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# Unpredictability shortens planning horizons

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## Abstract

Recent research has identified intertemporal impulsivity as a critical cognitive variable for explaining the autocatalytic nature of socioeconomic status. However, how exactly this relationship transpires has yet to be clearly identified, with several possible cognitive mechanisms proposed in the literature. We designed an experimental paradigm where participants farmed crops under budgetary constraints and intermittently faced random resource demands. We discovered that, as a result of unpredictable resource shocks, people's preferences shifted from long-term choices to short-term ones. We also found people's self-reported sense-of-control scores to be predictive of the magnitude of their preference shifts. On the basis of these results, we argue that steep inter-temporal discounting arises as a rational adaptation to persistently experiencing long-term planning failures due to unpredictable resource shocks.

**Keywords:** time preference; unpredictability; resource shocks; control; time-perception; future neglect

## Introduction

Economic precarity as the primary driver of poverty-related present-centric behaviour has been prominently established through decades of research (Lewis, 1966; Wilson, 2009, 2012). Multiple accounts of humanistic (Hays, 2004; Lamont, 2009) and empirical investigations (Banerjee & Duflo, 2007; Schilbach, Schofield, & Mullainathan, 2016) have established that the lived experience of poverty leads to specific patterns of behaviour that are detrimental to one's self-interest. Early experiments investigating this phenomenon in the lab demonstrated how the amount of time children could avoid eating a marshmallow to win two in the future could strongly predict future socioeconomic success (Mischel, 2014). More recently, it has been shown that children's ability to delay eating marshmallows can be strongly affected by extraneous factors like whether experimenters offering them marshmallows have previously been trustworthy or deceptive (Kidd, Palmeri, & Aslin, 2013). Other studies have induced such shifts in people's time preferences by creating constraints in their environment (Mani, Mullainathan, Shafir, & Zhao, 2013) or by introducing unexpected income shocks (Haushofer, Schunk, & Fehr, 2013) in the lab. Moreover, field studies like experience effects literature suggest that people who have encountered adverse negative outcomes in certain ventures tend to avoid those avenues in the future; e.g., people who survived a stock market crash are unlikely to put money in equity again, but

they would park their money in bonds (Malmendier & Nagel, 2011, 2016).

Now, what could be the psychological determinant behind such preference shifts? There are two primary viewpoints on this: one implicating mortality reasons (Griskevicius, Tybur, Delton, & Robertson, 2011; Pepper & Nettle, 2017) and the other economic constraints (Shah, Mullainathan, & Shafir, 2012). Pepper and Nettle (2017) propose the mortality risk hypothesis, where they identify eventual mortality doom as the reason people shift to short-term plans (for example, if I am going to die soon, then there is no point in saving for the future). On the other hand, the scarcity theory posits that economic scarcity (such as living on a limited budget or lacking essential resources) is the immediate cause of present-centric behaviour; they propose attentional tunnelling and higher cognitive load as potential mediators of the process.

However, both views have been subjected to criticism. The mortality risk hypothesis is difficult to verify in a laboratory, and the supposed association between savings and income or life expectancy and crime rates appears absent in certain instances (Srivastava & Srinivasan, 2017). The scarcity hypothesis also faces replicability issues (Camerer et al., 2018; González-Arango et al., 2021; Shah, Mullainathan, & Shafir, 2019) and a lack of field evidence for attentional tunnelling or cognitive load causing increases in temporal discounting (de Bruijn & Antonides, 2021). We believe that people living in uncertain, precarious environments with an urgent need for resources are more likely to have their long-term plans fail due to their incapacity to inject resources on demand. This inability to mitigate resource demands leads them to plan on shorter time horizons - a phenomenon we call the '**resource shock**' hypothesis.

We hypothesize that when people operate within budgetary constraints, any urgent, demanding resource shock will result in the failure of long-term plans. Consequently, they will reduce their planning horizon to a timescale in which they can control the consequences of their behaviour. Experiments on event control and agency have shown that the sense of agency is strongly sensitive to the timescale on which people can effectively exercise control (Kumar & Srinivasan, 2017). This finding has a natural corollary: people preferentially choose timescales where they can act most effectively—an ecologically rational strategy.

Our proposal refutes the presence of an all-pervasive ‘scarcity’ mentality among individuals from lower socio-economic classes. Even though we hypothesize about behaviour endemic in people from lower socio-economic strata, we believe anyone encountering unpredictable resource shocks would naturally act in this manner. This idea is corroborated by a recent finding that temporal discounting occurs to varying degrees across 61 countries, is exacerbated by poor financial conditions, and is not limited to people from a specific socio-economic status or mindset (Navajas, Freiras, et al., 2022).

To test our hypothesis, we needed a dynamic and intricate experimental setup comprising a precarious environment with resource constraints, unpredictably high demands, and multiple risky inter-temporal choices to fructify in that environment. Having designed such a paradigm, we conducted two experiments: with experiment 1, we tested out our primary hypothesis, and with experiment 2, we checked whether it was a lack of resources or the unpredictable nature of resource shocks that was leading to this time preference shift. Experiment 2 also tested whether cognitive control or time perception played any role in the process.

### Experiment 1

This was an exploratory study to see if a dynamically precarious game environment could induce a shift in people’s intrinsic time preferences.

### Task Design



Figure 1: A snap-shot of the game GUI.

Our experimental paradigm was designed in the form of a farming simulator on GameMaker: Studio 2.1.5 using GML language, where participants had a choice to make any proportion of a set of three crops: one with low prospect and time risk (rice), one with high prospect and low time risk (apple), and one with low prospect and high time risk (teak), equating the effective profit for apple and teak. Even

though participants were informed of the yield time and profit upon the yield of each crop, they were encouraged to learn about the risk associated with each crop by playing the game (details of which can be found in Table 1).

Crops			
Type	Apple	Rice	Teak
Yield Time	1 trial	1 trial	6 trials
Buying Price	50 coins	50 coins	50 coins
Selling Price	350 coins	275 coins	1700 coins
Loss Factor	0.3 (0.8)	0.2 (0.5)	0.2 (0.5)

Table 1: Table depicting crop attributes for each crop type. Bracketed values in Loss Factor denote increased crop loss on resource shock trials.

Each trial was designed to start with the “crop sow” phase, followed by the “crop growth” phase, and finally, the “crop harvest” phase. Each participant completed 120 trials, which were equally distributed amongst five blocks. The game started with a practice block followed by four randomized, alternating low-variance(LV) and high-variance(HV) blocks (i.e., 24 trials per block).

During the “crop sow” phase, participants sowed crop seeds onto a brown patch of land. Regardless of crop type, a seed-buying price of 50 coins was deducted from their money for each crop. A fixed amount of coins were also debited as a ‘budget’ to elicit the idea of functioning under a constrained pool of money. Lastly, participants had to pay for resources costs (for resources like fertilisers and pesticides) from this budget in the “crop growth” phase <sup>1</sup>.

During the “crop growth” phase, participants could see their crops growing in real-time. As the game went on, people could see the passing month and year, the corresponding resource cost deductions, and the monthly crop loss and land rent debits from their total money, all updated in real-time (as seen on the left-hand side of Figure 1). What are crop losses and land rents? The game’s central idea was to simulate a resource-limited environment with monthly debits that could go overboard with some probability. The resource shock was quantified by trials where the resource cost, sampled from a random, normal distribution, was higher than the budget (around 5% and 33% for low and high variance blocks). Thus, in this phase, the resource input requirements would be “under” budget in most cases, with baseline crop loss and land rent inputs. However, on some occasions, people would face an increased resource demand which would go “over” budget, along with increased crop losses and land rent in those harvest cycles. This trial-level experimental manipulation depicted a precarious environment, which we later called the “resource shock” trial. The crop losses and land rents were sampled from a binomial distribution such

<sup>1</sup>This budget was taken from the cumulative pool of money they were making in the game, but this pool was not lower-bounded at zero, thus removing any possible subsistence or liquidity constraints from game-play.

that the scaled loss factor (as depicted in Table 1) was low in the absence of resource shocks and high otherwise.

Finally, during the “crop harvest” phase, the game paused, and participants harvested the full-grown crops. When harvested, the selling price of each crop was added to their money as income. After harvesting, participants had to sow crops on the plot of land again and start the next trial. Participants’ crop profit, crop loss, resource cost deductions, and land rent were displayed on a ledger for the past ten trials (as seen on the top of Figure 1). They were updated after every trial, and participants were advised to consult them to get a comprehensive view of their incomes and expenses. Lastly, each participant was explicitly asked to play such that they maximised their total money. A ranking-based system was also designed to reward the top performers (up to thrice their participation money) alongside their compensation.

### Sample

Based on pilot data using G\*Power3.1 (Faul, Erdfelder, Lang, & Buchner, 2007), we arrived at a sample size of 72 with power = 0.9, alpha = 0.05, and effect size = 0.35 (using one-tailed one-sample t-test). We collected data from 79 participants. One participant’s data was discarded as she admitted to having played the game desultorily, and another was discarded for incorrect data recording on the part of the game. Six more participants were identified as outliers using a 1.75\*IQR exclusion criterion. The final analysis was carried forward with 71 participants. All participants were recruited with informed consent and monetary compensation. An Institutional Ethics Committee approved the study.

### Results and Discussion

Since our metric of time preference shift was a trial-level change in crop preference, we developed a system of extracting that information before analysing the data. Because the teak harvest was only possible after six trials, we focused our analysis on the difference in the cumulative count of teak plants on the field for six trials before and after each resource shock for each participant. The difference in the cumulative teak on the plot across said six trials ( $\Delta_{teak}$ ) indicated the change in teak preference across each “Resource Shock”(RS) trial<sup>2</sup>. We averaged these differences to quantify the change in teak preference across all RS trials for every participant ( $\delta_{teak} = (\sum_1^m \Delta_{teak})/m$ ). We followed the same analysis procedure for calculating rice and apple preference change. A one-sided one-sample t-test yielded a significant effect ( $M = -0.642$ ,  $SD = 1.786$ ) of budgetary overrun on the shift in teak preference ( $t(70) = -3.031$ ,  $p = .002$ , 95% CI  $[-\infty, -0.289]$ , Cohen’s  $d = -0.36$ ,  $BF_{10} = 16.8$ ). Clearly, as a cohort, our participants reduced their preference

<sup>2</sup>If RS occurred in the last six trials of the game, we used the trials that were available before and after the RS trial to calculate teak preference shift. So, if the RS trial occurred on the second last trial, we calculated the preference shift with one trial before and one trial after that trial. Consequently, the last trial was excluded from the analysis.

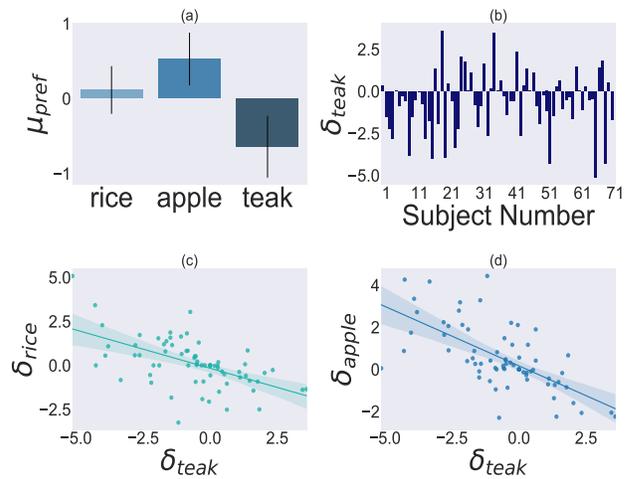


Figure 2: Results of Experiment 1: Panel (a) illustrates the mean change in crop preference ( $\mu_{pref}$ ) across all participants.  $\mu_{rice}$ ,  $\mu_{apple}$ , and  $\mu_{teak}$  are 0.11, 0.53 and -0.64 respectively. Error bars signify 95% CI. Panel (b) shows the teak preference shift ( $\delta_{teak}$ ) data for all participants( $n=71$ ). 44 participants showed negative teak preference. Panel (c) and (d) show the correlation between rice and teak and apple and teak preference change, respectively.

for planting teak after having experienced resource shocks, as predicted by our hypothesis<sup>3</sup>.

However, if people are less likely to plant teak, what do they do instead? A two-sided Wilcoxon signed rank test (since normality was violated) showed that the effect of budgetary overruns on shifts in apple preference ( $Mdn = 0.447$ ) was significant ( $W = 1502.00$ ,  $p = .011$ , 95% CI  $[0.097, 0.902]$ ,  $r = 0.359$ ,  $BF_{10} = 6.45$ ). However, the effect on rice preference ( $Mdn = 0.1$ ) was not significant ( $W = 1016.50$ ,  $p = .613$ , 95% CI  $[-0.264, 0.450]$ ,  $r = 0.075$ ). We also found significant correlations between apple vs teak and rice vs teak, with the first being of higher magnitude than the second. ( $\rho = -0.653$ , 95% CI  $[-0.769, -0.496]$ ,  $p < .001$ ,  $n = 71$  for apple-teak preference and  $\rho = -0.583$ , 95% CI  $[-0.719, -0.405]$ ,  $p < .001$ ,  $n = 71$  for rice-teak preference). Thus, the first experiment’s results indicated that people shifted from making long-term crop choices to short-term ones after facing resource shocks (i.e., from teak to apple).

### Experiment 2

Experiment 1 revealed that resource shocks in a precarious setting reduced people’s temporal planning horizons. However, economic precarity was induced by a combination of resource scarcity and the unpredictability of large shocks, and our design could not differentiate the relative role of both factors in inducing time preference changes. To achieve

<sup>3</sup>Using simulations, we found out that making teak was the optimal choice, one that gives the most profit, in both resource shock and non-resource shock trials.

such differentiation, we used a variation of the previous design. In this new design, on one condition, participants were notified of the coming resource shocks, induced in a strict periodic manner, while the other condition reproduced the unpredictable shocks experienced in Experiment 1. If unpredictability caused the shift in time preferences, task preference would differ between conditions. In addition, we also examined whether control and time perception played a role in the shift in time preference, as seen in Experiment 1.

### Task Design

We introduced some changes in the task design compared to the previous experiment. The changes are listed below; everything else was kept the same.

- Change in the block structure: Here, we started the experiment with the practice block, followed by one LV block, and finally, two concurrent HV blocks. We decided to limit the LV block to one because none of the data from this block was beneficial for analysis, and the two concurrent HV blocks created one extensive treatment block.
- Number of overruns in HV block: Since the HV block had 48 trials in total and was designed so that 33% of the resource costs would exceed budget, we kept the overruns faced by each participant constant at 16 (instead of an average of 10 as in the first experiment). This allowed us to examine the robustness of our hypothesis.
- Pre-sampled ordering of resource shocks: In experiment 1, resource debits were sampled in real-time. In this experiment, however, we had pre-sampled the resource cost debits, and all participants faced the same deductions from their budgets.
- Predictable and unpredictable resource shocks: In the ‘unpredictable’ condition, the resource shocks were randomly dispersed during the HV block, so people could not predict when they would happen. However, in the ‘predictable’ condition, it was regularly timed, i.e., each resource shock occurred every three years in the HV block, giving participants a sense of predictability of the turbulent times. Furthermore, people were notified of incoming turbulence before the experiment and the HV block started.
- Measures of control and time perception: The following questions were presented twice: once at the end of the LV block (i.e., the start of the HV block) and then at the end of the HV block (i.e., just before the game ended).
  - Control: Control has been operationalized in the psychology literature in multiple ways. Based on Rotter’s internal and external locus of control, Lachman and Weaver’s sense of control, Wallstone’s perceived control, and Rothbaum’s primary and secondary control formulations (Lachman & Weaver, 1998; Rothbaum, Weisz, & Snyder, 1982; Rotter, 1966; Wallston,

Wallston, Smith, & Dobbins, 1987), we decided that our state-level control measures would range across time and events, i.e., we inquired about people’s perceived constraints over past events (i.e., resource overruns), perceived mastery over future events (i.e., future planning), and perceived control over all events. Thus, our formulated state-level control questions were:

- \* During the trials, when crop losses increased, I felt that environmental factors were against me. I felt I could do little to change what was happening to me.
- \* I am certain that I can influence my future income in the upcoming trials. Whatever happens to my earnings depends only on me.
- \* I feel certain that I can adjust the environmental conditions according to my needs.

We asked people to rate the answers to these questions on a slider ranging from 0 to 1, where 0 was *strongly disagree* and 1 was *strongly agree*. Multiple trait-level loci of control scales have been designed following Rotter’s scale; however, Duttweiler’s ICI scale has been found to be the most reliable (Furnham & Steele, 1993). For the trait-level control measure in our experiment, we asked participants to complete this questionnaire post-participation.

- Time perception: Recently, researchers have also started to explore how time perception influences temporal discounting: considering a subjective time instead of a linear objective time seems to fit the data better and solve the paradox of time-inconsistency of the discount parameter (Bradford, Dolan, & Galizzi, 2019; Takahashi, Oono, & Radford, 2008; Zauberman, Kim, Malkoc, & Bettman, 2009). Hence, in addition to the three control questions, we also asked participants the following question: How long did the duration of the last trial (i.e., the last six months) feel to you? People were asked to use a slider marked 0 to 1, where 0 was *very short* and 1 was *very long*. This was our state-level time perception question. After the experiment, we also asked participants to complete a time perspective (ZTPi) questionnaire as a trait-level measure.

### Sample

We decided to do a sequential Bayesian data collection whereby we started with a sample size of  $n_{min} = 30$  in each condition and computed  $BF_{10}$  after every participant. We decided to conclude our data collection if the Bayes factor  $BF_{10}$  was greater than three (Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, 2017). We found that this criterion was met with 30 participants for both the unpredictable and predictable conditions ( $BF_{10}$  were 5.775 and 3.151, respectively, with default prior  $r = \sqrt{2}/2$ ). With 1.5\*IQR outlier exclusion criteria, we excluded one participant in the first group and none in the second. Hence, the final data analysis is done with 29 and 30 participants in the first and the second group, respectively. The institutional ethics

committee also approved this experiment.

## Results and Discussion

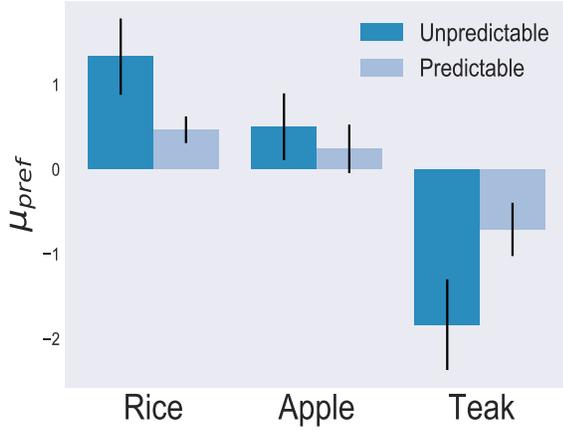


Figure 3: Results of Experiment 2: This diagram shows the mean change in crop preference ( $\mu_{pref}$ ) as found in ‘Unpredictable’ and ‘Predictable’ conditions. Error bars signify standard error.  $\mu_{rice}$ ,  $\mu_{apple}$ , and  $\mu_{teak}$  for the unpredictable condition were found to be 1.33, 0.50, and -1.83, and for the predictable condition to be 0.47, 0.24, and -0.71, respectively.

The Mann-Whitney test (since equality of variance was violated) revealed that the teak preference shift was smaller in magnitude in the predictable condition ( $Mdn = -0.409$ ) compared to the unpredictable condition ( $Mdn = -1.771$ ), and the decrease was statistically significant ( $W = 551.5$ ,  $p = 0.039$ ,  $r = 0.27$ ,  $BF_{10} = 1.906$ ). However, there was no statistically significant change in rice or apple preference shifts. Thus, we found a significant difference only in teak preference change between groups (see Figure 3).

We performed post hoc tests on each condition, comparing the mean change in crop preference against a null change. For the unpredictable condition, we see a similar trend as in the first experiment: teak preference showed a significant negative change ( $M = -1.834$ ,  $SD = 2.933$ ,  $t(28) = -3.368$ ,  $p = 0.001$ , 95% CI  $[-\infty, -0.908]$ , Cohen’s  $d = -0.625$ ,  $BF_{10} = 33.225$ ) as shown in Figure 4 (a). Rice preference, however, showed a significant positive change ( $M = 1.331$ ,  $SD = 2.467$ ,  $t(28) = 2.906$ ,  $p = 0.007$ , 95% CI  $[0.39, 2.27]$ , Cohen’s  $d = 0.540$ ,  $BF_{10} = 6.104$ ) and apple preference showed no shifts following shocks. Changes in teak with apple and rice were both significantly correlated (apple vs teak:  $r = -0.567$ ,  $p = 0.001$ , rice vs teak:  $r = -0.693$ ,  $p < 0.001$ ). The predictable condition also showed that the teak preference significantly fell post predictable resource shocks ( $M = -0.709$ ,  $SD = 1.751$ ,  $t(29) = -2.218$ ,  $p = 0.017$ , 95% CI  $[-\infty, -0.17]$ , Cohen’s  $d = -0.405$ ,  $BF_{10} = 3.151$ ) as shown in Figure 4 (c). Rice preference shifts also showed a significant positive change ( $M = 0.468$ ,  $SD = 0.878$ ,  $t(29) = 2.918$ ,  $p = 0.007$ , 95% CI  $[0.14, 0.8]$ , Cohen’s  $d = 0.533$ ,  $BF_{10} = 6.301$ ) while apple showed

no preference shifts post predictable shocks. Changes in teak with apple and rice were again significantly correlated (apple vs teak:  $r = -0.866$ ,  $p < 0.001$ , rice vs teak:  $r = -0.420$ ,  $p = 0.021$ ). Thus, the second experiment further demonstrates the robustness of our resource shock hypothesis.

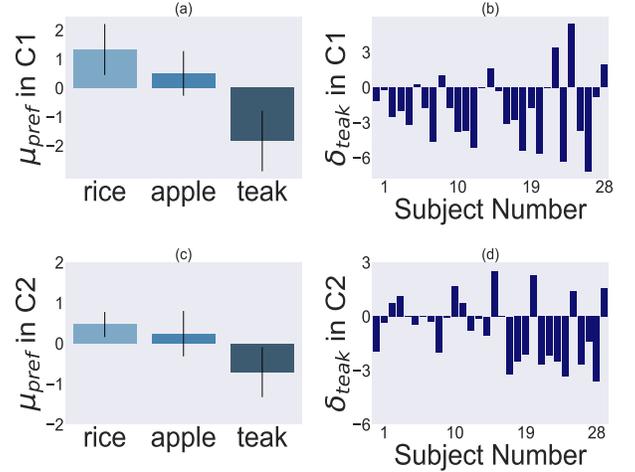


Figure 4: Panel (a) and (b) shows the mean change in crop preference ( $\mu_{pref}$ ) and the teak preference shift ( $\delta_{teak}$ ) data for all participants ( $n=29$ ) in ‘Unpredictable’ condition (C1). 21 participants showed negative teak preference post unpredictable resource shock. Panel (c) and (d) shows  $\mu_{pref}$  and  $\delta_{teak}$  for all participants ( $n=30$ ) in the ‘Predictable’ condition (C2). 20 participants showed negative teak preference after predictable resource shock. Error bars signify 95% CI.

To quantify state-level measures of control and time perception, we calculated difference scores for each dimension (Constraints, Mastery, Perceived Control(PC), Time perception(Duration)) of each participant in both conditions. The difference score was calculated by taking their difference across blocks ( $\delta_{score} = Score_{HV} - Score_{LV}$ ), which gave us four measures:  $\delta_{Constraints}$ ,  $\delta_{Mastery}$ ,  $\delta_{PC}$ , and  $\delta_{Duration}$ . In the unpredictable condition, as shown in figure 5 Panel (b), we found significant changes in  $\delta_{Constraints}$  ( $t(26) = 3.056$ ,  $p = 0.003$ , Cohen’s  $d = 0.59$ , 95% CI  $[0.096, \infty]$ ),  $\delta_{Mastery}$  ( $t(26) = -4.648$ ,  $p < .001$ , Cohen’s  $d = -0.89$ , 95% CI  $[-\infty, -0.177]$ ),  $\delta_{PC}$  ( $t(26) = -2.452$ ,  $p = 0.011$ , Cohen’s  $d = -0.472$ , 95% CI  $[-\infty, -0.027]$ ), but no significant change in  $\delta_{Duration}$ . In the predictable condition, as shown in figure 5 Panel (d), we found significant shifts in  $\delta_{Mastery}$  ( $t(29) = -2.742$ ,  $p = 0.005$ , Cohen’s  $d = -0.501$ , 95% CI  $[-\infty, -0.051]$ ),  $\delta_{PC}$  ( $t(29) = -2.266$ ,  $p = 0.016$ , Cohen’s  $d = -0.414$ , 95% CI  $[-\infty, -0.029]$ ),  $\delta_{Duration}$  ( $t(29) = 2.431$ ,  $p = 0.011$ , Cohen’s  $d = 0.444$ , 95% CI  $[0.038, \infty]$ ), but none in  $\delta_{Constraints}$ . Finally, we correlated these state-level difference scores and the trait-level measures with teak preference shifts to test our

auxiliary hypotheses as described below.

We wanted to see if our long-term choice, i.e., teak preference, was correlated to our control measures. We indeed found a significant correlation between participants' trait-level locus of control measure (LoC score) and their choice of the long-term crop in the game ( $r = 0.414$ ,  $p = 0.026$ ) in the unpredictable condition as shown in Figure 5 (a). However, no such correlation was found in the predictable condition as shown in Figure 5 (c). Amongst state-level measures, a significant negative correlation was observed only between  $\delta_{teak}$  and perceived control  $\delta_{PC}$  ( $r = -0.44$ ,  $p = 0.02$ ) in the unpredictable condition. This correlation was absent in the predictable condition. Lastly,  $\delta_{Constraints}$ , and  $\delta_{Mastery}$  were not correlated with  $\delta_{teak}$  in both conditions.

We tested similar correlations between teak preference and our time perception measures. Neither the trait-level measure (ZTPi time perspective questionnaire) nor state-level time duration ( $\delta_{Duration}$ ) showed any correlation with the teak preference shifts ( $\delta_{teak}$ ).

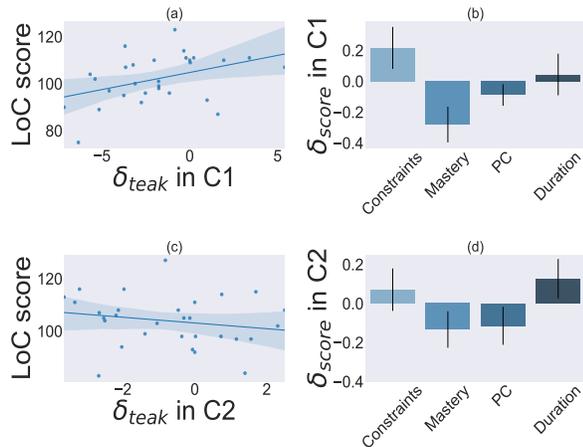


Figure 5: Measures of control and time perception: Panel (a) and (c) shows the correlation of trait-level control score with participant's shift in teak preference in the "Unpredictable" (C1) and "Predictable" condition (C2) respectively. Panel (b) and (d) illustrates the shifts in state-level control and time perception ( $\delta_{Constraints}$ ,  $\delta_{Mastery}$ ,  $\delta_{PC}$ , and  $\delta_{Duration}$ ) in the "Unpredictable" (C1) ( $n=27$ ) and the "Predictable" condition (C2) ( $n=30$ ) respectively. Error bars signify 95% CI.

## General Discussion

In this paper, we empirically demonstrated a relationship between economic precarity induced by unpredictable resource shocks and short-term reward preference, a phenomenon well-documented in the poverty literature. Across two experiments, we successfully induced planning horizon contraction in the lab as a function of resource shocks while participants worked in a resource-constrained environment. In the first experiment, we tested our hypothesis with a dynamic experimental paradigm showing real-time shifts in people's preferences. In the second experiment,

we found a much larger effect size in time preference changes for the unpredictable condition than the predictable condition, suggesting that while economic scarcity on its own may cause such time preference changes, this effect was significantly increased by having to deal with unpredictable resource shocks, even controlling for the level of scarcity thus produced. We also found the effect size of people's perceived constraints contracted by 157% (from 0.59 to 0.23) between the two conditions, further confirming unpredictability as a critical factor affecting people's behaviour. These results, thus, foreshadow planning failures as an essential mechanism for producing present-centred preferences in individuals.

Furthermore, in the second experiment, we found that trait-level control scores predicted how much people's planning horizons contracted as a function of unpredictable resource shocks they encountered. People's state-level perceived control also varied as a function of predictability - supporting our hypothesis that control indeed modulates the relationship between precarity and time preference. While some researchers have demonstrated a correlation between trait-level locus of control measures and financial discounting (Plunkett & Buehner, 2007), others have implied control as a factor in the process without being able to say so directly (Callan, Shead, & Olson, 2009). Consequently, our study showed that trait and state-level control measures predict the association between precarity and preference. We also found a connection between prediction error and time perception as indicated in the literature previously (Toren, Aberg, & Paz, 2020). In the second experiment, we found that people's duration judgement contracted in the 'unpredictable' condition. However, in the 'predictable' case, their duration perception expanded. Though we did not find a direct relationship between time perception and time discounting, our study reaffirmed the existence of a relationship between unpredictability and duration perception.

Our depiction of temporal horizon contraction in an experimental setup with repeated trials supports related observations made in the lab and field in one-shot experimental settings in the past (Del Ponte & DeScioli, 2019; Shah et al., 2012). The experimental results in Shah et al. (2012) suggested that scarcity focuses attention on solving scarcity-related problems, which in some situations can lead to future neglect. Our resource shock hypothesis adds to the scarcity theory by directly connecting budgetary constraints and future neglect through unpredictable resource demands. We successfully pinpointed how time preference waxes and wanes as a function of unpredictability, explicitly identifying the failure of future-facing plans as the source of future neglect and also identifying control as a possible mediator. This theoretical advance has immediate practical implications for welfare economics. In particular, if unpredictable resource shocks are responsible for impulsive and myopic behaviour, only interventions that reduce budgetary constraints, like cash transfers, but not debt relief, will reduce such behaviour and break the poverty trap.

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