013).

[2] One coupon is for one 50 kg bag of fertilizer.

Table 3 provides information about the ability of households to mobilize cash for various purposes such as household urgent needs, urgent investment opportunity and for purchase of fertilizer for the next production season.

We can compare these amounts with the amounts used in our experiments and which varied from 1000 MK to 20000 MK. We can see that the cash mobilization of households falls within this range for the large majority of households. The mean amount that households state that they are able to mobilize to buy fertilizer for the next production year was 15240 MK while the median was 5750 MK. The mean cash saving households had for purchase of fertilizer was 2410 MK while the median was zero. The mean amount households considered they were able to mobilize in a day for an urgent family need (such as hospitalization) was 2328 MK while the median was 1050 MK. The mean amount households thought they could mobilize in a day for an urgent investment opportunity was 7341 MK and the median was 3000 MK. This demonstrates that the amounts offered in our experiments were substantial to them and they had good reasons to think carefully about their responses.

4. Theoretical framework

We start with an additively-separable inter-temporal utility function with exponential discounting as the benchmark model. We assume that respondents are risk averse. They are given the choice between two prospects M_A at time $t1$ and M_B at time $t2$ where $t1 \geq 0$ and $t1 < t2$.

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

where δ is the continuous time discount rate and y is background consumption. Present bias may occur if t_1=0 as immediate temptation may affect decisions, transaction costs may be perceived to be lower related to immediate payments than for delayed payments, or uncertainty about payment may be lower than for delayed payments (Coller and Williams 1999; Andersen et al. 2008). The appropriate level of background consumption (y) is questionable and relates to the degree of asset integration and time perspective for consumption of M_A and M_B. It may also relate to the sizes of t_1 and t_2. Consumption smoothing, larger sizes of the prospects relative to short-term consumption levels may imply that these prospects are consumed over a relatively longer period. It is also possible that prospects received further into the future are perceived to be consumed over a longer period. To our knowledge, no research has investigated this. However, adjusting y rather than deviating from exponential discounting to explain "time-inconsistent" behavior is what we will explore. Shocks are likely to lead to y_1 being small and that may increase the temptation to go for M_A rather than M_B in order to smooth consumption. This may alternatively be captured through a higher discount rate for such households. Liquidity constraints in combination with shocks are likely to have such an impact. Since we lack data on short run consumption levels we resort to capturing such effects through the discount rates and assess how sensitive they are to shocks, wealth indicators and framing conditions of the experiments.

The Utility differential;

2) $\nabla U = U_A - U_B$

may be captured by a probit (or a logistic) function such that

3) $prob(U_A) = \Phi(\nabla U)$

$\Phi(.)$ is the cumulative density function (cdf).

The latent index may also be written in ratio form;

4) $\nabla U = U_A / (U_A + U_B)$

capturing the probability that prospect A is chosen which does not require a probit or logit specification (Harrison and Rutström2008).

A further extension of the estimation of the above models is to include stochastic errors. We applied the Luce specification that also was used by Holt and Laury (2002) in estimation of risk preferences and by Laury et al. (2011) in estimation of time preferences;

5) $\nabla U = {U_A}^{1/\mu} / \left({U_A}^{1/\mu} + {U_B}^{1/\mu}\right)$

where μ is the stochastic (Luce) error. Alternative functional forms for the utility function may be chosen. A commonly used and convenient utility function is the CRRA function (e.g. Binswanger 1980; 1981; Wik et al. 2004);

6) $U(x) = (1-r)^{-1} x^{(1-r)}$

where *r* is the constant relative risk aversion coefficient (CRRA). This function collapses to a logarithmic function when $r = 1$. The problem is that the function is not continuous around r=1 and the utility becomes negative when r>1. If respondents have *r*s that are distributed below and above one the discontinuity may cause problems in maximum likelihood estimation. Another alternative utility function is

7) $U(.) = \left(y_1 + M_A\right)^{\rho}$ where $\rho \neq 0$ and r=1-ρ

A problem with this function is that marginal utility turns negative when ρ is negative and r>1.

An alternative utility function is the Expo-power utility function due to Saha (1993) and was used by Holt and Laury (2002) in their assessment of risk preferences using MPL;

8) $$U(x)=\frac{\left(1-\exp\left(-\alpha x^{1-r}\right)\right)}{\alpha}$$

This function allows relative risk aversion to vary with income as long $\alpha \neq 0$, r = CRRA if $\alpha = 0$, and α = CARA if $r = 0$. Based on lab experiments with students in the US, Holt and Laury (2002) estimated r=0.269 (0.017) and α = 0.029 (0.0025).

We have used the simple logarithmic CRRA function in our analysis as we had convergence problems with the more flexible specifications in equations 6 and 8. The logarithmic function is conservative in the sense that it implies a higher degree of risk aversion than what Holt and Laury (2002) found when estimating risk aversion among students in the US and what Andersen et al. (2008) found in Denmark when jointly estimating risk and time preferences. While there are some findings indicating that poor people tend to be more risk averse in the sense that they have 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. There should therefore be less risk of an upward bias in the time preference estimates with the use of the logarithmic utility function. A disadvantage with our approach is that we cannot jointly estimate risk and time preference rates like done by Andersen et al. (2008).

With the prospects and the utility function specified it is possible to construct a log-likelihood function that is used for maximum likelihood estimation of relevant parameters such as δ, the noise parameter μ, treatment (prospect) characteristics (Z) and respondent characteristics (X);

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

The choice of exponential discounting allows us to test for deviations from this with our randomized treatments. Significant treatment effects can allow us to reject the H_0 hypothesis that respondents use exponential discounting in their decisions. We do not need to choose alternative functional forms e.g. to test for hyperbolic or quasi-hyperbolic discounting. Our treatments test for the significance of such deviations from the benchmark (H_0) model. We aim to test the following hypotheses:

H1. Respondents possess present bias such that their discount rates are higher if comparison is made between now and a future date than if the comparison is between to future dates (quasi-hyperbolic discounting).

H2. Discount rates decline with size of the future prospect (magnitude effect).

H3. Discount rates decline with the length of the period between the two offers (duration effect or hyperbolic discounting)

H4. Previous high discount rates estimated for poor people are caused by poor quality experimental methods and ignorance of their risk aversion/concave utility functions.

H5. Discount rates of poor people remain high after having controlled for present bias and concavity of the utility function; such high discount rates reflect their limited market access, poverty, vulnerability and exposure to shocks.

Hypotheses H1-H3 can be directly tested with our randomized treatments. H4 can be assessed by judging the estimated utility discount rates for risk averse individuals using a logarithmic utility function. Similarly, H5 can be explored by assessing the correlation between discount rates, household wealth characteristics and exposure to shocks.

5. Experimental design and procedures

Risk preferences were estimated with a combination of the Holt and Laury (2002) multiple price list (MPL) design with hypothetical real world design (choice between alternative crop varieties with varying probabilities of drought) as well as with money.

A MPL design was also used to elicit time preferences (Coller and Williams 1999). Treatments were designed to assess the impact of present bias and front end delay, the degree of time delay till the late payment alternative, and the magnitude of the late payment alternative. While others have used MPLs that are ordered in increasing order of the larger (later) amounts offered (Pender 1996; Andersen et al. 2011), these can lead to substantial censoring in a developing country setting (Pender 1996; Yesuf and Bluffstone 2009). We therefore chose to fix the future amount and ordered the smaller current/near future amounts in decreasing order. This allows for much higher discount rates without any censoring problem. Even with this design 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 individual basis till a switch point was identified. The design of our MPLs is presented in Appendix 1. The basic treatment variations are presented in Table 4.

Table 4. 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)

Note: MK=Malawian Kwacha

This gives 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 for our purpose as the estimates were to be used for farm input decisions that are typically of a 3-6 months nature from the investment till the crop is harvested. The amounts that smallholder households typically spend on farm inputs are also in the range of 5000 to 20000 MK (Table 3). We preferred to compare two future points in time in most treatments (20) but included sufficient number of treatments (7) with a comparison of current time and a future point in time to test for present bias. The numbers in parentheses in Table 4 indicate how many of the treatments contained each of the treatment levels.

The treatments were randomized across households. Each household was confronted with 9 out of the 27 series such that a complete set of 27 series was obtained from three households in the same village.

The time preference experiments were run jointly with risk preference and input demand experiments. The order of these experiments was randomized. We tested for order effects of the experiments.

In each series the starting point was randomized by the experimental enumerator to minimize the effect of starting point bias. Ten cards from a card deck were used for this. After getting the answer for this random task the enumerator was told to go to the end point of the series in the direction where a switch point is expected. The direction would depend whether the respondent chose the near future (current) amount or the far future amount. If the near future amount had been selected, the bottom task in the series would be chosen. If the respondent then switched to the future amount, the enumerator would move to the series in the middle between the two series already tested and then continue to quickly narrow in the switch point. There were cases when a switch point was not identified before the bottom of the series. The enumerator then added rows by offering even smaller near future (current) amounts till a switch point was detected. In the analysis of the data we tested for starting point bias by creating a variable that interacted the starting point dummy with the row number in the series that had been randomly chosen as 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 tested the experimental formats on each other after having been introduced to the designs. Next they were involved in field testing of the designs in one location where the real experiments should not take place, also with close follow up by the author. After some modifications of the design and refinements of the way to carry out the interviews, a plan for implementation was established. Within each district there was a number of villages that had been sampled (typically 4 villages per district). The experiments took one day in each village and one district was to be completed in one week. A suitable school (in most cases) within the village or in the close proximity was identified as the field laboratory. A classroom was typically chosen and tables and chairs organized in each corner of the room such that each enumerator could interview a respondent without being disturbed by the others. The respondents were setting with the back to the centre of the classroom. Those that had not played the experiments were waiting at sufficient distance outside and were unable to see what was happening inside. Those that had completed all experiments received their payments (in cash and kind) were asked to go home and not talk to anybody outside that had not played yet.

The enumerators randomized the order of the experiments and carried out all three types of experiments but rotated the respondents between themselves.

Due to the limited literacy and numeracy of the respondents the enumerators had to spend time explaining the details to them and make them understand the concepts of probability and random choice. We decided to leave out providing them information about the implied annual discount rates that each task was associated with as most of them were not familiar with the concept of annual discount rate.

All respondents received pay-outs in the risk preference and input demand experiments while there was a 10% probability that they would get pay-out in the time preference experiments, based on drawing a card from the ten cards. For a winner, a new card would be drawn to identify one of the nine series they had gone through, and another card for the task in that series. Their choice in that task determined whether they would receive the near future payment or the far future payment. Our organizer of the survey from University of Malawi took the responsibility to ensure proper payment at the time it should be made.

6. Methods of data analysis

An initial analysis with non-parametric methods was carried out by retaining the two tasks in each series that captured the switch points. Continuous time discount rates were used assuming exponential discounting and risk neutrality/full asset integration (Rabin 2000) while sensitivity of the discount rates to the different treatments were assessed graphically, see the following descriptive analysis. This allowed us to assess the presence of present bias, magnitude effects and length of time delay effects visually based on local polynomial regressions.

The multiple price lists (MPLs) allow us to indentify an interval within which the discount rate should be. After identifying these intervals for continuous time discount rates, average rates were calculated between these upper and lower bounds and these averages are used for further exploration with local polynomial regressions how the discount rates varied with the treatments.

Parametric regressions were used to estimate the structural models using the maximum likelihood approach. Models with logarithmic utility functions and Luce errors were used to take into account risk aversion (concavity of the utility function). Logarithmic utility implies a constant relative risk aversion (CRRA) coefficient equal to 1 which is higher than that found by Andersen et al. (2008) in Denmark.

The structural models with Luce stochastic errors were estimated with Stata 12.1. Standard errors were adjusted by clustering on individual respondents. The question about choice of background consumption level was handled by first using a low daily wage rate in the informal labor market (*ganju* wage=300 MK). An alternative specification (robustness check) included the district-wise median *ganju* wage rate. With joint parametric estimation this led to too low (negative) discount rates in the series with 12 months time delay. We therefore decided to multiply the base consumption level with the duration of the time delay, assuming that consumption over a longer period is considered when two points in time are farther apart. With this adjustment the discount rates were more plausible. Finally, the discount rates were adjusted for inflation as the inflation rate was above 20% at the time the experiments were carried out.

The estimated model was used to predict average time preference rates and their distributions for the alternative treatments that are presented in tables and figures.

7. Results and analysis

7.1 Descriptive and Non-parametric analyses

We start the presentation by looking at graphical outputs of the aggregate data for switch points. The tasks capturing the switch point indicate an interval within which the discount rate should be located. Non-parametric regression is used in Figure 1 and illustrates the continuous time discount rate band extrapolated to the continuous time horizon from one month to 12 months based on the 1, 3, 6 and 12 month series used in the experiments for the 1000 MK series (lowest magnitude amounts). It is evident that the discount rates are declining with the length of the time horizon as has also been found in earlier studies. The discount rates are above 100% for the shorter time horizons but decline to below 100% for the longest time horizon. These estimates are assuming risk neutrality (linear utility functions).

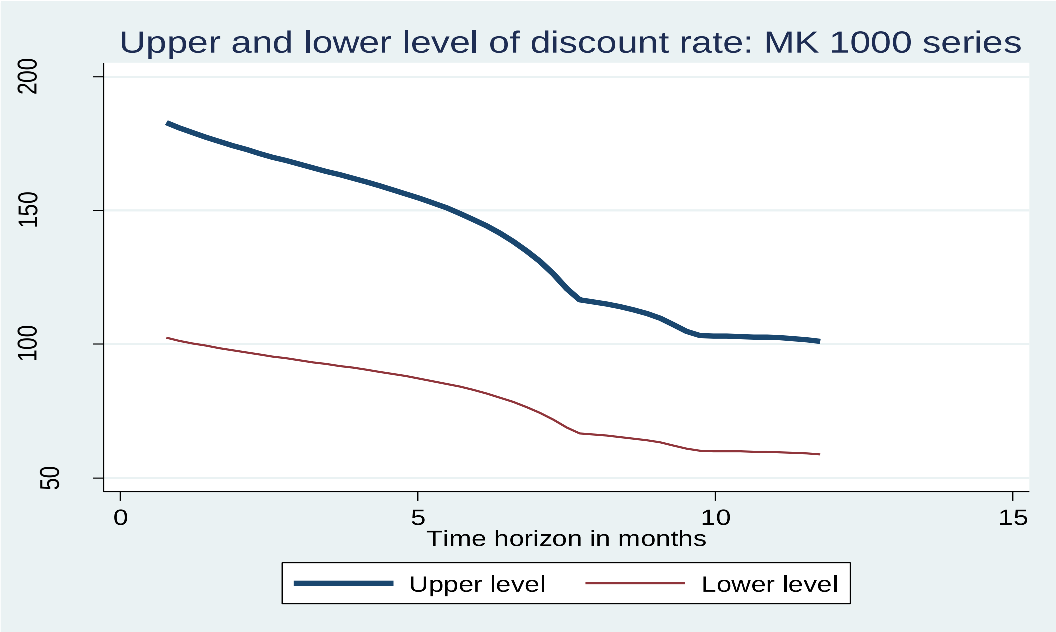

Figure 1. Interval estimates of discount rates by time horizon for small amounts (1000 MK).

Figure 2 illustrates the same for the 10000 MK series (10x higher amounts) to assess the magnitude effect. While it can be seen that the discount rates decline with time horizon, it can also be seen that the discount rates are substantially lower than for the 1000 MK series, where the rates in the middle of the interval decline from about 85% to below 40%.

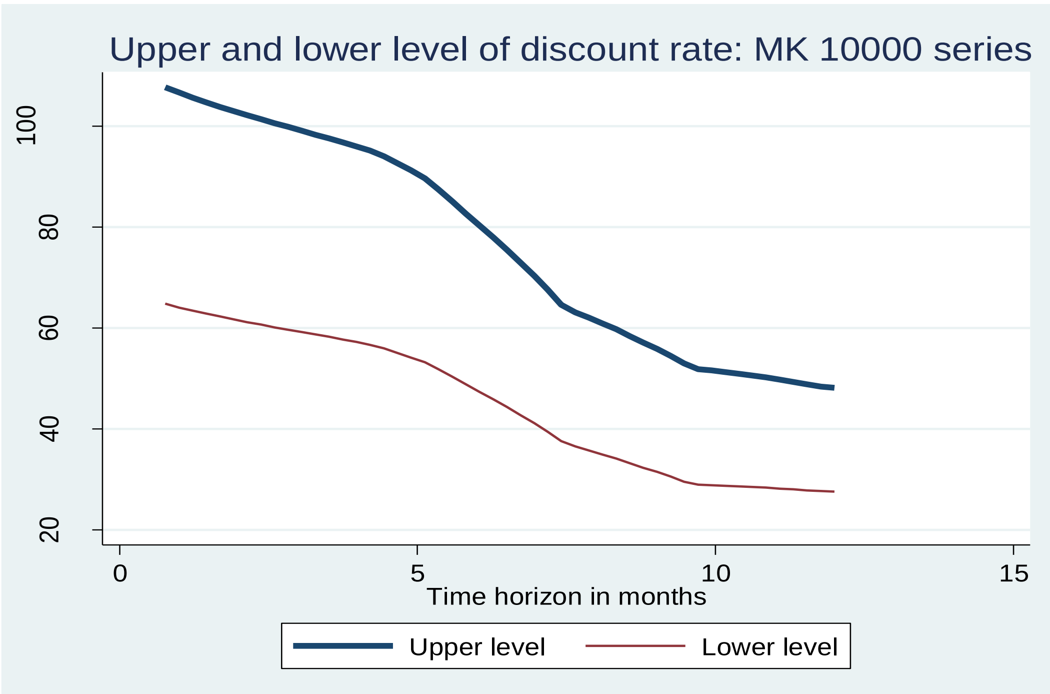

Figure 2. Interval estimates of discount rates by time horizon for larger amounts (10000 MK).

We have generated new variables as the arithmetic means of the upper and lower range estimates for the continuous time discount rates and combined these for all levels of end point amounts offered in Figure 3. A 95% confidence interval is included for the 1000 MK series to assess whether it is significantly higher than the other series. We see that this is the case while the other series with 5000 MK, 10000 MK, and 20000 MK are much closer to each other and not significantly different.

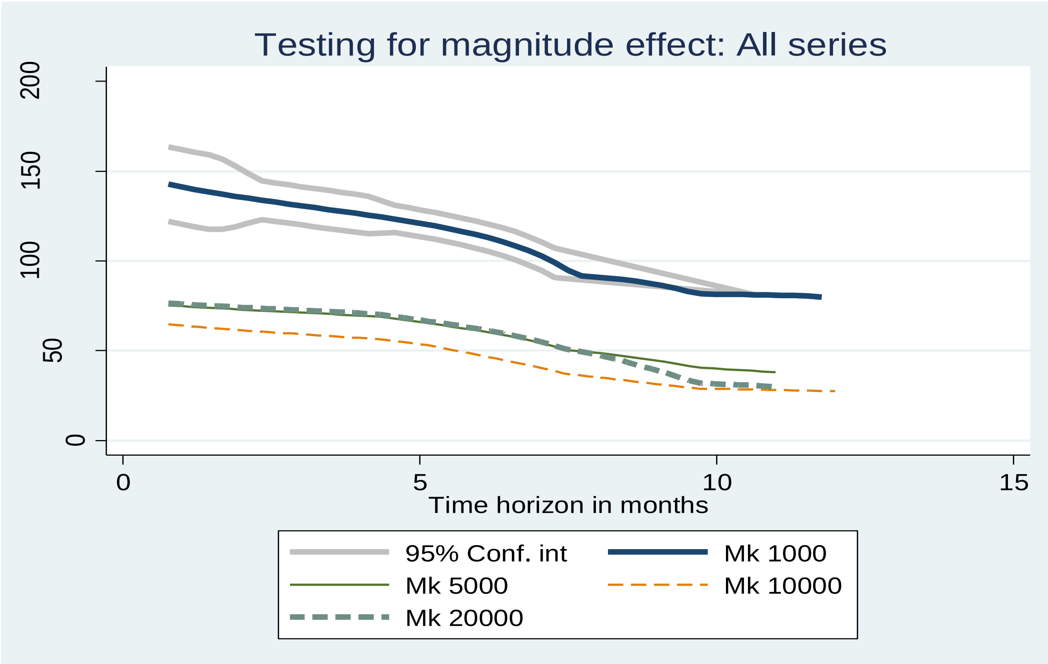

Figure 3. Magnitude effect on discount rates with 95% confidence interval for Mk1000

Next, the presence of present bias in the responses is examined. Figure 4 compares all series where the initial point in time was current time with all the series where the initial point in time was one week or one month delayed.

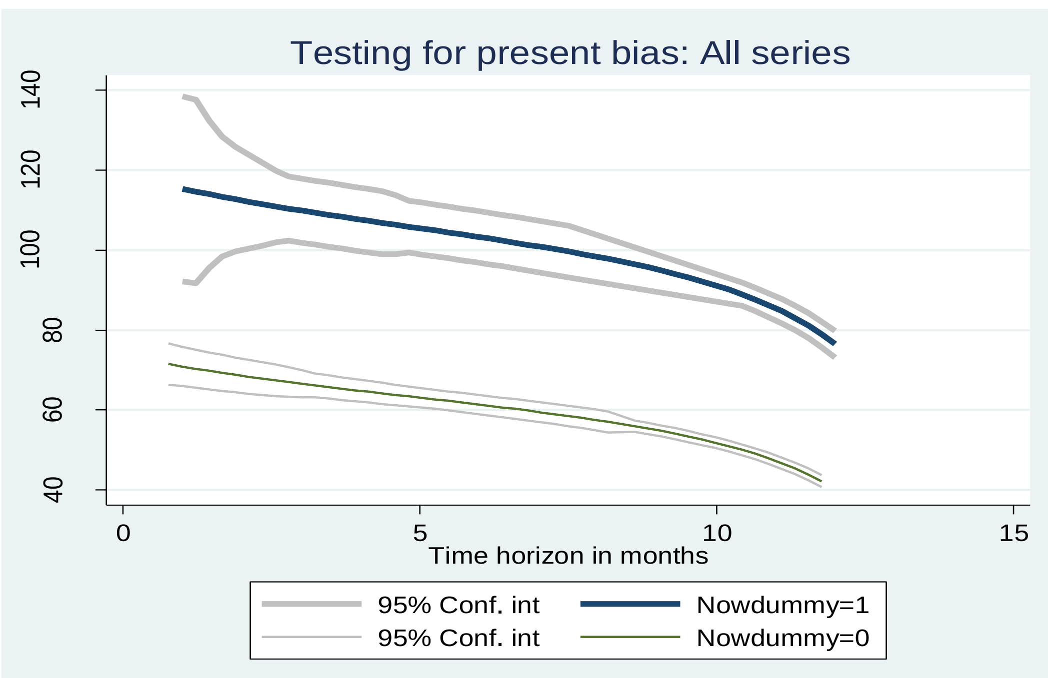

Figure 4. Present bias in discount rates: All series

Figure 4 demonstrates a highly significant present bias for all series and this present bias is there whether the time horizon is short or long. Figure 5 shows the present bias for small amounts (1000 MK series) and Figure 6 for the 10000 MK series.

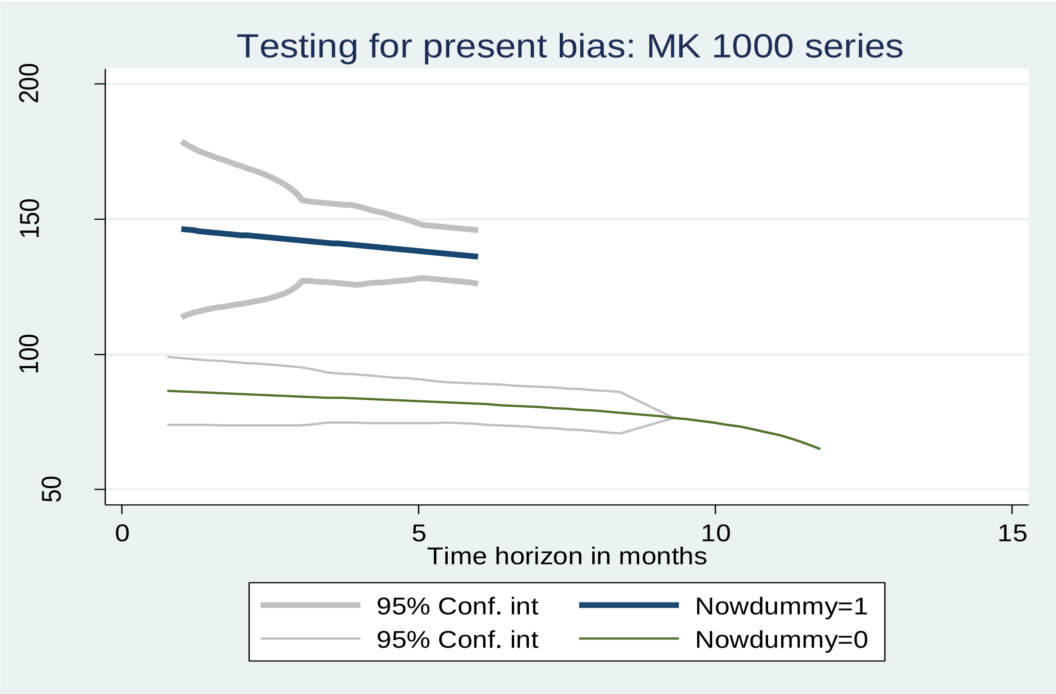

Figure 5. Present bias in discount rates for small amounts (1000 MK)

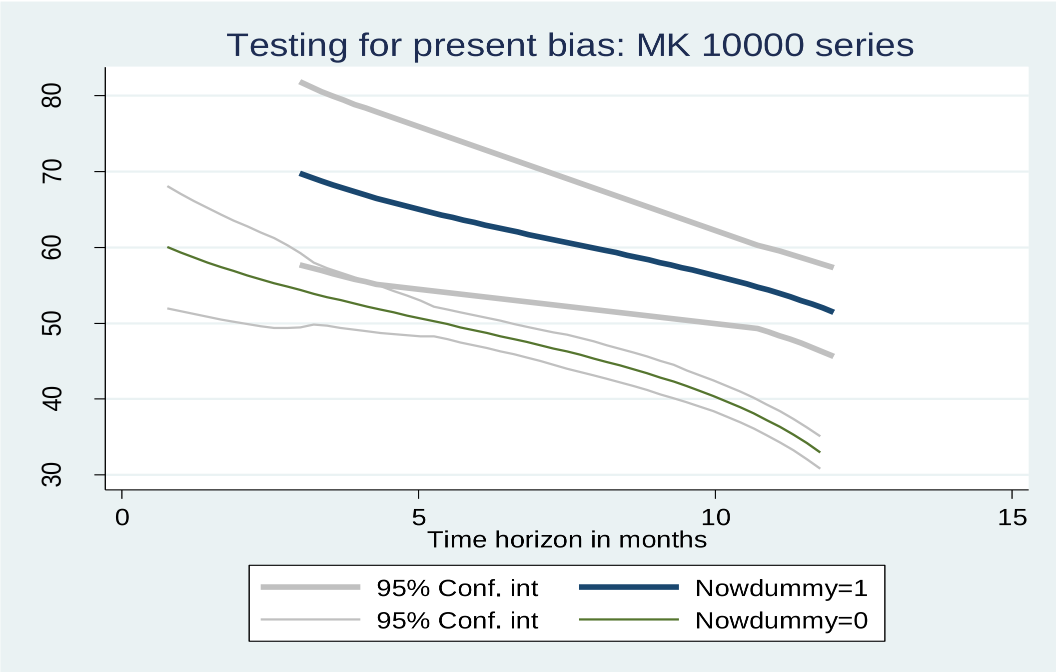

Figure 6. Present bias in discount rates for medium amounts (MK10000)

This exploration of the data based on assumptions of risk neutrality confirm earlier findings of magnitude effects with higher discount rates for small amounts, present bias as universal for small and large amounts and for varying time horizons, and declining discount rates with time horizon. Overall the discount rates are very high compared to some studies in developed countries using a similar methodology but where risk and time preferences were estimated jointly (Andersen et al. 2008). Convergence problems forced us to use another approach when correcting for risk aversion in the following parametric analyses.

7.2 Parametric results and discussion

The parametric regression results based on the structural maximum likelihood models with logarithmic utility functions where base consumption is constant are presented in Table 5 and where base consumption is adjusted for the length of time interval are presented in Table 6. Adjusting the base consumption level to time horizon is based on the assumption that short horizons involve "zooming in" on a more narrow set of decisions based on a smaller consumption base. This adjustment leads to less variation in discount rates across time horizons. This is also illustrated in Figure 7 (without base consumption adjustment) and Figure 8 (with adjustment of base consumption to length of time horizon). The structural model without base consumption adjustment predicts negative discount rates for 12 months horizon while this implausible result is scaled away with the base consumption adjustment approach. The "zooming in or out" adjustment of base consumption depending on the length of time horizon seems a more intuitive and logical adjustment than throwing in an extra "hyperbolic" discounting parameter.

We go through the results with each of the hypotheses in mind. First, the H1 hypothesis about present bias is assessed. A dummy variable for front end point in time being current was included in the models, using one week delay as the baseline. The variable was significant at 5% level and with a positive sign. The parameters indicate that the present bias was 8.1-8.3%. Hypothesis H1 therefore cannot be rejected. Studies that had compared current amounts with future amounts are likely to have upward biased time preference rate estimates. This may point in direction of quasi-hyperbolic discounting but this depends on the following hypotheses tests as well.

The test above was using one week delay of the near future point in time. However, we also had series with one month delay in the front end point. Another dummy variable was included to capture the difference between one week (baseline) and one month delay. From Table 6 it can be seen that this dummy variable was also positive and significant at 5% level in both models. The coefficients were 7.5-7.9% and implied higher rates for one month delays than one week delays. This was a surprising finding that we do not have a good explanation for.

Next we tested for a magnitude effect by varying the future prospect values from MK1000 to MK5000, MK10000 and MK20000. Table 6 shows that the coefficients for the dummies for these levels were highly significant (all at 0.1% level) and with negative signs using MK1000 as the baseline. The absolute values of the coefficients were increasing with the magnitude of the prospects providing strong evidence of a magnitude effect. The magnitude effect was clearly strongest in the interval from 1000 MK to 5000 MK while it was diminishing with higher amounts. Based on this we cannot reject hypothesis H2.

A further test for hyperbolic discounting is related to whether discount rates fall with the length of the time horizon. This is hypothesis H3 that was tested by inclusion of four different distant future points in time; one, three, six and 12 months. Table 6 shows that that the dummies for these different lengths in time horizons, using one month as the baseline, were highly significant (all at 0.1% level) and with negative signs. The coefficients were therefore significant even after the base consumption level was adjusted for the length of the time interval. The coefficients were substantially reduced, however, as compared to in Table 5 where base consumption level was not adjusted for the length of the time interval. This is strong evidence of hyperbolic discounting also after having controlled for present bias and base consumption level. The strongest hyperbolic effect appears to be there with very short horizons as the parameter difference is much larger between one month and three months than between three and six and between six and 12 months. Hypothesis H3 can therefore not be rejected.

The next hypothesis questions the high discount rates in previous studies and whether they were caused by present bias and ignorance of risk aversion (concavity of utility functions). Our study has revealed that present bias was significant and has assessed the discount rates based on a concave utility function. Discount rates were found to be sensitive to the magnitude and time horizon. Our structural estimates show that discount rates still are very high with smaller amounts and shorter planning horizons. Tables 7 and 8 provide predictions from the structural models by district, time horizon and without and with present bias. Table 7 shows that the average inflation corrected continuous time discount rate was 55% for MK10000 across 3, 6 and 12 months series. Table 8 shows that the average time preference rate was 30% for the 12 months horizon and one week delayed initial point in time. This compares to 34% without delayed initial point in time.

Figures 7 to 10 provide predicted distributions of the discount rates from the structural models for the different treatments. Figure 7 is based on constant base consumption level (MK300) while base consumption in Figure 8 is linear in length of the time horizon. High discount rates are particularly persisting when the amounts are small and time horizons get shorter than 6 months and particularly when they are reduced from three months to one month (Figures 7 and 8). Figure 7 shows that a most of the distribution with a 12 month horizon has negative discount rate when base consumption is the same for all time horizons. Contrary to that discount rates remain positive also for the 12 months horizon when the base consumption level is linear in the length of the time interval (horizon). Adjustment of the base consumption to the length of the time horizon seems to give more plausible results.

Our final hypothesis states that high discount rates are caused by shocks and poverty in the context of imperfect markets. Table 6 shows that the dummy variable for exposure to shocks is significant at 10% level and with positive coefficients indicating that households exposed to drought had discount rate that were 23.9-26.1% higher than other households in the two model specifications. Such dry spells can be seen as a natural experiment and we argue that this is evidence of a causal effect of shocks on the rates of time preference.

We also explored the relationship between wealth and the discount rates by including farm size and an index for the number of farm tools that households have. While both variables had negative coefficients only the farm size variable was significant at 10% level. An increase in farm size by one ha was associated with a reduction in the discount rate by 5.7-6.2% in the two models in Table 6. These findings indicate that we cannot reject hypothesis H5. High discount rates in earlier studies in developing countries are therefore not only caused by weak methods but are also a consequence of imperfect markets, shocks and poverty that create consumption smoothing problems.

Table 6 also shows that the method is susceptible to starting point bias. The fact that we randomized the starting point implied that the estimates of average discount rates to a small extent were affected by this starting point bias. The analysis also revealed no significant enumerator bias.

8. Conclusions

Our study of the time preferences of a poor population in rural Africa has demonstrated the significance and extent of present bias, magnitude effects and time horizon effects by use of multiple price lists (MPL). Elicited time preference rates increase sharply with the shortening of time horizons below three months between the two points in time at which prospects are evaluated. For practical purposes it is important to frame the experiments to the appropriate time horizons and magnitude levels of interest. After controlling for present bias the elicited time preferences remained high for time horizons of three to twelve months with amounts at common levels for annual investments in agricultural production that households faced. With a 12 month horizon average continuous time discount rates were 30% with front end delay and 34% without front end delay when predicted with a parametric model (Table 8) while the overall present bias was estimated to increase the discount rates by 8.1-8.3% when all treatments were included. Experience of a shock in form of drought in the recent agricultural season was associated with an average increase in the discount rates of 23.9-26.1%. These estimates were based on using continuous time discount rates with a logarithmic utility function which assumes a relative risk aversion equal to one for all households. A negative correlation was also observed between farm size and the rates of time preference while some other asset wealth indicators were insignificant. Overall the findings are consistent with the findings of Holden et al. (1998) that poor people have high discount rates and shocks and asset poverty may lead to upward shifts in elicited time preferences in ways that may affect investment behavior.

Table 1. Household land, gross production income , shock exposure, cash saving for fertilizer purchase, having formal employment and non-agricultural business.

District	Stats	Farm size, ha	Farm value, MK	Sales revenue 2011/12 MK	Shock exposure dummy 2011/12	Formal employ-ment, dummy	Non-agricultural business, dummy
Thyolo	Mean	0.62	282378	31056	0.71	0.23	0.45
	St. Err.	0.06	42045	5751	0.07	0.06	0.07
	N	45	45	50	48	47	47
Zomba	Mean	0.89	349071	19987	0.73	0.07	0.45
	St. Err.	0.06	106443	7631	0.05	0.03	0.06
	N	73	73	83	74	73	73
Chiradzulu	Mean	0.75	218162	15678	0.70	0.27	0.42
	St. Err.	0.07	75031	3941	0.08	0.07	0.08
	N	37	37	42	37	37	36
Machinga	Mean	1.31	188486	23573	0.65	0.07	0.54
	St. Err.	0.12	48917	5690	0.07	0.04	0.07
	N	47	47	49	46	46	46
Kasungu	Mean	2.05	259124	78103	0.59	0.16	0.36
	St. Err.	0.27	41591	16564	0.05	0.04	0.05
	N	78	78	88	82	81	81
Lilongwe	Mean	1.19	774958	20721	0.76	0.18	0.51
	St. Err.	0.17	159184	7393	0.05	0.05	0.06
	N	60	60	71	63	61	61
Total	Mean	1.22	358321	34907	0.69	0.15	0.45
	St. Err.	0.08	40531	4656	0.02	0.02	0.03
	N	340	340	383	350	345	344

Source: Own survey data.

Table 2. Share of households applying for loan (and whether loan was given), having formal or informal employment and non-agricultural business, by district.

District	Stats	Apply loan 2011/12	Loan given 2011/12	Ganyu, informal employment 2011/12	Received subsidized fertilizer 2011/2012	Received subsidized fertilizer 2010/2011	Received subsidized fertilizer 2009/2010
Thyolo	Mean	0.35	1.00	0.43	0.98	0.96	0.91
	St. Err.	0.07	0.00	0.07	0.02	0.03	0.04
	N	46	16	47	47	47	47
Zomba	Mean	0.22	0.63	0.53	0.86	0.86	0.84
	St. Err.	0.05	0.13	0.06	0.04	0.04	0.04
	N	73	16	70	73	73	73
Chiradzulu	Mean	0.19	0.86	0.59	0.73	0.78	0.73
	St. Err.	0.07	0.14	0.08	0.07	0.07	0.07
	N	37	7	37	37	37	37
Machinga	Mean	0.30	0.86	0.64	0.70	0.65	0.59
	St. Err.	0.07	0.10	0.07	0.07	0.07	0.07
	N	46	14	45	46	46	46
Kasungu	Mean	0.30	0.90	0.51	0.65	0.76	0.75
	St. Err.	0.05	0.07	0.06	0.05	0.05	0.05
	N	81	21	81	79	78	79
Lilongwe	Mean	0.39	0.78	1.00	0.52	0.52	0.61
	St. Err.	0.06	0.09	0.00	0.06	0.06	0.06
	N	61	23	6	62	62	62
Total	Mean	0.29	0.84	0.54	0.73	0.75	0.74
	St. Err.	0.02	0.04	0.03	0.02	0.02	0.02
	N	344	97	286	344	343	344

Source: Own survey data.

Table 3. Ability of households to mobilize cash for different purposes, by district

District	Stats	Max. cash amount that can be mobilized in a day for urgent household expenditure MK	Max. cash that can be mobilized in a day for urgent investment opportunity MK	Total cash the household can mobilize for fertilizer purchase[1] MK	Cash savings of household for fertilizer purchase[1] MK
Thyolo	Mean	1854	4029	7994	1820
	Median	1000	2500	6250	0
	St.err.	507	631	960	467
	N	40	41	48	48
Zomba	Mean	1649	5780	10045	3277
	Median	1000	3000	3800	0
	St.err.	230	937	2260	932
	N	65	55	74	74
Chiradzulu	Mean	1756	5383	9236	2563
	Median	1100	2000	3000	0
	St.err.	294	1604	2091	998
	N	27	30	37	37
Machinga	Mean	2593	6495	11311	2446
	Median	1500	3000	2750	0
	St.err.	535	1428	3134	694
	N	43	39	46	46
Kasungu	Mean	3330	13900	28529	2256
	Median	2000	5000	12500	0
	St.err.	505	2688	6140	821
	N	71	64	82	82
Lilongwe	Mean	2809	5214	15960	1939
	Median	1500	1250	6000	0
	St.err.	601	1430	4797	478
	N	54	50	63	63
Total	Mean	2428	7341	15240	2412
	Median	1050	3000	5750	0
	St.err.	201	773	1848	326
	N	300	279	350	350

Source: Own survey data. *Note*: [1] We have assumed that missing observations means zero amount here.

Table 5. Time preference estimates, continuous time discount rates with constant background consumption, without and with inflation correction

	Without inflation correction	**With inflation correction**
Future amount: Baseline=1000MK		
Future amount: 5000MK	-0.526****	-0.569****
Future amount: 10000MK	-0.704****	-0.773****
Future amount: 20000MK	-0.749****	-0.819****
Far future point in time: Baseline=1 month		
3 months	-0.941****	-0.995****
6 months	-1.296****	-1.398****
12 months	-1.846****	-2.096****
Dummy for front end point=current	0.115***	0.122***
Dummy for front end point=1 month	0.098**	0.111**
Experienced drought shock in 2011/12, dummy	0.224*	0.259*
Random starting point dummy*Task number	-0.024****	-0.029****
Tool index	-0.012	-0.014
Farm size in ha, gps-measured	-0.050*	-0.058*
Enumerator dummies		
2.enumerator	-0.061	-0.073
3.enumerator	-0.103	-0.13
4.enumerator	0.235	0.289
5.enumerator	-0.171	-0.201
District dummies, 1=Thyolo		
2=Zomba	0.366**	0.433*
3=Chiradzulu	0.242	0.293
4=Machinga	0.097	0.124
5=Kasungu	0.307	0.369
6=Lilongwe	0.324	0.387
Constant	1.887****	1.825****
Luce error constant	0.061****	0.061****
Prob. > F	0.000	0.000
Number of observations	31631	31631

Note: Maximum likelihood models with logarithmic utility functions with Luce error. Models where the base consumption level=MK300. Inflation corrected models were adjusted with 20% (continuous time discount rate). Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.1%.

Table 6. Time preference estimates, continuous time discount rates with time period adjusted background consumption, without and with inflation correction

	Without inflation correction	**With inflation correction**
Future amount: Baseline=1000MK		
Future amount: 5000MK	-0.635****	-0.666****
Future amount: 10000MK	-0.854****	-0.908****
Future amount: 20000MK	-0.958****	-1.023****
Far future point in time: Baseline=1 month	.	.
3 months	-0.401****	-0.423****
6 months	-0.485****	-0.514****
12 months	-0.671****	-0.728****
Dummy for front end point=current	0.081**	0.083**
Dummy for front end point=1 month	0.075*	0.079*
Experienced drought shock in 2011/12, dummy	0.239*	0.261*
Random starting point dummy*Task number	-0.019****	-0.021****
Tool index	-0.019	-0.021
Farm size in ha, gps-measured	-0.057*	-0.062*
Enumerator dummies	.	.
2.enumerator	-0.083	-0.090
3.enumerator	-0.128	-0.141
4.enumerator	0.253	0.283
5.enumerator	-0.185	-0.202
District dummies, 1=Thyolo	.	.
2=Zomba	0.371*	0.410*
3=Chiradzulu	0.280	0.312
4=Machinga	0.139	0.154
5=Kasungu	0.342	0.379
6=Lilongwe	0.335	0.369
Constant	1.663****	1.603****
Luce error constant	0.037****	0.037****
Prob. > F	0.000	0.000
Number of observations	31631	31631

Note: Maximum likelihood models with logarithmic utility functions with Luce error. Models where the base consumption level=MK300*Months time delay. Time delay from first point in time till second point in time varied from 1 month to 12 months. Inflation corrected models were adjusted with 20% (continuous time discount rate). Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.1%.

Table 6. Predicted mean discount rates by district for future amounts=10000MK, future time is 3, 6 or 12 months and front end point in time is delayed 1 week or 1 month.

District	Mean	se(mean)	N
1=Thyolo	0.21	0.008	1126
2=Zomba	0.63	0.006	1851
3=Chiradzulu	0.50	0.009	887
4=Machinga	0.41	0.009	1178
5=Kasungu	0.65	0.007	1745
6=Lilongwe	0.74	0.008	1462
Total	0.55	0.004	8249

Note: Average inflation corrected continuous time discount rates with time horizon adjusted base consumption.

Table 8. Predicted average discount rates with variation in near and far future points in time

Months from near to far future point in time	**Near point in time is 1 week or 1 month**			**Near point in time=Current**		
	Mean	se(mean)	N	Mean	se(mean)	N
1	1.00	0.007	1101			
3	0.62	0.005	2376	0.66	0.007	1105
6	0.54	0.006	2297			
12	0.30	0.005	2475	0.34	0.007	1378

Note: With continuous time discount rates, logarithmic utility function, MK10 000 series, with inflation correction, and base consumption=MK300*Length of time interval in months.

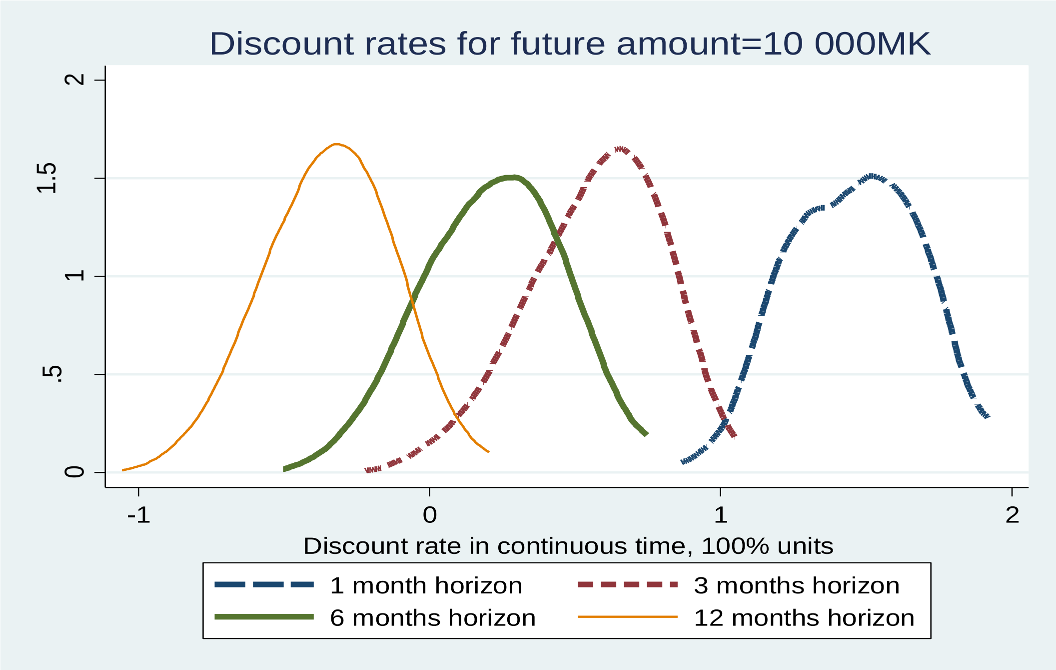

Figure 7. Predicted discount rate distributions for 10000 MK series with 1, 3, 6 and 12 months future horizons and delayed initial period with constant base consumption=MK300.

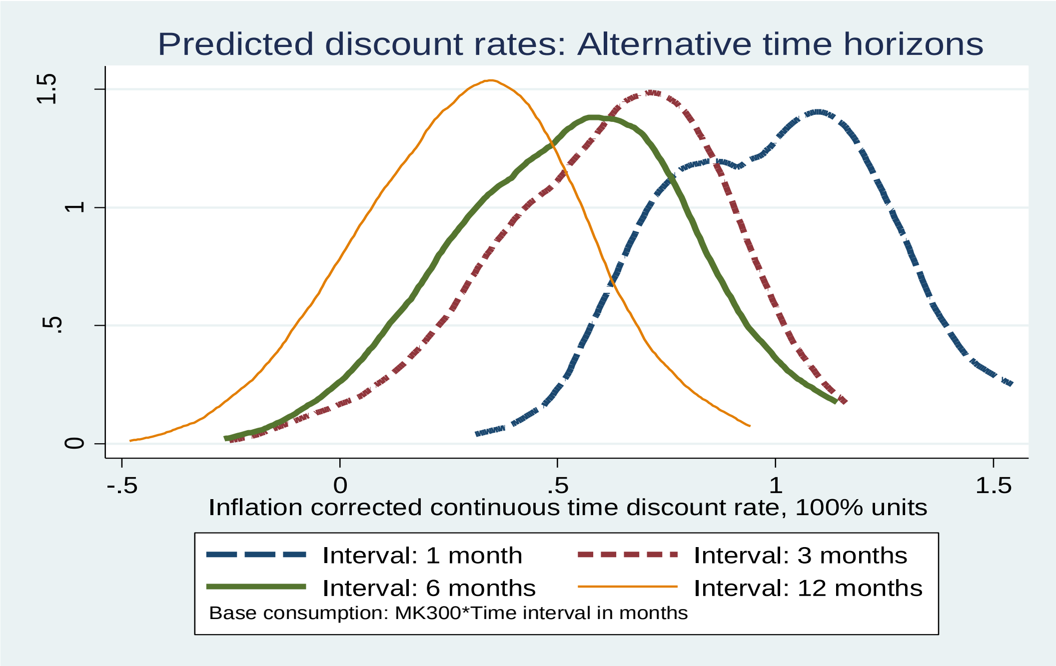

Figure 8. Predicted inflation corrected continuous time discount rate distributions for 10000 MK series with 1, 3, 6 and 12 months future horizons and delayed initial period with base consumption increasing in time period (=MK300*Number of months).

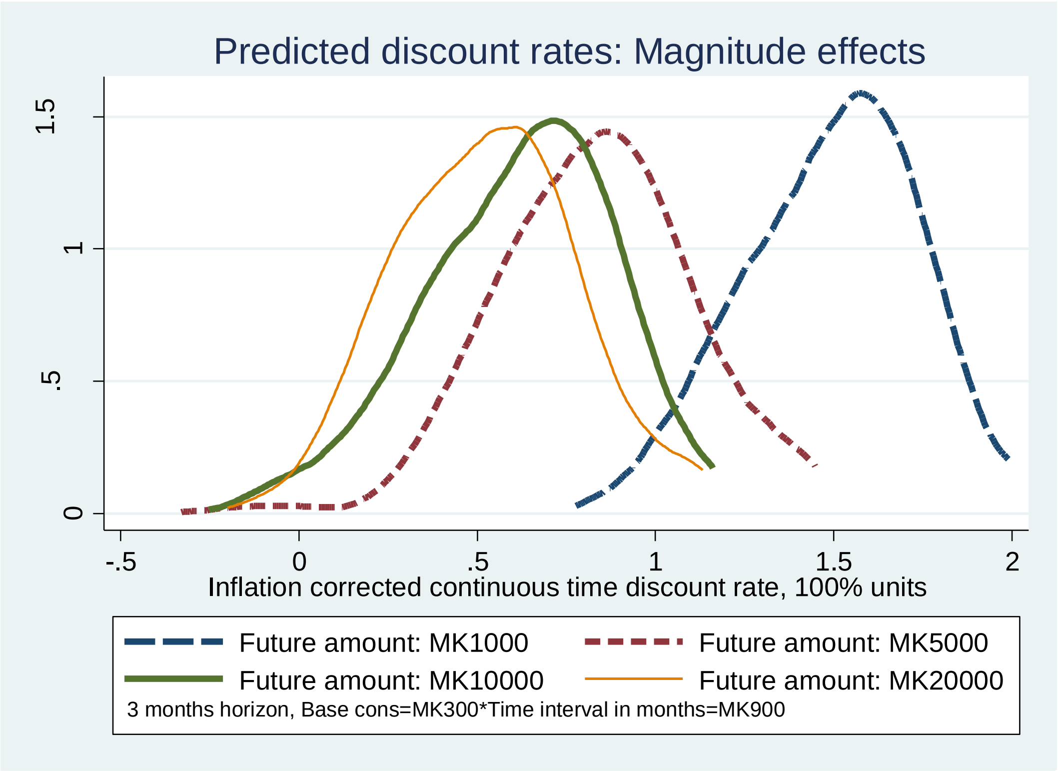

Figure 9. Predicted discount rates for alternative future amounts, with 3 months horizon, delayed initial payment time and logarithmic utility function with Luce error.

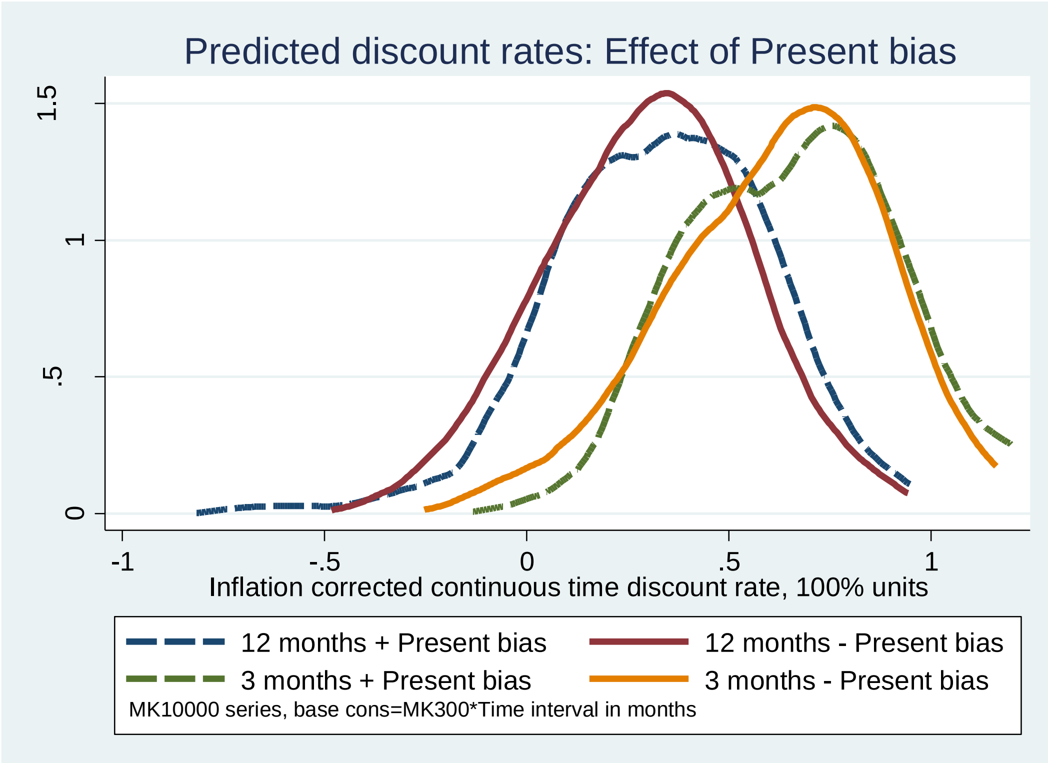

Figure 10. Present bias and time horizon with larger amount (MK10000).

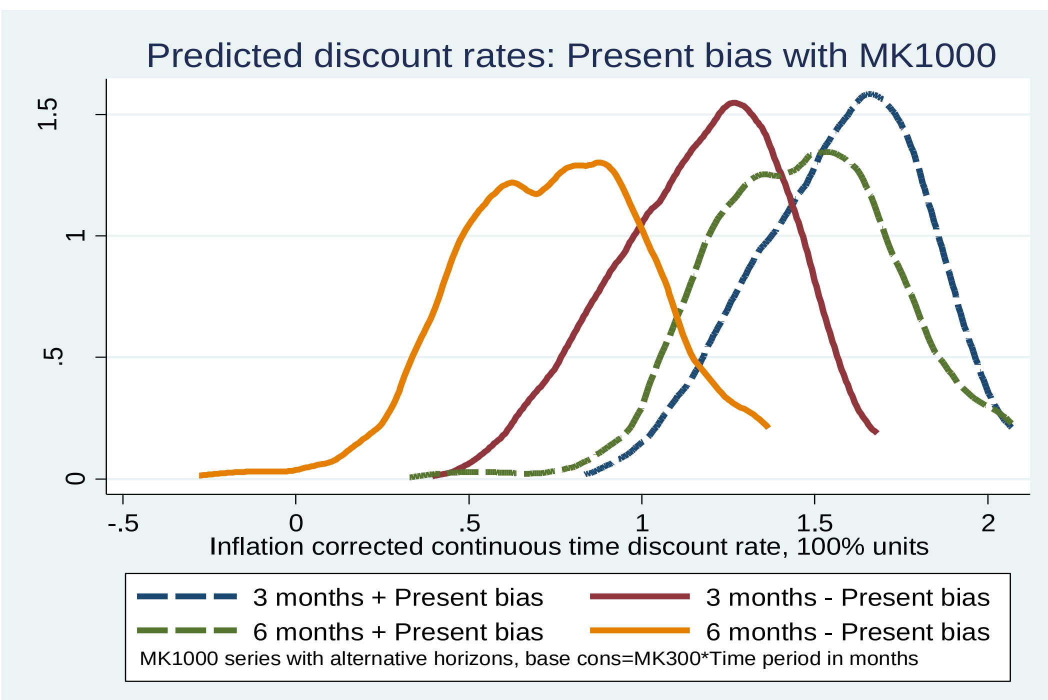

Figure 11. Present bias and time horizon in series with small amounts (MK1000).

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