Do risk and time preference explain household's demand for microinsurance? A lab in the field approach *

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Abstract

Microinsurance is one of the key instruments in addressing the risk and vulnerability of economic shocks for the low-income households in the global south. However, microinsurance take-up globally is puzzlingly low. The question is why? Using primary panel data with incentivized lab-in-the-field experiments conducted in five rural villages in India, the paper first examines the nature of risk and time preference of the individuals and then examines the association of risk and time preference, and prior shocks on microinsurance take-up. The findings highlight a few key insights. First, I find that majority of the individuals are not only risk averse, but they are loss averse and underweight large probability events. Second, I find that majority of the subjects are present biased. Third, I find that impatience is associated with a lower probability to purchase any insurance while risk-seeking individuals and individuals who experienced a prior shock such as a death in the family are associated with a higher probability to purchase any insurance. Finally, I find that individuals who are loss averse and underweight large probability incidents are associated with a lower probability to purchase any microinsurance.

Keywords: microinsurance, loss averse, present bias, probability weighting

JEL: C93, D12, D15, D81

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1 Introduction

Low-income households are frequently exposed to unprecedented shocks from numerous sources and they are not adequately protected from such risk exposures. Among the various shocks households face, health shocks are considered to be critical as they have undermining effects on households' finances directly by forcing out-of-pocket health expenditure (Asfaw et al., 2012). To mitigate the risk from these unparalleled shocks, people make informal risk-sharing arrangements through networks of friends, family and neighbours. However, these schemes are limited in outreach and cover only a fraction of the loss — making these mechanisms imperfect and inefficient. Moreover, households are usually struck with another crisis even before they have a chance to recover from one crisis.

Microinsurance is considered as one of the key instruments in addressing the risk and vulnerability of low-income households in the global south countries. Microinsurance is defined as the protection of low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved (Churchill, 2006). A follow-up question that might arise is — how is microinsurance different from regular insurance? The definition of microinsurance is the same as one might use for regular insurance, the only difference in comparison to regular insurance is that microinsurance has a clearly prescribed target group — low-income people. However, despite its importance in addressing risk and vulnerability, the demand for microinsurance is puzzlingly low. Which begs the question — why is the microinsurance demand so low?

Previous literature which examined the factors behind low take-up of microinsurance focused mostly on factors such as price, knowledge about the product, trust, transaction costs, etc (Cole et al., 2013; Dercon et al., 2019; Thornton et al., 2010; Cai et al., 2015; Giné et al., 2008; Patt et al., 2009; Bonan et al., 2011). Although, the aforementioned factors might explain part of the story, what has been largely missing from the microinsurance literature is the association of behavioural factors such as – risk preference and time preference on microinsurance take-up. Understanding the association of behavioural factors such as risk and time preference and behavioural biases such as loss aversion, probability weighting function (PWF) and present biased nature are quite important as they explain the insurance demand puzzle (Schmidt, 2016; Do Hwang, 2021; Pitthan and De Witte, 2021). One plausible explanation for the lack of studies examining the effect of risk and time preference and behavioural biases such as loss aversion, probability weighting and present biased nature on microinsurance take-up is that — examining risk and/or time preference without incentivized lab-in-the-field experiments might lead to hypothetical bias (Carpenter, 2002).[1] On the other hand, designing and conducting incentivized lab-in-the-field experiments are not only costly but it is also time-consuming and difficult to design and conduct where the sample of the study are not educated students.

[1]What Carpenter (2002) highlights by *hypothetical bias* is that people might react differently when the situation is hypothetical as compared to when the situation is real.

An individual who is risk-averse, loss-averse, and present biased (time-inconsistent preference) wouldn't want to buy insurance as the premium needs to be paid today but the potential benefit might be only experienced in the future. An individual with the aforementioned preferences might see buying insurance as a loss if the health risk does not materialize and given their present biased nature, the individual would want to spend on immediate consumption rather than delayed consumption. To top things off, if an individual's PWF is such that overweight small probability events and underweight large probability events (inverse S-shaped), this might explain the lack of insurance take-up, which I find in the results. As an individual underweights large probability events and assumes that they are unlikely to occur. So spending for an unlikely event and paying insurance premium beforehand might seem like a sunk cost. Furthermore, they might believe that, if and when the event occurs, it is better to cover it out of the pocket. If behavioural biases lead to efficiency loss or market failure, it is a policy-relevant question and has important policy implications.

My main research question is — how are behavioural factors linked with microinsurance take-up? To investigate this, I follow a two-step approach. In the first step, I examine an individual's risk and time preference. In the second step, I use the estimated preferences to assess their role in explaining microinsurance take-up. More specifically, I ask the following questions: (1) What are an individual's risk preferences? Are they risk averse, loss averse and overweight small probabilities and underweight large probabilities? (2) What about their time preference? Do they have time-consistent (exponential discounters) or do they have time-inconsistent preferences (hyperbolic discounters)? If they have time-inconsistent preferences, are they also present biased? (3) How is risk and time preference associated with microinsurance take-up? Are risk-averse, loss-averse, and present biased individuals less likely to take-up microinsurance? (4) How do prior household level shocks such as illness, injury, or death of a family member linked with microinsurance take-up? (5) How does the combination of these behavioural factors and individual biases explain the puzzlingly missing microinsurance market phenomenon?

The current work draws from the data that I collected from five rural villages in India. The data contains panel information of 166 households surveyed between 2018 and 2020. The survey data contains information on the socio-demographic position, consumption, health, assets, loans, and shocks of individuals in the villages. To examine risk and time preference, two simple experiments on risk and time preference and two more comprehensive experiments on risk and time preference were conducted. These experiments thus allow me to answer not only simple risk and time preference but also allow me to separate risk aversion, loss aversion, probability weighting of incidents and hyperbolic discounting and present bias. These estimates allow me to answer broad questions such as an individual's risk and time preference but also the specific nature of the risk preference and time preference. Moreover, with the detailed risk and time preference and behavioural biases such as loss aversion, probability weighting and present biased nature, I can answer questions pertaining to the take-up of microinsurance.

The findings indicate that a vast majority of individuals are not only risk averse but they are also loss averse, that is losses hurt them more in comparison to an equal amount of gain. I also find that individuals have inverse S-shaped PWF, which means they put more weight on incidents which are less likely to occur and underweight incidents which are more likely to occur. I also find that majority of the subjects are also present biased. On microinsurance take-up, I find that risk-seeking individuals and individuals who experience a prior household level shock such as death are more likely to buy microinsurance. Whereas, impatient individuals are significantly less likely to buy microinsurance. Lastly, I find that individuals who underweight large probabilities are less likely to buy health microinsurance. If behavioural biases lead to efficiency loss or market failure, it is a policy-relevant question and has important policy implications. One plausible solution to increase microinsurance take-up would be to have automatic enrollment with a voluntary opt-out mechanism.[2] The premium should be such that, a major part of it is borne by the government and a marginal part of the premium should be borne by the households.

The rest of the paper is presented in six sections. Section 2 provides a brief review of the related literature. Section 3 discusses the data and descriptive. Section 4 provides details about the four lab-in-the-field experiments, its procedure, parameter estimation and results. Section 5 delves into microinsurance and microinsurance take-up results and section 6 concludes.

2 Relevant Literature

Microinsurance holds the promise and can be a key instrument in addressing the vicious downward spiralling cycle of vulnerability and poverty for the low-income households in the global south. However, the demand for this key instrument dedicated to helping the poor has been exceptionally low. The question is whether the poor are too poor to demand microinsurance? Or is there something else that is hindering the microinsurance take-up, such as — behavioural biases? The current work addresses this key question. The current work is at the intersection of microinsurance and behavioural factors such as risk and time preference. So, I will first review the broader literature on microinsurance which has traditionally focused on non-behavioural factors such as price, transaction cost, trust, and financial literacy. Finally, I will review the limited but growing literature which examines the association of behavioural biases on microinsurance take-up.[3]

It is expected that lower prices will lead to higher demand but it is important to know to what extent demand responds to changes in prices. By offering random discounts to index insurance Cole et al. (2013) and Cole et al. (2014) finds that a 10 per cent increase in price would lead to a 7 to 11 per cent decrease in demand. Mobarak

[2] Choi et al. (2004) finds that the sign-up rates for 401(k) plan in the US increased retirement savings participation by 35 percentage points for employees observed three months after being hired by changing from an opt-in to an opt-out programme.

[3] For a detailed review see De Bock and Gelade (2012) and Eling et al. (2014). For a more recent review see Platteau et al. (2017).

and Rosenzweig (2013) find that, in comparison to an actuarially fair price, take-up rates increases by 18 per cent and 42 per cent for 50 per cent and 75 per cent discount respectively. Dercon et al. (2019) finds that a 20 per cent price discount voucher leads to a 12 per cent increase in the probability of purchasing health insurance. In a recent study from Burkina Faso where the poor were offered health insurance at half the usual price, Hillebrecht et al. (2021) finds that the demand of rural households is price inelastic.

Following the low demand and low take-up rates, prior researchers examined the effect on take-up when insurances were offered for free. When offering insurance for free in the first year, Karlan et al. (2014) observe an increase from 40 per cent to 100 per cent take up for their rainfall insurance in Ghana. In a similar study, Gaurav et al. (2011), offered a money-back guarantee on the premiums in a no payout situation. However, the treatment effect was meagre (6.9 percentage points) in comparison Karlan et al. (2014). Bonan et al. (2017) and Thornton et al. (2010) also find a modest take-up of 30 per cent. Thus, while price definitely seems to play a great role to influence the willingness to buy insurance, a low price itself is not enough to obtain high demand, other factors such as transaction cost, risk aversion, trust and financial literacy are thought of to have an impact.

In the global south, transaction costs might arise due to a lack of proper infrastructure, communication, minimal transport network, scarce bank and post offices in the rural areas. McGuinness (2011) found that the average transaction costs for the insured were much higher than the uninsured in India. Thornton et al. (2010) found that when Nicaraguan market vendors were allowed to sign up directly at their stall, uptake was 30 per cent more.

A wide range of literature suggests that trust is an important issue in the take-up decision of an individual. Giné et al. (2008) finds that members of the bore well user association in India as 37 per cent more likely to buy the insurance contract if they know the insurance provider personally. Cole et al. (2013) found out that if a local trusted agent from BASIX introduced an insurance educator into the visited households it plays a significant effect. Dong et al. (2009) identifies that trust in the management of community health scheme plays an important influence on the take-up decision. Dercon et al. (2019) using a trust game on a composite health insurance product in Kenya showed that low interpersonal trust levels have a significant effect on take-up.

Although trust issues somewhat explain the low demand for microinsurance, a low level of trust can also be due to low literacy and lack of awareness of the products (financial literacy). Cole et al. (2013) finds out that households that received a visit from an insurance educator increase the take-up rate by 20-25 per cent compared to households who just received information from flyers about a rainfall insurance product. Cai et al. (2015) shows that not only training is important but the quality of training is also important. Tower and McGuinness (2011), finds out that radio broadcasting camping leads to an 8 per cent increase in knowledge of insurance terms and products. However, Bonan et al. (2017) and IPA (2012) shows contrary results that training session on insurance and general insurance management seems to have no effect on the demand for insurance. Thus the effect of training on the demand for insurance seems to be too mixed in the literature to draw a definitive outlook.

Although the aforementioned factors are important in part explaining the microinsurance take-up, what has been largely missing is the behavioural underpinnings. This is puzzling because these behavioural factors have been shown to play a role in decision making under risk in both developed and developing countries. The seminal Prospect Theory by Kahneman and Tversky (1979; 1992) is still widely viewed as the best available description of how people evaluate risk in experimental settings. Barberis (2013) gives an overview of the literature on prospect theory applied to insurance markets and how PWF, loss aversion and reference dependence plays a role in framing insurance.[4] For crop insurance, Babcock (2015) finds that reference point, loss aversion and PWF are important determinants explaining crop insurance uptake among farmers in the USA. In the context of developing countries, Verschoor and D'Exelle (2022) show that not only PWF affects decision making but also that its magnitude is not fully in line with the evidence found in the western countries.

In the microinsurance literature, recent works have found that loss aversion and probability weighting are important determinants of index insurance take-up (Lampe and Würtenberger, 2020; Cecchi et al., 2022). Bauchet and Morduch (2019) finds that when an upfront payment is required, demand for life insurance in Mexico drops by 37–42 per cent. Similar results were found by Platteau and Ontiveros (2021) for the Indian micro-insurance health program. They found that the low rate of contract renewal can be explained by cognitive bias reflected in the short-term framing of insurance costs and benefits. The authors found that individuals are reluctant to renew their contract if they did not collect any (or enough) payout because the health risk did not materialize as they deem the deal unfair as the premium paid for the period elapsed is seen as wasted. Whereas, in another study from the state of Karnataka in India Ito and Kono (2010) find that majority of the 209 individuals are hyperbolic discounters and that they were more likely to purchase health insurance.

The literature on behavioural microinsurance provides mixed evidence on how the behavioural factors and biases are linked with microinsurance take-up. It is also perplexing why there have been so few studies. The current work contributes to three strands of literature. Firstly, it contributes empirical evidence to the lab-in-the-field experiment literature. Secondly, It contributes to the strand of literature which examines the determinants of microinsurance take-up. Finally, it contributes to the strand of literature

[4] Sydnor (2010) explains why individuals opt for a higher monthly premium, with a lower deductible even though the probability of filing a claim is very low. Kőszegi and Rabin (2007) argue that the reference point is the expectation about future outcomes, with the premium as an expected monthly expense. Only in the event of a claim the deductible arises. Loss aversion is higher for this unexpected deductible than for the expected premium leading to a willingness to pay a higher premium.

which examines the behavioural underpinning of insurance adoption.

3 Data and Research Sites

The data for the current research comes from a panel study that I conducted in five rural villages in the Nadia district of India. The first wave of the data comes from a survey conducted in 2018 and the second wave of the study was conducted in 2020. The timings of the waves were after harvest of the main crop i.e paddy and during the same time period to avoid seasonality.[5] The current work uses the two waves to study microinsurance take-up. The survey was carried out in five villages in the Chakdah block of Nadia district.[6] The villages were selected based on the criterion that, the villages must be in close proximity to Hooghly River to capture the natural risks such as floods and there is variation in religion, caste and mean village income. In village 4 and 5 majorities of the agricultural plots lies on the low land making them flood-prone during monsoon season. Villages 2 and 3 are moderately flood prone compared to villages 4 and 5. Village 1 is a relatively thriving village adjoining the urban centre and it is a fast-developing village in the district. Village 1 has a literacy rate of 78.98 % which is higher in comparison to the state average of 76.26 %. Approximately 35 households were selected from each of the five villages using a random sampling method. We aimed to interview the household head in the first wave. If the household head was not available we interviewed the household head's wife. Before the second wave, we reached out to the households before the survey date and scheduled a time that is feasible for the respondent in the first wave. We did that so that we have the same respondent in both waves. If the person was unavailable we interviewed the partner. There was no attrition between waves one and two. Some summary statistics are provided in table 1.[7]

The surveys were conducted with the aid of a team of trained research assistants. As the survey included experimental games, the research team underwent training so that the entire team comprehended the experimental games and were at the same level. The team also had specific instructions on how to explain the game. Each research assistant read the instructions out loud to the respondent so that there were no framing effects.

The surveys started at 9 am every morning and were concluded by 4 pm in the evening with a break for lunch in the middle. Before the survey began, each participant was informed that the entire survey was voluntary and that they can opt out at any

[5]There is a growing literature which examines how budget constraint and decision-making process might differ at different points in time. Carvalho et al. (2016) found that for US, households are more present-biased before payday (see also (Mani et al., 2020)). Haushofer and Fehr (2014) provides a great overview of the effect of poverty on risk-taking and time-discounting. For Bangladesh, Bryan et al. (2014) found that seasonal poverty and being cash constraint is much lower after harvest. Given these evidence, I conducted the survey and the experiments post-harvest.

[6]Survey location in appendix

[7]In rural India, people are unusually unaware of their true age. They know their approximate age. Given this issue, I took the age mentioned in the first wave as their true age and added the time between the waves to avoid any age discrepancy.

point. After the survey, each survey participant was also invited to take part in the experiments. Almost all the survey participants took part in the experiments. The average experimental earnings for each participant was 125 INR ($ 6.9 PPP) with a maximum of 460 INR ($ 25.53 PPP). Along with that, each household was given a show-up which was 10 per cent more than the daily rate for work under Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) to compensate for their time. The survey in each village was conducted on a single day to avoid any spill-over effects.

Table 1: Summary statistics

	(1)		(2)	
	Wave 1		Wave 2	
	mean	sd	mean	sd
Individual level				
Male	0.47	0.50	0.40	0.49
Age	41.14	12.73	41.14	14.85
Education (yrs)	6.86	3.96	7.20	6.30
Household level				
HH size	4.36	1.57	4.39	1.60
Land owned (Bighas)	0.49	0.95	2.04	2.62
Health Insurance	0.04	0.20	0.28	0.45
Life Insurance	0.19	0.39	0.16	0.36
Any insurance	0.21	0.41	0.40	0.49
Muslim	0.84	0.36	0.84	0.36
PC Consumption	7.37	0.44	7.51	0.41
Below Poverty HH	0.40	0.49	0.61	0.49
Experimental games				
Bet in risk game 1	29.39	14.13	35.00	16.39
SP time game 1	6.28	2.41	6.34	2.38
Risk averse ($\sigma < 1$)	0.84	0.36	.	.
Probability weighting ($\alpha < 1$)	0.75	0.43	.	.
Loss averse ($\lambda > 1$)	0.60	0.49	.	.
N	166		166	

4 Experiments

In the current work, we draw on four lab-in-the-field experiments to examine the behavioural aspects behind the missing microinsurance market in India. Two of the experiments are on risk preference and two on time preference. The two risk preference experiments that we use are following Schechter (2007) and Tanaka et al. (2010) which we will call risk game 1 and risk game 2 from now onward. The two time preference experiments[8] that we use draws on Kirby et al. (2002) and Benhabib et al. (2010) which

[8]A common critique in time preference elicitation method is — how much of the discounting and present biased behaviour can be attributed to true discounting and how much of the time discounting

we will refer to as time game 1 and time game 2 from now onward.[9] Risk game 1 and time game 1 were repeated in both the 2018 wave and 2020 wave while risk game 2 and time game 2 were used in the 2018 wave only. In subsection 4.1 we will go through the experimental procedure of each game along with an example. In subsection 4.2 we will highlight the results of the experiments and in section 5 we will use these results to identify plausible behavioural underpinnings of microinsurance take-up.

4.1 Experimental procedure & empirical strategy

In this subsection, we will go through the experimental procedure of each game along with an example.[10] We will first go through risk game 1 and then through risk game 2, time game 1 and finally time game 2.

4.1.1 Risk game 1

Table 2: Risk Game 1 (in INR)

		Bet amount					
Dice	**Multiplier**	**0**	**10**	**20**	**30**	**40**	**50**
1	**0**	0	0	0	0	0	0
2	**0.5**	0	5	10	15	20	25
3	**1**	0	10	20	30	40	50
4	**1.5**	0	15	30	45	60	75
5	**2**	0	20	40	60	80	100
6	**2.5**	0	25	50	75	100	125

At the beginning of risk game 1, each survey participant who opted to take part in the experiments was given an endowment of 50 Indian Rupees (INR).[11] The participants were told that they could keep the entire money or they could use part or full endowment and bet it in the game. If they decide to bet any money, they were informed that they could bet in multiples of 10 — 10, 20, 30, 40 or 50. The subjects were also informed that they could win or lose money depending on the results of the dice roll and their bet amount. The roll of dice would lead to selecting its corresponding multiplier for the bet amount. If the dice rolled to number zero, the entire bet amount would be lost as the multiplier is 0. Where as, if the dice rolled to number six, the entire bet amount would be multiplied

and present biased behaviour can be attributed to the lack of trust in receiving the delayed payment. Andersen et al. (2008) tackles this issue by using a front-end delay. In the current work, I address this concern by the use of current and post-dated cheques.

[9]There is a trade-off between simpler and richer lab-in-the-field experiments. Simpler lab-in-the-field experiments are easier to conduct and for the subjects to comprehend when the study sample is not highly educated. On the other hand, the simpler experiments may not be able to cleanly elicit the preferences and may be confounded with other variables. For example in risk game 1 risk aversion may be confounded with loss-aversion. The advantage of combining simpler instruments (risk game 1 and time game 1) along with richer instruments is that if some of the effects are not picked up by the simpler instruments the richer instruments can pick those up.

[10]Detailed experimental procedure can be found in Appendix 6

[11]1 USD in PPP terms were 18.14 INR

2.5 times as the corresponding multiplier for dice roll six is 2.5. For example, if someone bets 30 INR and the dice rolled to number four, then the person wins 45 INR from the game and his payoffs are 45 INR from playing the game and 20 INR of the 50 INR that he didn't bet on. So the person would have 65 INR in total from playing the risk game 1. However, say if the person bets 30 INR and the roll of dice leads to number one, then the person loses 30 INR from betting in the game and his payoffs are 0 INR from playing the game and 20 INR of the 50 INR that he didn't bet on. So the person would now have 20 INR in total having lost 30 INR from playing the risk game 1. Table 2 shows the respective pay-offs from each bet amount and its corresponding dice roll.

4.1.2 Risk game 2

We conducted risk game 2 as an alternative experiment to risk game 1 as, risk game 2 nests both expected utility and prospect theory and under its theoretical framework. In risk game 2, lotteries involved both gains and losses. In this game, respondents had to choose between two options, option A or option B for 35 questions divided into 3 series.[12] Series one and two had fourteen questions each and series three had seven questions. Similar to Tanaka et al. (2010) and Liu (2013) we used monotone switching. Subjects were informed that they could switch only once for a particular series from option A to option B and once that option B is selected they cannot revert back to option A for that particular series. After the respondents completed answering all the thirty-five questions, we put 35 balls in a bingo cage and draw one numbered ball to select 1 question out of thirty-five questions. We then played the selected question for real money. For example, if the number 21 ball is drawn, then question 21 was played for real money. Once the question was determined, we put 10 balls in the cage and play the selected question to determine the payoff. As the payoff from the game could be negative, subjects were informed that they wouldn't have to pay anything but that sum will be deducted from their total earnings.

Cumulative Prospect Theory & parameter estimation

We consider prospect theory as an alternative to expected utility (EU) theory as, risk references are not characterized solely by the concavity of the utility function as in EU but, risk preferences are also influenced by the nonlinear weighting of probabilities, risk aversion over gains and risk-seeking over losses, and aversion to loss in comparison to an equal amount of gain. We use cumulative prospect theory (CPT) and the one-parameter form of Prelec (1998) axiomatically derived weighting function.[13] Let $U(x, p; y, q)$ be the the expected prospect value over binary prospects consisting of the outcome x with probability p and outcome y with probability q. In prospect theory, gains and losses are

[12]Table 1 shows the detailed questions and options of the experiment

[13]The shape of Prelec (1998) is nearly identical to that of Tversky and Kahneman (1992) weighting function $w(p) = \frac{p^{\alpha}}{(p^{\alpha}+(1-p)^{\alpha})^{1/\alpha}}$. The key difference of Prelec (1998) specification in comparison to Tversky and Kahneman (1992) is that, it is based on behavioural axioms rather than the convenience of the functional form and it must cross 45° line at $p = 1/e \approx 0.37$. A decrease in α causes the Prelec's weighing function to be more concave to the left of $1/e$ and more convex to the right of $1/e$.

Table 3: Three Series of Pairwise Lottery Choices (in INR)

Series 1

Option A		Option B		Expected payoff difference (A-B)
Balls 1-3	**Balls 4-10**	**Balls 1**	**Balls 2-10**	
40	10	68	5	7.7
40	10	75	5	7.0
40	10	83	5	6.0
40	10	93	5	5.2
40	10	106	5	3.9
40	10	125	5	2.0
40	10	150	5	-0.5
40	10	185	5	-4.0
40	10	220	5	-7.5
40	10	300	5	-15.5
40	10	400	5	-25.5
40	10	600	5	-45.5
40	10	1000	5	-85.5
40	10	1700	5	-155.5

Series 2

Option A		Option B		Expected payoff difference (A-B)
Balls 1-9	**Ball10**	**Balls 1-7**	**Balls 8-10**	
40	30	54	5	-0.3
40	30	56	5	-1.7
40	30	58	5	-3.1
40	30	60	5	-4.5
40	30	62	5	-5.9
40	30	65	5	-8.0
40	30	68	5	-10.1
40	30	72	5	-12.9
40	30	77	5	-16.4
40	30	83	5	-20.6
40	30	90	5	-25.5
40	30	100	5	-32.5
40	30	110	5	-39.5
40	30	130	5	-53.5

Series 3

Option A		Option B		Expected payoff difference (A-B)
Balls 1-5	**Balls 6-10**	**Balls 1-5**	**Balls 6-10**	
25	-4	30	-21	6.0
4	-4	30	-21	-4.5
1	-4	30	-21	-6.0
1	-4	30	-16	-8.5
1	-8	30	-16	-10.5
1	-8	30	-14	-11.5
1	-8	30	-11	-13.0

Table 4: Risk curvature and probability weighing parameter values

Series 1 (questions 1-14)								*Series 2 (questions 15-29)*							
$\sigma\backslash\alpha$	0.4	0.5	0.6	0.7	0.8	0.9	1	$\sigma\backslash\alpha$	0.4	0.5	0.6	0.7	0.8	0.9	1
0.2	9	10	11	12	13	14	Never	0.2	Never	14	13	12	11	10	9
0.3	8	9	10	11	12	13	14	0.3	14	13	12	11	10	9	8
0.4	7	8	9	10	11	12	13	0.4	13	12	11	10	9	8	7
0.5	6	7	8	9	10	11	12	0.5	12	11	10	9	8	7	6
0.6	5	6	7	8	9	10	11	0.6	11	10	9	8	7	6	5
0.7	4	5	6	7	8	9	10	0.7	10	9	8	7	6	5	4
0.8	3	4	5	6	7	8	9	0.8	9	8	7	6	5	4	3
0.9	2	3	4	5	6	7	8	0.9	8	7	6	5	4	3	2
1	1	2	3	4	5	6	7	1	7	6	5	4	3	2	1

evaluated with respect to a *reference point*. The experimental design in Tanaka et al. (2010) assumes the reference point to be 0.[14] So, the sign of the outcome would signify if it is a gain or loss. A prospect is *non-mixed* if the two outcomes have the same sign (i.e. both positive $(x, y > 0)$ or both negative$(x, y < 0)$). During the editing phase, non-mixed prospects are segregated into two components: (i) riskless component – the minimum gain or loss which is certain to be obtained or paid and (ii) risky component – the additional gain or loss which is actually at stake (shown in equation 2). A prospect is a mixed if one of the outcomes is positive and the other is negative (say, $x < 0 < y$). The value of the prospect can be written as —

$$U(x,p;y,q) = \begin{cases} w^i(p+q)v(y) + w^i(p)(v(x) - v(y)) & \text{for} \quad x > y > 0 \quad \text{or} \quad x < y < 0 \\ w^-(p)v(x) + w^+(q)v(y) & \text{for} \quad x < 0 < y \end{cases} \tag{1}$$

where $w^i : [0,1] \to [0,1]$ is the probability weighting function for gains $(i = +)$ or for losses $(i = -)$, with $w^+(0) = w^-(0) = 0$ and $w^+(1) = w^-(1) = 1$. Note that $w^+ = w^-$ is assumed under the original prospect theory (OPT) by Kahneman and Tversky (1979). As $p + q = 1$, $w^+(0) = w^-(0) = 0$ and $w^+(1) = w^-(1) = 1$, the value of binary prospect (equation 1) can be written as —

$$U(x,p;y,q) = \begin{cases} v(y) + w^i(p)(v(x) - v(y)) & \text{for} \quad x > y > 0 \quad \text{or} \quad x < y < 0 \\ w^-(p)v(x) + w^+(q)v(y) & \text{for} \quad x < 0 < y \end{cases} \tag{2}$$

[14] Whether the reference point lies at the expected return, at status quo, or at zero has been a matter of extensive discussion (see Kőszegi and Rabin (2006), O'Donoghue and Sprenger (2018)). Chapman et al. (2018) using Dynamically Optimized Sequential Experimentation (DOSE) elicitation technique show that their preferred reference point ($ 0) correctly predicts 88% of the choices for all the participants. In comparison when the reference point is at the endowment, the expected utility of the lottery, or stochastic only 45%, 51% and 56% of the choices are correctly predicted. We assume the reference point to be at zero as in Tanaka et al. (2010), so that the results from India using the original elicitation method can be comparable across the literature and across countries a key argument put forward by Gneezy and Imas (2017) while using standardized and validated lab-in-the-field experiments.

$$\text{where} \quad v(x) = \begin{cases} x^\sigma & \text{for} \quad x > 0 \\ -\lambda(-x)^\sigma & \text{for} \quad x < 0 \end{cases} \tag{3.1}$$

$$\text{and} \qquad w(p) = exp(-(-ln(p)^\alpha) \tag{3.2}$$

where $v(x)$ is the piecewise value function[15] and $w(p)$ is the one-parameter form of Prelec (1998) axiomatically derived weighting function. The parameter (σ) dictates the curvature of the prospect value function and can be thought of as a measure of risk aversion. The second parameter (α) captures the non-linear probability weighting function — the degree to which low probability events are disproportionately weighted when valuing risky prospects. If $\alpha = 1$ the probability weighting function is linear as it is in EU. If $\alpha < 1$, then the probability weighting function is *inverted S-shaped*. Individuals with $\alpha < 1$ overweight small probability events and underweight large probability events. If on the other hand, $\alpha > 1$, then the probability weighting function is *S-shaped* and individuals underweight small probability events and overweight large probability events. The third parameter (λ) characterises the degree of loss aversion. If $\lambda > 1$, individuals are loss averse — losses hurt more compared to an equal amount of gain. The above model reduces to EU if we have linear probability weighting ($\alpha = 1$) and no loss aversion ($\lambda = 1$).

The three series lottery design in table 3 helps us to extract the three parameters of interest in the prospect theory. In table 3, each row is a choice between two binary lotteries – option A or option B. Similar to Tanaka et al. (2010) and Liu (2013) we used monotone switching. Subjects were informed that they could switch only once for a particular series from option A to option B and once that option B is selected they cannot revert back to option A for that particular series. The expected payoff difference from selecting option A instead of option B is given in the right-most column of table 3. As one moves down the rows in series 1, the higher payoff in option B increases. As everything else is fixed and between the rows only the higher payoff in option B increases, this leads to a reduction in the overall expected payoff difference between option A and B. After the sixth row, the expected payoff difference between options A and B is negative. From series 2 in table 3, we see that the expected payoff difference between options A and B is negative from the first row. While in the third series, the expected payoff difference between options A and B is negative from the second row. Thus, if individuals are risk-neutral expected utility maximizers, then they should switch to option B in question seventh of the first series, question one of the second series and question two in the third series.

The curvature of the value function (σ) and the probability weighting parameter (α) are jointly determined by the switching points in Series 1 and 2. For any subject who switches at row N, I can conclude that he prefers lottery A over lottery B at row $N - 1$ and prefers lottery B over lottery A at row N. I can obtain a set of two inequalities from

[15] In the Tversky and Kahneman (1992) CPT formulation, the value function was $v(x) = x^\sigma$ for $x \geq 0$, or $v(x) = -\lambda(-x)^\beta$ for $x < 0$. The issue with this formulation is that the loss aversion parameter is dependent on the scale of the data and not uniquely identified (see Wakker (2010)). On the other hand, if the two parameters are equal ($\alpha = \beta$) then this issue does not occur.

this switching point. Using a combination of switching points from series 1 and series 2, I am able to find the ranges of σ and α that satisfy this pair of inequalities. For example, when a subject switches from Option A to B at the seventh question in both Series 1 and 2, the following inequalities should hold.

$$
\begin{aligned}
10^\sigma + exp(-(-ln.3)^\alpha)(40^\sigma - 10^\sigma) &> 5^\sigma + exp(-(-ln.1)^\alpha)(125^\sigma - 5^\sigma) && (4.1)\\
10^\sigma + exp(-(-ln.3)^\alpha)(40^\sigma - 10^\sigma) &< 5^\sigma + exp(-(-ln.1)^\alpha)(150^\sigma - 5^\sigma) && (4.2)\\
30^\sigma + exp(-(-ln.9)^\alpha)(40^\sigma - 30^\sigma) &> 5^\sigma + exp(-(-ln.7)^\alpha)(65^\sigma - 5^\sigma) && (4.3)\\
30^\sigma + exp(-(-ln.9)^\alpha)(40^\sigma - 30^\sigma) &< 5^\sigma + exp(-(-ln.7)^\alpha)(68^\sigma - 5^\sigma) && (4.4)
\end{aligned}
$$

In the left hand side of the inequality 4.1, 10^σ captures the riskless component — the minimum gain which is certain to obtained or paid and $exp(-(-ln.3)^\alpha)(40^\sigma - 10^\sigma$ the risky component — the additional gain which is actually at stake. The ranges of σ and α that satisfy the inequalities 4.1 – 4.4 are $0.65 < \sigma < 0.74$ and $0.66 < \alpha < 0.74$. The point $(\sigma, \alpha) = (.7, .7)$ satisfies the condition.[16]

The loss aversion parameter λ is estimated by the switching point in series 3. The loss aversion parameter λ cannot be uniquely identified from switching point in series 3 and it is based on different levels of σ.[17]

4.1.3 Time game 1

At the beginning of the time game 1, each respondent was informed that they need to answer eight questions. The questions posed a choice problem of choosing an immediate reward of less money or a delayed reward of more money, the corresponding delay is mentioned in the time delay column T. The respondents were informed that one out of the eight questions would be chosen at random and that it is in their best interest to choose the option (present reward (option A) or delayed reward (option B)) which resembles their preference. They were also informed that once they switched to a later reward, they cannot switch back to the present reward. Once the subjects switched to a later reward, they were asked the next questions to check for consistency in preferences. If the subjects still selected delayed reward, their responses were recorded. If they selected the current reward after selecting a delayed reward, they were explained again that they could switch to a delayed reward only once in the experiment and once they selected a delayed reward, they cannot change to the present reward. Table B3 shows the choices in the time game 1 along with the corresponding exponential discount rate and hyperbolic discount rate.[18]. For example, if an individual selected option A for the first four questions and then selected option B (later reward) for the last four questions, then his/her switching point is question five and the corresponding hyperbolic discount rate is 0.016049. Suppose in

[16] All possible combinations of σ and α are shown in the appendix tables C1 and C2.

[17] All possible combinations of λ is shown in the appendix tables C3 and C4.

[18] The discount rate was calculated using a hyperbolic discount function, $V = A/(1 + kD)$, where V is the present value of A reward at the delay D, and k is a discount rate parameter following Kirby et al. (2002)

the random draw, question six was selected, then the person would win 38 INR in twenty days as the person selected a delayed reward.

Table 5: Time Game (in INR)

Q #	Option A	Option B	Time delay		
	X (rupee)	Y (rupee)	T (in days)	EDR	HDR
1	40	42	150	0.000325	0.000333
2	34	38	120	0.000927	0.00098
3	35	42	90	0.002026	0.002222
4	28	38	60	0.00509	0.005952
5	27	40	30	0.013101	0.016049
6	22	38	20	0.027327	0.036364
7	18	40	14	0.057036	0.087302
8	15	42	7	0.147088	0.257143

Note: EDR is *Exponential Discount Rates*
HDR is *Hyperbolic Discount Rates*

4.1.4 Time game 2

In time game 2, subjects make 75 choices between smaller rewards delivered today and larger rewards delivered at specified times in the future as follow — Option A: receive y INR today or Option B: receive x INR in t days. The reward x varies between 30 to 300 and the time delay t varies between three days and three months **(see appendix)**. The subjects were informed that they will be paid based on one of the choices. After the choices for all the 75 questions are recorded, we will put 75 balls in a bingo cage and draw one ball to determine which question will be paid for real money. Suppose question 18 is selected, and you chose plan A in question 18, then you will be paid 300 INR in 1 week. If you chose plan B for question 18, then you will be paid 150 INR today.

Table 6: Time game 2 example

	Plan A	Plan B
16	A: receive 300 INR in 1 week	B: receive 50 INR today
17	A: receive 300 INR in 1 week	B: receive 100 INR today
18	A: receive 300 INR in 1 week	B: receive 150 INR today
19	A: receive 300 INR in 1 week	B: receive 200 INR today
20	A: receive 300 INR in 1 week	B: receive 250 INR today
	I choose A for 16 -	I choose B for -20

Time game 2 parameters and estimation

We consider the quasi-hyperbolic discounted utility (QHD) model (Laibson, 1997) as an alternative to the standard model for understanding inter-temporal choices — discounted utility (DU) model originally introduced by Samuelson (1937) and later received a further boost to its dominance by Koopmans (1960). The advantage of the QHD is that it is designed to capture the dynamic inconsistent choices while conserving the tractability of the exponentially discounted model (EDU). In time game 2, we draw on a general model proposed by Benhabib et al. (2010) similar to Tanaka et al. (2010). The model allows us to test *exponential, hyperbolic, quasi-hyperbolic discounting,* and a more general form.[19] The three-parameter discounting by Benhabib et al. (2010) is as follows:

$$yD(y,t) = \begin{cases} y & \text{if} \quad t = 0 \\ \beta(1-(1-\theta)rt)^{\frac{1}{(1-\theta)}}y & \text{if} \quad t > 0 \end{cases} \tag{5}$$

The three parameters — r, β, and θ separate conventional time discounting (r), present-bias (β), and hyperbolicity (θ) of the discount function $yD(y,t)$. When $\beta = 1$, as θ approaches one, the discounted value reduces to exponential discounting (e^{-rt}) in the limit. When $\theta = 2$ and $\beta = 1$, it reduces to true hyperbolic discounting ($1/(1+rt)$). When $\theta = 1$ (in the limit) and β is free, it reduces to quasi-hyperbolic discounting (βe^{-rt}). The three-parameter form enables a way to compare three familiar models.

We denote the probability of choosing an immediate reward of x over the delayed reward of y in t days by $P(x > (y,t))$, and use a logistic function to describe this relationship as follows

$$P(x > (y,t)) = \frac{1}{1 + exp(-\mu(x - y\beta(1-(1-\theta)rt)^{1/(1-\theta)}))} \tag{6}$$

We estimate the parameters μ, β, θ, and r in the logistic equation above. The variable μ is a response sensitivity or noise parameter, conventional time discounting (r), present-bias (β), and hyperbolicity (θ).

4.2 Experiment results

In this subsection, we first present the results of the risk game 1 and time game 1 which were repeated in both the 2018 wave and 2020 wave. Next, we present the results of the risk game 2 and time game 2 which were conducted in the 2018 wave.

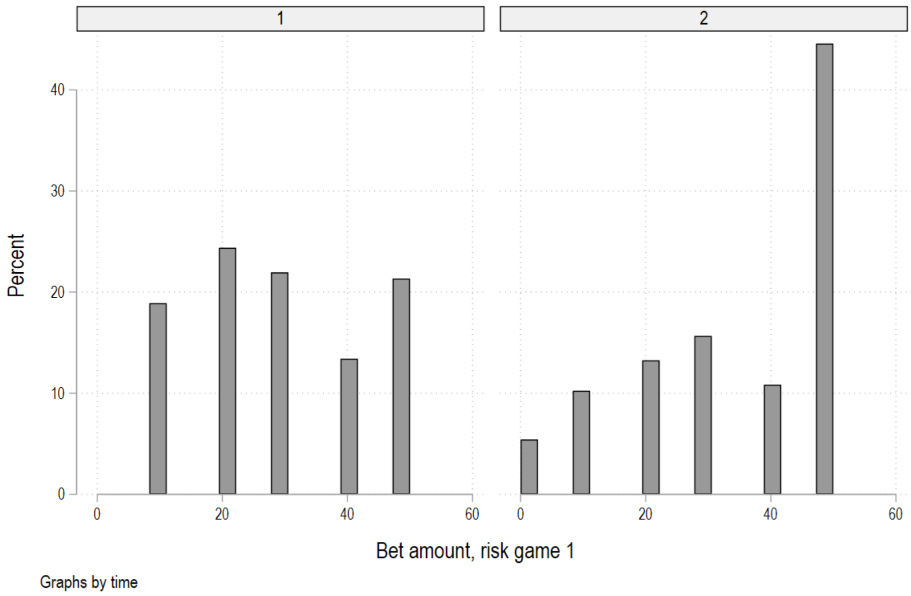
4.2.1 Risk game 1

In risk game 1, risk reference is captured by the betting behaviour of the individuals in the game. The left panel in figure 1 depicts the betting behaviour of the individuals in the first wave while the right panel depicts betting behaviour in the second wave. In the first wave, all the individuals decided to bet on the experiment. 18.9 per cent of the individuals betted 10 INR, the least amount possible. While 21.34 per cent betted the maximum amount of 50. In the second wave, 5.42 per cent of the individuals decided not to bet any amount and keep the whole endowment of 50 INR (safe outcome). While 10.24 per cent (a drop from 18.9 per cent) decided to bet 10 INR. As evident from figure 1, in the second wave, individuals on average betted less in all but one amount in comparison

[19] The original Benhabib et al. (2010) model includes the present bias in the form of fixed cost. We do not include the present bias in the form of fixed cost as Akin and Yavas (2007) estimate the model and find that present bias in the form of a fixed cost is not well supported by data.

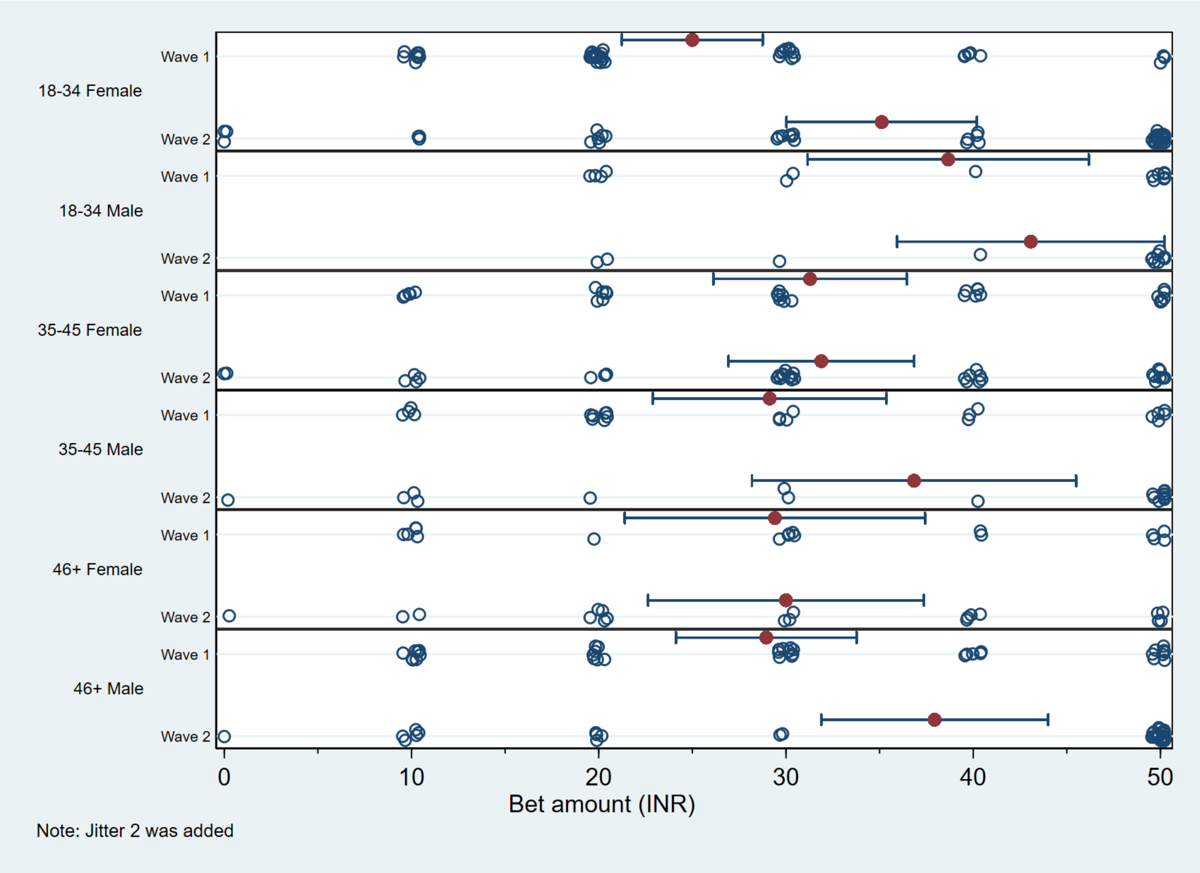
to the first wave. Close to half (44.58 per cent) of the individuals betted the maximum amount in the second wave.

Figure 1: Bet amount in risk game 1 by waves



Next, we investigate betting behaviour by demographic variables such as age and gender over waves. Figure 2 is a combination of a scatterplot with a jitter of 2 and a box and whiskers plot known as stripplot. From figure 2, we find that males and females in all age groups have a higher average bet amount in the second wave in comparison to the first wave. In the first wave, we find that females on average have bet more in comparison to males for all the age groups apart for the females who are younger (18-34 years). However, this trend changes in the second wave where the males of all age groups bet comparatively more than the females. One thing to note here is that the confidence intervals overlap and thus the differences are likely not statistically significant. This finding of gender effect is consistent with other studies which find that men are less averse to financial risk than women (e.g. Eckel and Grossman, 2008).

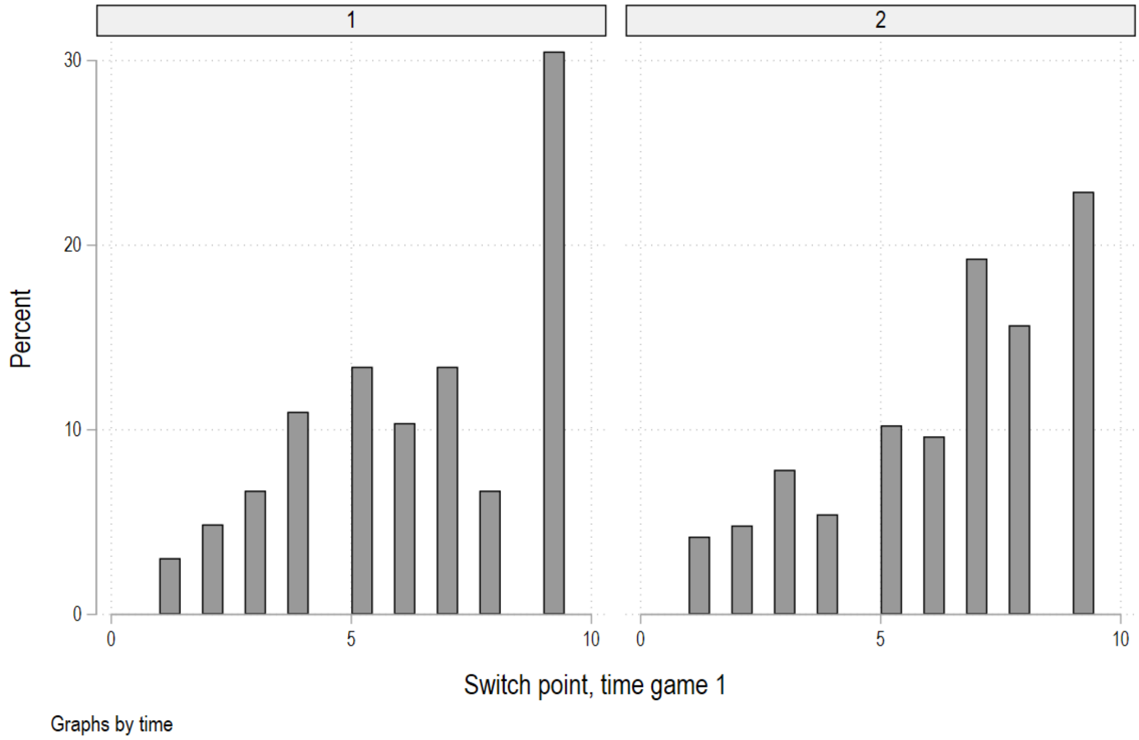
Figure 2: Betting in risk game 1



4.2.2 Time game 1

In time game 1, each individual had to answer eight questions regarding choosing an immediate reward of less money (option A) or a delayed reward of more money (option B). An individual's time preference or time discounting is captured using the switching point — the question in which the person switches from an immediate lower reward to a larger but later reward. The later the person switches from option A to option B, the higher is time discount rate, implying higher impatience. Figure 3 shows the histogram of switching points. In the first wave, we see that 25.62 per cent of the individuals switched on or before the fourth question, implying that they would rather wait 60 days (for switching point 4) to 150 days (for switching point 1) for a larger reward. 37.19 per cent of the individuals preferred to wait between 14 (for switching point 7) to 30 days (for switching point 5) for a larger delayed reward. While 6.71 per cent of the individuals wanted to wait 7 days for the larger delayed reward (2.8 times) and 30.49 per cent of the individuals always wanted to have the present reward.

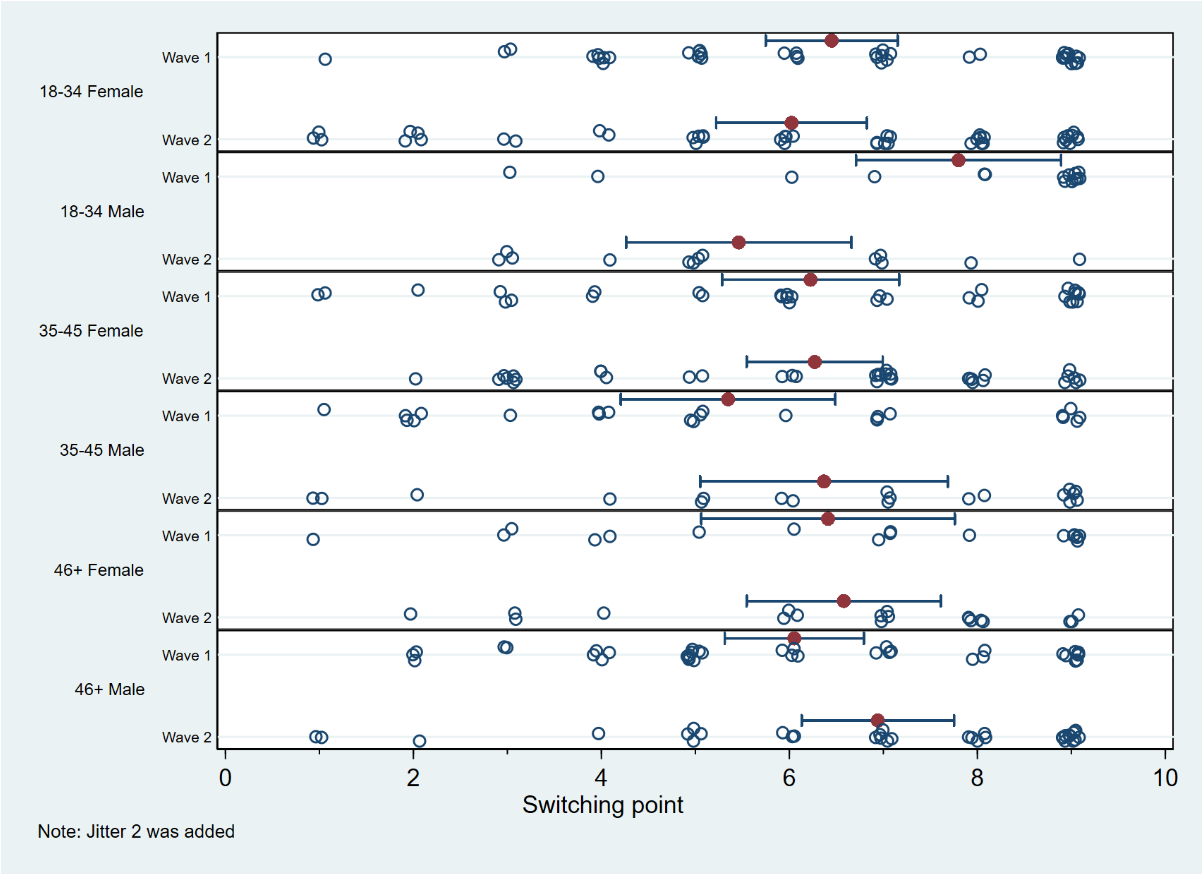
Figure 3: Switching point in time game 1



While in the second wave, we see that 22.29 per cent of the individuals switched on or before the fourth question which is 3.33 per cent lower in comparison to the first wave. 39.52 per cent of the individuals preferred to wait between 14 (for switching point 7) to 30 days (for switching point 5) for a larger delayed reward. While 15.66 (up for 6.71) per cent of the individuals wanted to wait 7 days for the larger delayed reward (2.8 times). While we see a lower per cent (22.89 per cent) of individuals always wanted to have the present reward. Comparing the switching point between the waves, we see that on average, the time discount rate has increased. However, we see a lower per cent of individuals in comparison to the first wave always wanting to have the present reward irrespective of the reward amount.

Next, we delve into where the heterogeneity in time discounting is coming from. From figure 4 we see that between the waves, females on average have a very consistent switching point, somewhere around switching point 6. In comparison, the average time discount rate depicted by the switching point for males who are older than 34 years, for both the groups has increased between waves. Interestingly, the time discount rate between the waves has comparatively decreased for younger males (18-34 years), from switching point 8 to switching point 5. The difference however is not statistically significant.

Figure 4: Switching point in time game 1



4.2.3 Risk game 2

Risk preference in the gain domain is captured jointly by series 1 and series 2. Whereas series 3 captures risk preference in the loss domain. Figures 5–7 shows the distribution of choices made by subjects in the different series. The number in the x-axis corresponds to the switching points in the series and the y-axis shows the percentage of people who switched in a particular question for the particular series. If individuals are risk-neutral expected utility maximizers, then they should switch to option B in question seventh of the first series, question one of the second series and question two in the third series as the expected payoff difference between option A & B turns negative in the seventh question of the first series, it is negative from the first question in the second series and it is negative for the second question in the third series.

From figures 5–7 we see that only four people switch on the seventh question in series one and forty-six people switch already at the first question in the second series, consistent with the expected utility maximizing preferences. However, a significant portion of the respondents either switched before question seven in the first series or after. Although for the second series a sizeable portion switches in the first question consistent with expected utility maximizing preferences, a huge chunk of the respondents switches after question one. What is even more intriguing is that a sizeable portion of the respondents

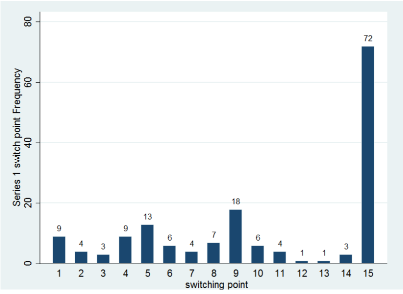


Figure 5: Series 1

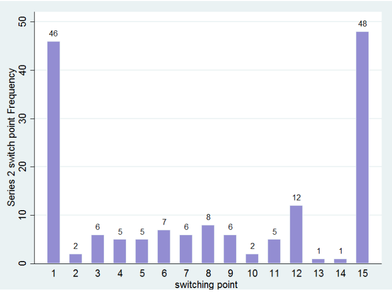


Figure 6: Series 2

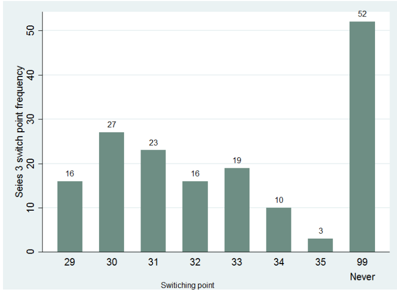
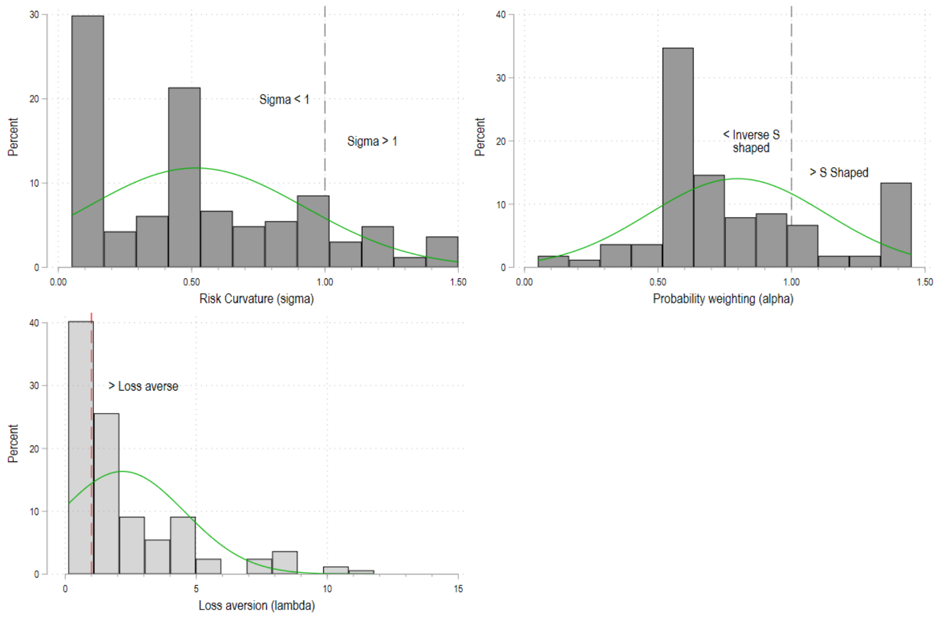


Figure 7: Series 3

do not switch to option B for either series one or series two, although the expected payoff difference is significantly negative. One plausible explanation for observing this kind of result is that people preferred a low risk and low payoff instead of a high risk and high payoff.

When we look into the third series which looks into risk preference in the loss domain, from figure 7 we see that twenty-seven of the respondents switch in the second question, consistent with expected utility maximization. Whereas, fifty-two of the total respondents never switched to option B which has an equal chance of higher payoff or higher loss. This shows that the vast majority of the respondent sample is loss averse ($\lambda > 1$).

Figure 8: Histogram of σ (curvature of power value function), α (probability sensitivity parameter, and λ (loss aversion parameter)



From figure 8, we see that broader portion of the respondent sample is risk-averse ($\sigma < 1$) and a small portion of the sample is risk loving and they overweight small probabilities and underweight large probabilities ($\alpha < 1$) as seen in figure 8.[20] Not

[20] Appendix figure A1 shows the probability weighting parameter. The left panel shows all the possible

only are the sample risk averse and overweight small probabilities and underweight large probabilities ($\alpha < 1$) but they are significantly loss averse ($\lambda > 1$) as seen from figure 8. The mean estimated value of (σ, α) are (0.51,0.79). Tanaka et al. (2010) in their Vietnamese found these estimates to be (0.59,0.74) and (0.63,0.74) for south and north villages. Liu (2013) who replicated this risk experiment with Chinese farmers found the average estimates to be (0.89, 0.69), which are reasonably close.

4.2.4 Time game 2

In order to estimate the time discounting parameters in time game 2, we fitted the logistic function equation (6) by using a nonlinear least-square regression procedure. In table 7 we estimated exponential (col(1)), hyperbolic(col(2)), quasi-hyperbolic(col(3)), and the unrestricted full discounting model (col(4)). We found the estimated values of r, β, and θ, using the full model (equation 6) to be 0.046, 0.710, and 2.93 respectively.

Table 7: Models of Time Discounting

	Exponential	Hyperbolic	Quasi-hyperbolic	Equation (6)
	(1)	(2)	(3)	(4)
Response sensitivity (μ)	0.00646***	0.00809***	0.00853***	0.00864***
	(0.000330)	(0.000453)	(0.000475)	(0.000487)
Time discount (r)	0.0412***	0.0794***	0.0122***	0.0462**
	(0.00271)	(0.00713)	(0.000929)	(0.0140)
Present Bias (β)			0.595***	0.710***
			(0.0250)	(0.0361)
Hyperbolicity (θ)				2.983***
				(0.379)
Observations	4974	4974	4974	4974
R^2	0.518	0.522	0.525	0.525

Notes: Robust standard errors are in parentheses. Standard errors are adjusted within-subject correlations
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We next estimate individual present bias. Similar to Benhabib et al. (2010) we use a non-linear least square algorithm to estimate individual present bias. From figure 9 which is a histogram of individual present bias, we see that 86.51 per cent of the individuals are present-biased ($\beta < 1$).

weights. From the right panel, we can clearly see that a significant portion of the respondents overweight small probability incidents and underweight large probability incidents.

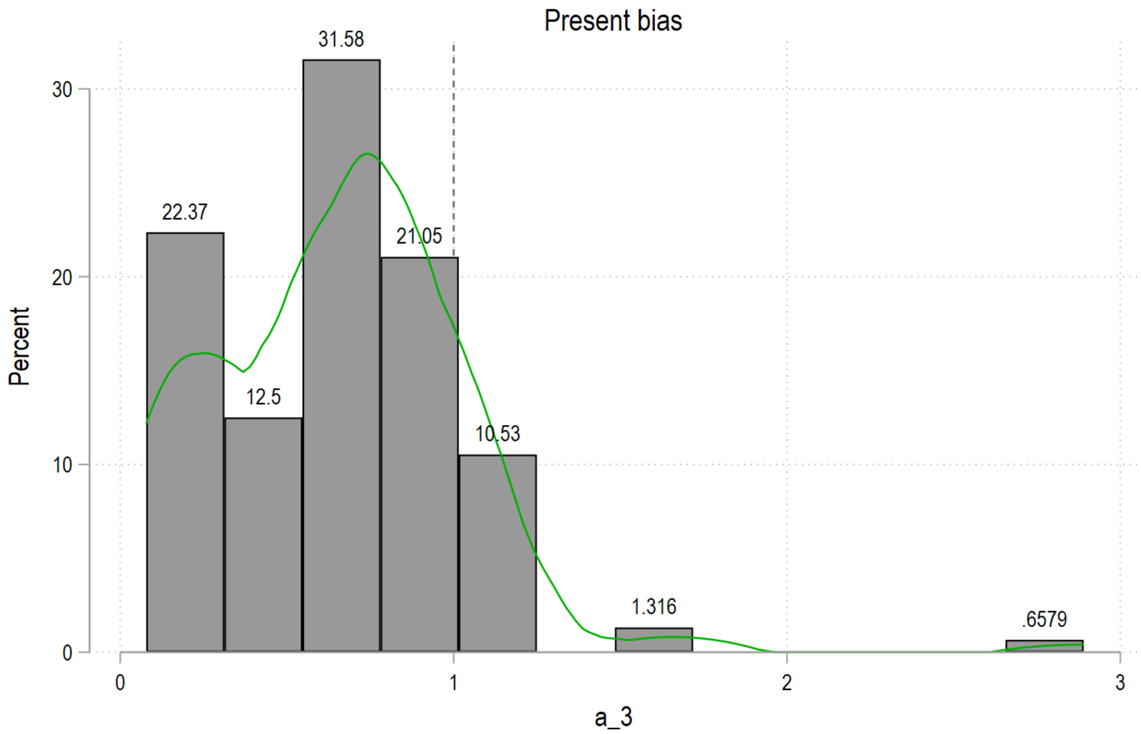


Figure 9: Present bias

5 Microinsurance

Microinsurance is the key instrument which aims to protect low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved. A follow-up question that might arise is — how is microinsurance different from regular insurance? The definition of microinsurance, in essence, is the same as one might use for regular insurance, the key difference in comparison to regular insurance is that microinsurance has a clearly prescribed target group — low-income people. So how poor does one need to be, to be considered for microinsurance? The answer varies by country, but generally, microinsurance is targeted toward those persons who are disregarded by the mainstream commercial and social insurance schemes such as people working in the informal economy as it is easier to offer insurance to people with a predictable flow of income than those without.

The word "micro" in microinsurance by no means refers to the size of the risk carrier or the microinsurance provider. There are various large companies that offer microinsurance in the Global South, such as AIG Uganda, Delta Life in Bangladesh and in the Indian context all insurance companies. Microinsurance covers a variety of different risks, including illness, death, crop loss, property loss or any risk that is insurable.

5.1 Microinsurance context in India

The case of India is quite unique as, in the year 2002, the Insurance Regulatory and Development Authority of India (IRDAI) enacted 'Obligations of Insurers to Rural or Social Sectors' to boost insurance penetration into the informal sector. Under this regulation, during the first financial year, all insurers need to underwrite 7 per cent of their total life insurance policies in the rural sector and five thousand lives in the social sector. These numbers increased to 16 per cent and twenty thousand lives for rural and social sectors respectively for the fifth year. In order to further augment the outreach, IRDAI enacted the microinsurance regulations 2005 which required private/public insurance companies to create and distribute microinsurance products in rural areas. In 2015, IRDAI revised the microinsurance regulation and increased the maximum coverage amount for various microinsurance products.

As of 31 March 2019, in India there were forty-four microinsurance products provided by sixteen insurance providers (detailed in appendix table C21). Out of the forty-four products, twenty-four were at the individual level and twenty were at the group level. Microinsurance premiums ranged from a minimum of 330 INR ($4.43) per person per annum or roughly 1.6 days of daily wage (MGNREGA 2022) to 750INR or roughly 3.6 days of daily wage. Most policies require a minimum of 5 members. The members can be from the same households or people from the same village engaged in similar livelihood. Coverage amount is 2,00,000 INR ($ 2685.18).

In the financial year 2018-19, 0.86 million individual microinsurance policies were underwritten, generating 320.98 million INR in premium. Whereas, at the group level 121.30 million people were covered, generating 32.05 billion INR in premium. If we look into the claims made for the policies, we find that for individual policies, total claims (9450 policies) were in the amount of 149.76 million INR and out of which 147.65 million INR were paid out for 9395 policies. While for the group level, total claims (3,01,976 policies) were in the amount of 8.83 billion INR and out of which 8.87 billion INR were paid out for 2,99,451 policies (IRDAI 2019).

The information for the IRDAI annual report (2019) highlights a few key insights. First, there are various microinsurance products available at the individual and group level. second, people do take up individual or group level microinsurance. However, this individual level microinsurance number has not increased but rather decreased from the 2008-09 level.[21] Third, although insurance providers do not have rich actuarial data and might have asymmetric information, they are not making losses but rather profits. Finally, the majority of claims submitted at the individual level or group level are paid by the insurance providers; the claims paid rate stands at 99.42 per cent and 99.16 per cent at the individual and group level, respectively. Although there was some demand for individual/group microinsurance, the demand for microinsurance in a country like

[21] During the 2008-09 financial year, 2.15 million individual policies were issued generating 365.65 million INR.

India where 93 per cent (NSSO, 2014) of the total workforce is engaged in the informal sector and doesn't have any insurance or social protection, the demand for such a key instrument is puzzlingly low, even more so when there are plenty of insurance providers and claims paid percentage is such high.

5.2 Microinsurance empirical strategy

In order to examine the factors associated with microinsurance take-up, we estimate the probit equation of the following form:

$$Y_{it} = \beta_0 + \beta_1 EP_{it} + \beta_2 Shocks_{it-1} + \beta_3 \mathbf{X}_{it} + \varepsilon_{it} \tag{7}$$

where Y is a dummy variable taking value one if an individual took up microinsurance and zero otherwise. *EP* refers to experimental variables (risk preference & time preference),[22] and *Shocks* refers to idiosyncratic shocks (illness, injury and death) that the households faced in period $t-1$ and $\boldsymbol{X}$ is set of controls, which includes age, sex, education, number of children, and per capita consumption. I cluster the standard errors at the individual level when it was the same respondent in both the waves. I clustered the standard errors at the household level when the household head was the respondent in one wave and the household head's wife in the other.

5.3 Microinsurance results

Table 8 presents the estimation results of equation (7), where *EP* is the risk-taking behaviour of the individual in risk game 1 which was repeated in both the 2018 wave and 2020 wave. Y is dummy variable taking value one if an individual took up any microinsurance that is either health microinsurance or life microinsurance and zero otherwise.[23] The control variables are education, and age which have been categorised into 3 dummies for age groups 18-34, 35-45, and 45+. Other controls include the number of children a household has and per-capita consumption split into four dummy variables for each quartile. We include household-level shocks such as illness, injury and death. The base groups for age and per-capita consumptions are age 45+ and per-capita consumption quartile 4 (top 25 per cent) respectively. In the fifth and tenth columns, we add household fixed effects and individual fixed effects to this specification (equation 7).

As insurance coverage is typically for the entire household, I first show responses at the household level in order to maximize the number of observations. I utilize the responses from the same household when it comes to the experimental game results and

[22] Risk and time are intertwined and it is crucial to understanding an individual's decision making under risk over time (Andreoni and Sprenger, 2012). I estimated the effect of risk and time preference jointly and separately on microinsurance take-up and the results do not vary. As such, I decided to keep them separate in table 8 and table 9 for clarity.

[23] Appendix tables C9 - C8 present estimates for life microinsurance and appendix tables C9 - C12 present estimates for health microinsurance.

this pertains to specifications (1)-(5) in table 8. On the other hand, a stricter test would be where it is the same individual who is taking part in the surveys and experiments in both waves. So, in that respect, my preferred specification includes versions of the model estimated using the same individuals and this pertains to specifications (6)-(10) in table 8. There is limited variation in the experimental games over time for the same individuals and including individual fixed effects would absorb quite a bit of the variation in the experimental answers. So, it's one of the reasons why including individual fixed effects may not be necessarily the best way forward but model specification (9), where I include a rich set of controls and also take into account the various household level shocks, is the specification that I base my inference on.

In table 8, I first present the household level panel estimates (columns (1)-(4)) and in columns (6)-(9), I present individual panel estimates. Whereas, in columns (5) and (10), I present results from household fixed effects and individual fixed effects estimation. From columns (1)-(4) we can see that risk-seeking individual are associated with a higher probability to purchase any (health/life) microinsurance.[24] We can also see that association with prior shock such as the death of a family member is positive and significant, which means individuals who experienced a death shock in the family are 29.5 per cent more likely to buy any (health/life) microinsurance (Appendix table C13 column (4)). These estimates are not only significant without controls but after we add in the controls in columns (2) and (4) the results are quite similar. When we look into the stricter requirement — estimates for the same individual in the panel (columns (6)-(9)), we see a largely similar result that risk-seeking individuals and individuals who experienced a prior shock such as the death of a family member are associated with a higher probability to purchase any (health/life) microinsurance. If we look into the marginal effects from our preferred specification (column (9)), we see that individuals who experienced the death of a family member are associated with a 47.7 per cent higher probability to purchase any microinsurance (Appendix table C13 column (8)).[25] These estimates are not only significant without controls but also in our preferred specification (column (9)) where we add in the controls and take into account the various household level shocks, the results are quite similar. The results are robust when we include household fixed effects (column (5)). However, when we individual fixed effects (column (10)), the association of risk-seeking nature with a higher probability to purchase microinsurance is no longer statistically significant. This could be due to the fact that individual fixed effects are absorbing quite a bit of the variation in the experimental answers.

[24] The demand for insurance should be higher for risk-averse individuals. However, several studies have found that risk-aversion can be negatively, and quite strongly, correlated with the demand for insurance (Giné et al., 2008; Cole et al., 2013; Dercon et al., 2019). One plausible explanation for this rather counter-intuitive result can be if the client distrusts the insurer to payout when required (Dercon et al., 2019), or the fact that in any insurance scheme the contract almost never perfectly covers the client for every potential loss. Ambiguity aversion provides another explanation as to why most risk-averse individuals dislike the insurance (Elabed and Carter, 2015; Bryan, 2019).

[25] One of the reasons for this significant association between death shock and any microinsurance take-up could be that the immediate effect of a death shock might be high but it might die down over the years.

In table 9, I present the estimation results of equation (7), where EP is the time discounting behaviour of the individual in time game 1. The set of controls, the base groups and the specifications are the same as in table 8. From columns (1)-(4), we can see that impatience is associated with a lower probability to purchase any (health/life) microinsurance. On the other hand, we can see that prior shock such as the death of a family member has a positive and significant association with microinsurance take-up, similar to the linkages with risk preference (table 8). These results are robust when we add in the controls (column (4)). If we look at the marginal effects, we see that impatience is associated with a 53.5 per cent lower probability of purchasing any microinsurance. whereas, death in the family is associated with a 31.3 per cent higher probability of purchasing any microinsurance (Appendix table C14 col (4)). The results are quite interesting as individuals who experienced death in the family would like to buy insurance but they are impatient – have a higher time discounting factor they would prefer to think about the present and not regarding the foreseeable future. When we look into the stricter requirement — estimates for the same individual in the panel (columns (6)-(9)), we see a largely similar result that impatience is associated with a lower probability to purchase any microinsurance. Whereas, individuals who experienced a prior shock such as the death of a family member are associated with a higher probability to purchase any microinsurance. If we look into the marginal effects from our preferred specification (column (9)), we see that individuals who experienced the death of a family member are associated with a 46.1 per cent higher probability to purchase any microinsurance (Appendix table C14 column (8)). However, when we add in the household fixed effects (column (5)) and individual fixed effects (column (10)), the significant negative association between impatience and the probability to buy microinsurance disappears. This could partly stem from the fact that fixed effects are absorbing quite a bit of the variation in the experimental answers.

Table 10 presents the estimation results of equation (7), where we estimate the effect of risk preference and time preference from risk game 2 and time game 2 which were conducted in 2018 wave (wave 1). Present biased is a dummy taking value one if an individual is present biased ($\beta < 1$) which is estimated from equation (6). Probability weighting is a dummy which takes value one if individual has inverted s-shaped probability weighting ($\alpha < 1$) estimated jointly using equations (1), (2), and (3). Loss averse is a dummy taking value one if an individual is loss averse ($\lambda > 1$), that is losses hurts more compared to an equal amount of gain. The control variables are same as in table 8 and 9 – education, age which has been categorised into 3 dummies for age groups 18-34, 35-45, and 45+. Other controls include the number of children a household has and per-capita consumption split into four dummy variables for each quartile. From columns (1)-(9) we find that none of the risk dummies (risk averse, loss-averse, probability weighting) or time dummy (present bias) have a significant effect on any microinsurance. We did however find that individuals who overweight low probabilities and underweight large probabilities ($\alpha < 1$) are less likely to take-up health microinsurance (Appendix table C11). This result has policy implications. If an individual inaccurately anticipates that they are going to be exposed to smaller shocks more frequently due to their behavioural bias, they might not want to buy microinsurance as they might undervalue the importance of insurance and would want to smooth out the risk informally through savings or through networks. However, as they underweight the occurrence of large events, when they are faced with the larger shock, the informal means to cope-up with the shocks would be inefficient and inadequate.

Next in table 11 we present the estimation results of equation (7) including the effect of household level shocks. Similar to table 10, from columns (1)-(9) we find that none of the risk dummies (risk averse, loss-averse, probability weighting) or time dummy (present bias) have any significant effect on any microinsurance take-up. We found that individuals with prior death shock are more likely to any microinsurance, similar to tables 8 and 9.

Lastly in table 12, we present the estimation results of equation (7) including the effect of household level shocks for any, life, and health microinsurance. We also include the interaction effect of an individual being loss averse ($\lambda > 1$) and having inverse *s-shaped* probability weighting — over-weighting small probability incidents and under-weighting large probability incidents. In columns (1) and (4), we present the correlation of behavioural factors with any microinsurance take-up without and with the occurrence of prior household level shock. columns (2) and (5) show the association of behavioural factors with life microinsurance take-up and columns (3) and (6) show health microinsurance take-up.

From columns (1) and (4) in table 12, we can see that loss-averse individuals are more likely to take-up any microinsurance and the effect persists when individuals are exposed to various shocks. However, if we examine the effect of individuals who underweight large probability incidents (inverted s-shaped) and are loss averse ($\lambda > 1$), we see that they are less likely to take-up any microinsurance and the correlation persists when individuals are exposed to various shocks. If we delve deeper into the type of microinsurance, from columns (2) and (5) we can see that loss-averse individuals are more likely to take-up life microinsurance and that the association persists even when individuals are exposed to various shocks. Moreover, if we examine the effect of individuals who underweight large probability incidents (inverted s-shaped) and are loss averse ($\lambda > 1$), similar to columns (1) and (4) we see that the individuals are less likely to take-up life microinsurance and the correlation persists when individuals are exposed to various shocks. If we look into columns (3) and (6) we see that individuals are more likely to take-up health microinsurance and the effect is only significant when individuals are exposed to various shocks (col(6)). Moreover, if we examine the effect of individuals who underweight large probability incidents (inverted s-shaped) and are loss averse ($\lambda > 1$), similar to columns (1) and (4), and columns (2) and (5) we see that the individuals are less likely to take-up health microinsurance and the association persists and even stronger when individuals are exposed to various shocks. Now what might explain this intriguing result?

An individual who is loss averse ($\lambda > 1$) in principal should definitely want to purchase insurance as losses hurt him/her more compared to an equal amount of gain. However, if an individual is a loss averse ($\lambda > 1$) and underweight large probability incidents (inverted s-shaped), he/she might think that since large probability incidents are less likely to occur and spending for such an event might seem like a sunk cost/loss. For example, the probability of getting sick in the future is affected by the current health status. Specifically, suppose that P (sick tomorrow | sick today) $>$ P (sick tomorrow | healthy today). A decision maker who under-weights large probability events and who is currently sick could underestimate the likelihood of falling ill again in the future. As a result, such a decision maker being loss averse ($\lambda > 1$) are less likely to buy microinsurance.

The results from the simpler lab-in-the-field experiments indicate that risk-averse and impatient individuals are less likely to take-up microinsurance and this association is significant. The association becomes insignificant when we include the individual fixed effects which could possibly be due to the fact that limited variation in the experimental answers over time is absorbed by the individual fixed effects. It is also worth highlighting that risk-aversion may be confounded with loss-aversion in risk game 1. In fact, if we look closer into the association of risk and time preference from the richer experiments on microinsurance take-up, we see that loss-averse individuals are more likely to take-up microinsurance. While individuals who are loss-averse and underweight large probability events are less likely to take-up microinsurance. One caveat to my results is that they represent associations, not necessarily causal impacts because of a possible association of other variables such as loan, credit constraint, and network effect which could influence microinsurance take-up that future work can investigate.

Table 8: Any insurance: Risk experiment 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance
Risk game 1	0.0172***	0.0178***	0.0179***	0.0190***	0.00762***	0.0199***	0.0193**	0.0209***	0.0204**	0.00501
	(0.00543)	(0.00591)	(0.00571)	(0.00630)	(0.00188)	(0.00746)	(0.00755)	(0.00785)	(0.00831)	(0.00345)
Education		0.0344**		0.0308*	0.00401		0.0235		0.0232	0
		(0.0175)		(0.0161)	(0.00785)		(0.0341)		(0.0333)	(.)
Male		-0.443**		-0.474**	-0.344***		0.167		0.271	0
		(0.194)		(0.208)	(0.0747)		(0.286)		(0.308)	(.)
Age (18-34)		-0.472*		-0.469*	-0.139		0.319		0.343	0
		(0.260)		(0.265)	(0.126)		(0.411)		(0.444)	(.)
Age (35-45)		-0.198		-0.184	0.0765		0.307		0.337	0
		(0.233)		(0.241)	(0.113)		(0.361)		(0.389)	(.)
No. of children		-0.0642		-0.0721	-0.518**		-0.257*		-0.248	0
		(0.0999)		(0.103)	(0.255)		(0.142)		(0.156)	(.)
P.C. Cons quartile 1		-0.316		-0.324	-0.0828		-0.546		-0.786*	-0.279
		(0.249)		(0.268)	(0.111)		(0.353)		(0.417)	(0.186)
P.C. Cons quartile 2		-0.501*		-0.474*	-0.128		-0.323		-0.369	-0.175
		(0.261)		(0.269)	(0.0967)		(0.323)		(0.341)	(0.141)
P.C. Cons quartile 3		-0.325		-0.322	-0.140		-0.603		-0.617	-0.353**
		(0.253)		(0.262)	(0.121)		(0.369)		(0.396)	(0.177)
Shock - Illness			-0.136	-0.152	-0.161**			-0.253	-0.219	-0.188*
			(0.182)	(0.194)	(0.0750)			(0.247)	(0.288)	(0.104)
Shock - Death			1.114***	1.058***	0.299**			1.525**	1.688**	0.339
			(0.391)	(0.384)	(0.129)			(0.645)	(0.757)	(0.205)
Shock - Injury			-0.445	-0.552	-0.185			-0.374	-0.370	-0.114
			(0.332)	(0.338)	(0.116)			(0.436)	(0.396)	(0.127)
Constant	-1.126***	-0.621*	-1.160***	-0.630*	0.938***	-1.265***	-1.002**	-1.289***	-1.051**	0.367**
	(0.218)	(0.328)	(0.236)	(0.348)	(0.302)	(0.312)	(0.452)	(0.334)	(0.493)	(0.167)
/										
lnsig2u	-1.566	-1.413	-1.432	-1.146		-11.39	-12.23	-11.17	-13.30	
	(0.953)	(0.916)	(0.901)	(0.829)		(19907.5)	(54005.3)	(17048.0)	(203594.9)	
Household FE	No	No	No	No	Yes	No	No	No	No	No
Individual FE	No	No	No	No	No	No	No	No	No	Yes
Observations	329	328	329	328	328	159	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table 9: Any insurance: Time experiment 1 and shocks (Panel)

	(1) Any insurance	(2) Any insurance	(3) Any insurance	(4) Any insurance	(5) Any insurance	(6) Any insurance	(7) Any insurance	(8) Any insurance	(9) Any insurance	(10) Any insurance
Time game 1	-1.622**	-1.645**	-1.766**	-1.755**	-0.410	-1.937*	-2.088*	-1.976*	-2.140*	0.163
	(0.762)	(0.779)	(0.775)	(0.807)	(0.348)	(1.074)	(1.149)	(1.088)	(1.196)	(0.531)
Education		0.0405**		0.0363**	0.00448		0.0449		0.0456	0
		(0.0187)		(0.0169)	(0.00900)		(0.0335)		(0.0335)	(.)
Male		-0.336*		-0.344*	-0.335***		0.250		0.362	0
		(0.183)		(0.189)	(0.0764)		(0.281)		(0.301)	(.)
Age (18-34)		-0.423*		-0.402	-0.146		0.293		0.338	0
		(0.250)		(0.248)	(0.132)		(0.407)		(0.430)	(.)
Age (35-45)		-0.191		-0.178	0.102		0.168		0.198	0
		(0.215)		(0.219)	(0.123)		(0.339)		(0.353)	(.)
No. of children		-0.0663		-0.0749	-0.408		-0.211		-0.199	0
		(0.0897)		(0.0917)	(0.258)		(0.131)		(0.148)	(.)
P.C. Cons quartile 1		-0.294		-0.299	-0.122		-0.482		-0.703	-0.314*
		(0.236)		(0.251)	(0.117)		(0.375)		(0.464)	(0.182)
P.C. Cons quartile 2		-0.471*		-0.444*	-0.170*		-0.320		-0.374	-0.195
		(0.243)		(0.246)	(0.102)		(0.318)		(0.339)	(0.147)
P.C. Cons quartile 3		-0.262		-0.249	-0.161		-0.546		-0.566	-0.389**
		(0.232)		(0.236)	(0.121)		(0.382)		(0.451)	(0.167)
Shock - Illness			-0.148	-0.148	-0.197***			-0.238	-0.247	-0.214**
			(0.171)	(0.181)	(0.0734)			(0.251)	(0.340)	(0.106)
Shock - Death			1.102***	1.026***	0.294*			1.415**	1.585**	0.332
			(0.361)	(0.354)	(0.149)			(0.641)	(0.777)	(0.243)
Shock - Injury			-0.390	-0.436	-0.182*			-0.497	-0.358	-0.106
			(0.351)	(0.349)	(0.108)			(0.451)	(0.427)	(0.116)
Constant	-0.380***	0.0193	-0.366***	0.0543	1.116***	-0.417**	-0.355	-0.392**	-0.368	0.543***
	(0.110)	(0.279)	(0.120)	(0.293)	(0.309)	(0.167)	(0.391)	(0.174)	(0.409)	(0.117)
/										
lnsig2u	-2.230	-2.200	-2.163	-1.932		-13.04	-13.45	-12.89	-13.52	
	(1.537)	(1.592)	(1.490)	(1.342)		(119083.9)	(243863.0)	(113182.9)	(399283.7)	
Household FE	No	No	No	No	Yes	No	No	No	No	No
Individual FE	No	No	No	No	No	No	No	No	No	Yes
Observations	329	328	329	328	328	159	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table 10: Any insurance: Wave 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance
Present biased ($\beta < 1$)	0.156				0.0764				0.0739
	(0.281)				(0.302)				(0.296)
Risk averse ($\sigma < 1$)		-0.0801				0.0610			0.0849
		(0.298)				(0.293)			(0.299)
Probability overweighting ($\alpha < 1$)			-0.148				-0.0859		-0.0895
			(0.250)				(0.253)		(0.260)
Loss averse ($\lambda > 1$)				0.170				0.139	0.148
				(0.228)				(0.227)	(0.237)
Education					0.0634**	0.0632**	0.0623*		0.0624*
					(0.0321)	(0.0319)	(0.0319)		(0.0323)
Male					-0.255	-0.255	-0.254	-0.147	-0.232
					(0.274)	(0.273)	(0.273)	(0.251)	(0.273)
Age (18-34)					-0.444	-0.448	-0.431	-0.267	-0.421
					(0.368)	(0.369)	(0.364)	(0.333)	(0.361)
Age (35-45)					-0.0210	-0.0149	-0.0137	0.0430	-0.00615
					(0.318)	(0.316)	(0.315)	(0.310)	(0.319)
No. of children					0.0988	0.0977	0.0945	0.106	0.0904
					(0.124)	(0.124)	(0.123)	(0.122)	(0.123)
P.C. Cons quartile 1					-0.562*	-0.581*	-0.577*	-0.643**	-0.579*
					(0.318)	(0.317)	(0.319)	(0.324)	(0.316)
P.C. Cons quartile 2					-0.888***	-0.906***	-0.904***	-0.892***	-0.893***
					(0.343)	(0.347)	(0.345)	(0.344)	(0.345)
P.C. Cons quartile 3					-0.674**	-0.680**	-0.673**	-0.672**	-0.665**
					(0.336)	(0.334)	(0.337)	(0.335)	(0.334)
Constant	-0.929***	-0.736***	-0.694***	-0.908***	-0.603	-0.581	-0.465	-0.293	-0.702
	(0.253)	(0.272)	(0.215)	(0.180)	(0.470)	(0.453)	(0.424)	(0.390)	(0.610)
Observations	166	166	166	166	165	165	165	166	165

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups.

Table 11: Any insurance: Wave 1 shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance
Present Biased ($\beta < 1$)	0.129				0.0501				0.0550
	(0.276)				(0.297)				(0.291)
Shock - Illness	-0.270	-0.266	-0.263	-0.333	-0.236	-0.237	-0.235	-0.283	-0.291
	(0.226)	(0.230)	(0.229)	(0.223)	(0.236)	(0.236)	(0.237)	(0.229)	(0.233)
Shock - Injury	-0.213	-0.221	-0.228	-0.280	-0.118	-0.121	-0.120	-0.162	-0.169
	(0.442)	(0.442)	(0.440)	(0.439)	(0.458)	(0.455)	(0.457)	(0.458)	(0.456)
Shock - Death	0.895**	0.922**	0.900**	0.993**	0.995**	0.995**	0.996**	1.074**	1.063**
	(0.411)	(0.411)	(0.407)	(0.395)	(0.442)	(0.441)	(0.438)	(0.418)	(0.423)
Risk averse		-0.131				0.0174			0.108
		(0.308)				(0.296)			(0.304)
Probability overweighting			-0.0900				-0.0300		-0.0422
			(0.255)				(0.261)		(0.270)
Loss averse				0.340				0.281	0.310
				(0.231)				(0.234)	(0.242)
Education					0.0611**	0.0609**	0.0606**	0.0590*	0.0594*
					(0.0306)	(0.0306)	(0.0305)	(0.0309)	(0.0310)
Male					-0.225	-0.226	-0.225	-0.189	-0.183
					(0.278)	(0.277)	(0.277)	(0.274)	(0.276)
Age (18-34)					-0.418	-0.421	-0.416	-0.401	-0.388
					(0.351)	(0.351)	(0.348)	(0.349)	(0.347)
Age (35-45)					-0.0199	-0.0172	-0.0170	-0.0109	-0.00423
					(0.318)	(0.316)	(0.315)	(0.320)	(0.322)
No. of children					0.0971	0.0963	0.0954	0.0879	0.0832
					(0.132)	(0.133)	(0.131)	(0.132)	(0.132)
P.C. Cons quartile 1					-0.639*	-0.648*	-0.647*	-0.652*	-0.660*
					(0.344)	(0.341)	(0.344)	(0.345)	(0.344)
P.C. Cons quartile 2					-0.892**	-0.902**	-0.901**	-0.888**	-0.887**
					(0.359)	(0.361)	(0.359)	(0.358)	(0.361)
P.C. Cons quartile 3					-0.679**	-0.680**	-0.678**	-0.629*	-0.644*
					(0.340)	(0.337)	(0.341)	(0.340)	(0.340)
Constant	-0.864***	-0.652**	-0.693***	-0.953***	-0.538	-0.505	-0.469	-0.674	-0.792
	(0.272)	(0.277)	(0.227)	(0.209)	(0.507)	(0.476)	(0.441)	(0.427)	(0.631)
Observations	166	166	166	166	165	165	165	165	165

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups.

Table 12: All insurance: Wave 1 shocks

	(1) Any insurance	(2) Life insurance	(3) Health insurance	(4) Any insurance	(5) Life insurance	(6) Health insurance
Present biased ($\beta < 1$)	0.163	0.173	0.251	0.137	0.153	0.246
	(0.315)	(0.331)	(0.567)	(0.309)	(0.322)	(0.551)
Risk averse ($\sigma < 1$)	-0.0199	-0.0524	0	-0.00307	-0.0211	0
	(0.301)	(0.302)	(.)	(0.302)	(0.304)	(.)
Probability overweighting ($\alpha < 1$)	0.629	0.843	0.419	0.752	0.892	0.909
	(0.450)	(0.531)	(0.619)	(0.474)	(0.572)	(0.558)
loss averse ($\lambda < 1$)	1.025**	1.167**	0.803	1.259**	1.273**	1.405**
	(0.493)	(0.544)	(0.661)	(0.502)	(0.583)	(0.580)
Prob. overweighting × loss averse	-1.222**	-1.296**	-1.692*	-1.294**	-1.287**	-2.332***
	(0.579)	(0.630)	(0.906)	(0.595)	(0.657)	(0.834)
Education	0.0557*	0.0544	0.0876**	0.0526*	0.0507	0.0843*
	(0.0320)	(0.0351)	(0.0445)	(0.0309)	(0.0338)	(0.0462)
Male	-0.290	-0.412	-0.637	-0.240	-0.391	-0.738
	(0.274)	(0.293)	(0.548)	(0.280)	(0.298)	(0.600)
Age (18-34)	-0.385	-0.705*	0.469	-0.367	-0.672*	0.729
	(0.362)	(0.402)	(0.625)	(0.351)	(0.379)	(0.673)
Age (35-45)	-0.0391	-0.152	0.392	-0.0485	-0.133	0.468
	(0.321)	(0.332)	(0.528)	(0.326)	(0.334)	(0.689)
No. of children	0.123	0.0829	0.324	0.121	0.0681	0.390
	(0.124)	(0.134)	(0.221)	(0.133)	(0.140)	(0.243)
P.C. Cons quartile 1	-0.507	-0.777**	-0.00585	-0.587*	-0.818**	-0.0867
	(0.316)	(0.327)	(0.519)	(0.342)	(0.352)	(0.584)
P.C. Cons quartile 2	-0.827**	-0.824**	0	-0.817**	-0.819**	0
	(0.353)	(0.360)	(.)	(0.371)	(0.373)	(.)
P.C. Cons quartile 3	-0.532	-0.626*	-0.601	-0.499	-0.616*	-0.568
	(0.337)	(0.336)	(0.683)	(0.342)	(0.340)	(0.721)
Shock - Illness				-0.269	-0.281	-0.417
				(0.232)	(0.235)	(0.530)
Shock - Injury				-0.164	-0.149	0
				(0.457)	(0.444)	(.)
Shock - Death				1.032**	0.567	0.775
				(0.424)	(0.467)	(0.494)
Constant	-1.216*	-1.169	-2.901**	-1.378*	-1.204	-3.497***
	(0.738)	(0.804)	(1.137)	(0.780)	(0.843)	(1.212)
Observations	165	165	100	165	165	93

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups.

6 Conclusion

The poorest citizens of the poorest countries are typically exposed to unprecedented shocks from numerous sources and it tends to hit them the hardest. However, they are the ones that are least protected from such risk exposures. The mechanisms that they use to mitigate such challenges are often imperfect and inefficient — leading more people towards poverty. Poverty and vulnerability go hand in hand and lead to an escalating downward spiral, but microinsurance holds the promise and can be a key instrument which can aid in breaking this vicious cycle. The task for microinsurance is tall but if it is going to aid in breaking this vicious cycle, we need to understand why and how microinsurance markets fail, and why is the demand for microinsurance puzzlingly low. Knowing the problems is the first step towards tackling the challenge and it would help guide us towards finding the solutions (Morduch, 2006).

In the current work, I contribute to the microinsurance puzzle by delving into the behavioural factors such as risk and time preference and their association with microinsurance take-up. Although behavioural factors are quite important in understanding insurance take-up, it has very recently gained interest among the researchers working on general insurance (Harrison and Ng, 2019). Recent work on general insurance shows that behavioural factors such as risk and time preference are quite important in understanding insurance take-up as behavioural biases are linked with insurance take-up and partly explain the demand puzzle as highlighted by Do Hwang (2021); Pitthan and De Witte (2021). However, despite the importance of behavioural factors such as risk and time preference and behavioural biases such as loss aversion, and probability weighting, the literature on the microinsurance demand puzzle largely ignored the behavioural factors apart from a few handful of studies (Ito and Kono, 2010; Lampe and Würtenberger, 2020; Platteau and Ontiveros, 2021). Plausible explanations for the lack of studies examining the effect of risk and time preference on microinsurance take-up are — examining risk and/or time preference without incentivized lab-in-the-field experiments might lead to hypothetical bias. On the other hand, designing and conducting incentivized lab-in-the-field experiments are not only costly but it is also time-consuming, and difficult to design and conduct where the sample of the study are not educated students. Furthermore, tracking these individuals and household over time poses serious challenges and leads to sample attrition.

In order to overcome these challenges, in the current work, I exploit the rich incentivized lab-in-the-field panel data that I collected from five rural villages in India to first examine an individual's risk and time preference, then drawing upon the measured risk and time preference examine whether these behavioural factors are associated with microinsurance take-up? If so, how? Finally, I use prior household level shocks such as illness, injury, and death and their linkages with microinsurance take-up.

The findings from the study are quite intriguing. I find that a vast majority of individuals are not only risk averse but they are also loss averse, that is losses hurt them more in comparison to an equal amount of gain. I also find that individuals overweight small probabilities and underweight large probabilities, which means they put more weight on incidents which are less likely to occur and underweight incidents which are more likely to occur. Also, the majority of the subjects are present biased ($\beta < 1$). Drawing on the simpler lab-in-the-field experiments I find that risk-seeking individuals and individuals who experience a prior household level shock such as death are more likely to buy microinsurance. Whereas, impatience is associated with a lower probability to purchase any microinsurance. However, when I delve into the richer experiments I find that loss-aversion is associated with a higher probability to purchase any microinsurance. Whereas, individuals who underweight large probabilities (inverse s-shaped) and are loss-averse are associated with a lower probability to purchase any microinsurance.

An individual who is loss-averse, and present biased ($\beta < 1$) (time-inconsistent preference) might see buying insurance as an opportunity cost and given their present biased nature, the individual would want to spend on immediate consumption rather than delayed consumption. Individuals tend to misinterpret probabilities (Tversky and Kahneman, 1992). This misinterpretation has significant consequences — if individuals overweight small probability events and underweight large probability events, this might explain the lack of insurance take-up, as an individual assumes small probability events are more likely to occur and large probability events are extremely unlikely to occur. So spending for an unlikely event and paying insurance premium beforehand might seem like a sunk cost. Furthermore, they might believe that, if and when a small event occurs, it is better to cover it out of the pocket. If behavioural biases lead to efficiency loss or market failure, it is a policy-relevant question and has important policy implications. One of the most effective ways to overcome these behavioural biases is to provide *financial literacy* and *nudge* individuals in the right direction. Another plausible mechanism to increase microinsurance take-up would be to have automatic enrollment with a voluntary opt-out mechanism. Few follow-up questions might arise — Who should pay for the premium and how much should it be? For the first part of the question, the majority of the premium should be borne by the Centre and State governments and a marginal fraction of the premium should be borne by the households. The later part of the question is more of an actuarial question and falls beyond the purview of the current work.

In the current work, I set up to examine the puzzle of why the microinsurance take-up is so low and whether microinsurance take-up can be explained by behavioural factors such as risk and time preferences. Although I found some linkages between behavioural factors such as risk aversion, loss aversion and behavioural biases such as probability underweighting and present bias, and shocks with the microinsurance take-up they do not necessarily point towards causal evidence. Moreover, the current study was not able to completely identify and disentangle the mechanism through which these behavioural biases work. Further research is needed to identify and disentangle the mechanism through which these behavioural biases work and their effect on microinsurance.

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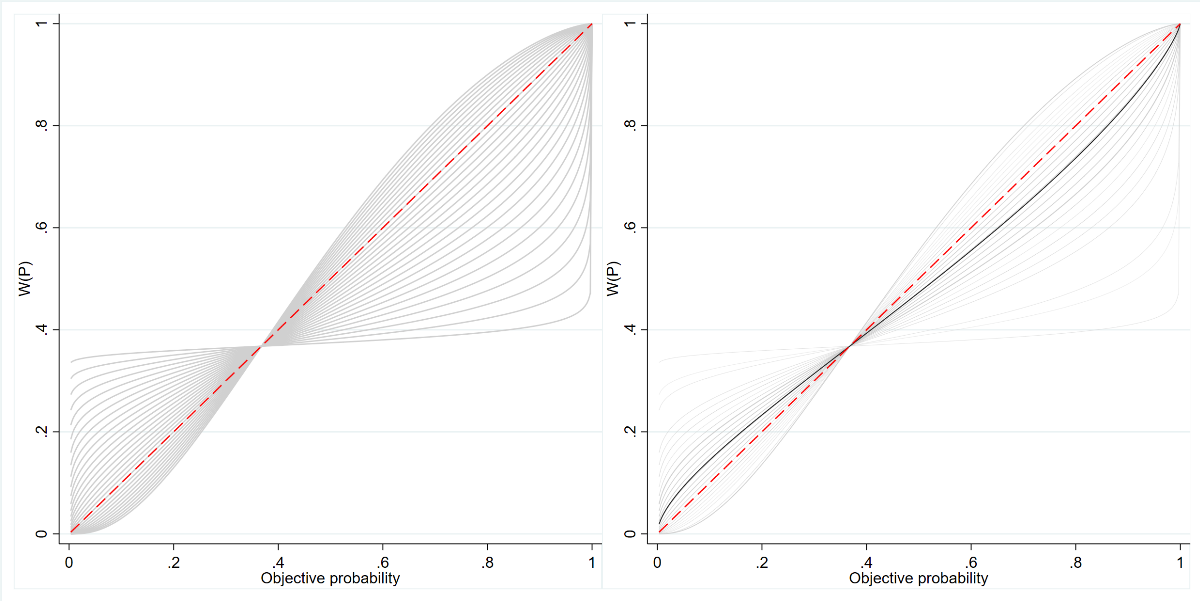
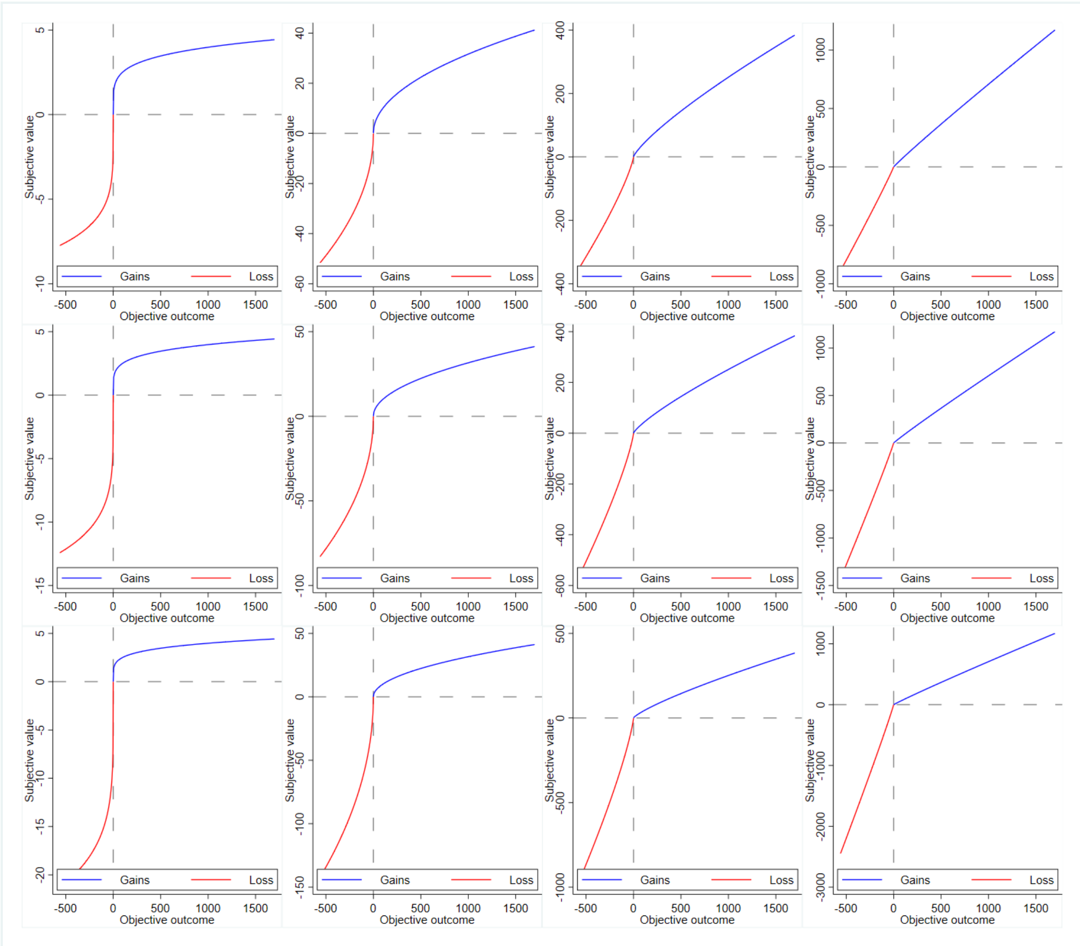
Appendix A: Graphs

Figure A1: Probability weighting parameter (α)



Note: The above figure shows the prelec probability weighting parameter. The dashed red line at 45 degree shows the true probability. The x-axis shows the objective probability and the y-axis shows the weighted probability. Left panel shows all the possible probability weights. The right panel shows the empirical estimates. From the right panel we can clearly see that a significant portion of the respondents overweights small probability incidents and underweights large probability incidents. The mean is shown by the solid black line.

Figure A2: Prospect Theory value function at different risk curvature (σ) and loss aversion (λ)



Note: The above figure shows the prospect theory value function for different σ and λ. The first row (the top 4 plots) shows the value function for $\lambda = 2.18$ and $\sigma = 0.2$, 0.5, 0.8 and 0.95 going from left to right. The second row (the middle 4 plots) shows the value function for $\lambda = 3.5$ and $\sigma = 0.2$, 0.5, 0.8 and 0.95 going from left to right. The last row (the bottom 4 plots) shows the value function for $\lambda = 6$ and $\sigma = 0.2$, 0.5, 0.8 and 0.95 going from left to right.

Appendix B: Experimental Procedure

Introductory comments

Thank you all for taking the time to come today. Today's games may take one to two hours, so if you think you will not be able to stay that long let us know now. Before we begin I want to make some general comments about what we are doing here today and explain the rules that we must follow. We will be playing games with money. Whatever money you win, will be yours to keep and take home. I will be providing the money to play the games. You should understand that this is not my own money. It is money given to me by the University of Helsinki to use for research. There are many researchers in different countries and across India playing these same games.

Before we proceed any further, let me stress something that is very important. Many of you were invited here without understanding very much about what we are planning to do today. If at any time you find that this is something that you do not wish to participate in for any reason, you are of course free to leave whether we have started the game or not.

We will be playing four games here today. If you have heard anything about any other games, you should try to forget about that. These games are completely different. It is important that you listen as carefully as possible. Do not worry if you do not completely understand the game as we will go through the examples here. You will have a chance to ask questions after that to be sure that you understand how to play.

B1 Risk game 1

At the beginning of the game, the player will receive 50 rupees (INR). The player will then have the opportunity to bet a share of this money. The player can bet 50, 40, 30, 20, or 10 INR, or can choose not to bet. After the player decides how much money he would like to bet, the player will roll a six-sided die. If the die lands on one, the player will lose the money he bet. If the die lands on two, the player will lose half of the money he bet. If the die lands on three, the player will recoup his bet, thus he will neither lose nor win money. If the die lands on four, the player will receive 1.5 times his bet. If the die lands on five the player will double his bet, and if the die lands on six the player will win 2.5 times his bet. Thus, rolls of one and two are bad, a roll of three is neither good nor bad, and rolls of four, five, and six are good.

This is the end of the game. The player will go home with the share of the original 50 INR he did not bet, plus whatever money he won in the bet. This game will only be played once with each person and then the game is over.

Here are a few examples *[These examples were all given using fake plastic money and a die. I gave the first three examples and an enumerator repeated the above instructions* *and then gave the last three examples.]*:

1. Imagine that the player bets 50 INR. He is left with no money. Debarshi throws the die. The die lands on 3. This means that Debarshi will give the player back his original bet. Thus the player will return home with 50 INR.

2. Now we will try another example. Imagine that the player bets 40 INR. He is left with 10 INR. Debarshi throws the die. The die lands on 2. This means that the player loses half of his bet. The player loses 20 INR and Debarshi gives him back 20 INR. Thus the player has the 10 INR he did not bet plus the 2000 INR that Debarshi gave back to him, and so he goes home with 30 INR.

3. Now we will try another example. Imagine that the player bets 30 INR. He is left with 20 INR. Debarshi throws the die. The die lands on 4. This means that Debarshi gives the player back his original bet plus an extra half of his original bet. This means he gives him 30 plus 15, i.e. 45 INR. Thus the player has the 20 INR he did not bet plus the 45 INR that Debarshi gave back to him, and so he goes home with 65 INR.

4. Now we will try another example. Imagine that the player bets 20 INR. He is left with 30 INR. Debarshi throws the die. The die lands on 5. This means that the player doubles his bet. The player bet 20, and two times 20 is 40, so Debarshi gives him back 40. Thus the player has the 30 INR he did not bet plus the 40 INR that Debarshi gave back to him, and so he goes home with 70 INR.

5. Now we will try another example. Imagine that the player bets 50 INR. He is left with nothing. Debarshi throws the die. The die lands on 1. This means that the player loses his entire bet. Thus the player goes home with 0 INR.

6. Now we will try another example. Imagine that the player does not bet anything. He is left with all 50 INR. There is no need for Debarshi to throw the die. The player goes home with 50 INR.

Note that, the more money the player bets, the more he can win, but the more he can lose as well. He could go home with more or less than 50 INR as a result. Please remember that you are not betting the money you may have brought with you in your pocket here today. The money you will be using to bet is money that I have given you for that purpose. How much do want to bet?

Table B1: Risk Game (in INR)

		Bet amount					
Dice	**Multiplier**	**0**	**10**	**20**	**30**	**40**	**50**
1	**0**	0	0	0	0	0	0
2	**0.5**	0	5	10	15	20	25
3	**1**	0	10	20	30	40	50
4	**1.5**	0	15	30	45	60	75
5	**2**	0	20	40	60	80	100
6	**2.5**	0	25	50	75	100	125

B2 Time game 1

In this game, you will receive money either today or sometime in the future, depending on the choices you make. There are 8 questions. In each question, we will offer you two options: option A and option B. We would like you to choose either option A or option B for each question. You will be paid based on one of your choices. We will put 8 balls in a bingo cage and draw one ball to determine which question will be paid for real money.

Example

Table B2: Example of time Game 1 (in INR)

Question #	Option A	Option B	Time delay		
	X (rupee)	Y (rupee)	T (in days)	EDR	HDR
1	○40	42	150	0.000325	0.000333
2	○34	38	120	0.000927	0.00098
3	○35	42	90	0.002026	0.002222
4	28	○38	60	0.00509	0.005952
5	27	○40	30	0.013101	0.016049
6	22	○38	20	0.027327	0.036364
7	18	○40	14	0.057036	0.087302
8	15	○42	7	0.147088	0.257143

Switching Point: 4

Imagine if you choose option A for the first three questions and option B for the last five questions. After the eight questions are answered. We will put 8 balls in the bingo cage and draw a ball. Imagine that the ball number is 3, then the question number is played for money and you will win 35 INR now.

The experiment

Table B3: Time Game 1 (in INR)

Question #	Option A	Option B	Time delay		
	X (rupee)	Y (rupee)	T (in days)	EDR	HDR
1	40	42	150	0.000325	0.000333
2	34	38	120	0.000927	0.00098
3	35	42	90	0.002026	0.002222
4	28	38	60	0.00509	0.005952
5	27	40	30	0.013101	0.016049
6	22	38	20	0.027327	0.036364
7	18	40	14	0.057036	0.087302
8	15	42	7	0.147088	0.257143

Switching Point:

B3 Risk game 2

In this game, your earnings will depend partly on your decisions and partly on chance. There are 3 series of questions. Series 1 consists of 14 questions. Series 2 consists of 14 questions, and Series 3 consists of 7 questions. So, there are 35 questions in total. In each question, we will offer you two plans: Plan A and Plan B. We would like you to choose either Plan A or Plan B for each question. After you complete the record sheet, we put 35 balls in a bingo cage and draw one numbered ball to select 1 question out of 35 questions. We will play the selected question for real money. For example, if the number 21 ball is drawn, we will play Question 21 for real money. Once the question is determined, we will put 10 balls in the cage and play the selected question.

Example

This example is the same as Series 1 (Questions 1-14). Please look at the record sheet.

There are two Plans, A and B for each question. There are 10 numbered balls ①, ②, ③, ④, ⑤, ⑥, ⑦, ⑧, ⑨, and ⑩ in a bingo cage. You should choose either A or B for each question. Let's look at Question 1

		Plan A		Plan B
1		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		68 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

We will draw one numbered ball out of the cage.
If Number 1 ball comes out, those who chose Plan A will received 40 INR and those who chose plan B will receive 68 INR. If Number 3 ball comes out, those who chose Plan A will received 40 INR and those who chose plan B will receive 5 INR. If Number 6 ball comes out, those who chose Plan A will received 10 INR and those who chose plan B will receive 5 INR. You should choose either A or B for each question from Question 1 to Question 14.

Now, let us look at Series 3. In series 3, you may lose some money.

There are two Plans, A and B for each question. There are 10 numbered balls ①, ②, ③, ④, ⑤, ⑥, ⑦, ⑧, ⑨, and ⑩ in a bingo cage. You should choose either A or B for each question.

		Plan A		Plan B
1		Receive 25 INR if ① ④ ⑤ ⑥ ⑦ Lose 4 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ④ ⑤ ⑥ ⑦ Lose 21 INR if ⑥ ⑦ ⑧ ⑨ ⑩

If Number 1,2, 3, 4 or 5 ball comes out, those whose Plan A will receive 25 INR and those whose Plan B will receive 30 INR. If Number 6, 7, 8, 9 or 10 ball comes out, those chose Plan A will lose 4 INR and those who chose Plan B will lose 21 INR. We will subtract money from your earnings from your total earnings.

Suppose the respondent choose Plan A from Question 1 to Question 6, and Plan B from Question 6 to Question 14. Then you should fill in the **record sheet** as follows

Table B4: Example of Risk game 2 (Series 1)

		Plan A		Plan B
1	✓	40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		68 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
2	✓	40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		75 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
3	✓	40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		83 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
4	✓	40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		93 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
5	✓	40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		106 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
6	✓	40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		125 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
7		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	150 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
8		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	185 INRif ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
9		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	220 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
10		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	300 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
11		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	400 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
12		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	600 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
13		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	1000 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
14		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩	✓	1700 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

Responses

I choose Plan A for Questions 1 to ...

I choose Plan B for Questions ... to 14

Record Sheet

Table B5: Risk game 2 **(Series 1)**

		Plan A		Plan B
1		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		68 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
2		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		75 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
3		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		83 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
4		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		93 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
5		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		106 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
6		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		125 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
7		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		150 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
8		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		185 INRif ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
9		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		220 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
10		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		300 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
11		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		400 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
12		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		600 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
13		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		1000 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩
14		40 INR if ① ② ③ 10 INR if ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩		1700 INR if ① 5 INR if ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

Responses

I choose Plan A for Questions 1 to ...

I choose Plan B for Questions ... to 14

Table B6: Risk game 2 **(Series 2)**

		Plan A		Plan B
15		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		54 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
16		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		56 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
17		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		58 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
18		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		60 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
19		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		62 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
20		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		65 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
21		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		68 INRif ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
22		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		72 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
23		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		77 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
24		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		83 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
25		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		90 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
26		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		100 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
27		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		110 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩
28		40 INR if ① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ 30 ⑩		130 INR if ① ② ③ ④ ⑤ ⑥ ⑦ 5 INR if ⑧ ⑨ ⑩

Responses

I choose Plan A for Questions 15 to ...

I choose Plan B for Questions ... to 28

Table B7: Risk game 2 **(Series 3)**

		Plan A		Plan B
29		Receive 25 INR if ① ② ③ ④ ⑤ Lose 4 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 21 INR if ⑥ ⑦ ⑧ ⑨ ⑩
30		Receive 4 INR if ① ② ③ ④ ⑤ Lose 4 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 21 INR if ⑥ ⑦ ⑧ ⑨ ⑩
31		Receive 1 INR if ① ② ③ ④ ⑤ Lose 4 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 21 INR if ⑥ ⑦ ⑧ ⑨ ⑩
32		Receive 1 INR if ① ② ③ ④ ⑤ Lose 4 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 16 INR if ⑥ ⑦ ⑧ ⑨ ⑩
33		Receive 1 INR if ① ② ③ ④ ⑤ Lose 8 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 16 INR if ⑥ ⑦ ⑧ ⑨ ⑩
34		Receive 1 INR if ① ② ③ ④ ⑤ Lose 8 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 14 INR if ⑥ ⑦ ⑧ ⑨ ⑩
35		Receive 1 INR if ① ② ③ ④ ⑤ Lose 8 INR if ⑥ ⑦ ⑧ ⑨ ⑩		Receive 30 INR if ① ② ③ ④ ⑤ Lose 11 INR if ⑥ ⑦ ⑧ ⑨ ⑩

Responses

I choose Plan A for Questions 29 to ...

I choose Plan B for Questions ... to 35

B4 Time game 2

In this game, you will receive money either today or sometime in the future, depending on the choices you make. There are 75 questions. In each question, we will offer you two plans: Plan A and Plan B. We would like you to choose either Plan A or Plan B for each question.

B4.1 Example

This example is the same as Question 1. Please refer to the record sheet. There are 2 plans, A and B, offered to you. If you choose Plan A, you will receive 20 INR today. If you choose Plan B, you will receive 120 INR in 1 week. Questions 1-5 are one series. If you choose Plan A for Question 1 to Question 3, and Plan B for Question 4 and 5, please answer as follows:

Table B8: Example 1

	Plan A	Plan B
1	A: receive 120 INR in 1 week	B: receive 20 INR today
2	A: receive 120 INR in 1 week	B: receive 40 INR today
3	A: receive 120 INR in 1 week	B: receive 60 INR today
4	A: receive 120 INR in 1 week	B: receive 80 INR today
5	A: receive 120 INR in 1 week	B: receive 100 INR today
	I choose A for 1 - 3	I choose B for 4 -5

If you choose Plan A for all 5 questions, please answer as follows:

Table B9: Example 2

	Plan A	Plan B
1	A: receive 120 INR in 1 week	B: receive 20 INR today
2	A: receive 120 INR in 1 week	B: receive 40 INR today
3	A: receive 120 INR in 1 week	B: receive 60 INR today
4	A: receive 120 INR in 1 week	B: receive 80 INR today
5	A: receive 120 INR in 1 week	B: receive 100 INR today
	I choose A for 1 - 5	I choose B for X -5

Please choose either Plan A or Plan B for each of the 75 questions. You will be paid based on one of your choices. We will put 75 balls in a bingo cage and draw one ball to determine which question will be played for real money. For example, if the number 21 ball is drawn, we will do Question 21 for real money. Suppose Question 21 is selected, and you choose Plan A in Question 21, you will be paid 50 INR today. If you chose Plan B in Question 21, you will receive 300 INR in 1 month.

Table B10: Time game 2

		Plan A		Plan B
1		A: receive 120 INR in 1 week		B: receive 20 INR today
2		A: receive 120 INR in 1 week		B: receive 40 INR today
3		A: receive 120 INR in 1 week		B: receive 60 INR today
4		A: receive 120 INR in 1 week		B: receive 80 INR today
5		A: receive 120 INR in 1 week		B: receive 100 INR today

I choose A for 1 - I choose B for -5

		Plan A		Plan B
6		A: receive 120 INR in 1 month		B: receive 20 INR today
7		A: receive 120 INR in 1 month		B: receive 40 INR today
8		A: receive 120 INR in 1 month		B: receive 60 INR today
9		A: receive 120 INR in 1 month		B: receive 80 INR today
10		A: receive 120 INR in 1 month		B: receive 100 INR today

I choose A for 6 - I choose B for -10

		Plan A		Plan B
11		A: receive 120 INR in 3 month		B: receive 20 INR today
12		A: receive 120 INR in 3 month		B: receive 40 INR today
13		A: receive 120 INR in 3 month		B: receive 60 INR today
14		A: receive 120 INR in 3 month		B: receive 80 INR today
15		A: receive 120 INR in 3 month		B: receive 100 INR today

I choose A for 11- I choose B for -15

		Plan A		Plan B
16		A: receive 300 INR in 1 week		B: receive 50 INR today
17		A: receive 300 INR in 1 week		B: receive 100 INR today
18		A: receive 300 INR in 1 week		B: receive 150 INR today
19		A: receive 300 INR in 1 week		B: receive 200 INR today
20		A: receive 300 INR in 1 week		B: receive 250 INR today

I choose A for 16 - I choose B for -20

		Plan A		Plan B
21		A: receive 300 INR in 1 month		B: receive 50 INR today
22		A: receive 300 INR in 1 month		B: receive 100 INR today
23		A: receive 300 INR in 1 month		B: receive 150 INR today
24		A: receive 300 INR in 1 month		B: receive 200 INR today
25		A: receive 300 INR in 1 month		B: receive 250 INR today

I choose A for 21 - I choose B for -25

		Plan A		Plan B
26		A: receive 300 INR in 3 month		B: receive 50 INR today
27		A: receive 300 INR in 3 month		B: receive 100 INR today
28		A: receive 300 INR in 3 month		B: receive 150 INR today
29		A: receive 300 INR in 3 month		B: receive 200 INR today
30		A: receive 300 INR in 3 month		B: receive 250 INR today

I choose A for 26 - I choose B for -30

		Plan A		Plan B
31		A: receive 30 INR in 1 week		B: receive 5 INR today
32		A: receive 30 INR in 1 week		B: receive 10 INR today
33		A: receive 30 INR in 1 week		B: receive 15 INR today
34		A: receive 30 INR in 1 week		B: receive 20 INR today
35		A: receive 30 INR in 1 week		B: receive 25 INR today

I choose A for 31 - I choose B for -35

		Plan A		Plan B
36		A: receive 30 INR in 1 month		B: receive 5 INR today
37		A: receive 30 INR in 1 month		B: receive 10 INR today
38		A: receive 30 INR in 1 month		B: receive 15 INR today
39		A: receive 30 INR in 1 month		B: receive 20 INR today
40		A: receive 30 INR in 1 month		B: receive 25 INR today

I choose A for 36 - I choose B for -40

		Plan A		Plan B
41		A: receive 30 INR in 3 month		B: receive 5 INR today
42		A: receive 30 INR in 3 month		B: receive 10 INR today
43		A: receive 30 INR in 3 month		B: receive 15 INR today
44		A: receive 30 INR in 3 month		B: receive 20 INR today
45		A: receive 30 INR in 3 month		B: receive 25 INR today

I choose A for 41 - I choose B for -45

		Plan A		Plan B
46		A: receive 240 INR in 3 days		B: receive 40 INR today
47		A: receive 240 INR in 3 days		B: receive 80 INR today
48		A: receive 240 INR in 3 days		B: receive 120 INR today
49		A: receive 240 INR in 3 days		B: receive 160 INR today
50		A: receive 240 INR in 3 days		B: receive 200 INR today

I choose A for 46- I choose B for -50

	Plan A	Plan B
51	A: receive 240 INR in 2 week	B: receive 40 INR today
52	A: receive 240 INR in 2 week	B: receive 80 INR today
53	A: receive 240 INR in 2 week	B: receive 120 INR today
54	A: receive 240 INR in 2 week	B: receive 160 INR today
55	A: receive 240 INR in 2 week	B: receive 200 INR today

I choose A for 51 - I choose B for -55

	Plan A	Plan B
56	A: receive 240 INR in 2 month	B: receive 40 INR today
57	A: receive 240 INR in 2 month	B: receive 80 INR today
58	A: receive 240 INR in 2 month	B: receive 120 INR today
59	A: receive 240 INR in 2 month	B: receive 160 INR today
60	A: receive 240 INR in 2 month	B: receive 200 INR today

I choose A for 56- I choose B for -60

	Plan A	Plan B
61	A: receive 60 INR in 3 days	B: receive 10 INR today
62	A: receive 60 INR in 3 days	B: receive 20 INR today
63	A: receive 60 INR in 3 days	B: receive 30 INR today
64	A: receive 60 INR in 3 days	B: receive 40 INR today
65	A: receive 60 INR in 3 days	B: receive 50 INR today

I choose A for 61 - I choose B for -65

	Plan A	Plan B
66	A: receive 60 INR in 2 weeks	B: receive 10 INR today
67	A: receive 60 INR in 2 weeks	B: receive 20 INR today
68	A: receive 60 INR in 2 weeks	B: receive 30 INR today
69	A: receive 60 INR in 2 weeks	B: receive 40 INR today
70	A: receive 60 INR in 2 weeks	B: receive 50 INR today

I choose A for 66 - I choose B for -70

	Plan A	Plan B
71	A: receive 60 INR in 2 months	B: receive 10 INR today
72	A: receive 60 INR in 2 months	B: receive 20 INR today
73	A: receive 60 INR in 2 months	B: receive 30 INR today
74	A: receive 60 INR in 2 months	B: receive 40 INR today
75	A: receive 60 INR in 2 months	B: receive 50 INR today

I choose A for 71 - I choose B for -75

Appendix C: Tables

C1 Experiment tables

Table C1: Risk curvature parameter values (sigma σ)

σ	Switching question in Series 1														
Series 2	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**Never**
1	1.50	1.40	1.35	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.65	0.55	0.50
2	1.40	1.30	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.60	0.55	0.50
3	1.30	1.20	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45
4	1.20	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.50	0.45	0.40
5	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.40	0.35
6	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35
7	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30
8	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25
9	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20
10	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20
11	0.80	0.70	0.65	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15
12	0.75	0.65	0.60	0.55	0.50	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20	0.15	0.10
13	0.65	0.60	0.55	0.50	0.45	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15	0.10	0.10
14	0.60	0.55	0.50	0.45	0.40	0.35	0.35	0.30	0.25	0.20	0.15	0.10	0.10	0.10	0.05
Never	0.50	0.45	0.40	0.40	0.35	0.30	0.30	0.25	0.20	0.15	0.10	0.10	0.05	0.05	0.05

Note: Similar to Tanaka et al. (2010) σ is approximated to the nearest .05 increments. When subjects do not switch, the approximate values at the boundaries were used.

Table C2: Probability weighing parameter values (alpha α)

α	Switching question in Series 1														
Series 2	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**Never**
1	0.60	0.75	0.75	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30	1.40	1.45
2	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.35	1.40
3	0.55	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30
4	0.50	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25
5	0.45	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20
6	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15
7	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10
8	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05
9	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00
10	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
11	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
12	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85
13	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80
14	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
Never	0.05	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.45	0.55	0.55	0.65	0.60

Note: Similar to Tanaka et al. (2010) α is approximated to the nearest .05 increments. When subjects do not switch, the approximate values at the boundaries were used.

Table C3: Lambda Min

Switch →	1	2	3	4	5	6	7
Sigma ↓							
0.05	0.116858333	1.226533333	2.001025	2.410583333	4.738025	5.888358333	10.40936667
0.1	0.122808333	1.238433333	1.955408333	2.371908333	4.585308333	5.717791667	10.16938333
0.15	0.12975	1.250333333	1.91475	2.339183333	4.447466667	5.565075	9.95915
0.2	0.136691667	1.262233333	1.878058333	2.311416667	4.323508333	5.428225	9.775691667
0.25	0.143633333	1.275125	1.845333333	2.288608333	4.212441667	5.308233333	9.618016667
0.3	0.151566667	1.289008333	1.816575	2.269766667	4.114266667	5.201133333	9.484141667
0.35	0.1595	1.302891667	1.790791667	2.255883333	4.026008333	5.108908333	9.374066667
0.4	0.167433333	1.316775	1.768975	2.246958333	3.948658333	5.028583333	9.285808333
0.45	0.176358333	1.33165	1.750133333	2.241008333	3.881225	4.960158333	9.218375
0.5	0.185283333	1.346525	1.734266667	2.239025	3.821725	4.902641667	9.171766667
0.55	0.194208333	1.362391667	1.721375	2.241008333	3.772141667	4.856033333	9.143008333
0.6	0.204125	1.37925	1.710466667	2.246958333	3.7295	4.819341667	9.134083333
0.65	0.214041667	1.396108333	1.702533333	2.256875	3.6938	4.792566667	9.142016667
0.7	0.223958333	1.412966667	1.696583333	2.269766667	3.666033333	4.773725	9.1678
0.75	0.234866667	1.431808333	1.693608333	2.285633333	3.644216667	4.7648	9.210441667
0.8	0.245775	1.449658333	1.691625	2.305466667	3.629341667	4.762816667	9.26895
0.85	0.257675	1.469491667	1.692616667	2.328275	3.620416667	4.769758333	9.345308333
0.9	0.269575	1.488333333	1.695591667	2.35505	3.61645	4.783641667	9.436541667
0.95	0.281475	1.509158333	1.70055	2.3848	3.618433333	4.805458333	9.543641667
1	0.294366667	1.529983333	1.7065	2.417525	3.625375	4.834216667	9.6676
1.05	0.307258333	1.5518	1.714433333	2.453225	3.637275	4.869916667	9.806433333
1.1	0.321141667	1.573616667	1.72435	2.4919	3.654133333	4.911566667	9.961133333
1.15	0.335025	1.596425	1.735258333	2.534541667	3.67595	4.96115	10.1317
1.2	0.3499	1.619233333	1.747158333	2.579166667	3.701733333	5.017675	10.31813333
1.25	0.364775	1.643033333	1.762033333	2.627758333	3.732475	5.079158333	10.521425
1.3	0.37965	1.667825	1.776908333	2.679325	3.767183333	5.148575	10.74058333
1.35	0.395516667	1.692616667	1.793766667	2.733866667	3.805858333	5.223941667	10.9766
1.4	0.412375	1.7184	1.811616667	2.791383333	3.849491667	5.30625	11.229475
1.45	0.429233333	1.745175	1.83145	2.852866667	3.897091667	5.394508333	11.49920833
1.5	0.446091667	1.77195	1.851283333	2.917325	3.947666667	5.488716667	11.78778333

Table C4: Lambda Max

	Switch →	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Sigma ↓								
0.05	0.11609475	1.226136667	2.00081675	2.40981975	4.737568833	5.887733583	10.40925758	12
0.1	0.12252075	1.237630083	1.955338917	2.37173975	4.584643917	5.717038	10.16928417	12
0.15	0.129234333	1.249559833	1.914393	2.338915583	4.44686175	5.564251917	9.958445917	12
0.2	0.1362355	1.261955667	1.877691417	2.31110925	4.323052167	5.428086167	9.775007417	12
0.25	0.143534167	1.274817583	1.844976333	2.2881125	4.212183833	5.3073805	9.617362167	12
0.3	0.15114025	1.288145583	1.816029583	2.269707167	4.113294833	5.2011135	9.48407225	12
0.35	0.159063667	1.301969417	1.790613167	2.255724667	4.025532333	5.108313333	9.37387825	12
0.4	0.167304417	1.316279167	1.768538667	2.245976583	3.948112917	5.028137083	9.28561	12
0.45	0.175872417	1.331094667	1.749597833	2.240314167	3.8803325	4.959801333	9.218265917	12
0.5	0.184777583	1.346415917	1.733622083	2.2386085	3.8215465	4.902621833	9.17092375	12
0.55	0.19403975	1.362252833	1.72045275	2.24072075	3.77117975	4.855954	9.142790167	12
0.6	0.203639083	1.378615333	1.70992125	2.246541833	3.728706667	4.8192425	9.133161083	12
0.65	0.213605333	1.39552325	1.701898667	2.255972583	3.693661167	4.791981583	9.1414415	12
0.7	0.223948417	1.41295675	1.696246167	2.268913833	3.665597	4.773715083	9.167105833	12
0.75	0.234658417	1.4309555	1.69284475	2.285296167	3.64414725	4.764036417	9.209707833	12
0.8	0.24574525	1.449499667	1.691585333	2.305050167	3.628954917	4.762588583	9.2688905	12
0.85	0.257238667	1.468609083	1.692348917	2.328106417	3.619702667	4.76905425	9.344376167	12
0.9	0.269118833	1.488293667	1.69504625	2.35442525	3.61612275	4.78315575	9.435926833	12
0.95	0.281405583	1.508563333	1.699578167	2.383947167	3.61796725	4.804655083	9.543383833	12
1	0.294108833	1.529408167	1.70587525	2.41666225	3.624998167	4.833324167	9.666657917	12
1.05	0.3072385	1.550848	1.71384825	2.452530833	3.637017167	4.869004333	9.805709417	12
1.1	0.320794583	1.572882833	1.72342775	2.491523167	3.653865583	4.911546833	9.960558167	12
1.15	0.334787	1.5955325	1.73455425	2.533649167	3.67538475	4.960802917	10.13126367	12
1.2	0.34921575	1.618797	1.747148417	2.578898917	3.701425917	5.016703167	10.31796475	12
1.25	0.364100667	1.642676333	1.761170583	2.6272625	3.731889917	5.079148417	10.52082008	12
1.3	0.379451667	1.667180417	1.776571167	2.678749833	3.766667667	5.148099	10.74006767	12
1.35	0.39526875	1.692319167	1.79328075	2.733390667	3.805669917	5.223525167	10.97598517	12
1.4	0.411551917	1.7181025	1.8112795	2.791185	3.848847083	5.305397167	11.22888992	12
1.45	0.428330917	1.744530417	1.830507917	2.852162583	3.896119833	5.393734833	11.49913892	12
1.5	0.445595833	1.771612833	1.850946167	2.916363083	3.947458417	5.488567917	11.78717842	12

B2 Life microinsurance

	(1) Life insurance	(2) Life insurance	(3) Life insurance	(4) Life insurance	(5) Life insurance	(6) Life insurance	(7) Life insurance	(8) Life insurance	(9) Life insurance	(10) Life insurance
main										
Risk	0.0175*	0.0164*	0.0183*	0.0176*	0.00216	0.0163	0.0179	0.0159	0.0206	0.000410
	(0.00917)	(0.00982)	(0.00936)	(0.0101)	(0.00153)	(0.0112)	(0.0113)	(0.0115)	(0.0133)	(0.00226)
Education		0.0561*		0.0541*	0.00542		0.0665		0.0766	0
		(0.0314)		(0.0309)	(0.00583)		(0.0676)		(0.0702)	(.)
Male		-0.408		-0.443	-0.0871**		0.662		0.808	0
		(0.306)		(0.312)	(0.0431)		(0.588)		(0.683)	(.)
Age (18-34)		-0.854		-0.837	-0.0881		1.292		1.555	0
		(0.568)		(0.576)	(0.0804)		(0.951)		(1.128)	(.)
Age (35-45)		0.314		0.400	0.119		1.924**		2.321**	0
		(0.449)		(0.464)	(0.0877)		(0.865)		(1.016)	(.)
No. of children		-0.115		-0.142	0.0518		-0.664**		-0.769**	0
		(0.208)		(0.214)	(0.0823)		(0.315)		(0.370)	(.)
P.C. Cons quartile 1		-0.806*		-0.814*	-0.0652		-1.883**		-2.351**	-0.314**
		(0.428)		(0.445)	(0.0926)		(0.811)		(0.945)	(0.130)
P.C. Cons quartile 2		-1.112**		-1.119**	-0.119		-1.326**		-1.543**	-0.239**
		(0.457)		(0.464)	(0.0794)		(0.561)		(0.663)	(0.117)
P.C. Cons quartile 3		-1.131**		-1.170**	-0.125		-2.065***		-2.412**	-0.349***
		(0.453)		(0.473)	(0.0853)		(0.739)		(0.956)	(0.126)
Shock - Illness			-0.107	-0.178	-0.0147			-0.445	-0.628	-0.00711
			(0.312)	(0.318)	(0.0508)			(0.408)	(0.393)	(0.0661)
Shock - Death			0.566	0.429	0.0630			0.276	1.044	0.116
			(0.539)	(0.596)	(0.0986)			(0.718)	(0.988)	(0.140)
Shock - Injury			-0.188	-0.401	-0.0703			-0.372	-0.686	-0.117
			(0.544)	(0.604)	(0.100)			(0.637)	(0.770)	(0.107)
Constant	-2.272***	-1.520**	-2.306***	-1.545**	0.117	-2.049***	-2.043**	-1.965***	-2.218*	0.378***
	(0.501)	(0.646)	(0.532)	(0.693)	(0.126)	(0.576)	(0.958)	(0.608)	(1.143)	(0.124)
/										
lnsig2u	0.790*	0.899*	0.807*	0.995*		0.0799	0.0893	0.125	0.403	
	(0.472)	(0.489)	(0.479)	(0.519)		(0.765)	(0.797)	(0.768)	(0.900)	
Household FE	No	No	No	No	Yes	No	No	No	No	No
Individual FE	No	No	No	No	No	No	No	No	No	Yes
Observations	329	328	329	328	328	159	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C5: Life insurance: Risk 1 and shocks (Panel)

	(1) Life insurance	(2) Life insurance	(3) Life insurance	(4) Life insurance	(5) Life insurance	(6) Life insurance	(7) Life insurance	(8) Life insurance	(9) Life insurance	(10) Life insurance
main										
time	-2.269	-2.364	-2.253	-2.327	-0.0944	-2.096	-1.983	-1.840	-1.748	0.197
	(1.396)	(1.489)	(1.388)	(1.522)	(0.217)	(1.768)	(1.917)	(1.763)	(2.054)	(0.315)
Education		0.0584*		0.0557*	0.00557		0.0771		0.0862	0
		(0.0323)		(0.0312)	(0.00615)		(0.0663)		(0.0672)	(.)
Male		-0.373		-0.393	-0.0844**		0.709		0.831	0
		(0.299)		(0.302)	(0.0422)		(0.601)		(0.687)	(.)
Age (18-34)		-0.852		-0.830	-0.0900		1.119		1.289	0
		(0.552)		(0.552)	(0.0805)		(0.953)		(1.079)	(.)
Age (35-45)		0.314		0.373	0.125		1.655**		1.921**	0
		(0.426)		(0.427)	(0.0914)		(0.838)		(0.936)	(.)
No. of children		-0.130		-0.150	0.0828		-0.562*		-0.621*	0
		(0.194)		(0.197)	(0.0843)		(0.294)		(0.329)	(.)
P.C. Cons quartile 1		-0.796*		-0.801*	-0.0762		-1.838**		-2.214**	-0.316**
		(0.421)		(0.432)	(0.0918)		(0.804)		(0.871)	(0.128)
P.C. Cons quartile 2		-1.033**		-1.030**	-0.131*		-1.239**		-1.413**	-0.243**
		(0.431)		(0.429)	(0.0792)		(0.541)		(0.603)	(0.116)
P.C. Cons quartile 3		-1.061**		-1.083**	-0.132		-1.930***		-2.214**	-0.354***
		(0.423)		(0.426)	(0.0842)		(0.720)		(0.878)	(0.125)
Shock - Illness			-0.114	-0.162	-0.0248			-0.395	-0.585	-0.0112
			(0.287)	(0.308)	(0.0500)			(0.378)	(0.381)	(0.0633)
Shock - Death			0.495	0.370	0.0610			0.189	0.921	0.118
			(0.514)	(0.572)	(0.103)			(0.672)	(0.898)	(0.138)
Shock - Injury			-0.0682	-0.249	-0.0693			-0.391	-0.519	-0.109
			(0.551)	(0.596)	(0.100)			(0.598)	(0.688)	(0.109)
Constant	-1.406***	-0.745	-1.392***	-0.715	0.166	-1.257***	-1.327	-1.201***	-1.386	0.376***
	(0.303)	(0.488)	(0.309)	(0.504)	(0.116)	(0.369)	(0.810)	(0.395)	(0.896)	(0.0893)
/										
lnsig2u	0.635	0.775	0.612	0.820		-0.0955	-0.0281	-0.0598	0.217	
	(0.473)	(0.489)	(0.472)	(0.500)		(0.826)	(0.889)	(0.837)	(0.951)	
Household FE	No	No	No	No	Yes	No	No	No	No	No
Individual FE	No	No	No	No	No	No	No	No	No	Yes
Observations	329	328	329	328	328	159	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C6: Life insurance: Time 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance
Life insurance									
Present biased	0.197				0.0705				0.0760
	(0.293)				(0.318)				(0.311)
Risk averse		-0.185				-0.0229			0.0484
		(0.299)				(0.296)			(0.301)
Probability overweighting			-0.0411				0.0547		0.0408
			(0.260)				(0.262)		(0.270)
Loss averse				0.224				0.216	0.201
				(0.236)				(0.237)	(0.247)
Education					0.0623*	0.0619*	0.0625*		0.0618*
					(0.0355)	(0.0354)	(0.0353)		(0.0358)
Male					-0.404	-0.407	-0.409	-0.283	-0.378
					(0.291)	(0.290)	(0.289)	(0.260)	(0.287)
Age (18-34)					-0.755*	-0.759*	-0.772*	-0.584	-0.758*
					(0.410)	(0.411)	(0.403)	(0.359)	(0.398)
Age (35-45)					-0.120	-0.119	-0.121	-0.0503	-0.112
					(0.332)	(0.330)	(0.328)	(0.323)	(0.333)
No. of children					0.0500	0.0504	0.0522	0.0605	0.0479
					(0.132)	(0.132)	(0.132)	(0.130)	(0.132)
P.C. Cons quartile 1					-0.837**	-0.845**	-0.847**	-0.920***	-0.843**
					(0.334)	(0.332)	(0.336)	(0.344)	(0.330)
P.C. Cons quartile 2					-0.894**	-0.905**	-0.906**	-0.893**	-0.888**
					(0.352)	(0.353)	(0.352)	(0.350)	(0.353)
P.C. Cons quartile 3					-0.789**	-0.783**	-0.786**	-0.774**	-0.764**
					(0.341)	(0.338)	(0.341)	(0.342)	(0.339)
Constant	-1.049***	-0.736***	-0.859***	-1.030***	-0.327	-0.244	-0.303	-0.0962	-0.546
	(0.265)	(0.272)	(0.225)	(0.189)	(0.477)	(0.446)	(0.437)	(0.396)	(0.623)
Observations	166	166	166	166	165	165	165	166	165

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups.

Table C7: Life insurance: Wave 2

Table C8: Life insurance: Wave 2 and shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance
Life insurance									
Present Biased	0.186				0.0532				0.0569
	(0.287)				(0.314)				(0.304)
Shock - Illness	-0.303	-0.298	-0.304	-0.367	-0.267	-0.266	-0.274	-0.311	-0.322
	(0.233)	(0.236)	(0.235)	(0.230)	(0.244)	(0.243)	(0.242)	(0.236)	(0.239)
Shock - Injury	-0.145	-0.155	-0.165	-0.218	-0.118	-0.119	-0.123	-0.153	-0.159
	(0.445)	(0.446)	(0.442)	(0.441)	(0.447)	(0.446)	(0.449)	(0.443)	(0.443)
Shock - Death	0.391	0.427	0.397	0.477	0.435	0.441	0.451	0.518	0.522
	(0.438)	(0.439)	(0.432)	(0.430)	(0.491)	(0.492)	(0.484)	(0.485)	(0.483)
Risk averse		-0.201				-0.0339			0.0910
		(0.309)				(0.300)			(0.309)
Probability overweighting			0.0111				0.107		0.0942
			(0.263)				(0.268)		(0.277)
Loss averse				0.345				0.298	0.314
				(0.238)				(0.248)	(0.257)
Education					0.0591*	0.0587*	0.0597*	0.0568*	0.0579*
					(0.0341)	(0.0341)	(0.0341)	(0.0344)	(0.0345)
Male					-0.404	-0.407	-0.412	-0.362	-0.362
					(0.296)	(0.294)	(0.294)	(0.290)	(0.292)
Age (18-34)					-0.711*	-0.714*	-0.737*	-0.695*	-0.711*
					(0.387)	(0.387)	(0.381)	(0.382)	(0.377)
Age (35-45)					-0.109	-0.109	-0.112	-0.0959	-0.0953
					(0.329)	(0.328)	(0.326)	(0.332)	(0.333)
No. of children					0.0317	0.0321	0.0352	0.0243	0.0258
					(0.138)	(0.139)	(0.138)	(0.139)	(0.140)
P.C. Cons quartile 1					-0.882**	-0.885**	-0.888**	-0.895**	-0.898**
					(0.357)	(0.350)	(0.355)	(0.358)	(0.356)
P.C. Cons quartile 2					-0.900**	-0.906**	-0.908**	-0.893**	-0.890**
					(0.366)	(0.364)	(0.364)	(0.363)	(0.366)
P.C. Cons quartile 3					-0.799**	-0.791**	-0.796**	-0.744**	-0.757**
					(0.344)	(0.340)	(0.345)	(0.345)	(0.342)
Constant	-0.963***	-0.648**	-0.818***	-1.009***	-0.209	-0.134	-0.238	-0.362	-0.563
	(0.280)	(0.278)	(0.239)	(0.214)	(0.510)	(0.468)	(0.455)	(0.422)	(0.646)
Observations	166	166	166	166	165	165	165	165	165

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups.

B3 Health microinsurance

	(1) Health insurance	(2) Health insurance	(3) Health insurance	(4) Health insurance	(5) Health insurance	(6) Health insurance	(7) Health insurance	(8) Health insurance	(9) Health insurance	(10) Health insurance
main										
Risk	0.0123	0.0148*	0.0131	0.0157*	0.00569***	0.0136*	0.0137*	0.0151*	0.0148*	0.00294
	(0.00850)	(0.00852)	(0.00940)	(0.00863)	(0.00169)	(0.00800)	(0.00823)	(0.00850)	(0.00871)	(0.00298)
Education		-0.00139		-0.00538	-0.00266		0.00897		0.00581	0
		(0.0155)		(0.0166)	(0.00462)		(0.0300)		(0.0279)	(.)
Male		-0.555*		-0.555*	-0.314***		-0.448		-0.367	0
		(0.289)		(0.312)	(0.0657)		(0.292)		(0.307)	(.)
Age (18-34)		-0.239		-0.233	-0.0233		-0.309		-0.311	0
		(0.221)		(0.219)	(0.110)		(0.338)		(0.338)	(.)
Age (35-45)		-0.273		-0.273	0.0491		-0.462		-0.504	0
		(0.220)		(0.218)	(0.117)		(0.308)		(0.316)	(.)
No. of children		0.00287		-0.000961	-0.568***		-0.0315		-0.00680	0
		(0.0870)		(0.0902)	(0.217)		(0.146)		(0.143)	(.)
P.C. Cons quartile 1		0.181		0.180	-0.0302		0.351		0.132	-0.0335
		(0.243)		(0.255)	(0.0918)		(0.360)		(0.392)	(0.141)
P.C. Cons quartile 2		0.0327		0.112	0.00727		0.289		0.281	0.00717
		(0.263)		(0.257)	(0.0843)		(0.374)		(0.376)	(0.117)
P.C. Cons quartile 3		0.238		0.272	-0.0277		0.186		0.190	-0.0998
		(0.227)		(0.227)	(0.110)		(0.363)		(0.366)	(0.158)
Shock - Illness			0.0113	-0.00322	-0.159**			0.00340	0.0509	-0.156
			(0.234)	(0.220)	(0.0656)			(0.238)	(0.254)	(0.0970)
Shock - Death			0.949**	0.924**	0.306**			1.337**	1.282**	0.218
			(0.461)	(0.421)	(0.152)			(0.528)	(0.544)	(0.278)
Shock - Injury			-0.490	-0.601	-0.119			0.0110	0.00915	-0.00834
			(0.521)	(0.537)	(0.118)			(0.478)	(0.515)	(0.165)
Constant	-1.391**	-1.213***	-1.462**	-1.274***	0.839***	-1.495***	-1.326***	-1.623***	-1.409***	0.121
	(0.569)	(0.423)	(0.636)	(0.421)	(0.263)	(0.304)	(0.499)	(0.351)	(0.528)	(0.152)
/										
lnsig2u	-14.30	-13.40	-15.13	-12.83		-15.18	-13.94	-13.96	-14.23	
	(985815.7)	(344609.3)	(2706330.9)	(210404.5)		(.)	(.)	(.)	(.)	
Household FE	No	No	No	No	Yes	No	No	No	No	No
Individual FE	No	No	No	No	No	No	No	No	No	Yes
Observations	329	328	329	328	328	159	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C9: Health insurance: Risk 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance
main										
time	-0.587	-0.656	-0.748	-0.779	-0.138	-1.362	-1.735	-1.489	-1.798	0.0233
	(0.749)	(0.781)	(0.789)	(0.819)	(0.295)	(1.158)	(1.177)	(1.148)	(1.182)	(0.417)
Education		0.00413		0.000235	-0.00215		0.0278		0.0262	0
		(0.0138)		(0.0152)	(0.00521)		(0.0310)		(0.0295)	(.)
Male		-0.498		-0.489	-0.306***		-0.382		-0.288	0
		(0.379)		(0.451)	(0.0702)		(0.287)		(0.294)	(.)
Age (18-34)		-0.233		-0.216	-0.0283		-0.315		-0.299	0
		(0.234)		(0.227)	(0.116)		(0.344)		(0.340)	(.)
Age (35-45)		-0.278		-0.278	0.0626		-0.548*		-0.579*	0
		(0.224)		(0.222)	(0.121)		(0.310)		(0.309)	(.)
No. of children		0.00844		0.000544	-0.487**		-0.00696		0.0177	0
		(0.0842)		(0.0903)	(0.219)		(0.139)		(0.136)	(.)
P.C. Cons quartile 1		0.177		0.187	-0.0592		0.409		0.199	-0.0538
		(0.245)		(0.254)	(0.0941)		(0.348)		(0.375)	(0.136)
P.C. Cons quartile 2		0.0282		0.0982	-0.0251		0.277		0.259	-0.00406
		(0.260)		(0.255)	(0.0855)		(0.361)		(0.364)	(0.117)
P.C. Cons quartile 3		0.247		0.282	-0.0466		0.220		0.221	-0.120
		(0.229)		(0.227)	(0.110)		(0.351)		(0.352)	(0.147)
Shock - Illness			-0.0359	-0.0605	-0.185***			0.00477	0.0189	-0.171*
			(0.351)	(0.318)	(0.0656)			(0.239)	(0.252)	(0.101)
Shock - Death			0.918	0.884*	0.298*			1.276**	1.226**	0.212
			(0.558)	(0.490)	(0.163)			(0.539)	(0.553)	(0.297)
Shock - Injury			-0.525	-0.599	-0.115			-0.0738	0.00582	-0.00675
			(0.571)	(0.579)	(0.110)			(0.479)	(0.521)	(0.159)
Constant	-0.922**	-0.722**	-0.933*	-0.727**	0.958***	-0.911***	-0.873**	-0.966***	-0.927**	0.231**
	(0.425)	(0.310)	(0.492)	(0.305)	(0.267)	(0.145)	(0.429)	(0.162)	(0.437)	(0.101)
/										
lnsig2u	-14.41	-15.29	-13.56	-15.11		-13.94	-14.21	-14.25	-15.51	
	(1527516.3)	(3362404.8)	(883714.0)	(3383836.4)		(.)	(.)	(.)	(.)	
Household FE	No	No	No	No	Yes	No	No	No	No	No
Individual FE	No	No	No	No	No	No	No	No	No	Yes
Observations	329	328	329	328	328	159	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C10: health insurance: Time 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance
Health insurance									
Present biased	0.199				0.333				0.258
	(0.474)				(0.535)				(0.527)
Risk averse		0				0			0
		(.)				(.)			(.)
Probability overweighting			-0.682*				-0.750**		-0.542
			(0.363)				(0.375)		(0.353)
Loss averse				-0.0601				-0.333	-0.120
				(0.353)				(0.368)	(0.382)
Education					0.0814*	0.0826*	0.0884*		0.0909*
					(0.0441)	(0.0431)	(0.0525)		(0.0470)
Male					-0.471	-0.440	-0.458	-0.359	-0.423
					(0.508)	(0.580)	(0.549)	(0.461)	(0.575)
Age (18-34)					0.302	0.332	0.366	0.475	0.436
					(0.599)	(0.635)	(0.643)	(0.533)	(0.640)
Age (35-45)					0.360	0.455	0.267	0.415	0.337
					(0.548)	(0.550)	(0.565)	(0.546)	(0.527)
No. of children					0.220	0.280	0.181	0.243	0.259
					(0.168)	(0.231)	(0.169)	(0.166)	(0.206)
P.C. Cons quartile 1					0.0849	-0.0936	-0.0951	-0.0752	-0.150
					(0.470)	(0.533)	(0.451)	(0.495)	(0.518)
P.C. Cons quartile 2					0	0	0	0	0
					(.)	(.)	(.)	(.)	(.)
P.C. Cons quartile 3					-0.589	-0.763	-0.683	-0.664	-0.859
					(0.566)	(0.651)	(0.631)	(0.545)	(0.655)
Constant	-1.890***	-1.645***	-1.296***	-1.691***	-2.723***	-2.366***	-1.858***	-1.694**	-2.174**
	(0.434)	(0.179)	(0.270)	(0.269)	(0.833)	(0.683)	(0.580)	(0.830)	(0.888)
Observations	166	140	166	166	119	100	119	119	100

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups.

Table C11: Health insurance: Wave 2

	(1) Health insurance	(2) Health insurance	(3) Health insurance	(4) Health insurance	(5) Health insurance	(6) Health insurance	(7) Health insurance	(8) Health insurance	(9) Health insurance
Health insurance									
Present Biased	0.129				0.403				0.258
	(0.491)				(0.531)				(0.516)
Shock - Illness	-0.00533	-0.0371	-0.0239	-0.0230	-0.277	-0.153	-0.263	-0.242	-0.182
	(0.347)	(0.357)	(0.356)	(0.336)	(0.428)	(0.466)	(0.442)	(0.438)	(0.462)
Shock - Injury	0	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Shock - Death	0.794*	0.732	0.726*	0.831*	0.660	0.646	0.606	0.652	0.602
	(0.438)	(0.450)	(0.406)	(0.457)	(0.469)	(0.491)	(0.478)	(0.464)	(0.471)
Risk averse		0				0			0
		(.)				(.)			(.)
Probability overweighting			-0.627*				-0.679*		-0.519
			(0.367)				(0.397)		(0.354)
Loss averse				0.113				-0.0763	0.0410
				(0.366)				(0.350)	(0.361)
Education					0.0884*	0.0794*	0.0912*	0.0843*	0.0862*
					(0.0459)	(0.0451)	(0.0515)	(0.0451)	(0.0461)
Male					-0.428	-0.395	-0.419	-0.419	-0.380
					(0.531)	(0.586)	(0.565)	(0.537)	(0.583)
Age (18-34)					0.432	0.360	0.474	0.378	0.474
					(0.570)	(0.617)	(0.607)	(0.570)	(0.628)
Age (35-45)					0.293	0.341	0.229	0.323	0.240
					(0.607)	(0.612)	(0.609)	(0.590)	(0.582)
No. of children					0.254	0.287	0.200	0.238	0.253
					(0.177)	(0.245)	(0.185)	(0.180)	(0.224)
P.C. Cons quartile 1					0.0649	-0.147	-0.125	0.0197	-0.199
					(0.515)	(0.586)	(0.500)	(0.517)	(0.566)
P.C. Cons quartile 2					0	0	0	0	0
					(.)	(.)	(.)	(.)	(.)
P.C. Cons quartile 3					-0.642	-0.740	-0.727	-0.620	-0.818
					(0.571)	(0.655)	(0.640)	(0.568)	(0.671)
Constant	-1.870***	-1.671***	-1.349***	-1.830***	-2.859***	-2.326***	-1.931**	-2.404***	-2.213**
	(0.497)	(0.243)	(0.261)	(0.342)	(0.987)	(0.761)	(0.751)	(0.842)	(0.998)
Observations	152	128	152	152	110	93	110	110	93

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups.

Table C12: Health insurance: Wave 2 and shocks

B4 Marginal effects

B4.1 Margins: Any insurance

Table C13: Marginal effects: Any insurance Risk 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance
Risk	0.00534***	0.00528***	0.00532***	0.00530***	0.00634***	0.00587***	0.00630***	0.00578***
	(0.00151)	(0.00153)	(0.00151)	(0.00151)	(0.00206)	(0.00198)	(0.00209)	(0.00198)
Education		0.0102**		0.00859*		0.00714		0.00655
		(0.00510)		(0.00444)		(0.0102)		(0.00916)
Male		-0.131**		-0.132**		0.0506		0.0766
		(0.0527)		(0.0521)		(0.0861)		(0.0846)
Age (18-34)		-0.139*		-0.130*		0.0922		0.0919
		(0.0747)		(0.0717)		(0.115)		(0.111)
Age (35-45)		-0.0615		-0.0538		0.0888		0.0900
		(0.0723)		(0.0710)		(0.0983)		(0.0948)
No. of children		-0.0190		-0.0201		-0.0782*		-0.0700*
		(0.0294)		(0.0285)		(0.0405)		(0.0393)
P.C. Cons quartile 1		-0.0991		-0.0955		-0.178		-0.232**
		(0.0784)		(0.0792)		(0.109)		(0.107)
P.C. Cons quartile 2		-0.152**		-0.136*		-0.111		-0.121
		(0.0772)		(0.0752)		(0.109)		(0.106)
P.C. Cons quartile 3		-0.102		-0.0949		-0.194*		-0.191*
		(0.0785)		(0.0761)		(0.109)		(0.107)
Shock - Illness			-0.0403	-0.0423			-0.0762	-0.0620
			(0.0532)	(0.0528)			(0.0712)	(0.0748)
Shock - Death			0.331***	0.295***			0.459**	0.477**
			(0.114)	(0.105)			(0.182)	(0.200)
Shock - Injury			-0.132	-0.154*			-0.113	-0.105
			(0.0988)	(0.0934)			(0.132)	(0.111)
Observations	329	328	329	328	159	159	159	159

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C14: Marginal effects: Any insurance Time 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance
time	-0.534**	-0.524**	-0.562**	-0.535**	-0.635*	-0.648*	-0.616*	-0.622
	(0.246)	(0.241)	(0.240)	(0.238)	(0.351)	(0.367)	(0.344)	(0.403)
Education		0.0129**		0.0111**		0.0139		0.0133
		(0.00585)		(0.00507)		(0.0103)		(0.00924)
Male		-0.107*		-0.105*		0.0775		0.105
		(0.0549)		(0.0540)		(0.0859)		(0.0844)
Age (18-34)		-0.134*		-0.122*		0.0896		0.0966
		(0.0766)		(0.0729)		(0.122)		(0.116)
Age (35-45)		-0.0635		-0.0565		0.0497		0.0544
		(0.0712)		(0.0697)		(0.0975)		(0.0921)
No. of children		-0.0211		-0.0228		-0.0654*		-0.0578
		(0.0284)		(0.0277)		(0.0385)		(0.0376)
P.C. Cons quartile 1		-0.0988		-0.0958		-0.161		-0.215*
		(0.0789)		(0.0797)		(0.115)		(0.114)
P.C. Cons quartile 2		-0.152**		-0.138*		-0.111		-0.124
		(0.0768)		(0.0749)		(0.108)		(0.106)
P.C. Cons quartile 3		-0.0884		-0.0807		-0.179		-0.180
		(0.0781)		(0.0755)		(0.110)		(0.114)
Shock - Illness			-0.0473	-0.0451			-0.0742	-0.0717
			(0.0534)	(0.0538)			(0.0736)	(0.0854)
Shock - Death			0.351***	0.313***			0.441**	0.461**
			(0.112)	(0.105)			(0.186)	(0.210)
Shock - Injury			-0.124	-0.133			-0.155	-0.104
			(0.111)	(0.106)			(0.141)	(0.117)
Observations	329	328	329	328	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C15: Marginal effects: Any insurance Wave 1

	(1) Any insurance	(2) Any insurance	(3) Any insurance	(4) Any insurance	(5) Any insurance	(6) Any insurance	(7) Any insurance	(8) Any insurance	(9) Any insurance
Present biased	0.0449				0.0204				0.0197
	(0.0809)				(0.0806)				(0.0788)
Risk averse		-0.0231				0.0163			0.0226
		(0.0859)				(0.0785)			(0.0798)
Probability overweighting			-0.0426				-0.0230		-0.0239
			(0.0719)				(0.0675)		(0.0691)
Loss averse				0.0488				0.0378	0.0396
				(0.0653)				(0.0617)	(0.0632)
Education					0.0170**	0.0169**	0.0167**		0.0166**
					(0.00825)	(0.00821)	(0.00821)		(0.00830)
Male					-0.0682	-0.0682	-0.0678	-0.0399	-0.0618
					(0.0719)	(0.0718)	(0.0717)	(0.0677)	(0.0714)
Age (18-34)					-0.113	-0.114	-0.110	-0.0693	-0.107
					(0.0912)	(0.0911)	(0.0900)	(0.0858)	(0.0894)
Age (35-45)					-0.00621	-0.00442	-0.00403	0.0125	-0.00181
					(0.0941)	(0.0934)	(0.0930)	(0.0905)	(0.0938)
No. of children					0.0264	0.0261	0.0253	0.0288	0.0241
					(0.0328)	(0.0329)	(0.0326)	(0.0327)	(0.0324)
P.C. Cons quartile 1					-0.186*	-0.192*	-0.191*	-0.215*	-0.191*
					(0.106)	(0.106)	(0.107)	(0.110)	(0.105)
P.C. Cons quartile 2					-0.266***	-0.271***	-0.270***	-0.276**	-0.266***
					(0.103)	(0.104)	(0.103)	(0.108)	(0.103)
P.C. Cons quartile 3					-0.216**	-0.219**	-0.217**	-0.223**	-0.214**
					(0.107)	(0.107)	(0.108)	(0.112)	(0.107)
Observations	166	166	166	166	165	165	165	166	165

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups.

Table C16: Marginal effects: Any insurance Wave 1 and shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance	Any insurance
Present Biased	0.0357				0.0128				0.0139
	(0.0763)				(0.0761)				(0.0738)
Shock - Illness	-0.0745	-0.0733	-0.0727	-0.0908	-0.0604	-0.0607	-0.0602	-0.0717	-0.0735
	(0.0620)	(0.0630)	(0.0628)	(0.0605)	(0.0601)	(0.0601)	(0.0603)	(0.0581)	(0.0590)
Shock - Injury	-0.0587	-0.0609	-0.0630	-0.0763	-0.0302	-0.0310	-0.0307	-0.0410	-0.0427
	(0.121)	(0.122)	(0.121)	(0.119)	(0.117)	(0.116)	(0.117)	(0.116)	(0.115)
Shock - Death	0.247**	0.254**	0.248**	0.271***	0.254**	0.254**	0.255**	0.273***	0.269***
	(0.109)	(0.109)	(0.108)	(0.103)	(0.110)	(0.109)	(0.109)	(0.102)	(0.103)
Risk averse		-0.0360				0.00446			0.0274
		(0.0849)				(0.0757)			(0.0771)
Probability overweighting			-0.0248				-0.00767		-0.0107
			(0.0703)				(0.0668)		(0.0682)
Loss averse				0.0927				0.0712	0.0785
				(0.0627)				(0.0593)	(0.0615)
Education					0.0156**	0.0156**	0.0155**	0.0150*	0.0150**
					(0.00762)	(0.00763)	(0.00761)	(0.00764)	(0.00766)
Male					-0.0575	-0.0578	-0.0577	-0.0480	-0.0463
					(0.0699)	(0.0696)	(0.0697)	(0.0683)	(0.0688)
Age (18-34)					-0.102	-0.103	-0.102	-0.0975	-0.0944
					(0.0839)	(0.0837)	(0.0830)	(0.0832)	(0.0826)
Age (35-45)					-0.00563	-0.00487	-0.00481	-0.00304	-0.00118
					(0.0896)	(0.0891)	(0.0888)	(0.0893)	(0.0897)
No. of children					0.0248	0.0246	0.0244	0.0223	0.0210
					(0.0334)	(0.0335)	(0.0330)	(0.0332)	(0.0329)
P.C. Cons quartile 1					-0.201*	-0.204*	-0.204*	-0.201*	-0.204*
					(0.109)	(0.108)	(0.109)	(0.107)	(0.107)
P.C. Cons quartile 2					-0.259**	-0.262**	-0.262**	-0.254**	-0.255**
					(0.104)	(0.105)	(0.104)	(0.103)	(0.104)
P.C. Cons quartile 3					-0.211**	-0.212**	-0.211**	-0.195*	-0.200*
					(0.105)	(0.105)	(0.106)	(0.105)	(0.105)
Observations	166	166	166	166	165	165	165	165	165

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups.

B4.2 Margins: life insurance

Table C17: Marginal effects: Life insurance Risk 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance
Risk	0.00248**	0.00208*	0.00256**	0.00214*	0.00259	0.00235*	0.00246	0.00234*
	(0.00122)	(0.00117)	(0.00122)	(0.00115)	(0.00173)	(0.00134)	(0.00173)	(0.00129)
Education		0.00711*		0.00657*		0.00870		0.00872
		(0.00373)		(0.00358)		(0.00783)		(0.00743)
Male		-0.0516		-0.0539		0.0866		0.0919
		(0.0378)		(0.0371)		(0.0726)		(0.0714)
Age (18-34)		-0.0957		-0.0895		0.123		0.126
		(0.0619)		(0.0596)		(0.0909)		(0.0869)
Age (35-45)		0.0465		0.0568		0.219***		0.228***
		(0.0649)		(0.0636)		(0.0674)		(0.0652)
No. of children		-0.0145		-0.0172		-0.0869**		-0.0875***
		(0.0264)		(0.0263)		(0.0337)		(0.0330)
P.C. Cons quartile 1		-0.122*		-0.119*		-0.316***		-0.338***
		(0.0640)		(0.0655)		(0.0947)		(0.0930)
P.C. Cons quartile 2		-0.158***		-0.153**		-0.254***		-0.262***
		(0.0596)		(0.0597)		(0.0912)		(0.0899)
P.C. Cons quartile 3		-0.160***		-0.159***		-0.331***		-0.342***
		(0.0605)		(0.0595)		(0.0896)		(0.0894)
Shock - Illness			-0.0149	-0.0217			-0.0687	-0.0715
			(0.0437)	(0.0388)			(0.0631)	(0.0460)
Shock - Death			0.0790	0.0521			0.0427	0.119
			(0.0745)	(0.0725)			(0.110)	(0.108)
Shock - Injury			-0.0263	-0.0487			-0.0575	-0.0781
			(0.0756)	(0.0717)			(0.0983)	(0.0850)
Observations	329	328	329	328	159	159	159	159

Robust standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C18: Marginal effects: Life insurance Time 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance	Life insurance
time	-0.336	-0.311	-0.335	-0.300	-0.347	-0.265	-0.299	-0.210
	(0.208)	(0.194)	(0.206)	(0.194)	(0.302)	(0.266)	(0.297)	(0.251)
Education		0.00768*		0.00718*		0.0103		0.0104
		(0.00400)		(0.00380)		(0.00781)		(0.00752)
Male		-0.0491		-0.0507		0.0949		0.1000
		(0.0380)		(0.0377)		(0.0758)		(0.0760)
Age (18-34)		-0.0983		-0.0936		0.113		0.115
		(0.0607)		(0.0590)		(0.0965)		(0.0922)
Age (35-45)		0.0487		0.0566		0.197***		0.204***
		(0.0645)		(0.0631)		(0.0716)		(0.0696)
No. of children		-0.0171		-0.0194		-0.0753**		-0.0748**
		(0.0257)		(0.0257)		(0.0335)		(0.0329)
P.C. Cons quartile 1		-0.124*		-0.123*		-0.315***		-0.338***
		(0.0643)		(0.0664)		(0.0977)		(0.0960)
P.C. Cons quartile 2		-0.153**		-0.150**		-0.247***		-0.259***
		(0.0602)		(0.0607)		(0.0951)		(0.0949)
P.C. Cons quartile 3		-0.156***		-0.156***		-0.322***		-0.338***
		(0.0600)		(0.0591)		(0.0924)		(0.0933)
Shock - Illness			-0.0170	-0.0209			-0.0641	-0.0704
			(0.0427)	(0.0400)			(0.0623)	(0.0488)
Shock - Death			0.0737	0.0477			0.0308	0.111
			(0.0761)	(0.0741)			(0.108)	(0.106)
Shock - Injury			-0.0101	-0.0322			-0.0635	-0.0624
			(0.0819)	(0.0760)			(0.0972)	(0.0814)
Observations	329	328	329	328	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).

Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

B4.3 Margins: health insurance

Table C19: Marginal effects: Health insurance Risk 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance
Risk	0.00298**	0.00348**	0.00308**	0.00355***	0.00311*	0.00306*	0.00327*	0.00313*
	(0.00143)	(0.00144)	(0.00139)	(0.00135)	(0.00180)	(0.00177)	(0.00181)	(0.00178)
Education		-0.000327		-0.00122		0.00200		0.00123
		(0.00361)		(0.00361)		(0.00669)		(0.00591)
Male		-0.131***		-0.126***		-0.100		-0.0777
		(0.0459)		(0.0468)		(0.0626)		(0.0635)
Age (18-34)		-0.0591		-0.0555		-0.0768		-0.0743
		(0.0533)		(0.0524)		(0.0837)		(0.0805)
Age (35-45)		-0.0664		-0.0639		-0.107		-0.110
		(0.0512)		(0.0513)		(0.0725)		(0.0699)
No. of children		0.000676		-0.000218		-0.00703		-0.00144
		(0.0205)		(0.0204)		(0.0326)		(0.0302)
P.C. Cons quartile 1		0.0413		0.0385		0.0754		0.0254
		(0.0569)		(0.0557)		(0.0756)		(0.0755)
P.C. Cons quartile 2		0.00693		0.0232		0.0601		0.0585
		(0.0560)		(0.0546)		(0.0774)		(0.0780)
P.C. Cons quartile 3		0.0559		0.0609		0.0365		0.0377
		(0.0554)		(0.0529)		(0.0701)		(0.0712)
Shock - Illness			0.00266	-0.000729			0.000736	0.0108
			(0.0556)	(0.0497)			(0.0514)	(0.0534)
Shock - Death			0.223***	0.209***			0.289***	0.271**
			(0.0748)	(0.0788)			(0.103)	(0.106)
Shock - Injury			-0.115	-0.136			0.00237	0.00194
			(0.110)	(0.110)			(0.103)	(0.109)
Observations	329	328	329	328	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C20: Marginal effects: Health insurance Time 1 and shocks (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance	Health insurance
time	-0.145	-0.157	-0.178	-0.180	-0.316	-0.388	-0.327	-0.383
	(0.186)	(0.189)	(0.187)	(0.190)	(0.266)	(0.259)	(0.249)	(0.247)
Education		0.000991		0.0000543		0.00622		0.00558
		(0.00340)		(0.00352)		(0.00694)		(0.00630)
Male		-0.119**		-0.113*		-0.0855		-0.0614
		(0.0541)		(0.0600)		(0.0626)		(0.0619)
Age (18-34)		-0.0589		-0.0526		-0.0805		-0.0738
		(0.0546)		(0.0531)		(0.0872)		(0.0828)
Age (35-45)		-0.0687		-0.0659		-0.126*		-0.126*
		(0.0516)		(0.0520)		(0.0734)		(0.0687)
No. of children		0.00202		0.000126		-0.00156		0.00377
		(0.0203)		(0.0209)		(0.0312)		(0.0290)
P.C. Cons quartile 1		0.0409		0.0409		0.0886		0.0391
		(0.0617)		(0.0611)		(0.0749)		(0.0744)
P.C. Cons quartile 2		0.00607		0.0206		0.0560		0.0525
		(0.0563)		(0.0561)		(0.0735)		(0.0745)
P.C. Cons quartile 3		0.0594		0.0645		0.0431		0.0440
		(0.0593)		(0.0582)		(0.0676)		(0.0690)
Shock - Illness			-0.00856	-0.0140			0.00105	0.00402
			(0.0796)	(0.0681)			(0.0524)	(0.0536)
Shock - Death			0.219***	0.205***			0.280***	0.261**
			(0.0758)	(0.0787)			(0.106)	(0.108)
Shock - Injury			-0.125	-0.139			-0.0162	0.00124
			(0.111)	(0.111)			(0.105)	(0.111)
Observations	329	328	329	328	159	159	159	159

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01
Note: P.C. Cons quartile 1 refers to per capita consumption of the lowest quartile (bottom 25 %).
Age (46+) and P.C. Cons quartile 4 are the base groups. Cols(5) and (10) uses Fixed-effects (FE) model (xtreg)

Table C21: Microinsurance products

SL No.	Insurer	SL NO	Group Category	Members	Premium type	Premium frequency	Premium	Benefits and exclusions
1	Aditya Birla Sun Life Insurance Co. Ltd.	1	ABSLI Group Bima Yojana	5	Single		330	Age - 14-79 Policy term - 1 to 10 yrs Sum - 1k to 200k
2	Bajaj Allianz Life Insurance Co. Ltd.	2	Bajaj Allianz Life Group Sampoorn Suraksha Kavach	5 (min) to unlimited	Single/ regular		max 750 p.a /member	Age - 14-79 Policy term - 0.5 to 3yrs/ 1-10yrs Sum - 1k to 200k
3	Canara HSBC OBC LifeInsurance Co. Ltd.	3	Canara HSBC OrientalBank Of Commerce Life Insurance Sampooma Kavach Plan		Single/ regular	Annual, Half-Yearly, Quarterly & Monthly		Age - 18-60 Policy term - 1 to 10 yrs Sum - 1k to 50k
4	Edleweiss Tokio Life Insurance Co. Ltd.	4	Edelweiss Tokio Life -Jan Suraksha	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	max 750 p.a /member	Age - 18-60 Policy term - 1 to 7 yrs Sum - 1k to 50k
5	Exide Life Insurance Co. ltd.	5	Group Micro TermInsurance	5 (min) to unlimited	2 Single/ regular	Annual, Half-Yearly, Quarterly & Monthly		Age - 18-64 Policy term - Sum - 1k to 200k
6	HDFC Life Insurance Co. ltd.	6	HDFC Life Group Suraksha	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly		Age - 14-69 Policy term - 1 to 10 yrs Sum - 1k to 200k
6	HDFC Life Insurance Co. ltd.	7	HDFC Life Group Jeevan Suraksha	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	1.15 per member to max 750 p.a /member	Age - 18-80 Policy term - 1 to 10 yrs Sum - 1k to 200k
7	ICICI Prudential LifeInsurance Co. Ltd.	8	ICICI Pru Shubh Raksha Credit					
7	ICICI Prudential LifeInsurance Co. Ltd.	9	ICICI Pru Shubh Raksha One	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly		Age - 14-70 Policy term-1to12months Sum - 1k to 200k
7	ICICI Prudential LifeInsurance Co. Ltd.	10	ICICI Pru Shubh Raksha Life	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly		Age - 18-69 Policy term - 1 to 10 yrs Sum - 1k to 200k
8	IDBI Federal Life Insurance Co. Ltd.	11	Group Microsurance Insurance Plan	20 (min)	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	max 750 p.a /member	Age - 18-60 Policy term - 5 yrs Sum - 5k to 50k
9	India First Life Insurance Co. Ltd.	12	India First Life Group MicroInsurance Plan	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	max 750 p.a /member	Age - 14-69 Policy term - 1 to 10 yrs Sum - 1k to 200k
10	Kotak Matindra Life Insurance Co. ltd.	13	Kotak Raksha Group Micro-Insurance Plan	5 (min) to unlimited	2 Single/ regular	Annual, Half-Yearly, Quarterly & Monthly		Age - 18-70 Policy term -1/2-7/5-7yrs Sum - 5k to 200k
11	PNB Met LifeIndia Insurance Co. Ltd.	14	PNB MetLife Bima Yojana	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	max 750 p.a /member	Age - 18-69 Policy term -1-7yrs Sum - 1k to 200k
12	Pramerica Life Insurance Co. Ltd.	15	Pramerica Life Sarv Suraksha	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	max 750 p.a /member	Age - 18-65 Policy term -1 yr Sum - 1k to 200k
12	Pramerica Life Insurance Co. Ltd.	16	Pramerica Life Sampoorna Suraksha	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	max 750 p.a /member	Age - 18-65 Policy term -1 yr Sum - 1k to 200k
13	SBI Life Insurance Co. Ltd.	18	SBI Life Grameen Super Suraksha	5 (min) to unlimited	Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	27.50-20600/35-4900	Age - 18-60 Policy term -2-5yr Sum - 5k to 200k
13	SBI Life Insurance Co. Ltd.	19	SBI Life Shakti		regular	Annual	85-6900	Age - 18-60 Policy term - 5yr Sum - 10k to 200k
14	Shriram Life Insurance Co. Ltd.	20	Shriram Jana Sahay Shriram Life Sujana		Single/ regular	Annual, Half-Yearly, Quarterly & Monthly	27.50-20600/35-4900	Age - 18-65 Policy term - 1yr Sum - 5k to 200k
15	TATA AIA Life Insurance Co. Ltd.	21	-					
16	Life Insurance Corporation of India	22	LIC's One Year Renewable Group Micro Term Assurance Plan	25 (min) to unlimited	regular	Half-Yearly, Quarterly & Monthly		Age - 18-64 Policy term -1/2-7/5-7yrs Sum - 5k to 200k