Environmental Shocks, Rates of Time Preference and Conservation: A Behavioural Dimension of Poverty Traps?

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Abstract

This paper investigates the direct effect of environmental shocks on rates of time preference. Using panel data from household surveys in rural Ethiopia, we examine determinants of changes in households' discount rates among agricultural households. Time preferences are measured using a choice experiment and time-invariant characteristics are controlled for using household fixed-effects. Rates of time preference are found to increase significantly in response to shocks, a finding that is robust to a variety of specifications and controls. We also find that rate of time preferences are negatively correlated with the adoption of soil conservation measures. This suggests that poverty trap thresholds are multidimensional and that "downward spirals" are likely to be precipitated by behavioural responses in addition to the direct impacts of shocks on assets.

I. Introduction

Shocks are a ubiquitous part of life in developing countries. Poor households are frequently subject to environmental shocks such as severe droughts, economic shocks such as extreme price fluctuations, and health shocks that cause morbidity and mortality of households' members. Shocks affecting an entire community at once, such as extreme weather events, can be difficult to insure against and the ensuing income fluctuations are often thought to be a cause of poverty itself (Carter and Barrett 2006; Deaton 1992; Dercon 2002; Townsend 1995; Zimmerman and Carter 2003).

Understanding impacts of shocks is of paramount importance and has been the subject of many studies centred on understanding the dynamics surrounding poverty. Prior analysis has focused on consumption, savings, and asset accumulation but has largely ignored the question of whether the underlying attitudes and preferences of household members might be directly affected when a household is hit – perhaps repeatedly – by unexpected extreme events. For example, it is well-established that shocks can set households on dynamic paths toward low-wealth equilibria known as poverty traps, essentially by pushing a household beyond a critical asset threshold under which its ability to save,

invest in productive capital, and mitigate risk is severely threatened.[1] But the thresholds themselves are notoriously hard to measure. We propose that this could in part be due to an underlying behavioural response of households, which could of course vary across households and depend on many other conditions including the timing and/or compounding of multiple shocks. This paper examines one possible direct behavioural impact of exogenous weather shocks: changes in time preferences of affected households. We also discuss ways that this specific behavioural response can perpetuate paths toward poverty traps.

While observed rates of time preferences are known to be strongly and negatively related to wealth, and thus could increase in response to shocks due to negative impacts on wealth, they also could be impacted by shocks directly through other means.[2] Shocks might drive up rates of time preferences by changing expectations of future wealth relative to current wealth and by increasing uncertainty over these expectations. The former channel is straightforward, as discount rates include a component based on the expected growth rate of consumption; if current wealth suddenly changes relative to expectations of future wealth, *i.e.* if these expectations are updated based on the

[1] Empirical evidence demonstrates that shocks can induce greater inequality over time (e.g. Rosenzweig and Binswanger 1993 and Rosenzweig and Wolpin 1993), and the existence of poverty traps is well documented, both theoretically and empirically (see, for example, Azariadis and Drazen 1990, Banerjee and Newman 1994, Dasgupta and Ray 1986). The core hypothesis in this literature is that multiple dynamic wealth equilibria are possible; a low-wealth, stable equilibrium can thus "trap" households, and a "threshold" at which households' path dynamics switch is also implied. Recent theoretical work (Barrett and Carter, 2006) indicates that the threshold itself should be a function of individual characteristics, such as specific skills and entrepreneurial aptitude of household members. Recent empirical studies attempt to uncover thresholds around which wealth dynamics diverge and to explore the role that path dependence in household welfare plays in driving endemic poverty. (Lybbert et al., 2004; Barrett, et al., 2006; Yesuf and Bluffstone 2009).

[2] Poulos and Whittington (2000) estimate time preferences in the context of life-saving health programs, and point to a surprising dearth of empirical research on individuals' actual discount rates in LDCs. Damon et. al. (2008) investigate impacts of health interventions on natural resource management in western Kenya, and find initial evidence of an effect on time preferences. We know of no other study specifically investigating the impact of shocks on time preferences.

realization of shocks, then these altered expectations will have a direct effect on discount rates. A second channel is less theoretically straightforward but we hypothesize that it might also be important, as increasing future uncertainty can potentially drive up discount rates. While some researchers (e.g. Loewenstein and Prelec 1992) have suggested an analogy between risk and time preferences, the idea that individual time preferences can directly change due to future uncertainty hasn't been formally studied until recently (Halevy 2008), and has not yet been studied in a developing country context. Lastly, we posit that a shock can have a direct, behavioural effect on the pure rate of time preference, *i.e.* the component of a household's discount rate that is unrelated to expectations of consumption growth and is just a pure measure of impatience. With this hypothesis, we venture into the behavioural literature and psychological elements could be at play. Safety net policies can play a major role in breaking the vicious cycles leading to poverty traps but the effectiveness of these policies relies on their ability to identify critical conditions and understand underlying dynamics of household wealth, and many fundamental empirical questions about these dynamics remain unstudied. Where are the critical thresholds and, moreover, what accounts for them? While many researchers have pointed to the broad importance of these questions, the empirical problems inherent in answering them are equally well-known. .

We use unique panel data from household surveys in the Ethiopian highlands to investigate how exogenous environmental shocks such as severe droughts affect individual time preferences. Time preferences are measured using a stated choice experiment, and time-invariant household characteristics are controlled for using

household fixed-effects. The choice experiment to estimate the RTP and the surveys were conducted three years apart, in 2004 and 2007. One of the questions entailed the timing of the shock (e.g. the date of the shock). We are thus able to map environmental shocks from 1998 to 2006 using retrospective survey questions. We use this natural experiment setting. Our identification strategy exploits variation in the timing of the experienced shock. Farmers that have been recently hit by the shock will have experienced a recent change in their welfare compared to those who experienced the shock much earlier on (e.g. years ago). Our estimation strategy exploits this underlying heterogeneity. Specifically we split our sample of famers that experienced a weather shock in two sub-group – households who experienced a shock within one year from the experiment and those whose negative experience is more distant in time. We find that discount rates increase significantly in response to shocks. We then divide the sample again to distinguish whether the shock was reported in the first round, the second round, or in both rounds, and we keep as our baseline group those who did not experience any shock. We find that more recent shocks have significant impacts on time preferences while older shocks do not. This result provides preliminary evidence of the dynamic behavioural effects of environmental shocks, and may highlight household adaptive capacity.

Implications of a direct effect of shocks on individual discount rates can be vast. From the perspective of identifying the underlying dynamics of poverty traps, a discount rate effect could imply that asset measures alone might not provide a complete enough picture to indicate vulnerability. A downward spiral could be perpetuated well in advance of any given threshold, stemming from altered incentives to conserve. Knowing where a

particular threshold lies might not be enough – and, moreover, these behavioural influences might challenge the notion that the thresholds themselves can even be defined by assets alone. For example, if shocks differentially affect households' time preferences, then certain households could be vulnerable to entering dynamic paths toward low-wealth equilibria at higher asset levels than other households.

In the next section, we lay out our theoretical framework. Section III describes the survey data, and Section IV discusses our empirical findings. Section V concludes the paper.

II. Theoretical Framework

Our theoretical foundation starts with the Ramsey discounting framework. A household makes intertemporal consumption and investment decisions to maximize its lifetime utility using a rate of time preference, *RTP*, to discount future consumption. The rate of time preference can be expressed with the following equation:

$$r = \delta + \eta g \qquad (1)$$

where $\eta \equiv -\frac{C \cdot U''(C)}{U'(C)}$ and $g = \frac{dC/dt}{C}$, and δ is a household's "pure" rate of time preference.

The two terms on the right hand side of Equation (1) represent the two distinct reasons households might discount future consumption. The pure rate of time preference is positive if current well-being is valued higher than well-being in the future; in other words, δ is a measure of pure impatience, and may or may not be equal to zero. The two

components of the second term are the growth rate of consumption and the elasticity of marginal utility. We can see that, for a non-zero elasticity of marginal utility, the growth rate of future consumption directly impacts a household's rate of time preference. A positive elasticity of marginal utility reflects the standard assumption of diminishing marginal utility so, in this standard case, an increase in a household's expectation of g will directly increase its RTP. The intuition is straightforward – if a household grows wealthier over time then an additional unit of consumption tomorrow will be less valuable than a unit today, so as a household makes consumption and savings decisions today, the weight it places on an additional dollar tomorrow relative to today is affected by its expectation of g.

Any shock that can change expectations of the growth rate of consumption can thus alter a household's discount rate. Specifically, by lowering current consumption relative to future consumption, a shock can essentially increase g and thereby increase the rate at which a household is willing to trade off future consumption for current consumption.
Since we analyze the overall effect of shocks on household discount rates, we consider the other possible component of this impact – through the pure rate of time preference (also known as the "utility discount rate"). We are therefore also interested in the effect that a shock can have on the first term in equation (1).

Here we follow in the tradition of many empirical studies over the past two decades in that we depart from the classical framework in one important regard: pure time preference is not assumed to be constant. (See Frederick, Loewenstein, and Donoghue

(2002) for an extensive review of discounted utility anomalies throughout the empirical literature.) Households are expected intertemporal utility maximizers. In our framework, we allow a household's rate of time preference to depend on a vector of state variables **θ**. For a given consumption profile c = (c_t,.. . ,c_T), a household's intertemporal utility function is then described by the utility function:

$$U(c,\theta) = \sum_{t=0}^{\infty} \beta^t(\theta) u(c_t) \qquad (2),$$

$$\text{where } \beta(\theta) = \frac{1}{1+\delta(\theta)}$$

and where *u(t)* is the household's instantaneous utility function and *β(θ)* is the pure time preference which is a function of **θ.** In the classic discounted utility (DU) model, *β* is assumed to be constant. Our framework is a similar and arguably more general departure from the classic DU model than many recent well-known characterizations of DU anomalies. For example, hyperbolic discounting can be thought of as a case in which *β* is declining in *t*, an element of **θ**. We follow in the tradition of Becker and Mulligan (1997), who posit that a wide variety of factors such as wealth, education, religion, and uncertainty – can potentially impact time preferences.[3] We depart from all prior studies of which we are aware by considering the effect on *β* of exogenous state variables when household characteristics are controlled for.

We hypothesize that one important variable in **θ** could be the recent occurrence of an extreme event, and that this variable can have a direct behavioural impact on *β*. We test

[3] The mechanism by which wealth, education, and other variables affect time preferences in Becker and Mulligan's model is through effort devoted to "patience formation". Our model does not require an assumption on mechanism.

this hypothesis in the remainder of the paper, focusing on exogenous environmental shocks.[4]

III. Data

Ethiopia is a prime area to investigate the behavioural dimension of environmental shocks. Ethiopia's exposure to weather shocks is very well documented. During the last forty years, Ethiopia has experienced many severe droughts, leading to production levels that fell short of basic subsistence levels for many farm households (Relief Society of Tigray (REST) and NORAGRIC at the Agricultural University of Norway 1995, p. 137) with adverse effects on farm household consumption and welfare (Dercon 2004, 2005).

We use data collected from East Gojjam and South Wollo in the Amhara region in the highlands of Ethiopia. The vast majority of the population in these areas is dependent on rain fed agriculture. The altitude is above 1500 meters and particularly South Wollo has a very precipitous landscape with the Rift Valley to the East and the Blue Nile gorge to the West. Rainfall is erratic and the area is notorious for recurrent droughts over the last decades, necessitating both domestic and international relief interventions. The steep hills are to a large extent denuded of vegetation. Marginal lands are cultivated due to high population pressure, and soil erosion is a serious problem for the already low productivity in agriculture. In short, this might very well be one of the poorest and most vulnerable populations in the world.

[4] By controlling for wealth in our empirical specification, we are essentially directly testing the hypothesis that this first term of Equation (1), the pure rate of time preference, is impacted by shocks.

A panel data collection effort was initiated in this area in the late 1990's by the Addis Ababa University in collaboration with the University of Gothenburg. The purpose of the data collection was to understand the links between poverty and natural resource utilization in the Highlands of Ethiopia. To date, four rounds of the Ethiopian Environmental Household Survey (EEHS) have been collected in 2000, 2002, 2005 and 2007. The last two rounds of the survey, which are being used in this paper, cover 1,720 households in 14 villages in the two regions. In these two rounds, the data include two features that are used in the paper. One is a module that asks which shocks the households have experienced in the previous two years. The second feature is an experiment that elicits subjective time preferences by asking respondents a series of questions in which they choose between a payment of ETB 50[5] today and a higher value[6] in 12 months time. While this was a hypothetical experiment, it was developed as part of a larger project (Yesuf 2004; Yesuf and Bluffstone 2009) which made a number of methodological tests, including real payments.

Basic descriptive statistics are presented in Table 1. The dependent variable used in our analysis is the rate of time preference (RTP) estimated from the choice experiment data, and the key independent variable of interest is a dummy variable indicating that a household experienced an environmental shock in the two years preceding the interview. Shocks that the survey asked about include drought, flooding, frost, and hailstorms affecting the harvest. Almost one in two households reported shocks in previous years. We included in the analysis characteristics of the household head (age, gender).

[5] ETB 50 in June 2005 was equal to approximately USD 5.70 while in June 2007 it was worth about USD 5.50.
[6] The values were ETB 65, 80, 105, 130, 160, 195 presented as repeated, randomized choice sets.

Moreover we control for household composition by including the number of adults and the number of children in the household. We include some controls for assets endowments such as livestock (aggregated in tropical livestock units) and land. We also controlled for the availability of fertilizer. In addition we inserted some location variables such as distance to the market town and altitude. These to control for market access and marginality. Table 1 provides information on the variables employed in the analysis.

V. Econometric strategy and results

The choice experiment to estimate the RTP and the surveys were conducted three years apart, in 2004 and 2007. We also recorded if in this period the household experienced weather shocks or not. Given that the weather shock can be considered random we can we can use this variation as a treatment - in a quasi experiment set up. We can estimate the causal effect of shocks on rate of time prefernces. We explore different estimation strategies. We first exploit the fact that the same households were followed in the two rounds. Some of these did experience the shocks while other did not. We can thus use a simple differences in differences estimator. We estimate the following equation:

$$\Delta RTP_h = \alpha_0 + \beta_1 \, Shock_h + e_h \qquad (1)$$

The left hand side of (1) presents the change in the value of the RTP for the household h over the course of the three years when the treatment happened. We are interested in the estimated coefficient β_1. Equation (1) can be extended using household characteristics prior to the quasi experiment. The inclusion of these pre-treatment variables is very important to both improve the efficiency of the estimates and adjust for conditional

randomization. Table 2 reports the estimation results of the differences in differences estimator.

[TABLE 2 about here]

If the environmental shock is randomly assigned then it will be uncorrelated with the observable household characteristics. We therefore present the results of a linear probability model[7] - in the table 3 – where the variable shock is regressed against all the pre treatment variables used in the model (4). No variable is significant up to the conventional 5 per cent level. We thus have no clear evidence that the shocks were not randomly received.

[Table 3 – about here]

As robustness check we present the results from standard panel fixed effects estimator in column (5). In the subsequent column (that is column 6) we report the results for fixed and time effects. We therefore use a larger sample. The estimated coefficient for the variable of interest is very consistent and stable. These latter estimates are robust to unobservable heterogeneity. The standard errors have been clustered at the village level. This to control for the possible correlation patterns within units of the same village. We control for household-level characteristics including gender, age and, household composition. We also insert controls for wealth with two variables that capture endowments at the household level: livestock and land. We also include location variables, namely distance from the closest market town and altitude. It should be stressed that we do attach any specific causal interpretation to these controls.

To appreciate the implications of these RTP, we provide a further analysis where we regress the RTP against soil and water conservation measures. These type of investment

[7] We also used a probit. Results were very consistent.

are extremely important to maintain the productive base of the household. Farmers that invest in these type of activities are usually more resilient to future shock and – generally – better manage their soils. We present a reduced form analysis. We find that the increase in the TOP is negatively correlated with the extent of soil and water conservation strategies that have been adopted at the farm level. This is measured by the number of plots that are allocated to these strategies.

To further probe the analysis we designed the quasi experiment in an alternative fashion. In each survey round, respondents were asked whether they experienced an nvironmental shock in the years preceding the interview date. Environmental shocks that respondents were asked about include drought, flood, erosion, and frosts. One of the questions entailed the timing of the shock. We are able to map environmental shocks from 1998 to 2006 using retrospective survey questions. Our identification strategy exploits variation in the timing of the experienced shock.

27% of the households experienced the exogenous shock during the cropping season immediately before the first round of survey took place. That is less than one year – a very recent shock that affected their harvest. Similarly, 35% experienced the shock in the cropping season directly before the second survey round. Farmers that have been recently hit by the shock will have experienced a recent change in their welfare compared to those who experienced the shock much earlier on (e.g. years ago). We hypothesize that households experiencing the shock more than one year (that is more than one cropping season ago) before rounds should not exhibit a behavioral change. They would have

already exhibited the change before rounds, and since then have had time to cope with the implications of the shock.

The estimation strategy can exploit this underlying heterogeneity. Specifically we split our sample of famers that experienced a weather shock in two sub-group – households who experienced a shock within one year from the experiment and those whose negative experience is more distant in time. Thus we can contrast the households who experienced the shock within recently with those whose shock was further back in time. We analyze differences in time preferences between these two groups. As mentioned, time preferences are measured using a stated choice experiment.

We estimate the following equation to analyze differences in rates of time preference between the two sub- groups:

$$RTP_{ht} = \alpha_h + \beta \text{ Recent Shock}_h + \gamma \mathbf{x}_{ht} + \delta \mathbf{z}_h + e_{ht} \qquad (2)$$

Again RTP_{ht} is the outcome of interest - the rate of time preference for household h at time t (first or second round of the survey). **x** represents a vector of time-varying controls, **z** represents a set of time-invariant controls. α_h denotes a fixed effect for household *h*. Each household *h* that we include in this estimation has experienced an exogenous weather shock at some point in our reporting period, and Recent Shock_h is a dummy variable indicating whether household h's shock was in the cropping season just prior to the survey round.

The coefficient β represents the effect of an exogenous environmental shock on time preferences within one year of experiencing the shock, relative to the baseline group (those that experienced the shock earlier in time).

[Table 5 – About here]

Table 5 reports our results. The estimated coefficient for shock is positive and highly significant in all the specifications. We also find that our results are very consistent. As an additional check of the validity of our identifying assumptions we estimate an alternative specification in which we directly compare the group of farmers that experienced the shock within one year to those who experienced the shock more than one year from the survey in the random sample. The results are reported in the table 6. This regression provides an important "falsification test." Since households should not experience such large changes in their welfare if they have been exposed to shock in the more distant past, the estimated coefficient should not be statistically significant. The results indicate that this is indeed the case.

Finally, we also divided the sample to distinguish whether a shock was reported within one year before a) the first round and b) the second round. We keep as baseline group households that experienced the shock earlier in time. Again, we find that discount rates increase significantly in response to shocks. Results are reported in the table 4.

[Table 6– About here]

[Table 7 – About here]

VI. Conclusion

We present evidence that environmental shocks have a positive impact on rates of time preference. These findings imply that measures of a household's asset levels their fluctuations could, alone, be inadequate indicators of vulnerability. Households could set off on dynamic paths toward poverty traps not only because of direct shocks to asset levels, but also due to deeper behavioural influences that cause household members to be less forward-looking. Thus, a straightforward notion of a critical asset threshold might not be enough to help recognize the most critical circumstances. Further research is needed to investigate differential impacts of shocks on rates of time preferences, to more precisely identify whether certain households could be vulnerable to entering dynamic paths toward low-wealth equilibria at higher asset levels than other households.

This paper also contributes to a broader understanding of individual discount rates and the factors that comprise them. For one thing, the positivist position in the debate surrounding the choice of discount rates for social policies holds that high observed RTPs in developing countries imply a higher discount rate for social and economic policies in developing countries than in the U.S. and Europe (see for example Poulos and Whittington 2000). But if high discount rates are not only related to the overall level of wealth, but also are intricately tied to current conditions – and thus perhaps even endogenous to the policy being evaluated – this finding could challenge the notion that observed discount rates are an appropriate guide to the social rate with which policies should be evaluated or designed. In other words, observed discount rates in the face of

shocks and uncertainty are perhaps not as fundamental a parameter as use for policy evaluation might demand.

Understanding the determinants of time preferences of course also has implications well beyond the choice of social discount rates. High rates of time preference disincentivize investment (Deaton, 1991), both in physical and natural capital, and thus threaten conservation. This has been demonstrated empirically even when property rights are secure (Holden et al. 1998). Understanding impacts of various types of shocks on time preferences can shed new light on the forces that might drive up observed discount rates among the poor, contributing to our understanding of a central determinant of investment in environmental conservation. As negative shocks are found to undermine incentives to conserve natural resources, we can for example imagine vicious cycles or "traps" of environmental degradation being perpetuated by shocks, analogous to the way that poverty traps are perpetuated.

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Table 1 Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
Rate of time preference (RTP)	1.0378	0.534	0	1.36
Conservation (Number of plots under soil and water conservation)	1.4	0.75	0	13
Shock	37.9%			
Shock before first round	27 %			
Shock before second round	38%			
Age	51.185	14.804	15	97
Gender (1=male)	1.158	0.365	1	2
Number of Children	2.804	1.410	1	7
Number of Adults	2.703	1.184	1	8
Livestock (in equivalent units)	8.46	11.35	0.9	59

Land (in hectares)	1.173	0.784	0.1	3.5
Altitude (masl)	2549	32.37	1979	3060
Distance to market town (in minutes)	77.96	56.964	0	280

Table 2 Shock and Rate of time preference -difference in difference and panel data estimator

	Dependent Variable: ΔRTP Diff in Diff				Dependent Variable: RTP Panel Data	Panel Data with time effects
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.149**	0.157**	0.127***	0.117***	0.106***	0.107***
	(0.0556)	(0.0532)	(0.0391)	(0.0346)	(0.0381)	(0.0380)
Age		0.000217	-0.000135	0.0000271	-0.000948	-0.00179
		(0.00111)	(0.00103)	(0.000951)	(0.00281)	(0.00279)
Gender		-0.0876	-0.0660	-0.0508	-0.0128	-0.00421
		(0.0555)	(0.0511)	(0.0521)	(0.0500)	(0.0480)
Education		0.00114	-0.000232	-0.00390	0.0114	0.00943
		(0.00760)	(0.00696)	(0.00703)	(0.00628)	(0.00624)
# of Adults		-0.0167	-0.0155	-0.0185	-0.000700	0.000619
		(0.0124)	(0.0123)	(0.0138)	(0.0153)	(0.0148)
# of Children		-0.0373**	-0.0334	-0.0298	0.0173	0.0204
		(0.0170)	(0.0161)	(0.0178)	(0.0136)	(0.0136)
Livestock			-0.00469**	-0.00417**	0.00486	0.00101
			(0.00199)	(0.00174)	(0.00314)	(0.00301)
Land			-0.169***	-0.145***	0.0979***	0.198***
			(0.0357)	(0.0263)	(0.0252)	(0.0347)
Altitude				0.0000187		
				(0.0000130)		
Distance from the market town				-0.000458		
				(0.000586)		
Constant	-0.0775	0.129	0.336***	0.219	0.875***	0.772***
	(0.0943)	(0.116)	(0.0942)	(0.150)	(0.155)	(0.154)
N	1237	1195	1195	1175	2113	2113
adj. R^2	0.111	0.120	0.158	0.180	0.148	0.172

Clustered Standard errors in parentheses ** $p < 0.05$, *** $p < 0.01$

Table 3 Testing for random assignement

	Dependent Variable: Shock
Age	0.000356
	(0.000527)
Gender	0.0148
	(0.0192)
Education	0.000748
	(0.00351)
# of Adults	0.0147
	(0.00739)
# of Children	0.00378
	(0.00712)
Livestock	-0.000934

	(0.000642)
Land	-0.0245
	(0.0187)
Altitude	0.00000363
	(0.00000294)
Distance from the market town	0.000402
	(0.000312)
Constant	0.121**
	(0.0462)
N	2518
adj. R^2	0.007

Robust Standard errors in parentheses: ** $p < 0.05$

Table 4 Rate of time and Adoption of soil conservation measures

	Dependent variable: Conservation
RTP	-0.422***
	(0.130)
Constant	3.786***
	(0.141)
Fixed effects	Yes
Time effects	Yes
N	2856
adj. R^2	0.346

Clustered Standard errors in parentheses: ** $p < 0.05$, *** $p < 0.01$

Table 5 Empirical analysis – using the timing of the shock

	Dependent variable: Rate of time preference
Shock before Surveys	0.156***
	(0.0548)
Fixed effects	no

Time Effects	no
N	439
adj. R^2	0.776

Robust Standard errors in parentheses ** $p < 0.05$, *** $p < 0.01$ **Other regressors omitted. Control group: household that experienced the shock more than one year ago**

Table 6 Robustness analysis - full sample

	Dependent variable: rate of time preference
Shock within one year before survey	**0.0422***
	(0.0247)
Shocks more than one year before survey	**0.00362**
	(0.0257)
N	**2325**
adj. R^2	**0.798**

Robust Standard errors in parentheses. Other regressors omitted.

**** $p < 0.05$, *** $p < 0.01$**

Table 7. Alternative specification

	Dependent variable: rate of time preference
Shock within one year before first round	**0.291*** **
	(0.068)
Shocks within one year before second round	**0.12** **
	(0.06)
N	**430**
adj. R^2	**0.813**

Robust Standard errors in parentheses. Based on the same specification as (4) in table 2. Other regressors omitted. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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