Precarity and Preference

A computational and empirical investigation of impatience

A thesis submitted in fulfilment of the requirements

for the degree of Doctor of Philosophy

by

Arjun Mitra

19128261

to the

DEPARTMENT OF COGNITIVE SCIENCE

INDIAN INSTITUTE OF TECHNOLOGY KANPUR

March 2026

POST GRADUATE OFFICE
THESIS SUBMITTED
ON 04/09/2025
I. I. T., KANPUR - 16

Certificate

It is certified that the work contained in this thesis entitled **"Precarity and Preference - A computational and empirical investigation of impatience"** by **Arjun Mitra** has been carried out under my supervision and that it has not been submitted elsewhere for a degree.

Dr. Nisheeth Srivastava
Professor
Departments of Cognitive Science and
Computer Science and Engineering
Indian Institute of Technology Kanpur
March 2026

Declaration

This is to certify that the thesis titled **"Precarity and Preference - A computational and empirical investigation of impatience"** has been authored by me. It presents the research conducted by me under the supervision of **Dr. Nisheeth Srivastava**.

To the best of my knowledge, it is an original work, both in terms of research content and narrative, and has not been submitted elsewhere, in part or in full, for a degree. Further, due credit has been attributed to the relevant state-of-the-art and collaborations with appropriate citations and acknowledgments, in line with established norms and practices.

Arjun Mitra
Roll No. 19128261
Department of Cognitive Science
Indian Institute of Technology Kanpur

Abstract

Name of the student: **Arjun Mitra** Roll No: **19128261**

Degree for which submitted: **Doctor of Philosophy (PhD)**

Department: **Cognitive Science**

Thesis title: **Precarity and Preference - A computational and empirical investigation of impatience**

Thesis supervisor: **Dr. Nisheeth Srivastava**

Month and year of thesis submission: **August 2025**

Why do we become impatient? Why do we often choose an immediate reward when we know holding out for a better future outcome is a wiser alternative? Is it a flaw in our design? Do some of us fundamentally lack impulse control, or are we the product of our environment? Historically, both structural and cultural factors have been implicated in impulsive behavior. While insights from sociological and anthropological accounts may point in different directions, this thesis attempts to unravel the answers to these questions by identifying the role of environmental precarity in shaping individuals' preferences and their psychological determinants through a computational and empirical perspective.

Undervaluing and discounting the future has often been highlighted as a critical behavioral trait of individuals living in low socio-economic conditions. Using computational models, we pinpoint precise environmental conditions under which individuals' future plans may shift towards *now*. Frequent turbulence, modeled as multiple unpredictable over-the-budget expenses, leads people to forego future rewards and prefer the immediate. We also find that future planning is sustainable in a stable environment with no significant unforeseen expenses. Thus, we identify an unpredictable, turbulent world as a precursor for individuals' breakdown of future plans, which we call a 'resource shock' hypothesis.

We empirically test these predictions using a home-grown farming game that simulates the lived experiences of impoverished individuals. We find that individuals' preference for long-term plans decreases when they face unpredictable turbulence among university students and farmers working as gardeners in the institute. We also find that such present-focused behavior is absent when turbulence is absent or predictable, highlighting impatience as an adaptive phenomenon that manifests as a response to environmental precarity.

While we document short-term preference only as a function of unpredictable turbulence, mathematical models explain such observed deviations as a loss of self-control. For example, exponential or hyperbolic discounting models suggest that these preference shifts reflect an underlying change in the utility of future plans, which can be captured only as shifts in discount rates, a metric that quantifies impulse control. However, we observe that a perceived distortion in mental time can explain our documented preference shifts, as captured by the same discounting models. By manipulating time in these models, we find that an felt expansion of time can lead to lowered preference for the future, which can be misconstrued as a lack of impulse control.

Interestingly, we also find that subjective time-based preference shifts correspond to shifts in discount rates when delays are treated as invariant and objective. This led us to formulate a reinterpretation framework that mathematically quantifies observed changes in discount rates as time distortions. Using multiple lab and field studies, we find that estimated time distortions that can account for observed shock-based preference shifts closely align with perceptual studies. Furthermore, we estimated and validated time distortions in the lab using our farming game, which showed that individuals who perceived time as extending during shocks later preferred short-term plans.

Overall, this thesis proposes a mechanism by which individuals' planning horizons can change due to exposure to turbulent and stable environments and identifies subjective time as a potential psychological determinant of impatience. Thus, when exposed to precarious conditions, individuals may feel the future increasingly distant and act more impatiently. This is especially true for individuals living in impoverished conditions, who are most vulnerable to such shocks due to a lack of liquidity. Our work urges observing impatience not as a character flaw but as a response to precarity and necessitates policy designs and welfare interventions that proactively protect people from unpredictable shocks.

Acknowledgements

I would like to express my deepest gratitude to my advisor, Dr. Nisheeth Srivastava, for his invaluable guidance and support throughout this project. Everything I have learnt in these past five years - how to think, the value of hard work, perseverance and ultimately *anicca* - I owe to him.

During these years, Professor Narayanan Srinivasan has been a steady source of wisdom and clarity. His unfettered willingness to engage with my ideas, and our extensive conversations on how to design, analyze, and, most importantly, think scientifically have left a lasting impact on me and my work.

To Swarag, thank you for the coffee walks and extensive rants, the much-needed distractions. To Dhuni and Riya, thank you for the food parties and being my *Fidus Achates* when I needed one the most. To Divya, thank you for meeting me beyond the field of wrong and right doings.

Lastly, even though you may not read this, thank you Maa for being you. This work is as much yours as it is mine.

Contents

Acknowledgements **vii**

List of Figures **xii**

List of Tables **xvii**

List of Publications **xviii**

1 Introduction **1**
- 1.1 Preferences and impatience 2
- 1.2 Precarity and lived experiences 3
- 1.3 Time and time again 3
- 1.4 Organization of thesis 4

2 Knowns and Unknowns - A literature review **7**
- 2.1 Poverty and precarity 7
- 2.2 Poverty and impatience 9
- 2.3 Precarity and impatience 10
- 2.4 Precarity and subjective time 12
- 2.5 Precarity, subjective time and impatience 15
- 2.6 Summary and looking ahead 16

3 How precarity affects preferences **17**
- 3.1 Simulating precarity in-silico 17
- 3.2 Robustness checks 20
- 3.3 Summary and looking ahead 22

4 Method of investigation **24**
- 4.1 Game mechanics: Harvest Horizons 25
  - 4.1.1 Farming game design 26
  - 4.1.2 Precarity as resource shocks 26
  - 4.1.3 Crops as inter-temporal choices 27
- 4.2 Game-play walk-through 29
- 4.3 Optimal Crop Choice 30
- 4.4 Summary and Looking ahead 32

5 Precarity and preference shifts **33**
5.1 A 'resource shock' hypothesis . . . 33
5.2 Exp 1: Preference shifts in Volatility among Students . . . 34
5.2.1 Methods . . . 34
5.2.1.1 Experimental design . . . 34
5.2.1.2 Participants . . . 35
5.2.1.3 Analysis procedure . . . 36
5.2.2 Results . . . 37
5.2.2.1 Long-term crop preference shifts . . . 37
5.2.2.2 Short-term crop preference shifts . . . 37
5.2.2.3 Are preference shifts sticky? . . . 38
5.2.3 Robustness checks . . . 39
5.2.4 Discussion . . . 39
5.3 Exp 2: Preference shifts in Volatility among Farmers . . . 41
5.3.1 Methods . . . 41
5.3.1.1 Design changes from Exp 1 . . . 41
5.3.1.2 Participants . . . 42
5.3.1.3 Analysis procedure . . . 43
5.3.2 Results . . . 43
5.3.3 Discussion . . . 44
5.4 Exp 3: Preference shifts during Stability . . . 44
5.4.1 Methods . . . 44
5.4.1.1 Design changes from Exp 1 . . . 44
5.4.1.2 Participants . . . 45
5.4.1.3 Analysis procedure . . . 45
5.4.2 Results . . . 46
5.4.2.1 Long-term crop preference shifts . . . 46
5.4.2.2 Short-term crop preference shifts . . . 46
5.4.3 Robustness checks . . . 47
5.4.4 Discussion . . . 48
5.5 Exp 4: Preference shifts and Predictability . . . 48
5.5.1 Methods . . . 49
5.5.1.1 Design changes from Exp 1 . . . 49
5.5.1.2 Participants . . . 50
5.5.1.3 Analysis procedure . . . 50
5.5.2 Results . . . 50
5.5.2.1 Crop preference shifts across conditions . . . 51
5.5.2.2 Crop preference shifts in 'Unpredictable' condition . . . 53
5.5.2.3 Crop preference shifts in 'Predictable' condition . . . 53
5.5.3 Robustness checks . . . 54
5.5.4 Discussion . . . 55
5.6 Summary and Looking ahead . . . 56

6 Subjective time and preference shifts **57**

6.1 Subjective time in Exponential model . . . 58
6.1.1 Simulation procedure . . . 58
6.1.2 Simulation results . . . 60
6.2 Subjective time in Hyperbolic model . . . 62
6.2.1 Simulation procedure . . . 62
6.2.2 Simulation results . . . 63
6.3 Discussion . . . 63
6.4 Robustness checks . . . 64
6.5 Summary and Looking ahead . . . 67

7 Precarity, subjective time and preference shifts 68
7.1 Framework connecting discount shifts with time warps . . . 69
7.1.1 Framework using exponential discounting . . . 70
7.1.2 Framework using hyperbolic discounting . . . 71
7.2 Reinterpreting preference shifts as time distortions . . . 73
7.2.1 Methods . . . 73
7.2.1.1 Haushofer et al. (2013) . . . 75
7.2.1.2 Bickel et al. (2016) . . . 75
7.2.1.3 Falco et al. (2019) . . . 76
7.2.1.4 Meles et al. (2024) . . . 77
7.2.1.5 Blain et al. (2025) . . . 78
7.2.2 Results . . . 78
7.3 Effects of lab-induced precarity on intertemporal choices . . . 80
7.3.1 Estimating time distortions from Exp 4 . . . 80
7.3.1.1 Methods . . . 80
7.3.1.2 Results . . . 81
7.3.2 Exp 5: Validating preference shifts and time distortions . . . 82
7.3.2.1 Methods . . . 82
Design changes from Exp 4 . . . 82
Participants . . . 84
Analysis protocol . . . 84
7.3.2.2 Results . . . 85
7.4 Summary and Discussion . . . 87

8 General Discussion and Conclusion 89
8.1 Limitations & Future work . . . 95
8.2 Conclusion . . . 97

A Turbulence, Crop Attributes, and Design Choices in Harvest Horizons 100
A.1 Determination of variance for volatility . . . 100
A.2 Determination of crop yields . . . 101
A.3 Design and Analysis choices for Harvest Horizons . . . 102

B Derivations used in Chapter 6 **104**
B.1 Deriving u(l) from p(l) using soft-max function 104
B.2 Deriving k from u(l) using discounting models 105
B.2.1 Exponential discounting 105
B.2.2 Hyperbolic discounting 106

C Summary of statistical tests and effect sizes **108**

Bibliography **110**

List of Figures

1.1 Bird's-eye schematic illustrating how historical accounts motivate the theoretical framework, which informs computational modeling and experimental design, culminating in observed behavioral outcomes. 6

3.1 Resource Shock Model - (A) Expected reward as a function of planning duration under high and low budgetary allocations and rare (5%) versus frequent (30%) resource shocks. Frequent shocks reduce expected reward and shift the optimal planning duration toward shorter horizons, with this effect being more pronounced under low budgets. (B) Change in optimal planning duration as a function of shock probability, showing a faster contraction of the optimal planning horizon as resource demands increase when budgets are low. 19

3.2 Resource Shock Model (A)- Demonstrates the effect of differently sized starting budgets (low and high) and probability of resource shock (0.05 and 0.30) on expected rewards associated with plans that become increasingly more rewarding over time. The nature of this cost deduction and reward increment varied between conditions: **(A)** Gaussian cost with linear reward increment, **(B)** Log-normal cost with linear reward increment, **(C)** Gaussian cost with exponential reward increment, and **(D)** Log-normal cost with exponential reward increment. 21

3.3 Resource Shock Model (B)- Demonstrates the effect of differently sized starting budgets (low and high) and probability of resource shock (ranging from 0 to 0.55) on optimal planning duration. Across all conditions, optimal planning duration falls for both high and low budgetary conditions as the probability of shocks increases. This fall is found to be steeper when the budgetary allocation is low. The nature of cost deduction and reward increment was varied, as mentioned in the above figure. 22

4.1 Game GUI: At the top of the user interface is the 'Ledger', which displays real-time trial-wise farming-based resource debits and credits. Farming debits included resource debits or farming inputs ('Resource Cost'), loss of crops ('Crop Loss'), and rent for the farming land ('Land Rent'). Farming-based credits included 'Crop Yield', i.e., the money earned from harvesting crops. The ledger also displayed each crop variety and the associated profits, total money earned by the player ('Money Made'), and our formulation of resource scarcity ('Budget'). Our depiction of environmental precarity was designed as an increased resource cost, crop loss, and land rent in the game. Since participants were encouraged to learn about the risk profile of each crop, we displayed the net loss incurred by each crop after each trial. The middle of the user interface displays the soil where participants could sow and harvest their chosen crops. The participants were informed that crop sowing patterns on the soil or time (month of the year) did not impact crop loss or yield (check out youtube for a demo). 25
4.2 Game Design - this figure depicts the workings of the farming-simulator experimental paradigm. The top panel shows one of the experimental block structures used in the game. The bottom panel shows the varied crop attributes, how every trial traversed through the crop-sowing to the crop-harvesting phase accompanied by crop loss and the critical manipulation of a precarious farming environment. 27
4.3 Flowchart showing experimental manipulations with varied stochasticity: If resource cost drawn randomly was less than the budget then it manifested in-game as lower crop loss and land rent. Otherwise, if sampled resource cost was greater than Budget, then it depicted tumultuous times with higher crop loss and land rent. 28
4.4 Optimal Crop Choice: These ternary plots show the optimal crop choice under conditions of fixed, low endowment and (A) low, (B) moderate, and (C) high incidences of resource shocks. The teak plantation is the optimal choice in low resource shock conditions. However, as the probability of shock increases, the optimality shifts away from teak. At high probability (p(shock) = 0.8), teak plantation yields a negative net profit — suggesting endowment depletion before harvest is fructified. The values 0 and 40 on the axes denote null and total plantation of those respective crops on the field. 31

5.1 Game Analysis - this figure shows our analysis protocol for the farming-simulator experimental paradigm. For each participant, we identify the trials on which resource shocks occurred, and change in crop preferences is determined by taking the difference in the cumulative amount of crops on six trials before and after each resource shock trial. We chose six trials before and after, as teak takes six trials to be harvestable. Each participant's mean change in crop preference is calculated by taking the mean difference in crop preferences across all resource shocks encountered in the game. Lastly, all shock trials occurring on the last six trials in the game was excluded from analysis. 36

5.2 Results of Experiment 1: Panel **(a)** illustrates the mean shift in preference ($\mu_{\delta_{pref}}$) for all crop choices induced by resource shocks across all participants. The mean shift in rice, apple, and teak preference is 0.01, 0.33, and -0.34 suggest lowered preference for the long-term crop post exposure to shock. Error bars signify 95% CI. Panel **(b)** shows the teak preference shift (δ_{teak}) data for all participants (n=69). Forty participants showed negative teak preference post-resource shock. 37

5.3 Depiction of game GUI as designed for the second experiment. We changed the dialect to Hindi to accommodate native Hindi-speaking farmers. 42

5.4 Subplot (a) shows the mean change in crop preference across all farmers. The mean change in rice, apple and teak preference is 0.80, 0.09 and -0.89 respectively. Subplot (b) depicts the change in teak preference for all participants (n=70). 36 participants showed negative teak preference change post shocks. 43

5.5 Panel **(a)** shows the mean slope of the best-fit line to each crop type across the two LV blocks for all participants. Teak showed a significant positive slope, and both Apple and Rice displayed a negative one as the game progressed. Error bars are 95% CIs. Panel **(b)** shows the slope of the best-fit line for only teak across all participants. 13 out of 19 people showed a positive change in teak preference as the game progressed. 46

5.6 This diagram shows the mean shift in crop preference induced by resource shocks as found in 'Unpredictable' and 'Predictable' conditions. Teak preference shifts show statistical significance only in the 'Unpredictable' condition. The mean change in crop preference across all participants is denoted by $\mu_{\delta_{pref}}$, and error bars signify standard error. $\mu_{\delta_{rice}}$, $\mu_{\delta_{apple}}$, and $\mu_{\delta_{teak}}$ for the 'Unpredictable' condition were found to be 1.19, 0.41, and -1.6, respectively. Similarly, $\mu_{\delta_{rice}}$, $\mu_{\delta_{apple}}$, and $\mu_{\delta_{teak}}$ for the 'Predictable' condition were 0.24, -0.49, and 0.25, respectively. 51

5.7 'Unpredictable' Condition: Panel **(a)** illustrates the mean shift in crop preference ($\mu_{\delta_{pref}}$) across all participants. $\mu_{\delta_{rice}}$, $\mu_{\delta_{apple}}$, and $\mu_{\delta_{teak}}$ were found to be 1.19, 0.41, and -1.6, respectively. Error bars signify 95% CI. Panel **(b)** shows the teak preference shift (δ_{teak}) data for all participants (n=28). 20 participants showed negative teak preference post unpredictable resource shock. 52

5.8 'Predictable' Condition: Panel **(a)** illustrates the mean shift in crop preference ($\mu_{\delta_{pref}}$) across all participants. The mean shift in rice, apple, and teak preference is 0.24, -0.49, and 0.25, respectively. Error bars signify 95% CI. Panel **(b)** shows the within-participant teak preference shift (δ_{teak}) data for all participants (n=30). 13 participants showed negative teak preference post predictable resource shock. 54

6.1 Figure (a) depicts how deviations in time Δt perturb the probability of choosing a later reward Δp when the future reward is discounted exponentially. We find that the probability of choosing the future outcome decreases as time dilates. When $\Delta t > 0$ such that perceived time > objective time, we find $\Delta p < 0$ such that $p(l)$ at subjective time < $p(l)$ at the objective time. Figure (b) shows how discount rates Δk change as a result of observed shifts in preference Δp when psychological scaling of objective time is disregarded and instead clock time is considered. We find that for all prior probability values p, as the preference for the delayed rewards decreases, the discounting increases - when $\Delta p < 0$ (corresponding to $\Delta t > 0$), we find $\Delta k > 0$, that is, an increase in the discount rate and vice versa. 61

6.2 Figure (a) shows how changes in time Δt lead to shifts in the probability of choosing a delayed reward Δp when the reward is discounted hyperbolically. As time dilates (i.e., $\Delta t > 0$ such that subjective time > objective time), the probability of choosing the future outcome falls ($\Delta p < 0$) for all values of prior probability p. Figure (b) shows how discount rates change Δk as a function of shifts in preference Δp brought on by deviations in perceived time. For all values of prior probability p, as the preference for delayed rewards decreases, the discounting increases when time is objective and invariant. 63

6.3 Figures (a) and (b) show how the probability of later reward changes as a function of perceived time in an exponential discount model when the later reward is 1.1 and 2 × the sooner reward. We find that our results hold even when the later reward is varied. As time dilates, the probability of choosing the later reward decreases and vice versa. 65

6.4 Figures (a) and (b) show how discount rates shift as a function of time-based changes in choice probability when the later reward is 1.1 and 2 × the sooner reward. We find that as the probability of choosing the later reward decreases, the discount rate increases and vice versa. 65

6.5 Figures (a) and (b) show how the probability of later reward changes as a function of perceived time in a hyperbolic discount model when the later reward is 1.1 and 2 × the sooner reward. We find that our results hold even when the later reward is varied. As time dilates, the probability of choosing the later reward decreases and vice versa. 66

6.6 Figures (a) and (b) show how the probability of later reward changes as a function of perceived time in a hyperbolic discount model when the later reward is 1.1 and 2 × the sooner reward. We find that our results hold even when the later reward is varied. As time dilates, the probability of choosing the later reward decreases and vice versa. 66

7.1 This figure shows the median scaled time distortions $\Delta t/t$ and its confidence intervals calculated from shifts in preference for studies reported in Table 7.1. The zero line depicts null time distortion caused by shock encounters (perceived time equal to clock time). Meles et al.(2024)a and b refer to the effects of droughts and rainfall shortfalls on shifts in preference separately. . 79

7.2 Figure (a) shows the mean change in choice probability ($\mu_{\Delta p}$) across crops as a result of lab-induced environmental precarity (n = 27). Error bars represent 95% CI. Figure (b) shows that the decreases in observed teak probability (Δp(teak)) are associated with increases in time distortions (Δt) estimated from the data (r = -0.87, p < 0.001). 81

7.3 The first and second subplots display the game GUI of our farming experiment in stable and volatile farming conditions. In both images, the top of the GUI shows the 'Ledger,' which displays the trial-wise debits and credits of participants for the past ten trials and gets updated in real time. The left portion of the GUI displays the time (month and year), farming expenditures, and crop losses for each crop for the ongoing trial. Cumulative farming expenses, crop losses, and land rents are shown as 'Resource Cost,' 'Crop Loss,' and 'Land Rent' on the Ledger. The middle of the GUI shows the field plot where participants cultivate crops. Participants were notified that crop sowing patterns on the soil or time (month/year) did not affect crop losses or yields. The game can be played online here. 83

7.4 This figure displays the felt time question that participants responded to at different junctures in the game. 84

7.5 Figure (a) shows the mean change in probability of crop choice ($\mu_{\Delta p}$) as a result of lab-induced environmental precarity (n = 96). Error bars represent 95% CI. Figure (b) shows that the individuals who experienced time to be extending compared to their own baseline ($\Delta\bar{t}$) showed an increased fall in long-term preference (Δp(teak)) (r = -0.24, p = 0.008). 85

List of Tables

4.1 Table depicting detailed crop attributes for each crop type. Bracketed values in the Loss Factor denote increased crop loss on resource shock trials. . . . 29

7.1 Summary of studies examining the impact of negative income or expense shocks on temporal choices. The different columns denote the sample characteristics, observed effects and strength of the observed effects in terms of changes in discount rates. The final column shows the estimated time distortions (median and 95% CI) derived from observed changes in discount rates using our theoretical framework. 74

7.2 Summary statistics of time distortion distributions and their correlation with shifts in long-term teak preference. All correlations are Pearson's r, and bracketed values denote p-values. 86

C.1 Summary of statistical models and effect sizes. 109

List of Publications

- Mitra, A., Srivastava, N., & Srinivasan, N. (2023). Unpredictability shortens planning horizons. Proceedings of the Annual Meeting of the Cognitive Science Society, 45.

- Mitra, A., & Srivastava, N. (2024). Changes in time preference may simply be induced by changes in time perception. Proceedings of the 22nd International Conference on Cognitive Modelling, 100–106. Applied Cognitive Science Lab, Penn State.

- Mitra, A., Srinivasan, N., & Srivastava, N. (2025). Present-focused behavior as a rational adaptation to precarity. Open Mind, 9, 452–474.

- Mitra, A., & Srivastava, N. (2025). Perceived temporal distortions may explain the effect of precarity on intertemporal choices. Frontiers in Psychology, 16, Article 1671647.

Dedicated to

বাবা -

তুমি গেছো, স্পর্ধা গেছে, বিনয় এসেছে।

মা -

শেষ জয়ে যেন হয় সে বিজয়ী তোমারি কাছেতে হারিয়া।

Gather ye rosebuds while ye may,
Old Time is still a-flying;
And this same flower that smiles today
Tomorrow will be dying.

- Robert Herrick

1 Introduction

Annawadi, Mumbai. A thriving slum in the city that never sleeps. There are movie stars with all the glitter and glamour, and then there's Mr. Kamble - once an abandoned infant, then dweller of pavements, and now a doer of hopeless jobs. In his thirties, Mr. Kamble had a stroke of luck - he landed a permanent job cleaning public toilets while falsifying municipal sanitation workers' records so they could work elsewhere while collecting their pay. Over time, he has left the pavement and built a room for himself and his family.

As luck would have it, he developed a coronary issue, which led the sanitation department to lay him off, asking him to get the necessary surgery and doctor's clearance. Even though public hospitals offer such operations free of cost, Mr. Kamble found no surgeons who would do it without a bribe. Hopeless, jobless, and even food-less on some days, he spends most of his time in the temple courtyard and the rest at the local political babu's feet waiting for another blessing to turn his life around [1].

Our encounters with the destitute are often limited to novels or films, where their struggles are framed within a story arc that promises triumph against all odds (think Slumdog

[1] excerpted from *Behind the Beautiful Forevers: Life, Death, and Hope in a Mumbai Undercity* by Katherine Boo.

Millionaire). We long for an ending in which they overcome adversity and emerge victorious. In many ways, these narratives reflect not only their imagined triumphs but also a reminder of our personal struggles, our own yearning for hope, and the possibility of triumph. However, real life seldom follows such story arcs.

On your way to the office or lab, you may have noticed a group of homeless people sitting on the curb or a destitute woman begging for money at the traffic crossing with her child on her lap. I urge you to think about what went differently. What decisions changed the trajectory of their lives and ours? Even though one may argue a thin line separates us and them, what differentiates their triumphs and our own triumphs and misfortunes? Is it moral failings? Do the homeless beg because they lack the will to work? Or is it that they never got the opportunities and advantages that we had? Would we act and behave similarly if exposed to their lived experiences? This work will attempt to answer such questions and hopefully convince you of the humane explanation.

1.1 Preferences and impatience

Turning to the scientific literature reveals arguments supporting both sides of this debate. Some argue that the causes of why people find themselves trapped in penury are often malformed norms and values that children learnt from their caregivers, or simply a failure in controlling one's impulses or urges (Lewis, 1966; Moynihan, 1965). Others counter that cultural or character-flaw explanations are simply victim-blaming as much larger forces, such as structural inequalities and enforced discrimination (think slavery in America or the caste system in India), are often at play (Ryan, 1976; Wilson, 2009, 2012) which gives rise to the cultural conditions that breed poverty.

While sociological and anthropological accounts argue over the role of cultural and structural factors, the common thread of observation that emerges from all economic and psychological studies is that people living in poverty tend to be impatient (Pepper & Nettle, 2017). They would rather focus on the present than ponder about the future, adopting *carpe diem* born out of necessity rather than indulgence. But what makes them impatient? Is it greed or a lack of impulse control that leads them to gather all the rosebuds today? Or is it the case that the future may be a distant dream, so they get what they can *now*?

1.2 Precarity and lived experiences

Addressing the above questions require closer attention to the lived realities of poverty. Traits and behaviors often emerge from the environment we find ourselves in. Phenomenological research in psychology points out that people living in poverty frequently experience a loss of autonomy, threatened self-esteem, social devaluation, and a sense of insecurity about their futures (Underlid, 2007). For instance, in Underlid (2007)'s work, one individual's inability to pay utility bills due to a lack of funds leads to a frozen bank account, forcing them to borrow money from their daughter at the last minute. They were even looking forward to getting a job through a training course, which may not materialize due to their failing health.

Such lived experiences highlight that the ecological and mental struggles these individuals face often stem from the inherent uncertainty and unpredictability of life. An unexpected bill, inability to borrow money, and poor health can cause them to focus on the immediate problems. With little income or savings, such uncertainties can present an unbearable burden, leading them to disavow the future. Impatience then arises not from a lack of impulse control but from an inability to deal with the uncertainties inherent in this world.

Planning for the future involves gambling against time, as the future is often clouded with the uncertainty of one's own existence or the fruit of their labor not materializing. While most of us can survive a sudden medical bill, a sudden layoff, or a raging pandemic can make our lives uncertain and our efforts inconsequential. Thus, living in precarious conditions and exposure to random extrinsic turbulence makes people impatient. If we were exposed to the lived experiences of those living under $2 a day, I think we would react the same.

1.3 Time and time again

Now, if we grant that living in precarious conditions makes people impatient, the question remains: What changes psychologically to induce impatiently? Is it a loss of control over one's environment? Does an unexpected expense create mismatches in expectations and outcomes, leading individuals to plan over time periods where they can exercise control? Does unpredictable turbulence lead to increased attention to immediate problems, leaving fewer mental resources to think about the future?

While lack of control and/or increased attention to the present may manifest from environmental precarity, converging evidence suggests that subjective time may be the key psychological factor at play. One influential account of time perception is the pacemaker–accumulator model, which posits that perceived time depends on the rate of an internal pacemaker whose pulses are accumulated to estimate duration (Gibbon et al., 1984). Increased arousal to a stressful event can perturb our internal clocks, leading to distortions in our perceived time. Such time distortions can also be minimized by inducing a sense of illusory control that negates the effect of emotionally charged events (Mereu & Lleras, 2013).

Thus, I think environmental turbulence modulates our sense of time reshaping our choices and decisions across it. For example, if one encounters an unexpected medical bill that eats up a large chunk of their savings, then planning to get the degree may not only appear infeasible from a budgetary perspective but also look increasingly distant mentally. Our lives are not governed by any clock but by how we think and feel about time - time that has gone by and time that we have left. So, if the *present* is inundated with uncertainty and instability, the *future* may seem like a distant, unachievable dream, making it natural to gather all rosebuds today.

1.4 Organization of thesis

The key questions I explore in this work are - Do people, exposed to the lived experiences of deprivation, act impatiently? Does their perceived sense of time alter and affect preferences as a result of precarity? I attempt to answer these questions in this thesis by focusing on three questions: (i) how simulated precarity in the lab alters planning horizons in a resource-constrained setting, (ii) whether and how such conditions affect psychological factors such as subjective time, and (iii) how these psychological distortions relate to observed shifts in intertemporal choice. These questions are addressed through computational modeling and a series of behavioral experiments in this thesis which is organized as follows:

> Chapter 2 discusses the past literature on poverty, precarity, subjective time, and impatience. We underscore what the literature tells us (the knowns) and what can be derived from it (the unknowns).

Chapter 3 explores our computational investigation of how precarity (in the form of unpredictable resource demands) can influence choice behavior and planning horizons.

Chapter 4 discusses the experimental paradigm designed to test our theory. Since we had to simulate environmental turbulence and test its effects on preferences, we designed a farming game, the details of which are in this chapter.

Chapter 5 presents the empirical evidence evaluating the behavioral predictions generated by the proposed framework, focusing on the effects of environmental precarity on choice behavior and planning horizons.

Chapter 6 explores the theoretical implications of considering subjective time (instead of an objective clock time) on preferences using discounting models.

Chapter 7 shows our theoretical framework designed to reinterpret changes in discount rates as time distortions. This chapter also includes the empirical validation of the effect of precarity-induced time distortions on preferences.

Chapter 8 discusses our investigation, what we find, and its implications. We also discuss possible future investigations and conclude the thesis.

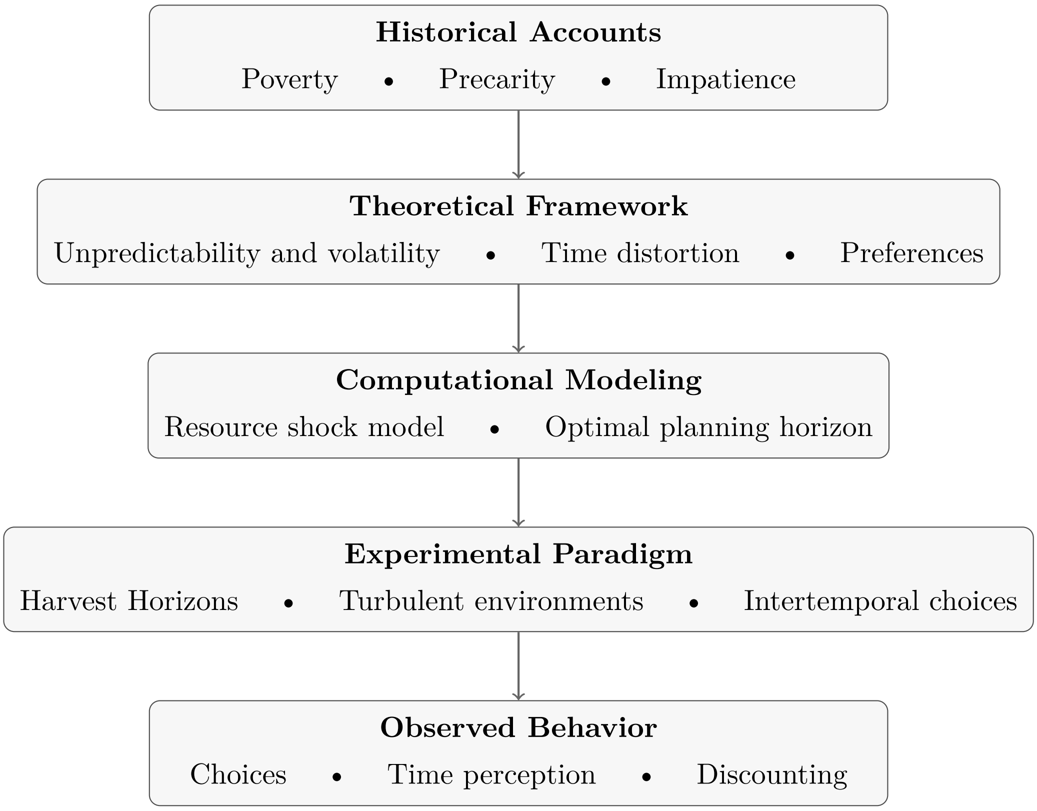


Figure 1.1: Bird's-eye schematic illustrating how historical accounts motivate the theoretical framework, which informs computational modeling and experimental design, culminating in observed behavioral outcomes.

2

Knowns and Unknowns - A literature review

In the previous chapter, we argued that one has to peer into the lived experiences of those living in poverty to understand why they may act impatiently. In this chapter, we deep dive into the scientific literature and weave out connections between poverty and precarity, how living in precarious conditions may affect patience and preferences, and the role of psychological factors such as subjective time in this mechanism.

While economic growth has lifted a significant number of people out of poverty in India and around the world, it is estimated that around 75 million people in India and 700 million worldwide live on $2.15 a day. To understand why we suspect the role of precarity on preferences, we have to go back in time and identify the sociological, anthropological, psychological, and economic reasons behind the sustenance of the poverty trap [1].

2.1 Poverty and precarity

Soon after the Civil Rights Act of 1964, the US government, under the leadership of President Johnson, commissioned Daniel Patrick Moynihan, then Assistant Secretary of

[1] Parts of this section have been previously published as a research paper (Mitra et al., 2025)

Labor, to submit a report identifying the causes and effects of persistent poverty and inequality in African-American communities. The Moynihan Report suggested that the breakdown of family structure, absence of fathers, and matriarchal families in African-American communities led to the sustenance of poverty. The report traced these patterns back to the legacy of slavery, oppression, and discrimination as the underlying structural factors that contributed to the breakdown of families (Moynihan, 1965).

At the same time, Oscar Lewis, an anthropologist, developed the concept of 'culture of poverty' based on his ethnographic work in Mexico and Puerto Rico. Lewis argued that persistent poverty creates a subculture with values and worldviews perpetuating behaviors such as present orientation, fatalism, and institutional distrust across generations. Like Moynihan, he argued that structural inequalities, such as economic marginalization, caused these cultural patterns. Once these patterns were established, they created values and norms perpetuating and self-reinforced within these communities (Lewis, 1966).

However, many scholars and activists rejected the conceptualization of a culture of poverty and its effects on behavior by the 1970s and 80s. William Ryan, for example, critiqued Moynihan's approach as 'victim blaming', such that the explanations focused more on the deficiencies of minority communities than on the systemic forces that create inequality (Ryan, 1976). Moynihan later embraced these structural explanations, suggesting that focusing on culture diverted attention from ongoing systemic disparities.

A marked shift in perspective came from William Julius Wilson's work on race and poverty. He rejected conservative and liberal arguments about the social conditions prevalent in American 'inner cities'. Instead, the key issue is not cultural but structural, namely, urban segregation that isolates poor communities from mainstream economic opportunities. According to him, rampant de-industrialization and job losses created widespread unemployment and family instability, leading to persistent poverty (Wilson, 2012).

While these early debates between cultural and structural factors continue, the scientific consensus suggests that one's immediate environment plays a larger role in determining people's behavior. For example, while African-American women are often stereotyped as 'welfare queens', ethnographic work challenges such simplistic portrayals. Hays (2004) highlights some of the day-to-day challenges faced by marginalized women, such as navigating bureaucratic red tape, working at multiple minimum-wage jobs, and managing childcare. These accounts highlight how social and environmental uncertainties, rarely alleviated by welfare benefits, affect our decision-making and underscore the need to understand these lived experiences to understand why people act the way they do.

2.2 Poverty and impatience

Since the 2000s, the broader academic movement shifted from cultural explanations to structural analysis of poverty and its effects. Numerous psychologists and economists have invested their efforts in understanding the causes and effects of living in dire poverty. A striking aspect of this new surge of research is the consistent observation of impatient behaviors among such communities. Pepper and Nettle (2017) suggests that people living in low socio-economic conditions often exhibit impulsive or highly present-oriented behaviors. Documented behaviors, such as high prevalence of unhealthy behavior like smoking, gambling, and drug abuse (Pampel et al., 2010), excessive expenditure on entertainment even under constrained resources (Banerjee & Duflo, 2007) among individuals at the lowest rungs of the socio-economic ladder, demonstrate behavior consistent with this inadequate consideration of the future (Pepper & Nettle, 2017).

Such an association has also been documented in cross-country datasets where national levels of patience are linked to economic outcomes (Dohmen et al., 2015). The authors find robust correlations between patience levels and GDP per capita, and the effect holds across countries, regions within countries, and even individuals. Personal surveys among US adults show that personality and present-centric behavior are also somewhat correlated (Ludwig et al., 2019). The authors find that individuals belonging to high-income strata (> $200K) show more planfulness and less impulsivity, whereas low-income individuals ($ 0 - 20K) show slight immediate-reward bias.

Empirical research on the economic lives of people living under $1-2 per day across multiple countries highlights key behavioral patterns such as high exposure to risks, limited insurance, lack of savings, high reliance on informal credits that highlight how precarity shapes their lives (Banerjee & Duflo, 2007). The authors suggest that structural constraints, such as a lack of insurance, limited credit infrastructure, and limited bargaining power, often drive people's choices. Overall multiple strands of evidence from economics and psychology suggest that people living in poverty tend to act more present-focused. Thus the question remains, why would that be the case? Do living in poverty shape future preferences or are they inherently intrinsic?

2.3 Precarity and impatience

Probes into our nature of impatience started with Walter Mishcel. Mischel's famous marshmallow experiments suggested that simple wait time measurements in childhood could predict future socio-economic achievements (Mischel, 2014). In these experiments, preschool children ($\sim$ 4 years old) were made to choose between getting a single marshmallow immediately or waiting 15 minutes to receive another. The authors suggested that the ability to delay gratification was a marker for children's self-regulation. Using follow-up studies, they indicated that kids who could self-regulate exhibited higher cognitive control, planning ability, and better SAT scores when they were 15 years old (Shoda et al., 1990).

While Mischel's experiment suggests that individuals' willpower would dictate how they fare in life, recent replications suggest that socio-economic factors may also dictate the ability to delay gratification. A conceptual replication of the marshmallow experiment found the effects much smaller than initially reported when controlled for the child's family background, cognitive ability, and home environment (Watts et al., 2018). Kidd et al. (2013) manipulated environmental unreliability by pairing some kids with reliable and unreliable experimenters (kept or broke prior promises made to children, like retrieving crayons). The authors found that kids in the reliable condition waited an average of 12 minutes, whereas children in the unreliable condition waited 3 minutes. This study suggests that children's ability to delay gratification depends on their trust in the environment.

A point to note here is that most studies discussed in the prvious section are correlations between documented behaviors and socio-economic strata. While some studies indicate that poverty is often associated with maladaptive behaviors, the root of impatience can not be pinpointed to solely attributed to personal deficits or a lack of willpower. Thus, identifying personal deficits as the causal factor for impatience seems to be a statistical and scientific error. Furthermore, people's lived experiences, associated social and economic precarity, and structural uncertainties may be the causal force that induces hyper-focus on immediate problems and thereby impatience. In such cases, spending on entertainment while living on small income becomes a means to build a social network that can protect against life's uncertainties and may even be an escape mechanism. Thus, while impatience emerges as a prominent theme in the literature, the underlying mechanism of how or what leads to impatience is still unknown.

So, we naturally start by identifying the causal factors that induce an inability to delay gratification. One such variable is extrinsic mortality risks that individuals cannot control or overcome. Life history theories suggest that people growing up poor are cued by the mortality risks, like higher crime rates or violent neighborhoods in their environment, to prefer sooner rewards than people growing up in resource-rich environments (Griskevicius et al., 2011). It has also been argued that people adjust their preferences based on their ability to ensure their longevity (Daly & Wilson, 2005a). As previously discussed Pepper and Nettle (2017) have proposed an 'uncontrollable mortality risk' hypothesis arguing that one will rationally not invest in the future if one frequently faces these extrinsic mortality risks and cannot mitigate them.

However, mortality risks have been found to account for only 0.13% of the observed discounting from datasets across 53 countries (Riis-Vestergaard & Haushofer, 2017). Furthermore, mortality risk theories are rarely empirically testable since it is difficult to elicit veridical mortality risk judgments from people in controlled settings. Additionally, while mortality risk may be a possible 'ultimate' cause for such behavior, there must be more 'proximate' causes that promote impulsivity.

Attempting to provide a proximate explanation, some researchers have proposed a 'scarcity hypothesis', i.e., patterns of thought and irrational, impulsive behavior brought about by having to make economic decisions in a resource-scarce environment (Haushofer & Fehr, 2014; Mani et al., 2013; Shah et al., 2012). In this line of research, researchers induce impulsive behavior in the lab by making individuals operate under limited resources (time, money, or game points). These studies show that under high monetary demands, people with scarce resources tend to over-borrow and save less for the future to mitigate immediate demands (Shah et al., 2012, 2019).

The scarcity hypothesis suggests that limited resources impose a cognitive tax on individuals, which reduces available mental resources for future planning. Using easy and difficult financial scenarios with poor and rich participants, Mani et al. (2013)'s study show that poor participants performed significantly worse in cognitive control and fluid intelligence tasks when confronted with a difficult financial cost. They found similar results with Indian farmers who performed worse on pre-harvest cognitive tests than post-harvest. Thus, this theory identifies resource scarcity, functioning in a low-resource environment, as the proximate cause for present-centered behavior.

While the experience of resource scarcity is undoubtedly an essential aspect of present-centeredness among individuals in low socio-economic communities, we think the critical element that induces an inability to wait is unforeseen expenses that deplete resources. Given the intrinsic uncertainty spanning intertemporal choices, we believe people shift to a shorter planning horizon when the uncertainty associated with future plans is exacerbated.

Evidence for such a phenomenon comes from numerous lab and field studies such as Kidd et al. (2013)'s marshmallow replication where he manipulated environmental reliability and were able to perturb children's ability to delay gratification. Haushofer et al. (2013) conducted a lab experiment where participants were assigned to 'rich' and 'poor' income groups using varied starting endowments and asked to perform a task. Within the task, some participants received either an income loss (negative shock), or an income gain (positive shock), or no change in income. After the task, they performed a temporal discounting task, which measured their 'present bias'. Using this metric, the authors found that the negative shock group showed increased present bias, even when their incomes were similar to the low-endowment-always-poor group. On the other hand, positive shocks did not affect present bias. This study highlighted that income volatility, one formulation of precarity, drives people to favor immediate rewards.

Similar studies using variations in income or expenses formulated as income loss narratives (Bickel et al., 2016), unpredictable environmental perturbations like rainfall anomalies (Falco et al., 2019) or self-reported droughts among farmers (Meles et al., 2024), even perceived loss of income during COVID19 (Blain et al., 2025) show that individuals act more impatient when their environment is uncertain and they encounter a sudden expense or loss. Financial situations deteriorate significantly due to sudden increased expenses, especially for households that spend a substantial portion of their income on necessary goods like home energy and food (Cocco et al., 2016). Similar large-scale survey studies using household data have shown that households' propensity to consume increases immediately after encountering an unexpected, one-time expense that amounts to 10% of their income (Colarieti et al., 2024). Thus, we identify the experience of precarity as the causal factor that systematically induces steeper discounting within individuals.

2.4 Precarity and subjective time

As noted above, some researchers have proposed the existence of a 'scarcity mindset' - patterns of thought brought about by having to make economic decisions with scarce resources (Haushofer & Fehr, 2014; Mani et al., 2013; Shah et al., 2012) to explain the presence of impulsive behavior in individuals belonging to the low socio-economic communities. The 'scarcity mindset' literature has primarily considered selective attention and cognitive load as possible mediators. Individuals operating under artificially induced scarcity in lab conditions attend more to scarcity-related information and neglect other sources of potentially useful information while completing lab tasks (Shah et al., 2012, 2019). Similarly, inducing cognitive load in lab experiments has led to steeper time discounting (Deck & Jahedi, 2015). This led some theorists to propose that resource scarcity causes attentional tunneling toward immediate problems, leading to neglect of the future, which imposes a cognitive tax that reduces mental bandwidth to deal with the future (Schilbach et al., 2016).

However, these postulated mechanisms have been criticized on theoretical and empirical grounds. Field evidence for attentional shifts causing choice differences is sparse and inconsistent (de Bruijn & Antonides, 2021). Lichand and Mani (2020) studied the effects of scarcity on attentional tunneling among Brazilian farmers who regularly face droughts and rainfall anomalies. They found that farmers who experienced less rainfall were more likely to tunnel before payday than after. Methodologically, de Bruijn and Antonides (2021) note that scarcity researchers used payday variations, which may not reflect variations in income but variations in liquidity in farming households, and thus, attentional tunneling may result from liquidity constraints and not low resources. Further, attention selection operates on the time-scale of seconds in lab-based studies (Tomm & Zhao, 2017). This makes it difficult to attribute to them behavioral patterns evident across months or years of individuals' lives and generations of communities' existence (Lewis, 1966; Pepper & Nettle, 2017; Wilson, 2012).

Empirical evidence for reduced mental bandwidth in low socio-economic individuals is also mixed and inconclusive (de Bruijn & Antonides, 2021). While some field studies have found evidence supporting poverty impairing cognitive functions, others have not. For example, Ong et al. (2019) investigated the effect of a debt relief payment on cognitive functioning and found that low-income Singaporeans performed better on Flanker tasks post-payment than pre-payment. Along the same lines, Lichand and Mani (2020) found that Brazilian farmers, who experience a lack of rainfall signifying income uncertainty, performed worse on cognitive control tasks. On the other hand, Fehr et al. (2019) found that lower scores of cognitive control tasks were associated with low-income Zambian farmers and did not carry over to seasonal variations in financial conditions. On the same lines, Carvalho et al. (2016) found that US low-income households faced more challenging economic circumstances before payday than after, but greater pre-payday scarcity did not impede cognitive functions.

These insights made us question whether attention tunneling and reduced mental bandwidth may be valid psychological determinants of impatience. As a result, we looked into traditional explanations of preference and utility shifts to find answers. Standard discounted utility models pinpoint the reason for such future undervaluation, as shifts in the discount rate are often interpreted as a loss of self-control. This is evident in exponential, hyperbolic (Laibson, 1997) or quasi-hyperbolic formulations (Mazur, 1984) where the utility of a delayed reward at time T is given by

$$U(t) = \int_{t_0}^{T} f(t)u(t)dt \tag{2.1}$$

and the discount function $f(t)$ is given by

$$\text{exponential discounting:} f(t) = e^{-kt}$$
$$\text{hyperbolic discounting:} f(t) = \frac{1}{1+kt}$$
$$\text{quasi-hyperbolic discounting:} f(t) = \beta\delta^t \quad \forall \quad t > 0$$

In all such formulations, changes in the discount rate k (or the present bias parameter β) alter the perceived utility of delayed rewards $u(t)$; however, the delay t is assumed to remain invariant. On the contrary, extensive investigations in the time perception literature suggest that perceived time is a function of the amount of information processed in the judged interval (Thomas & Weaver, 1975), and expectation-outcome mismatches led by unpredictable stimuli can lead to distortions in duration judgments (Pariyadath & Eagleman, 2007). This suggests that delay distortion can be a psychological factor that alters the perceived utility of a delayed reward when volatility is encountered.

The idea that our subjective time is distorted by our physical, environmental, or mental events is not new. For example, fear has been shown to distort our perception of time, where duration is judged to be longer, and this lengthening extends with the length of duration (Fayolle et al., 2015). To account for these, an internal clock model conceptualized time perception as an information-processing system consisting of a pacemaker, switch, and an accumulator where, at an event onset, the pacemaker generates impulses to be stored in the accumulator, and at the event offset, the intervening switch opens up to stop the impulse transfer (Gibbon et al., 1984). Researchers have used this model to explain the mechanism of how non-temporal or emotional events might affect people's time perception; for example, redirection of attention to external events or inattention can lead to shortened perception of time via loss of impulses, or an increase in arousal can fire up the pacemaker, leading to a subjective feeling of time expansion (Droit-Volet & Meck, 2007).

If subjective time is malleable to our lived experiences, how would economic precarity affect perceived time? To answer this question, we draw on insights from the perceptual literature, where the effect of unpredictability on time perception is typically investigated using oddball paradigms. In these experiments, participants attend to a low-probability, novel stimulus (*oddball*) in a sequence of high-probability, repetitive stimuli and estimate its duration. The oddball is presented at varying durations (longer or shorter than the repetitive stimuli), and participants note whether they perceive it as longer or shorter than the standard stimuli. Across multiple studies, researchers have found that unpredictable stimuli are perceived to be longer than predictable ones (Pariyadath & Eagleman, 2007; Tse et al., 2004; Ulrich et al., 2006). These observations have been explained using an information processing account where unpredictable stimuli distort time by engaging attention and increasing the amount of information processed per objective time (Tse et al., 2004), or an arousal-based account where increased arousal speeds up the internal clock, causing longer perceived duration and better temporal discrimination than predictable stimuli (Ulrich et al., 2006).

From a theoretical perspective, Pepper and Nettle (2017) suggests that mortality risks in one's immediate environment can lead one to act impatiently. Thus, if one fears losing their job, or getting evicted from their home, or getting shot in the streets, they would naturally discount the future because the future may feel inaccessible and unattainable. Thus, precarious conditions may alter people's conceptualizations and perceptions of time, making delayed rewards seem farther away than they actually are. As a result, people may not choose to delay gratification, which suggests that impatience is not a lack of willpower but a rational response to contextual and psychological changes.

2.5 Precarity, subjective time and impatience

It is plausible that people operate on an internal, subjective time scale distinct from objective time, which may be distorted by environmental turbulence, thereby affecting temporal preferences. Experimental evidence suggests that subjective prospective judgments of duration are non-linear and concave in nature (Zauberman et al., 2009), and models of inter-temporal choice show that an exponential discounting with logarithmic time perception fits the data better than simple exponential or hyperbolic one (Takahashi et al., 2008), indicating human time perception may not be linear and similar to clock time as previously assumed.

Furthermore, some have suggested that expectation-outcome mismatches may regulate psychological time and its perceived slowing and speeding, and an altered sense of time aims to minimize this error (Eagleman, 2004). Thus, if one encounters a discrepancy in their environment, their time perception may adjust accordingly. Indeed, it has been found that positive and negative prediction errors bias time perception differently, increasing and decreasing perceived time, respectively (Toren et al., 2020).

Now, the question remains whether economic precarity alters our subjective sense of time; how would that affect decisions over time? To find a definite answer, we look into investigations of the effects of perceived time on intertemporal choices in the decision-making literature. Empirical studies suggest that individuals who overestimate delays tend to choose smaller, immediate rewards compared to people who underestimate them (Suo et al., 2014). McGuire and Kable (2012) showed that when the delay in inter-temporal choices seems to be increasing over time (like waiting for a phone call) compared to being diminishing over time (like waiting for a bad movie to end), people show preference reversals - they often prefer the delayed rewards initially and then forgo them later.

Similarly, Lee et al. (2025) found that participants preferred smaller immediate rewards in tasks where they were made to wait after every trial compared to deferred waiting after all trials. Xu et al. (2020) found that manipulating the sense of time in the lab affects individuals' rate of future discounting. In this experiment, the sense of time was manipulated by varying the pace of time counting, and the authors found that discount rates decreased when switching from a faster pace to a slower one, and vice versa. Overall, these results suggest that subjective time distortions play a key role in delay discounting and relative changes in felt time may affect impatience. While only a few studies have investigated these effects, the evidence seems to point in the same direction: one, unpredictable stimuli distort duration judgments; two, environmental perturbations cause people to opt for sooner rewards; and three, perceived delay overestimations may lower future orientation.

2.6 Summary and looking ahead

Based on sociological and anthropological reports, we suspect that economic precarity may affect people's ability to plan for the future. However, how that transpires is not well understood. Prior work has proposed attention and cognitive load as potential mediators of such effects. In contrast, the present thesis advances the hypothesis that precarity may also distort subjective time perception, thereby reshaping preferences and planning horizons. In the following chapter, we start by simulating how environmental precarity may influence planning and choice behavior. These simulations motivate the subsequent empirical investigations of precarity and preferences and the possible mediatory role of subjective time.

3

How precarity affects preferences

To offer a mechanistic explanation as to why people's temporal preferences shift, we propose that recurrent, unpredictable expenses (which we term *resource shocks*) lead to depletion of endowment, and, consequently, planning failures for long-term plans. People in poverty often deal with low budgets, which tend to deplete faster due to resource shocks often in the form of sudden expenses or loss of income. We think this leads to abandonment of future plans and increases focus on immediate problems instead. Even high budgetary allocations may deplete when resource shocks are multiple and substantial in nature, leading us to theorize that the frequency and intensity of resource shocks (and not endowments or budgets) are the critical elements that push people to be impulsive [1].

3.1 Simulating precarity in-silico

As an *in silico* presentation of our proposal, we estimate how the expected rewards of future plans and the optimal planning duration (when expected rewards are maximum) change with the plan's delay to fructification (plan duration). We do this by modulating

[1]This section was previously published as a research paper (Mitra et al., 2025)

the frequency of unpredictable resource shocks. In this simulation, an agent starts a plan to be completed at time $t = T$ with an initial endowment of resources and a known anticipated reward. At each time step $t < T$, one of two things happens: either the endowment is depleted by a resource shock with a probability of 0.05 or 0.30 (i.e., infrequent or frequent), or the reward to be obtained increases as the observer gets closer to time T. At time T, the simulation ends either with a complete depletion of the observer's endowment resulting in null payoff or with a positive payoff for waiting. The expected reward is the mean payoff arising from each plan traversal over 10000 iterations. We repeat this process with different initial resource endowments to check if the same results are observed for both low and high endowments. Our simulations reveal some critical insights that we note below:

- In cases of infrequent resource shocks (p(shock) = 0.05), we find that the expected reward of the future plan increases monotonically with plan duration, even under low resource endowments. The same trend was observed for high endowments. This suggests that rational observers should prefer long-term plans when functioning under resource constraints and in the absence of shocks.

- When endowments are low and resource shocks become prominent (p(shock) = 0.30), the expected rewards associated with future plans deplete to zero considerably faster compared to infrequent shocks, as shown in Figure 3.1A. This suggests frequent shocks may deplete low endowments faster, making it infeasible for future goals to be sustained. This could be why people belonging to the low socio-economic community may find long-term plans unsustainable.

- Frequent resource shocks also deplete the expected utility of delayed rewards in plans with high endowment. Thus, resource shocks affect long-term planning irrespective of endowment, however, this depletion is less prominent compared to plans with low budgets. This suggests that increased endowment may provide buffer against unexpected expenses.

- Optimal duration, operationalized as the plan duration where expected reward of a future plan peaks, changes for both high and low endowments when resource shocks are frequent (p(shock) = 0.30). When resources shocks were infrequent, the optimal planning duration for both endowments is equal to the actual planning duration $t = 1000$. However, as resource shocks become more frequent, the optimal planning duration shrink to $t \approx 270$ and $t \approx 570$ for low and high budgets, as seen by optimal duration A and B in Figure 3.1A. Thus, low endowment coupled with frequent, unpredictable turbulence increasingly shortens the planning horizon suggesting these conditions may be necessary and sufficient in pushing people to be present-focused.

- Optimal planning duration reduces with increasing frequency of resource shocks for both low and high budgets. However, in the absence of resource shocks ($p < 0.05$), the optimal planning duration remains unchanged at $t = 1000$ even under low endowment, as shown in Figure 3.1B. Thus, a predictable environment coupled with low endowment might still provide space for individuals to plan for later. However, as unpredictability increases, planning for the future becomes increasingly nonviable for low-budget agents.

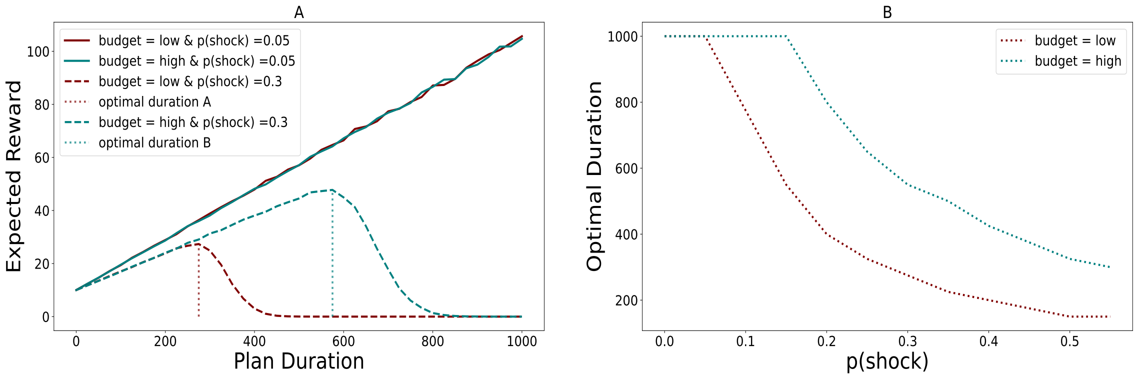


Figure 3.1: Resource Shock Model - (A) Expected reward as a function of planning duration under high and low budgetary allocations and rare (5%) versus frequent (30%) resource shocks. Frequent shocks reduce expected reward and shift the optimal planning duration toward shorter horizons, with this effect being more pronounced under low budgets. (B) Change in optimal planning duration as a function of shock probability, showing a faster contraction of the optimal planning horizon as resource demands increase when budgets are low.

Overall, the simulation suggests that frequent resource shocks make longer planning duration unsustainable by draining out resource endowments and minimizing the payoff for waiting. This is prevalent in both high and low endowments, with the minimization amplified when resource endowments are low. However, in the absence of resource shocks, future planning is sustainable even under conditions of low endowment.

Translated back to the context of our theory, waiting for extended periods for rewards while operating under budgetary constraints and frequent resource demands is risky, as plans may fail due to the planner's inability to commit extra needed resources promptly. This could be interpreted, for instance, as someone failing to pay a credit card bill installment because they lost their job. In such cases, it seems rational for agents to shift their planning horizon to a shorter temporal scale.

3.2 Robustness checks

Our simulation models the interaction between resource budgets, resource shocks, and maintenance of activities with long-horizon payoffs as occurring in discrete time $t, t \in \{0, 1, \cdots, T\}$. Observers in this simulation are endowed with a budget $B(0)$ (where $B(0) = 100$ or 200 signifying low or high) and a time-varying payoff $X(t)$ (where $X(0) = 10$), which increases as our agent gets closer to their goal and eventually paid out at $t = T$. They are also simulated to encounter infrequent or frequent ($p = 0.05$ or 0.30) resource shocks. Thus, at every time step t starting from $t = 0$ to $t = T$, the incidence of a resource shock is determined by randomly sampling values from a uniform distribution ($U[0,\ 1]$) and checking if this is less than the probability of shock.

If the sampled value is less than the critical limit, the observer encounters a resource shock and their resource budget $B(t)$ is depleted by an unexpected expense $\beta(t)$ leaving a reduced budget $B(t) = B(t-1) - \beta(t)$ and unchanged payoff $X(t) = X(t-1)$. Otherwise, they encounter no unexpected expenses keeping their budget intact $B(t) = B(t-1)$ and increasing their payoff for waiting $\alpha(t)$ i.e., $X(t) = X(t-1) + \alpha(t)$. Thus, as the observer reaches the endpoint $t = T$, either their endowment gets depleted $B(T) \leq 0$ resulting in null payoff $X(T) = 0$ or they have a surplus endowment $B(T) > 0$ with a positive payoff $X(T) > 0$. Expected utility of waiting for the future reward is calculated by deriving the average of the payoffs obtained by the observer over 10000 iterations.

Within this basic simulation framework, we consider four conditions following a 2×2 design, by modulating the nature of the reward increment $X(t)$ (linear/exponential) and the nature of the sampling distribution for the recurrent costs $\beta(t)$ (normal/heavy-tailed).

- The linear reward update was implemented as $X(t) = X(0) + \alpha(t)$, where, $\alpha(t) \sim N(0.1, 0.1)$.
- The exponential reward update was implemented as $X(t) = X(0) * \exp(\alpha(t))$ where, $\alpha(t) \sim N(0.001, 0.001)$.
- The sampling distributions used to sample $\beta(t)$ on every time-step were normal $\beta(t) \sim N(1, 1)$ and heavy-tailed i.e., log-normal $\beta(t) \sim \log N(1, 1)$.

Across these four conditions, we measured the expected utility of maintaining plans of length T for observers with $B(0)$ varied between 100 and 200 units, characterizing low and high budgets. The expected utility was calculated as the sample average of 10000 simulations for each of the four conditions as shown in Figure 3.2.

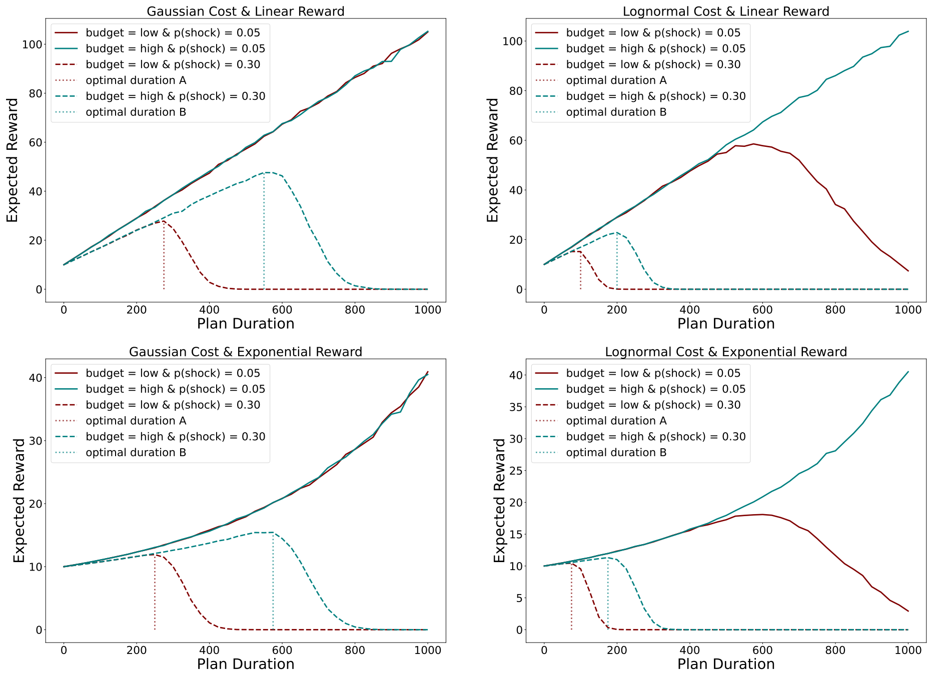


Figure 3.2: Resource Shock Model (A)- Demonstrates the effect of differently sized starting budgets (low and high) and probability of resource shock (0.05 and 0.30) on expected rewards associated with plans that become increasingly more rewarding over time. The nature of this cost deduction and reward increment varied between conditions: **(A)** Gaussian cost with linear reward increment, **(B)** Log-normal cost with linear reward increment, **(C)** Gaussian cost with exponential reward increment, and **(D)** Log-normal cost with exponential reward increment.

We also measured how optimal planning duration changes as a function of the probability of resource shocks across these four conditions. The optimal duration was calculated as the planning duration at which the expected utility of the future plan was maximized. This was also calculated as the sample average of 10000 simulations for each of the four conditions, as shown in Figure 3.3.

Across all four conditions of Gaussian or Log-normal cost and linear or exponential reward increment, we find that the optimal duration is much earlier for the low budget condition than the high one when the probability of shocks is high, as shown in Figure 3.3. Also, the low budget depletes to null only when the probability of the resource shock increases to 0.30 from 0.05, as shown in Figure 3.2. This bolsters our hypothesis that in a predictable environment, having low resource endowments would not affect people's temporal judgment. However, facing recurrent resource shocks in an unpredictable environment with

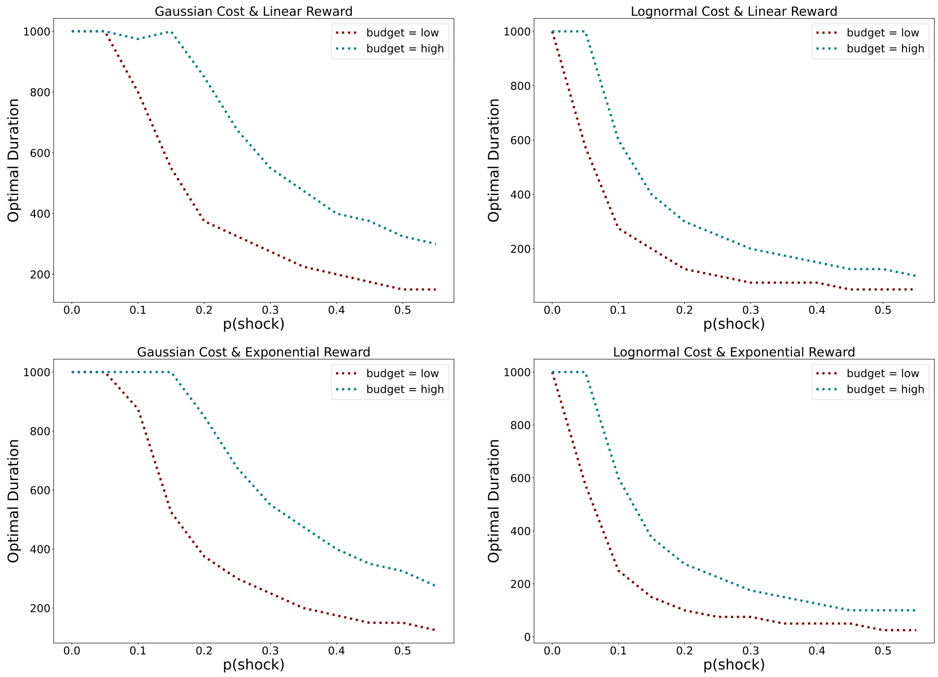


Figure 3.3: Resource Shock Model (B)- Demonstrates the effect of differently sized starting budgets (low and high) and probability of resource shock (ranging from 0 to 0.55) on optimal planning duration. Across all conditions, optimal planning duration falls for both high and low budgetary conditions as the probability of shocks increases. This fall is found to be steeper when the budgetary allocation is low. The nature of cost deduction and reward increment was varied, as mentioned in the above figure.

low budget conditions shortens people's planning horizons. We think this is one of the critical elements that induce the inability to delay gratification in people belonging to the low socio-economic communities, and these unpredictable resource shocks are why they find themselves trapped in the poverty cycle.

3.3 Summary and looking ahead

Planning horizons and optimal planning durations shrink to the short-term when one encounters frequent resource shocks. This is especially prominent when their starting endowment is small - highlighting the role of precarious conditions in low socio-economic communities. Shortening of planning horizons were also documented when endowments are double in size, and different cost and reward structures are taken into account. To empirically test whether these predictions hold true, we design a video game that simulates stable and volatile environmental conditions which is discussed in the next section.

4 Method of investigation

In this thesis, we try to empirically establish how people's temporal planning horizons change when subjected to a precarious environment in addition to our computational synthesis. To test our theory, we developed a novel experimental paradigm to characterize the effect of experimentally induced precarity on revealed temporal preferences [1].

We defined precarity as any exogenous, unpredictable event that may create uncertainty in an agent's immediate environment, thereby altering their mental and physical states (i.e., thoughts and behaviors). While we have operationalized precarity as heightened expenditures and losses in the game, it can also include non-economic exogenous perturbations such as health risks. In this operationalization, we define precarity as volatility and unpredictability: volatility indicates increased expense variance, leading to higher expenditures, and unpredictability suggests unexpected expenses that can lead to prediction errors.

[1]This section was previously published as a research paper (Mitra et al., 2025)

Figure 4.1: Game GUI: At the top of the user interface is the 'Ledger', which displays real-time trial-wise farming-based resource debits and credits. Farming debits included resource debits or farming inputs ('Resource Cost'), loss of crops ('Crop Loss'), and rent for the farming land ('Land Rent'). Farming-based credits included 'Crop Yield', i.e., the money earned from harvesting crops. The ledger also displayed each crop variety and the associated profits, total money earned by the player ('Money Made'), and our formulation of resource scarcity ('Budget'). Our depiction of environmental precarity was designed as an increased resource cost, crop loss, and land rent in the game. Since participants were encouraged to learn about the risk profile of each crop, we displayed the net loss incurred by each crop after each trial. The middle of the user interface displays the soil where participants could sow and harvest their chosen crops. The participants were informed that crop sowing patterns on the soil or time (month of the year) did not impact crop loss or yield (check out youtube for a demo).

4.1 Game mechanics: Harvest Horizons

Our motivation was to create a close-to-real-life platform where people would experience a precarious environment while planning and exercising their choices through various options, observe their outcomes, and subsequently re-calibrate based on the feedback. Thus, our experimental paradigm was designed as a farming simulator where participants played the role of a farmer who sowed and harvested crops over multiple trials while observing resource inputs and farming expenses. *Harvest Horizons* was designed on GameMaker: Studio 2.1.5 using GML language. The GUI shown in Figure 4.1 details the different design aspects.

4.1.1 Farming game design

To simulate a stable and volatile farming environment, we formulated a block design in the game such that farming expenses would be negligible in some blocks (Low Variance or LV) and significant in others (High Variance or HV). These LV and HV blocks were randomly presented to each participant after the presentation of a 'practice' block, during which participants got accustomed to the game, as shown in the top panel of Figure 4.2. Each block had 24 trials, and the game ran for five blocks or 120 trials. The blocks were designed to depict a real-life scenario where environmental events can be relatively smooth sailing (as in a low-variance block) or turbulent (as in a high-variance block).

At the start of each trial, participants had to sow crops of their choice on the soil comprising forty slots as shown in the bottom-middle panel, Figure 4.2. At the end of the trial, they harvested their full-grown crops and started the subsequent trial after resowing the plot. We also made an in-game ledger such that an account of various farming expenses and incomes was readily available enabling participants to make informed crop choices in all game blocks.

4.1.2 Precarity as resource shocks

The game's central idea was to simulate a resource-scarce environment where farming expenses could go overboard with some probability. Thus, the depiction of environmental precarity and our critical manipulation in this experimental paradigm was the occurrence of resource shocks alongside the formulation of a low budget. To this effect, a budget was deducted from participants' money at the start of every trial, which was used to pay for various resource costs or farming inputs.

Now, resource shocks were operationalized as farming expenses going overboard compared to the budget. To be precise, resource shocks were quantified by trials where resource debits in the form of farming expenses (sampled from a random, normal distribution) would rarely go overboard the budget in LV blocks and around one-third of the time in HV blocks.

Thus, in LV blocks, the farming expenses would rarely cross the budget, signifying a smooth, streamlined environment. However, during HV blocks, these expenses would frequently go overboard compared to the budget, suggesting a precarious environment and the occurrence of a resource shock. These increased resource debits would manifest as

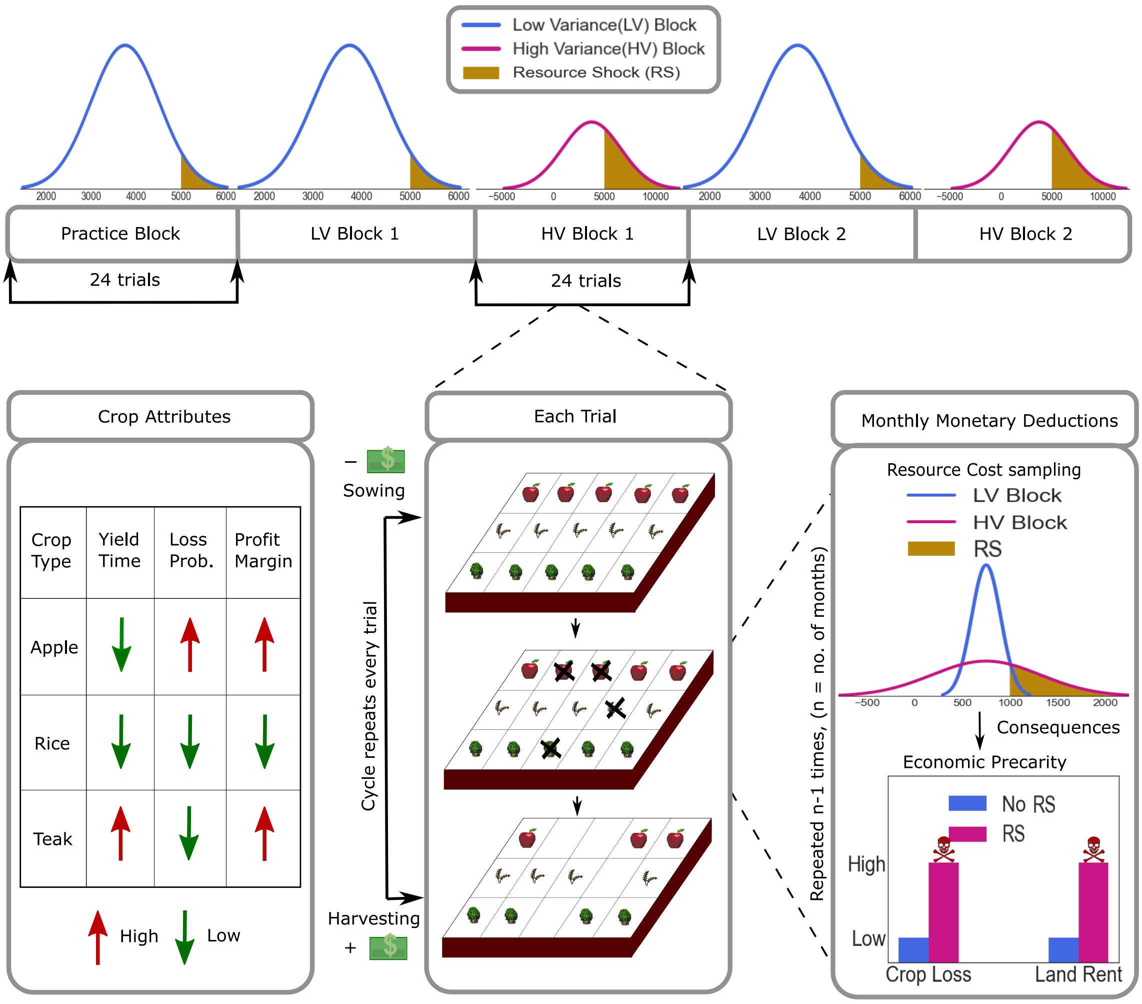


Figure 4.2: Game Design - this figure depicts the workings of the farming-simulator experimental paradigm. The top panel shows one of the experimental block structures used in the game. The bottom panel shows the varied crop attributes, how every trial traversed through the crop-sowing to the crop-harvesting phase accompanied by crop loss and the critical manipulation of a precarious farming environment.

increased crop losses and land rent in those harvest cycles as shown in the bottom-right panel of Figure 4.2 and summarized in 4.3.

4.1.3 Crops as inter-temporal choices

We designed inter-temporal choices in this game as three different crop varieties - Apple, Rice, and Teak - that differed in temporal and risk attributes (displayed on the bottom-left panel of Figure 4.2). Participants' choice of crops was our measure of temporal preferences - we wanted to see if people would opt to wait for a more rewarding crop in the face of resource shocks.

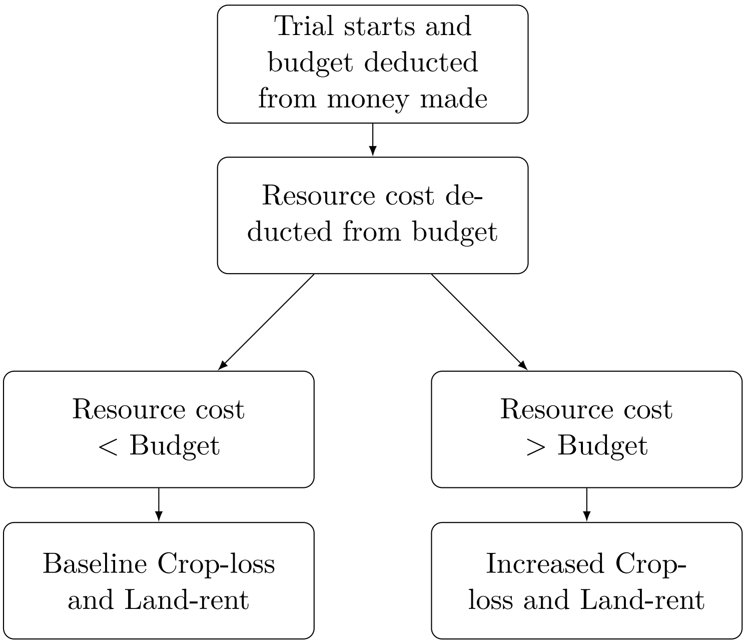


Figure 4.3: Flowchart showing experimental manipulations with varied stochasticity: If resource cost drawn randomly was less than the budget then it manifested in-game as lower crop loss and land rent. Otherwise, if sampled resource cost was greater than Budget, then it depicted tumultuous times with higher crop loss and land rent.

In our game, apples and rice were designed as the 'sooner, smaller reward' because they took minimal time to grow (yield time) and gave smaller earnings upon harvesting (profit margins). Apple was designed to be a risky choice than rice, i.e., apples would provide higher profits than rice. Still, they were susceptible to higher losses in the face of adversities (loss probability). On the other hand, teak was our depiction of the 'later, larger reward' as it had the longest growth time but yielded the most earnings. Thus, teak was the long-term non-risky choice, apple was the short-term risky option, and rice was the short-term non-risky bet. These crop attributes are documented in Table 4.1.

In other words, we depicted adverse situations in the game as resource shocks, occurring whenever the resource cost exceeded the budget, manifesting as increased crop loss and land rent. The crop losses (denoted by a loss factor) were sampled from a binomial distribution such that it was either low in the absence of a resource shock or high otherwise. This loss factor was designed such that apple was a high-risk crop and rice and teak were low-risk choices. Finally, land rent was also designed to be binary (high or low) in the presence or absence of a shock.

Table 4.1: Table depicting detailed crop attributes for each crop type. Bracketed values in the Loss Factor denote increased crop loss on resource shock trials.

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)

4.2 Game-play walk-through

Participants were made aware of what the game was, the choices available, and how to play it. The game started with a GUI similar to the one shown in Figure 4.1. Each trial was designed to last six months in the game, and participants played the life cycle of a farmer for 60 years. Participants were explicitly informed of the crop yield time and profit margins; however, they were encouraged to estimate the loss probability as they played the game.

In our experimental paradigm, participants were asked to sow crops on the entire field so that no slots would be left empty on each trial. Thus, any decrease in long-term crop choices would always be associated with a corresponding increase in short-term choices. They were notified that the brown patch of land was the plot for growing crops. They were made aware of all crop attributes except the loss probability. A green outline box around the cursor suggested the areas of soil available to sow, and a red outline box suggested areas that were not.

Sowing the crops on the plot was done with left mouse clicks. Sowing each unit of all crops was accompanied by a deduction of 50 coins as the buying price. Choosing which crops to grow (i.e., browsing through options) was done by revolving the mouse wheel. When crops were planted, participants pressed ‘space’ to start each trial. While the trial was ongoing, they could see the month and year of game-play, corresponding monthly resource cost deduction (from their budget), crop losses, and land rent deductions (from their game money), updated in real-time (as seen on the left-hand side of 4.1). At the end of each trial, the game paused, and participants had to harvest the full-grown crops (indicated by a sparkling effect) with the right mouse clicks. After harvesting, participants had to sow the plot again and start the subsequent trial. After harvesting, each crop’s selling price was added to their game money.

As shown at the top of Figure 4.1, participants' crop yield, crop loss, resource cost deductions, and land rent were saved in the ledger for each trial for the past ten trials. They were updated after every trial, and participants were advised to consult these to get a comprehensive view. The ledger also illustrated their net 'Money Made' (game money), budget in hand, and crop profit for each unit of all three crops. Each participant was explicitly asked to play to maximize their total game money, and a ranking-based system was also designed to reward the top performers (up to thrice their participation money) alongside their compensation.

4.3 Optimal Crop Choice

How would an economically optimal agent behave in this game? Would the long-term choice still be optimal under conditions of low endowment and intensifying shock frequencies? To answer these questions, we identified the optimal crop under simulated conditions of a fixed endowment and increasing shock probability [2]. We operationalize optimality in terms of mean net profit ('Net profit' on Figure 4.4) associated with each combination of crops such that $\sum(n_a, n_r, n_t) = 40$ where n_a, n_r and n_t are the number of apple, rice, and teak on plot respectively.

To obtain the optimal crop choice, we derived net profit associated with each possible crop combination under a fixed endowment ($X = 20000$) and low, moderate, and high probability of resource shocks ($p = 0.05, 0.3$ and 0.8). Since opting for teak entitled waiting for teak to reach its full-grown state over six trials, we calculated net profit cumulatively over six trials. On each trial $t \leq 6$, one of two things happens: our agent can observe a resource shock (determined by p), which leads to an increased crop loss and significant endowment depletion, or they encounter no shock leading to a baseline crop expense and a marginal endowment reduction. Thus, on each trial, the endowment is depleted by the crop expenses given by $X(t) = X(t-1) - l_i$ where l_i can be significant or baseline based on the incidence of a shock. If their endowment is completely depleted in this intervening period (i.e., $X(t) \leq 0$ in $1 \geq t < 6$), our agent quits the simulation run (or waiting for teak) with the net crop profit accumulated over all preceding t trials. Otherwise, they conclude the simulation run at $t = 6$ (i.e., waiting for teak to harvest) with the net profit accrued over all six trials. Net profit (P_{net}) is calculated using the difference between the cumulative capital inflow from crop harvest and capital outflow from crop expenses over t

[2] Even though we identify the optimal crop by simulating different shock conditions, these conditions and the resulting optimality are part of the game design.

trials, which is given by

$$P_{net} = \sum_{1}^{t}(p_i) - \sum_{1}^{t}(l_i) \qquad \text{where,} \tag{4.1}$$

$$p_i = s_i - b_i \qquad \text{and} \tag{4.2}$$

$$l_i = \mathrm{B}(1, \theta_i) * p_i * n_i \tag{4.3}$$

p_i and l_i are the crop yield and crop loss accrued by the i_{th} crop. Crop yield is obtained from s_i and b_i - the selling and buying price associated with the i_{th} crop. Crop losses l_i are obtained from a binomial distribution determined by loss factor θ_i associated with the i_{th} crop. s_i, b_i, and θ_i are based on the crop parameters used in the game. We iterate the above process 1000 times to calculate the mean net profit associated with each crop combination under conditions of a fixed, low endowment and increasing frequency of resource shocks. Figure 4.4 (A), (B), and (C) depict the optimal crop choice under these conditions.

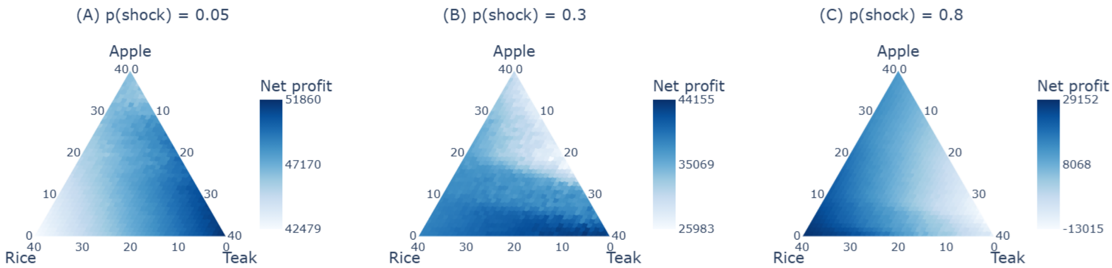


Figure 4.4: Optimal Crop Choice: These ternary plots show the optimal crop choice under conditions of fixed, low endowment and (A) low, (B) moderate, and (C) high incidences of resource shocks. The teak plantation is the optimal choice in low resource shock conditions. However, as the probability of shock increases, the optimality shifts away from teak. At high probability (p(shock) = 0.8), teak plantation yields a negative net profit — suggesting endowment depletion before harvest is fructified. The values 0 and 40 on the axes denote null and total plantation of those respective crops on the field.

We find that teak plantation leads to highest net profit over time when the probability of shock is low (p(shock) = 0.05). However, as the probability of shock increases by 0.25 (i.e., p(shock) = 0.30), the net profit obtained from the teak plantation shifts away from the maxima. Further increases in shock probability by 0.50 (i.e., p(shock) = 0.80) show that teak plantation produces a negative net profit compared to all other crop combinations. This suggests that waiting for teak to harvest under frequent resource shocks leads to endowment exhaustion before teak is harvested, leading to negative net profit (i.e., a zero crop yield and positive crop loss).

Among the short-term crops, apples provide more net profit than rice as they were designed to provide higher yields than rice under a low probability of shocks ($p = 0.05$). However, as the frequency of shocks increases ($p = 0.80$), apple production increases crop expenses due to its higher-risk profile, making rice production more profitable. Thus, while the short-term, risky choice (apple) is more profitable under low resource shocks, the low-risk, short-term crop (rice) is optimal under frequent shocks.

Overall, the optimal crop calculations suggest that the long-term choice is optimal under conditions of minimal turbulence. In other words, teak production pays off when the frequency of shocks is minimal, as arbitrary unexpected expenses do not deplete one's endowments. However, opting for the long-term choice under incessant turbulence is sub-optimal as heightened expenses may deplete endowments before the future plan is fructified. In such scenarios, proximal, non-risky rewards (similar to rice in our design) pay off immediately, replenishing one's endowment in the short term. Thus, while teak may be optimal in a streamlined environment, it may not be preferred when resource shocks are frequent.

4.4 Summary and Looking ahead

Our formulation of a precarious environment is motivated by the lived experiences of impoverished individuals. Instead of testing the interactions between resource scarcity and unpredictable shocks, we check if people's temporal preferences shift under low budgets and recurrent over-the-budget expenses. Thus, we simulated environmental precarity within the farming game using resource shocks and measured whether experiencing such shocks led participants to prefer options paid out earlier than later. In the following section, we test our theory using this farming game with university students and farmers employed in IIT Kanpur as gardeners.

5

Precarity and preference shifts

Our simulation suggests that frequent shocks make long term planning unsustainable by draining out endowments and minimizing expected utility of delaying gratification. This was prevalent in both high and low endowment conditions, but the effects were maximized when budgets were low and unpredictable shocks were frequent. Thus, waiting for rewards while operating under limited budget and frequent shocks can be risky, as plans may fail due to unpredictable environmental demands. Thus, while delaying gratification may be optimal in stable environments, it may not suitable when living in precarious conditions[1].

5.1 A 'resource shock' hypothesis

In this section, we empirically establish how people's temporal planning horizons change when subjected to a precarious environment. Our formulation of a precarious environment was motivated by the lived experiences of impoverished individuals. Thus, we check if people's temporal preferences shift under precarious conditions concocted with low endowments and frequent resource shocks. Based on the simulation, we hypothesize that

[1] This section was previously published as a research paper (Mitra et al., 2023, 2025)

people would adaptively prefer shorter-term plans when they experience unpredictable resource shocks while functioning under a low budget. We also hypothesize that they would prefer long-term goals in the absence of these shocks, in other words, preferentially choose timescales where they can act most effectively.

Our proposal resonates with the resource-rationality argument, which proposes that people tend to maximize the expected utility of their choices contingent on their cognitive limitations or ecological constraints (Bhui et al., 2021; Griffiths et al., 2015). The simulation results suggest that the expected utility for waiting is contingent on resource limitations and, more importantly, the recurrence of events that lead to the depletion of said resources. Thus, while waiting for the delayed reward is optimal in the traditional views of rationality, recurrent resource depletions make short-term planning rational in the 'resource-rational' (or bounded rationality) perspective.

To test these hypotheses, we had developed a novel experimental paradigm (discussed in the previous chapter) to characterize the effect of experimentally induced precarity on time preference. Using this paradigm, we conducted four studies: the first experiment tested whether student's time preference shifted when they were subjected to resource shocks while operating on a limited budget; the second experiment was a replication of the first with farmers; the third study was a 'pure control' experiment, which tested whether people would prefer long-term plans in the absence of such resource shocks, while still operating on a limited budget; and the fourth experiment attempted to pinpoint the critical feature of resource shocks that drives the observed shifts in preferences.

5.2 Exp 1: Preference shifts in Volatility among Students

In our first exploratory study, we simulated environmental precarity within a farming game using resource shocks and measured whether experiencing such shocks led participants to prefer short-term plans. We conducted this experiment in the lab with university students.

5.2.1 Methods

5.2.1.1 Experimental design

In the previous section, we described our experimental paradigm in detail. In short, participants played the role of a farmer in a farming simulator game where they choose between short-term (apple and rice) and long-term crop (teak). Short-term crops were also varied in risky prospects giving us risky apple and non-risky rice. We simulated resource shocks by varying the farming expenses debited from participant's budget on each trial. While these expenses were less than the budget in stable conditions, participants faced multiple unpredictable shocks depicted as farming expenses greater than the budget in volatility conditions (HV trials). This volatility resulted in increased crop loss and land rents - our depiction of precarity.

As noted in the previous section, we also found out that in stable conditions, choosing the long-term crop teak was the optimal or most profitable choice, while in volatile conditions, short-term choice rice was optimal. Using this paradigm, we were interested in checking how people's crop preferences changed (namely, teak) as a result of resource shocks.

5.2.1.2 Participants

Based on pilot data, we predicted a low-to-medium effect of our experimental manipulation. Using G*Power3.1 (Faul et al., 2007a), 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 who were recruited via offline and online adverts on campuses. One participant's data was discarded as they admitted to having played the game desultorily, and another was discarded for incorrect data records on the part of the game. Eight of these 77 participants were identified as outliers using a 1.75*IQR exclusion criterion on the teak preference shift data. The analysis was carried forward with 69 participants (30 females and $M_{age} = 25$ years).

All participants were recruited with informed consent and monetary compensation. Since the experiment took around sixty to seventy-five minutes, participants were compensated with a standard of ₹150 ($8 PPP adjusted) for their time. In addition to this, an incentive structure was implemented in the game, where top earners were provided with extra monetary rewards. This was done to nudge people to choose the profit-maximizing crop option in the game. To this effect, three participants were also awarded bonus payments of ₹500, ₹300, and ₹100 ($25, $15, and $5 PPP adjusted) based on their performance in-game. The Institutional Ethics Committee approved the study.

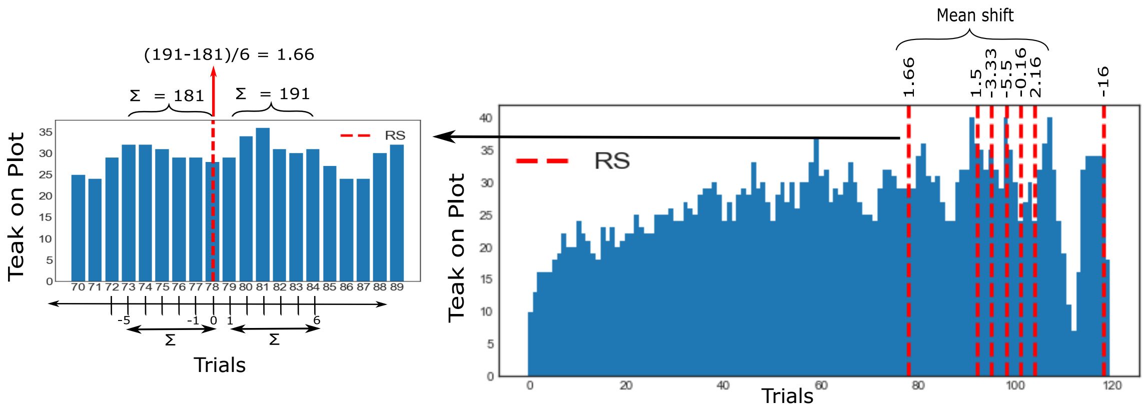
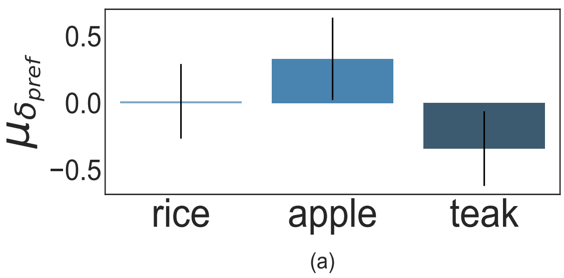


Figure 5.1: Game Analysis - this figure shows our analysis protocol for the farming-simulator experimental paradigm. For each participant, we identify the trials on which resource shocks occurred, and change in crop preferences is determined by taking the difference in the cumulative amount of crops on six trials before and after each resource shock trial. We chose six trials before and after, as teak takes six trials to be harvestable. Each participant's mean change in crop preference is calculated by taking the mean difference in crop preferences across all resource shocks encountered in the game. Lastly, all shock trials occurring on the last six trials in the game was excluded from analysis.

5.2.1.3 Analysis procedure

We performed a trial-by-trial analysis to study the effect of resource shocks on participants' choice of crops. We were primarily interested in teak preference, which represents the long-term plan, and its interaction with the short-term plans, i.e., apple and rice preference. Since the teak harvest could only be fructified after six trials, we focused our analysis on the *difference in the cumulative count of teak plants* in the field for six trials before and after each resource shock for each participant. Any shocks occurring on the last six trials were excluded from preference deviation calculation, as participants noted that they were motivated to not choose the long-term crop at the end of the game.

As described in Figure 5.1, the difference in the cumulative teak on the plot across said six trials (Δ_{teak}) indicated the change in teak preference across each RS trial. We averaged these differences to quantify the mean change in teak preference across all RS trials for every participant ($\delta_{teak} = (\sum_1^m \Delta_{teak})/m$ where m is the total number of RS trials per participant), as can be seen on the right panel of Figure 5.1. Finally, the cohort-level change in preference was obtained via the mean change in teak preference across all participants ($\mu_{\delta_{teak}} = (\sum_1^n \delta_{teak})/n$ where n is the number of participants).



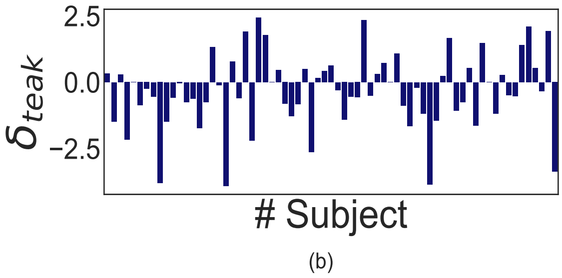


Figure 5.2: Results of Experiment 1: Panel **(a)** illustrates the mean shift in preference ($\mu_{\delta_{pref}}$) for all crop choices induced by resource shocks across all participants. The mean shift in rice, apple, and teak preference is 0.01, 0.33, and -0.34 suggest lowered preference for the long-term crop post exposure to shock. Error bars signify 95% CI. Panel **(b)** shows the teak preference shift (δ_{teak}) data for all participants (n=69). Forty participants showed negative teak preference post-resource shock.

5.2.2 Results

5.2.2.1 Long-term crop preference shifts

Our primary observable variable for this analysis was the number of plants of each variety present on a participant's field at any point in time, and our primary manipulation of interest was the resource-shock (RS) trials. A one-sided one-sample t-test yielded a significant effect (M = -0.34, SD = 1.39) of resource shocks on the shift in teak preference ($t(68)$ = -2.03, p = 0.023, 95% CI [-0.62, -0.06], d = 0.24, BF_{10} = 1.81). Clearly, as a cohort, our participants reduced their preference for planting teak after having experienced resource shocks, as predicted by our hypothesis. Figure 5.2(b) plots the mean change in teak preference for all participants, showing that the majority of our participants showed a reduction in teak preference, and the predicted effect also occurred within individuals.

5.2.2.2 Short-term crop preference shifts

What do people do instead if they are less likely to plant teak? We found that changes in teak preference were significantly correlated to shifts in both apple and rice preference ($r(67)$ = -0.61, p < .001, 95% CI [-0.74, -0.44] for apple-teak preference and $r(67)$ = -0.49, p < .001, 95% CI [-0.65, -0.29] for rice-teak preference). However, a shock-based computation of short-term crop preference shifts elicited that preference for apples significantly increased post resource shocks (M = 0.33, SD = 1.31, $t(68)$ = 2.08, p = 0.041, 95% CI [0.01, 0.65], d = 0.25, BF_{10} = 1) and no preference change for rice (M = 0.01, SD = 1.18, $t(68)$ = 0.08, p = 0.933, 95% CI [-0.27, 0.3], d = 0.01, BF_{10} = 0.13) was found. This suggests that people preferred the short-term risky apple more, corresponding to decreases in the long-term crop teak. Our results are summarized in Figure 5.2(a).

5.2.2.3 Are preference shifts sticky?

Finally, we wanted to see if the effects of resource shocks on the long-term planning horizon, as seen in high variance (HV) blocks, would carry over to a subsequent low variance (LV) block in which people do not experience such shocks. In other words, we wanted to see if preference changes induced by resource shocks were *sticky*. We sought evidence for stickiness in two ways:

- Do people show increased teak preference in the LV block immediately encountered after an HV block? If yes, this would suggest evidence for non-stickiness. Furthermore, was there an increase in teak preference in the second LV block compared to the first LV block when both are presented after an HV block? If yes, it would suggest more evidence for non-stickiness.
- Do people make more teak in an LV block presented right after an HV block compared to another LV block encountered just before that HV block? If yes, this would suggest that the effects of resource shocks were limited to only precarious HV blocks.

To run this first analysis, we checked if the effect of prior HV blocks showed up in the crop production on subsequent LV blocks (here, we included people whose order of game blocks was HV-HV-LV-LV or HV-LV-LV-HV). We indeed found an increase in mean teak produced in the first LV block compared to the immediate HV block, but it was not statistically significant ($\mu_{1stLV} = 27.28$, $\sigma_{1stLV} = 7.97$, $\mu_{priorHV} = 25.84$, $\sigma_{priorHV} = 5.67$, $t(15) = 1.36$, $p = 0.096$, 95% CI [-0.35, 3.23], $d = 0.20$, $BF_{10} = 1.12$). Furthermore, if there were no carryover effects of resource shocks from prior HV to subsequent LV blocks, we would see greater teak preference on the second LV block than the first LV block. Using a paired t-test, we found that teak production increases on the second LV block but was not statistically significant ($\mu_{1stLV} = 27.28$, $\sigma_{1stLV} = 7.97$, $\mu_{2ndLV} = 30.18$, $\sigma_{2ndLV} = 10.5$, $t(15) = 1.69$, $p = 0.056$, 95% CI [-0.01, 5.81], $d = 0.3$, $BF_{10} = 1.64$). The Bayes' factors in the analyses tell us that our results show anecdotal evidence for non-stickiness of preference shifts.

Lastly, to further test for non-stickiness, we selected participants who had faced at least one HV block between two LV blocks (i.e., order of blocks was either LV-HV-LV-HV or

LV-HV-HV-LV) and compared the mean teak produced on the two LV blocks, excluding the practice block and the last six trials as above. An increase in teak preference in the second LV block compared to the first would suggest non-sticky effect of the intervening HV block onto the subsequent LV block. A one-sided paired t-test showed a positive shift in teak preference in the subsequent LV block, but it was not statistically significant ($\mu_{priorLV} = 25.73$, $\sigma_{priorLV} = 7.87$, $\mu_{postLV} = 28.39$, $\sigma_{postLV} = 7.42$, $t(28) = 1.53$, $p = 0.068$, 95% CI [-0.24, 5.57], $d = 0.34$, $BF_{10} = 1.12$) — suggesting again anecdotal evidence of non-stickiness of resource shocks in teak production.

5.2.3 Robustness checks

Since we had a block design in our game, we investigated if participants' choice of teak varied as a function of environmental precarity across LV and HV blocks. We calculated participants' mean overall crop share across all LV and HV blocks, excluding the practice block. We found teak share ($M = 27.42$) to be much higher than that of apple ($M = 7.20$) or rice ($M = 5.38$). The same trend was also true for crop shares on only LV blocks ($M_{teak} = 27.42, M_{apple} = 7.51, M_{rice} = 5.07$) and only HV blocks ($M_{teak} = 27.42, M_{apple} = 6.89, M_{rice} = 5.68$). Crop preference shifts due to resource shocks were not detectable at the global block level, and people showed a higher preference for teak across all blocks and conditions. This suggests that at a global block level, participants preferred teak more; however, this preference changed at a granular trial level due to resource shocks.

In our analysis to check how teak preference shifted as a function of resource shocks encountered, we excluded eight participants based on our IQR exclusion criteria. To check the robustness of our results, we performed a similar analysis as performed before, including all outliers, and found our results held up. We found teak preference fell significantly as a function of resource shocks (M= -0.48, SD= 2.47, $t(76)$= -1.69, p= .048, 95% CI [-0.95, -0.01], d= 0.19). Apple showed an increase in preference post resource shock, but it was not statistically significant (M= 0.49, SD= 2.31, $t(76)$= 1.85, p= .068, 95% CI [-0.04, 1.02], d= 0.21). However, like above, rice showed no significant preference change.

5.2.4 Discussion

Our motivation with this experiment was to simulate an environment that people living in poverty are well versed in. We operationalized this environmental precarity by introducing randomly interspersed resource demands, which went overboard probabilistically. We hypothesized that when people, irrespective of their socioeconomic status, are subjected to such an environment, they naturally shift to a shorter planning horizon. As expected, when faced with economic precarity, designed as resource shocks coupled with crop loss, people did move away from long-term plans (in this context, planting teak in the simulator).

The observed decrease in planting the long-term choice teak was coupled with an increased preference for short-term crops. However, we found that people preferred the risky-sooner bet (apple) more than the safer-sooner option (rice). This is evident from the significant increase in apple preference post-shock and the higher correlation between apple and teak preference shifts compared to rice and teak preference shifts. This implies that our sample was motivated to maintain a high crop-profit margin, and hence, they shifted their preference from a high-profit, low-risk, long-term investment to a high-profit, high-risk, short-term option.

Even though our empirical results point to changes in inter-temporal preference as a function of resource shocks, we think additional mechanisms like decision rules or heuristics may have affected the preference shifts owing to the complexity of the game design. For instance, individuals' choice of crops may be affected by variety seeking, as we expect them to switch between crop varieties to determine the optimal crop in conditions of null and frequent turbulence. Even though the practice block was designed to minimize such effects, we cannot say with certainty that variety seeking was indeed contained within this block. Furthermore, anchoring effects may have also affected some individuals' decisions as we find that some individuals show null teak preference shifts (4 people as documented in Figure 5.2(b)), implying people identified the optimal crop and did not shift from their preferred choice later on.

Now, were these long-term preference shifts sticky? Based on the experience effects literature (Malmendier, 2021), one may expect that the effects of overruns would be sticky, such that the shortened planning horizon during significant precarity continues to persist in later scenarios of stability. Our results seem to anecdotally suggest that the contracted planning horizon did not carry over to the subsequent blocks in which participants did not face resource shocks. Thus, resource shock-induced time preference changes seem to be transient, at least in this virtual environment.

The discrepancy in our results and previous literature may result from how negative shocks operate in this virtual environment and real-life scenarios. In the gaming paradigm, the manifestation and consequence of a negative shock operated on a time scale of minutes compared to real-life shocks (say, a stock market crash), which can extend over months or years. Furthermore, the ramifications of negative shocks in the game are limited compared to real-life shocks. In our experiments, shocks would result in a transient monetary deficit, which is recoverable in subsequent trials. Real-world shocks of substantial magnitude, often seen in a recession or stock market crashes, may erode one's wealth, leading to permanent shifts in preference. Thus, the stickiness of preference changes can depend on the time-scales, magnitude or frequency of unpredictable shocks.

5.3 Exp 2: Preference shifts in Volatility among Farmers

We conducted the first experiment using a sample of university students with no farming experience and generally belong to relatively affluent families (Kaur, 2021). Our observed shifts in preference can therefore be criticized both on the grounds of ecological validity and representativeness. Therefore, we conducted a lab-in-the-field version of our experiment with low-income farmers in India to address these issues. The average farming household in India earns approximately Rs 1,20,000 $\sim$ USD 6000 (PPP adjusted) in a year, with this amount being nearly half in Uttar Pradesh, the site of our study (Satyasai, 2016). The fixed payment in our experiment was thus more than 1.5% of an average participant's monthly income, and the performance-linked bonus was up to 10% of their household's monthly income. Thus, these low-income participants would experience the simulator in a much more consequential manner than our previous sample and bring their background understanding of the economics of farming to bear on the exercise.

5.3.1 Methods

5.3.1.1 Design changes from Exp 1

We implemented a minor change in the game structure (listed below) to conduct the study with farmers who are not used to participating in experiments -

- The game language and instructions were translated to Hindi so that farmers participating in the experiment would be able to understand the task better. Figure 5.3 depicts the changes implemented.
- Decrease in trials per block: In the previous experiment, the farming game started with 24 practice block trials, followed by four randomized LV and HV blocks with 24 trials each. In this experiment, we kept 24 trials for practice block, but shortened

Figure 5.3: Depiction of game GUI as designed for the second experiment. We changed the dialect to Hindi to accommodate native Hindi-speaking farmers.

the LV and HV blocks to 12 trials each to contain the experiment duration to a maximum of 1.5 hours.

In all other aspects of the paradigm namely the depiction of adversity through resource shocks was the same.

5.3.1.2 Participants

We recruited participants who are actively associated with farming. Gardeners of the Indian Institute of Technology Kanpur, who also work as farmers in the nearby villages, participated in the game. Our sample size was similar to the last experiment and we collected data from 70 individuals. None were identified as outliers using a 1.75*IQR exclusion criterion and the final analysis was done with 70 participants. Our incentivization and participation payoff structure was also similar to the last experiment. Since, most of the participants were unaccustomed to the workings of a computer, the experimenter aided the participants in the game-play such as mouse clicks and keyboard operations. The institutional ethics committee approved the study.

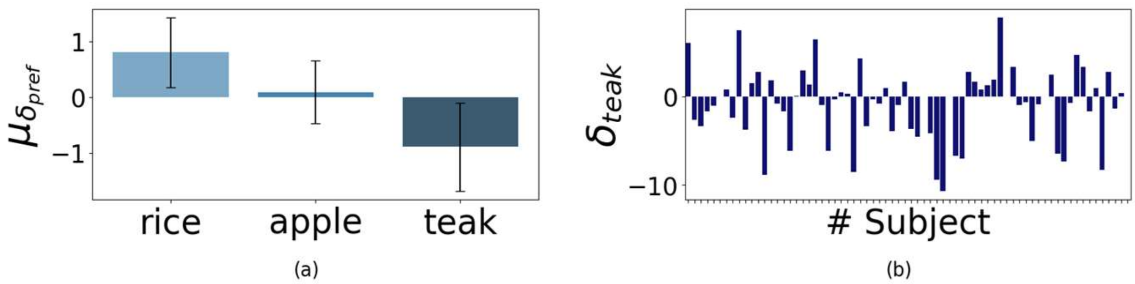


Figure 5.4: Subplot (a) shows the mean change in crop preference across all farmers. The mean change in rice, apple and teak preference is 0.80, 0.09 and -0.89 respectively. Subplot (b) depicts the change in teak preference for all participants (n=70). 36 participants showed negative teak preference change post shocks.

5.3.1.3 Analysis procedure

Our analysis procedure for this experiment was exactly the same as the last one. Our primary observable was the number of crops chosen by participants at any point in time, and our primary manipulation of interest was the occurrence of resource-shock (RS) trials. We performed a similar trial-by-trial analysis to study the effect of resource shocks on time preference based on participants' choice of crops. Finally, we also excluded the practice block and shocks occurring on last six trials from the final analysis.

5.3.2 Results

Similar to the previous experiment, we did t-tests on crop preference deviations to check if preference changed due to resource shocks. A one-sided one-sample t-test showed a significant effect (M = -0.89, SD = 4.02) of shocks on teak preference ($t(69)$ = -1.84, p = .035, 95% CI [-0.09, -1.69], Cohen's d = -0.22) as shown in Figure 5.4(a). Thus, long-term crop preference also decreased among farmers as a result of unpredictable volatility in the virtual environment.

Two-sided t-tests showed a non-significant effect (M = -0.09, SD = 2.41) of shocks on shift in apple preference ($t(69)$ = 0.31, p = 0.76, 95% CI [-0.49, 0.67], d = 0.06) but a significant effect (M = 0.80, SD = 2.67) on shift in rice preference ($t(69)$ = 2.49, p = .015, 95% CI [0.16, 1.44], Cohen's d = 0.30) as shown in Figure 5.4(a). Among the short-term crops, farmers preferred the safe short-term choice rice more which is also evident in its correlation with teak deviations (apple vs. teak: r = -0.77, $p < .001$; rice vs. teak: r = -0.81, $p < .001$).

5.3.3 Discussion

In both high (students) and low (farmers) socio-economic groups, a shift from long-term planning to short-term planning is observed across experiments 1 and 2. However, there are also important differences. When faced with adverse budgetary conditions, college students with no exposure to farming simply traded-off time preference for risk preference (from teak to apple). Under similar conditions, low-income farmers reduced their risk appetite, preferring to ensure a safe harvest (teak to rice).

We think this switch in risk preference among farmers is due to their habituation with the perils of precarious environments. This is evident from the fact that farmers and students show comparable shift in teak preference ($d = 0.22$ in farmers and 0.24 in students) despite farmers facing fewer shocks (μ(shocks) = 5.5) compared to young adults in the first experiment (μ(shocks) = 10.0). Thus, we think resource shocks were much more consequential to farmers compared to students, making them choose rice when shifting their preference away from teak.

5.4 Exp 3: Preference shifts during Stability

Experiment 1 and 2 used within-subject manipulation of resource shock frequency to stimulate change in time preferences. However, our model predicted that people would opt for long-term plans in the absence of resource shocks. So, how do people behave when there are no resource shocks? Would they be able to determine the optimal choice? To answer this question, we ran a 'pure control' version of the study, wherein participants saw only low-variance blocks of trials, i.e., no resource shocks. Based on the calculations illustrated in Figure 4.4, we expected an increase in preference for teak over time from participants.

5.4.1 Methods

5.4.1.1 Design changes from Exp 1

Since this experiment was designed to ascertain behavior in the absence of resource shocks, we removed the high variance blocks used in the previous experiment. Thus, the game design only consisted of two randomized low-variance blocks after the practice block. The number of trials per block was the same as in Experiment 1. All other methodological designs were kept unchanged.

5.4.1.2 Participants

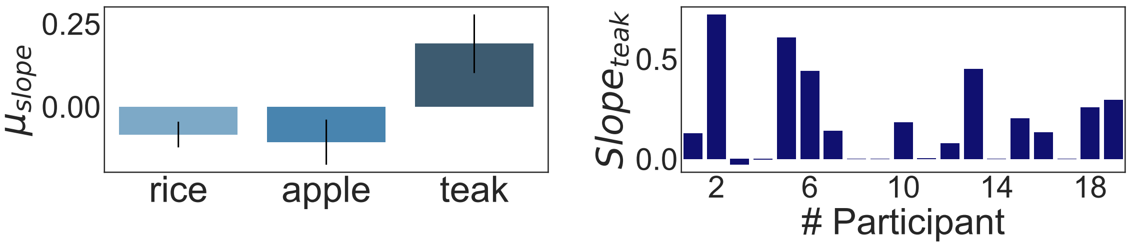
We used a Bayesian sample size calculation to determine the number of participants we needed to support the null hypothesis. The null hypothesis for this 'pure control' study was that there would be no change in long-term crop (teak) preference across participants (and the alternate hypothesis was a positive change in teak preference). Using SSDttest in R, we arrived at a sample size of 180 participants using a one-sided Bayesian t-test with the following specifications: effect size $\rho = 0.36$, power $\eta = 0.80$, $BF_{thresh} = 3.0$ and other default parameters (Fu et al., 2021).

Given this large sample size, we decided to collect data from participants in sets of 20 people. For each set, we also decided the stoppage rule for the data collection to be $BF_{10} > 3$ since BF_{thresh} was taken to be 3.0 (Fu et al., 2021). Using this criterion, we got the BF_{10} for the first set of 20 participants to be 5.68. We found one outlier using a 1.75*IQR exclusion criteria, and proceeded with a final sample size of 19 participants (8 females and $M_{age} = 26$ years).

All participants were recruited via an online advert in this experiment as well. Since the experiment took around thirty to forty-five minutes to be completed, participants were compensated with ₹100 ($4 PPP adjusted) for their time. In addition to this, three participants were also awarded bonus payment of ₹500, ₹300, and ₹100 ($25, $15 and $5 PPP adjusted) based on their performance in the game. The institutional ethics committee also approved this study.

5.4.1.3 Analysis procedure

Since, participants did not face any resource shocks, we devised a strategy for analyzing the data that did not involve shock-based computation of teak preference change. To this end, we calculated the number of teaks on the plot across the LV blocks for every participant and then fitted a linear line to estimate its slope. This 'best-fit' linear line was calculated based on the teak crop on the plot for all trials - excluding the practice block and the last six trials. We hypothesized that we would find a positive slope across participants, i.e., the amount of teak planted would increase for each participant.



(a) (b)

Figure 5.5: Panel **(a)** shows the mean slope of the best-fit line to each crop type across the two LV blocks for all participants. Teak showed a significant positive slope, and both Apple and Rice displayed a negative one as the game progressed. Error bars are 95% CIs. Panel **(b)** shows the slope of the best-fit line for only teak across all participants. 13 out of 19 people showed a positive change in teak preference as the game progressed.

5.4.2 Results

5.4.2.1 Long-term crop preference shifts

Across participants, we calculated the slopes of the best-fit lines as shown in Figure 5.5(b) and performed t-tests. We predicted we would get a positive overall teak preference as participants had not faced any resource shocks. A Bayesian one-sample t-test showed substantial evidence in support of the alternate ($BF_{10} = 50.58$). A frequentist one-sided one-sample t-test with $H_0 : \mu_0 = 0$ and $H_1 : \mu_0 > 0$ (where $\mu_0 =$ mean slope of overall teak preference across participants) showed that the 95% confidence interval did not include zero ($M = 0.19$, $SD = 0.22$, $t(18) = 3.725$, $p = .001$, 95% CI [0.01, 0.28], $d = 0.86$).

Further investigations into the slope effects of teak preference shifts conducted separately for each LV block revealed a statistically significant positive slope greater than zero in the first LV block ($M = 0.16$, $SD = 0.39$, $t(18) = 1.80$, $p = .04$, 95% CI [0.01, 0.32], $d = 0.41$) and a non-significant positive slope for the second LV block ($M = 0.19$, $SD = 0.53$, $t(18) = 1.51$, $p = 0.07$, 95% CI [-0.02, 0.4], $d = 0.35$). This suggests that most participants had figured out that making teak was the optimal strategy in the first half of the game and continued with it in the absence of shocks.

5.4.2.2 Short-term crop preference shifts

We tested similar slope-wise preference changes in apples and rice. Bayesian t-tests showed substantial evidence in support of overall apple ($BF_{10} = 3.86$) and rice preference change ($BF_{10} = 25.57$) as a function of the absence of shocks. A two-sided one-sample t-test showed a significant fall in apple and rice preference (for apple: $M =$ -0.11, $SD = 0.17$,

$t(18)$ = -2.71, p = 0.014, 95% CI: [-0.19, -0.02], d = -0.62, and for rice: M = -0.08, SD = 0.09, $t(18)$ = -3.73, p = 0.002, 95% CI: [-0.13, -0.04], d = -0.86).

Since both apple and rice showed significantly decreased preference over time, we looked at their correlations with increases in teak preference. We found that changes in apple and teak preference were correlated more compared to rice and teak (teak vs. apple: $r(17)$ = -0.91, $p < 0.001$, 95% CI: [-0.96, -0.78]; teak vs. rice: $r(17)$ = -0.68, p = 0.001, 95% CI: [-0.87, -0.33]). This suggests that in the absence of resource shocks, people preference shifted from the high-profit, proximal reward to the high-profit, delayed pay-off over time.

5.4.3 Robustness checks

For our analysis, we fitted a linear line to each participant's data to analyze how participants' teak preferences changed across two LV blocks. We then estimated its slope to check if participants chose more teak as the game progressed. However, a linear fit to the data assumes that the data follows a linear trend. To test the overall change in teak preference across participants without this assumption, we ran a t-test on the difference in the mean teaks on the plot for the last half and the first half of the game (excluding the practice block and the last six trials again).

This method of analysis showed a similar trend as our main analysis. We found a significant positive change in teak preference (M = 3.99, SD = 4.66, $t(18)$ = 3.63, $p < .001$, 95% CI [2.13, 5.84], d = 0.83, BF_{10} = 42.12), as hypothesized. In this analysis, the increase in teak preference is also accompanied by a significant decrease in apple and rice preference (for apple: M = -2.21, SD = 3.63, $t(18)$ = -2.59, p = .02, 95% CI: [-4.01, -0.42], d = -0.59; and for rice: M = -1.77, SD = 2.19, $t(18)$ = -3.43, p = .003, 95% CI: [-2.86, -0.69], d = 0.79). Overall, participants' mean overall crop share across both LV blocks showed teak share (M = 25.49) to be much higher than that of apple (M = 10.88) or rice (M = 3.63) - indicated preference for the long-term crop teak.

Now, including the outlier in the analysis showed similar changes in teak preference as reported in the main analysis. We found that teak preference slopes significantly increased over time (M = 0.15, SD = 0.26, $t(19)$ = 2.54, p = 0.01, 95% CI [0.05, 0.26], d = 0.57, BF_{10} = 5.76). Apple preference slopes decreased over time (M = -0.11, SD = 0.16, $t(19)$ = -2.9, p = 0.009, 95% CI [-0.19, -0.03], d = 0.65, BF_{10} = 5.47); however, rice preference slopes showed a negative trend but was not statistically significant (M = -0.045, SD = 0.19, $t(19)$ = -1.045, p = 0.31, 95% CI [-0.14, 0.05], d = 0.23, BF_{10} = 0.38).

5.4.4 Discussion

As the calculations illustrated in Figure 4.4 show, opting for the long-term plan (i.e., sowing teak) is the most profitable choice when resource shocks are minimal. Experiment 3's participants appear to have discovered this fact inductively, as their teak preference grows and their apple and rice preference falls over time in the absence of intermittent, unpredictable resource shocks. Thus, consistent with the behavior of a utility maximizer, it seems that participants learned the nature of the payoffs over multiple game trials. This finding further confirms that the fall in long-term preference for teak, as seen in Experiment 1 and 2, was indeed brought on by the simulated experience of precarity and not by any other elements of the game's design. Furthermore, this experiment provided empirical evidence for our simulation prediction that people with negligible resource shocks would still find the long-term horizon as their optimal planning duration.

5.5 Exp 4: Preference shifts and Predictability

Our experiment 1 and 2 showed that people shifted to a shorter planning horizon when confronted with multiple resource shocks. Experiment 3 showed that in the absence of shocks individuals could reasonably estimate the optimal choice and move toward a long-term planning horizon. Now the question remains, what about the experience of precarity led to this contraction in time preference? Were teak preference deviations driven merely by liquidity constraints?

We suspect that the unpredictability inherent in spurious resource demands is the prominent driver of increased shifts in preference. We think that people encountering low resources and unpredictable shocks should show lowered preference for the long-term option than people facing predictable shocks. Thus, we hypothesize that if unpredictability were primarily responsible for the shift in time preferences, we would observe a significant difference in teak preference between these unpredictable and predictable shocks.

Experiment 4 investigates this hypothesis using a between-subject design where participants function under a limited budget while the predictability of incoming resource shocks was varied. The first arm of the experiment was identical to Experiment 1 and 2, in which people were unpredictably exposed to resource shocks. In the second arm, participants faced constrained resources similar to the first arm; however, resource shocks were made predictable by informing the participants of their impending arrival. We assessed how people's crop preferences shifted in both conditions.

5.5.1 Methods

5.5.1.1 Design changes from Exp 1

To test our hypothesis, we implemented some changes in the paradigm listed below:

- Change in the block structure - In the first experiment, the experimental paradigm had four randomized LV and HV blocks (two of each) after the practice block. Here, we started the experiment with the practice block, then one LV block, and lastly, two consecutive HV blocks. The two consecutive HV blocks created one extensive HV block. We limited the LV block to one, as resource shocks were not observed in LV blocks, making them ineffectual for shock-based computation of preference shifts. Thus, participants faced the same number of HV trials and half of the LV trials as experiment 1.

- Pre-sampled ordering of resource shocks - In experiment 1, the real-time sampled overrun could occur on any trial during the gameplay. In this experiment, however, we had pre-sampled the resource cost debits before the game, and all participants faced the same resource debits from their budgets.

- Number of overruns in HV block - Since, the resource debits was sampled in real-time in the first experiment, each participant faced a variable number of resource overruns (average being 10). Now, the HV block was designed such that resource debits would exceed budget one third of the time and had 48 trials in total. Thus, we kept the overruns faced by each participant constant at 16 in this experiment. This provided additional data points for our treatment and permitted us to examine the robustness of our resource shock hypothesis.

- Unpredictable and predictable resource shocks - In the first condition of this experiment, the resource cost debits were randomly dispersed during the HV block such that people could not predict when the resource shocks would happen. In the second 'predictable' condition, however, it was regularly timed, i.e., each resource shock occurred every six trials in the HV block, giving participants a sense of predictability of the turbulent times.

- Participants' instructions - In this experiment, we asked people to do a 'comprehension check' after they read the game instructions, where they answered questions about the game environment and its controls. If unsure about any question or answered incorrectly, they were asked to return to the instruction sheet and answer again. This was done to ensure that people understood the instructions clearly. All pre- and post-experiment questionnaires were designed and implemented using PsyToolkit (Stoet, 2010, 2017). Lastly, to make the resource shocks predictable, participants were informed that after the initial practice block, they would experience some periods of stability, followed by extensive periods of turbulence, during which they would see increased resource cost deductions, land rent, and crop loss which is notified as "Crops are dying!" in-game. People were again notified of this at the start of the HV block.

5.5.1.2 Participants

Using a Fixed-N BFDA(Bayes Factor Design Analysis) design with default prior Cauchy(0, sqrt(2)/2), an expected effect size of 0.35 (from the first experiment), a sample size $n = 30$ and a boundary BF (BF_{thres}) = 3, we found the false positive and false negative evidence rates to be 0.021 and 0.140 respectively (Stefan et al., 2019). This is well below the general NHST criteria of accepted alpha and beta.

We decided to start off with $n_{min} = 30$ in each condition, and compute BF_{10} after every participant until the $BF_{exp} >= 3$ (Schönbrodt et al., 2017). Priors used in BF calculation were the default settings of JASP (JASP Team, 2022). Similar to the previous experiments, all participants were recruited via an online advert on campus. Since the experiment took around forty-five to sixty minutes to be completed, participants were compensated with $8 (PPP adjusted) for their time. In addition to this, three participants were also awarded bonus payment of $25, $15 and $5 (PPP adjusted) based on their performance in the game. The institutional ethics committee also approved this study.

5.5.1.3 Analysis procedure

We followed the same analysis protocol in this experiment as the first one: We derived the mean change in crop preferences across sample in both groups and compared them as a metric of how time preference shifted as a function of predictability.

5.5.2 Results

Similar to last two experiments, preference deviations were calculated without the practice block and last six trials for each participant. We collected data from 30 participants in

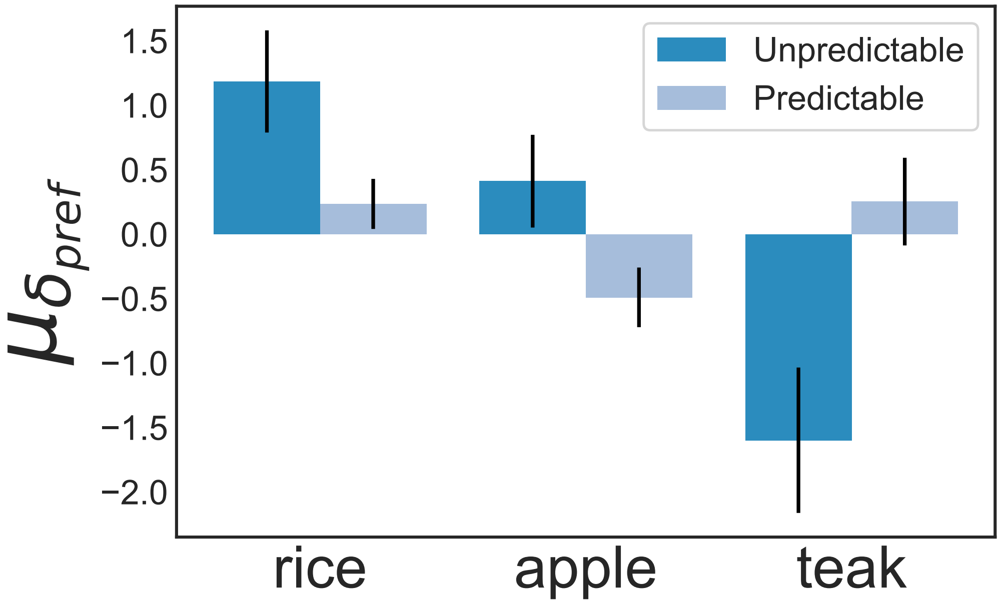


Figure 5.6: This diagram shows the mean shift in crop preference induced by resource shocks as found in ‘Unpredictable’ and ‘Predictable’ conditions. Teak preference shifts show statistical significance only in the ‘Unpredictable’ condition. The mean change in crop preference across all participants is denoted by $\mu_{\delta_{pref}}$, and error bars signify standard error. $\mu_{\delta_{rice}}$, $\mu_{\delta_{apple}}$, and $\mu_{\delta_{teak}}$ for the ‘Unpredictable’ condition were found to be 1.19, 0.41, and -1.6, respectively. Similarly, $\mu_{\delta_{rice}}$, $\mu_{\delta_{apple}}$, and $\mu_{\delta_{teak}}$ for the ‘Predictable’ condition were 0.24, -0.49, and 0.25, respectively.

each group and we excluded two participants in the first group and none in the second with the 1.75 × IQR outlier exclusion criteria [2]. Hence, the final data analysis is done with 28 (7 females, $M_{age} = 21$ years) and 30 participants (6 females, $M_{age} = 22$ years) in the first and the second group, respectively. The computed Bayes factor was found to be to be greater than our preset threshold ($BF_{10} = 12.88$ for teak difference between Unpredictable and Predictable condition $> BF_{thres} = 3$, with default prior r = $\sqrt{2}/2$).

5.5.2.1 Crop preference shifts across conditions

Since, the Brown-Forsythe test of equality of variance for teak preference shift showed significant heteroskedasticity ($F = 4.87$, $p = 0.03$), and we have unequal sample sizes for the two groups, we carried forward with Welch's t test. For teak preference change, we hypothesized the shift to be higher in magnitude in the unpredictable case than the predictable one. We did a two-sided test for apple and rice preference shifts since we did not hypothesize a directional claim. Welch's t-tests revealed that decreases in teak

[2]We used a 1.75 × IQR outlier calculation in all experiments instead of a 1.5 × IQR criterion because we wanted to use a more stringent data exclusion criteria

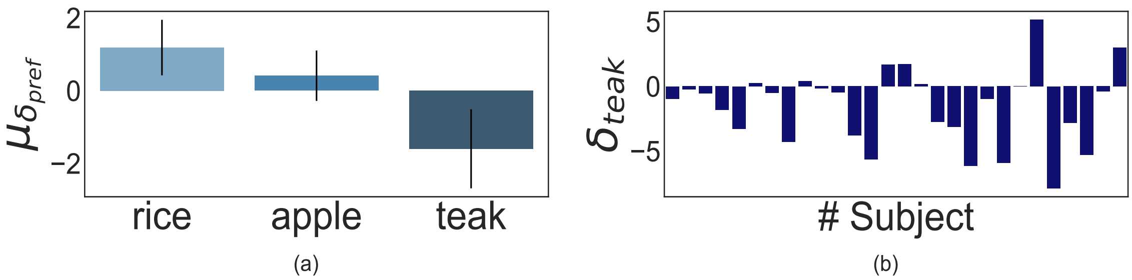


Figure 5.7: 'Unpredictable' Condition: Panel **(a)** illustrates the mean shift in crop preference ($\mu_{\delta_{pref}}$) across all participants. $\mu_{\delta_{rice}}$, $\mu_{\delta_{apple}}$, and $\mu_{\delta_{teak}}$ were found to be 1.19, 0.41, and -1.6, respectively. Error bars signify 95% CI. Panel **(b)** shows the teak preference shift (δ_{teak}) data for all participants (n=28). 20 participants showed negative teak preference post unpredictable resource shock.

preference were higher in magnitude in the Unpredictable condition (M = -1.6, SD = 0.56) compared to the Predictable condition (M = 0.25, SD = 0.34), and it was statistically significant ($t(44.69)$ = -2.81, p = 0.004, r = 0.27, 95% CI [-2.96, -0.75], d = 0.75, BF_{10} = 12.88).

Preference for short-term crops significantly increased in the Unpredictable condition, i.e., mean change in preference for rice and apple increased in the presence of unpredictable shocks compared to predictable ones (Rice: $M_{unpredictable}$ = 1.19, $SD_{unpredictable}$ = 2.06, and $M_{predictable}$ = 0.24, $SD_{predictable}$ = 1.05, $t(39.4)$ = 2.15, p = 0.04, 95% CI [0.06, 1.84], d = 0.58, BF_{10} = 1.78; and Apple: $M_{unpredictable}$ = 0.41, $SD_{unpredictable}$ = 1.87, and $M_{predictable}$ = -0.49, $SD_{predictable}$ = 1.25, $t(46.5)$ = 2.11, p = 0.04, 95% CI [0.04, 1.76], d = 0.56, BF_{10} = 1.65). These results suggest that participants decreased their preference for the long-term option and compensatorily increased their preference for the short-term choices in the presence of unpredictable resource shocks compared to when shocks were predictable.

We also asked people to rate, on a scale of 0 to 10, how uncertain they felt when they saw "Crops are dying!" (0 being 'not at all' and 10 being 'extremely') on both conditions. We found the average ratings for the unpredictable and predictable conditions to be 7.5 and 5.5, respectively. Thus, this indicates that our experimental manipulation was successful and suggests that unpredictability is a factor of interest. Next, we ran post hoc tests on each condition, comparing the mean change in crop preference as a function of predictable and unpredictable resource shocks against the null change.

5.5.2.2 Crop preference shifts in 'Unpredictable' condition

For the Unpredictable condition, we see a similar trend as the first experiment — teak preference showed a significant negative change as a function of resource shocks (M = -1.6, SD = 2.93, $t(27)$ = -2.83, p = 0.004, 95% CI [-2.54, -0.65], d = 0.54, BF_{10} = 10.44) as shown in Figure 5.7 (a). Thus, this study further confirmed the result of the first experiment — people's temporal planning horizon does contract due to multiple unforeseen resource overruns.

We found that preference shifts in apple and rice were both significantly correlated to changes in teak production post unpredictable shocks (apple vs. teak: $r(26)$ = -0.72, $p <$ 0.001, 95% CI [-0.86, -0.47]; and rice vs. teak: $r(26)$= -0.77, $p <$ 0.001, 95% CI [-0.89, -0.56]). However, only rice preference showed a significant increase (M = 1.19, SD = 2.06, $t(27)$ = 2.99, p = 0.006, 95% CI [0.37, 2.0], d = 0.565, BF_{10} = 7.25) and apple preference showed no significant change following shocks (M = 0.42, SD = 1.87, $t(27)$ = 1.14, p = 0.26, 95% CI [-0.33, 1.15], d = 0.22, BF_{10} = 0.36).

These findings suggest that people preferred the low-risk, short-term option more compared to the high-risk, short-term choice when they moved away from the long-term bet. This is at odds with the finding in experiment 1, where people preferred the high-risk, short-term crop choice more when their preference for the long-term crop decreased. We think people may have switched their risk preference in this experiment because they faced more resource overruns and choosing apples led to higher crop loss (and lowered net profit) than rice when frequency of shocks increased.

5.5.2.3 Crop preference shifts in 'Predictable' condition

Post hoc tests on the predictable condition showed that teak preferences did not change post resource shocks (M = 0.25, SD = 1.83, $t(29)$ = 0.75, p = 0.77, 95% CI [-0.32, 0.83], d = 0.14, BF_{10} = 0.5) as shown in Figure 5.8(a). This suggests that participants' preference for long-term crop choice did not fall in the presence of predictable resource overruns, even though they faced the same number of resource shocks as the previous condition.

Among the short-term crops, we found that rice showed no significant changes (M = 0.24, SD = 1.05, $t(29)$ = 1.214, p = 0.235, 95% CI [-0.16, 0.63], d = 0.22, BF_{10} = 0.38) while apple showed a significant negative shift in preference post predictable shocks (M = -0.49, SD = 1.25, $t(29)$ = -2.12, p = 0.04, 95% CI [-0.96, -0.02], d = 0.39, BF_{10} = 1.35) as shown in Figure 5.8 (a). These results suggest that while people's preference for long-term

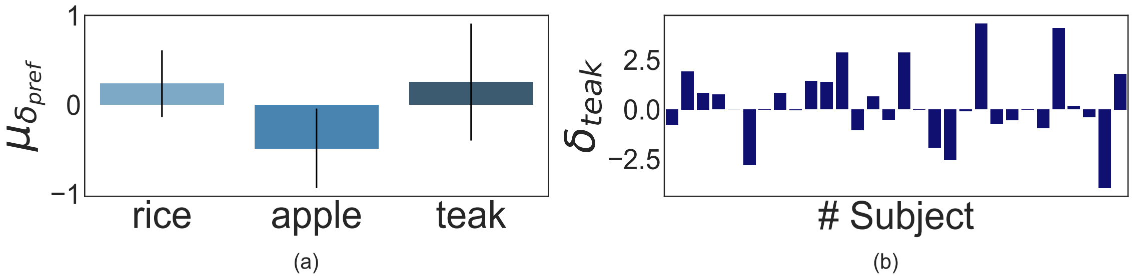


Figure 5.8: 'Predictable' Condition: Panel **(a)** illustrates the mean shift in crop preference ($\mu_{\delta_{pref}}$) across all participants. The mean shift in rice, apple, and teak preference is 0.24, -0.49, and 0.25, respectively. Error bars signify 95% CI. Panel **(b)** shows the within-participant teak preference shift (δ_{teak}) data for all participants (n=30). 13 participants showed negative teak preference post predictable resource shock.

crops did not change, their preference for risky short-term crops fell in the presence of predictable overruns. This finding aligns with our previous intuition that people lowered their preference for the risky short-term crop because choosing more apples in the presence of frequent shocks would lead to higher crop loss and lower net profit.

Overall, comparing the effects of predictable and unpredictable shocks on long-term preference shows that a negative shift in teak preference is observable only under unpredictable shocks. Thus, present-centeredness was induced by the unpredictability brought on by resource shocks. Anticipated resource shocks, of similar frequency, was insufficient to produce deviations in long-term preference.

5.5.3 Robustness checks

Similar to experiment 1, we found the mean teak share across LV and HV blocks to be much higher than apple or rice (Unpredictable: $M_{teak} = 26.19$, $M_{apple} = 8.34$, $M_{rice} = 5.47$, and Predictable: $M_{teak} = 27.68$, $M_{apple} = 7.47$, $M_{rice} = 4.85$). Thus, crop preference shifts due to resource shocks were not detectable at the global block level but at a local trial level.

Secondly, our main analysis was based on default Bayesian priors and so we performed additional analysis with alternate specifications. The BF ratio of the teak preference deviation in the Unpredictable group under different priors was greater than our BF_{thres} suggesting substantial evidence for the alternate ($BF_{10} = 10.44$ with default prior r = $\sqrt{2}/2$, $BF_{10} = 8.67$ with prior r = 1, $BF_{10} = 7.04$ with prior r = $\sqrt{2}$). Similarly the Predictable group showed no evidence for negative teak preference shift under alternate specifications thus supporting the null (BF_{10} = 0.5 with default prior r = $\sqrt{2}/2$, BF_{10} = 0.37 with prior r = 1, and BF_{10} = 0.27 with prior r = $\sqrt{2}$).

Now, based on our 1.75*IQR outlier exclusion criterion, we had excluded two participants in the Unpredictable group from our analysis. Both of these outliers had a positive teak deviation ~ 9 when the 95th percentile of the teak deviation distribution was 7.24. As a result of these extreme values, when the analysis was redone with the outliers, we found non significant drop in teak preference following unpredictable resource shocks (M = -0.89, SD = 3.88, $t(29)$ = -1.24, p = 0.11, 95% CI [-2.09, 0.31], d = 0.23, BF_{10} = 0.77). However, rice showed a significant positive change (M = 0.92, SD = 2.28, $t(29)$ = 2.16, p = 0.04, 95% CI [0.05, 1.78], d = 0.39, BF_{10} = 1.46) and apple showed no significant change (M = 0.2, SD = 2.02, $t(29)$ = 0.52, p = 0.6, 95% CI [-0.57, 0.96], d = 0.01, BF_{10} = 0.22).

Furthermore, including the outliers showed that the teak preference change between conditions was directionally consistent with the previous results but was not statistically significant $M_{unpredictable}$ = -0.89, $SD_{unpredictable}$ = 3.88, and $M_{predictable}$ = 0.25, $SD_{predictable}$ = 1.83, $t(58)$ = -1.44, p = 0.08, 95% CI [-2.47, 0.19], d = 0.37, BF_{10} = 1.24. Rice and apple preference shifts showed no significant change in production between conditions.

5.5.4 Discussion

Experiment 4 replicates the results of experiment 1 — when faced with resource shocks, people shift their planning horizon from a longer temporal scale to a shorter one. In our quest to find what is unique about the precarious environment, we found unpredictability to be the answer.

In the unpredictable condition, participants faced 16 unpredictable overruns each, and the effect size was 125% larger (Cohen's d increased from -0.24 to -0.54) than in experiment 1, where participants faced an average of 10 overruns. In the predictable condition, participants again faced 16 resource shocks, but they showed no significant change in long-term preferences and the effect size decreased compared to the experiment 1 (Cohen's d decreased from -0.24 to -0.14). Thus, our fourth experiment revealed that when individuals were confronted with more unpredictable resource shocks compared to the first experiment, the extent to which their temporal horizon contracted also increased significantly, and died down when shocks were made predictable. This demonstrates the robustness of our resource shock hypothesis—that the lived experience of precarity leads to reduced time preference—and demonstrates that the uncertainty associated with precarity considerably dominates this effect.

Among the short-term crop choices — we found that participants favored the low-profit, low-risk rice more in experiment 4 compared to the high-profit, high-risk apple in experiment 1 when switching their preference from the long-term crop choice. We think that this switch in risk preference can be understood in light of the optimal crop choice calculation, which shows that as the probability of resource shocks increase, choosing apple leads to increased crop loss and lowered net crop profit compared to rice. While our sample in this experiment encountered 16 resource shocks per game, participants in experiment 1 encountered 10 shocks on average. Since apple was the high-risk crop choice, increased shocks would lead to higher cumulative crop loss and lower crop yield than rice. Participants may have inductively arrived at this understanding because of the extensive HV block (as observed in the negative shift of apple preference in the predictable condition), which made them prefer the low-risk short-term crop option more in this experiment.

5.6 Summary and Looking ahead

Across all four experiments, we simulated economic precarity through resource shocks and found consistent evidence that unpredictable expenses shorten people's planning horizons from the long-term to the short-term. Both high and low socio-economic participants exhibited similar magnitudes of long-term preference decrements, which highlights the role of environmental factors (and not personal failings) in the ability to delay gratification. We also found that the magnitude of temporal preference shift was amplified when shocks were more frequent and unpredictable, and the effects dampened down when shocks were predictable, underscoring unpredictability as a key driver. These results suggest that unpredictable shocks are the main structural factors that induce impatience in individuals. However, how does precarity affect individuals psychologically, such that they exhibit present-focused behavior? We investigate this in the following section.

6

Subjective time and preference shifts

In the previous section, we found that people tend to act impatiently, i.e., focus more on the short-term rewards, when they encounter unpredictable shocks in their environment. Classical discounting models such as Samuelson's utility framework explain this inability to delay gratification as a function of how individuals assign utility to future rewards. In such a framework, discount rates, a proxy for an individual's self-control, are often considered constant over time. However, empirical evidence shows that people discount future rewards inconsistently, often displaying stronger impatience for sooner outcomes, also known as hyperbolic discounting. Irrespective of the nature of change in discounting over time, both models pinpoint the discount rate as a measure of intrinsic motivation to impulse control. Thus, if an individual acts impatiently as a result of living in precarious conditions, discounting frameworks would dictate that they lose control in the face of adversity.

A key assumption in these models is that the delay between sooner and delayed rewards is linear and objective. Yet research (discussed in Chapter 2) shows that time perception can be non-linear (Takahashi et al., 2008) and is often distorted by cognitive load (Block et al., 2010), emotion and attention-related factors (Martinelli & Droit-Volet, 2022), temporal expectations (Tanaka & Yotsumoto, 2017), and even experienced changes in stimulus patterns (Poynter & Homa, 1983). These findings challenge the traditional view of time as objective, indicating that variability in time perception may play a significant role in shaping people's willingness to wait for future rewards.

If we consider that people's perception of time is malleable to their lived experiences, then distortions in time should affect their inter-temporal decisions. This necessitates treating time in discounting models as a variable and testing whether the choice of delayed rewards changes as a function of subjective time. In this section, we do so by modulating the time parameter in standard discounting models. This modulation acts as a proxy for perceived time, thus allowing us to evaluate how choice probability changes when subjective time is greater or smaller than objective clock time. We also check if these time-based changes in probability can correspond to changes in discount rates [1].

6.1 Subjective time in Exponential model

Imagine one must wait a year for a reward, and the probability of waiting for the delayed reward is p. Mentally, this one year can feel like a year and a half to them (perceived time > objective time) or six months (perceived time < objective time). In the first case, deviations in time Δt would be positive as perceived time is greater than objective time, leading to time dilation. In the other case, Δt would be negative as perceived time is shorter than objective time, leading to time contraction. Keeping the discount rate constant, we find how deviations in time (Δt = perceived - objective time) bring about changes in choice probability Δp using both exponential and hyperbolic discount functions.

While we model time deviations from objective time for simplicity, it can also be assumed that time is distorted from an individual's baseline perception. For example, if an individual feels a year to be 11 months subjectively, then time deviations can be calculated from this baseline of 11 months instead of the clock time of 12 months. Conceptually, this exercise would reveal similar results whether objective or baseline perceived time is considered.

6.1.1 Simulation procedure

For our model, an agent has two choices - a smaller reward r_0 available now vs. a larger reward r_t available at an objective, calendar time t_o. If we assume the probability of

[1] This section was partly published as a conference proceeding (Mitra & Srivastava, 2024)

choosing the latter reward is $p(l)$, we can derive the utility $u(l)$ associated with it using a soft-max function

$$p(l) = \frac{exp(u(l))}{exp(u(l)) + exp(u(s))} \tag{6.1}$$

which yields

$$u(l) = ln\left(\frac{p(l) \times exp(u(s))}{1 - p(l)}\right) \tag{6.2}$$

where $u(s)$ is the utility of the smaller, immediate reward, which is assumed to be equal to r_0 (For derivations, please check Appendix B).

Now, exponential discounting suggests that future rewards r_t will be discounted exponentially, and thus, the utility of a delayed reward can be derived from

$$u(l) = r_t \times exp(-k \times t_o) \tag{6.3}$$

and our agent's discount factor k can be derived using objective time t_o by

$$k = \frac{1}{t_o} \times ln\left(\frac{r_t}{u(l)}\right) \tag{6.4}$$

Thus, for every prior probability of choosing a larger reward available in the distant future, we can derive its utility and the rate at which a decision-maker discounts that reward.

If we assume our agent mentally represents objective time t_o subjectively as t_s, then their perceived time can be greater (time dilation) or lesser (time contraction) than the objective time. Given this psychological scaling of time, we find the new utility associated with the delayed reward $u(l)'$ given t_s using

$$u(l)' = r_t \times exp(-k \times t_s) \tag{6.5}$$

Using $u(l)'$, we can find the new probability of choosing the latter reward $p(l)'$ by

$$p(l)' = \frac{exp(u(l)')}{exp(u(l)') + exp(u(s))} \tag{6.6}$$

Thus, given different values of t_s, we can quantify how deviations in time Δt can lead to shifts in the probability of choosing later outcomes Δp such that

$$\Delta t = t_s - t_o \tag{6.7}$$

$$\Delta p = p(l)' - p(l) \tag{6.8}$$

Furthermore, considering time to be objective, we plug $u(l)'$ back into exponential discount functions, which leads us to calculate the new discount factor

$$k' = \frac{1}{t_o} \times ln\left(\frac{r_t}{u(l)'}\right) \tag{6.9}$$

Thus, changes in discount rates can be derived from

$$\Delta k = k' - k \tag{6.10}$$

In other words, this lets us evaluate how changes in choice probability brought about by subjective time would correspond to changes in discount rates when time is objective.

6.1.2 Simulation results

For our model, our agent can choose from a sooner reward $r_0 = 100$ available at time $t_o = 0$ or wait a year $t_o = 365$ for a reward of $r_t = 150$. Given different probabilities of choosing the later reward $p(l)$ ranging from 0.1 to 0.9, we calculate $u(l)$ and k. Assuming that subjectively waiting for a year could vary between waiting for six months $t_s = 180$ days (time contraction by six months) and waiting for a year and a half $t_s = 545$ days (time dilation by six months), we calculate the new perceived utility of later reward $u(l)'$ probability of choice $p(l)'$. This tells us how Δp changes as a function of Δt while keeping the discount rate constant, as shown in Figure 6.1(a).

Lastly, we calculated the new discount factor k' associated with $u(l)'$ assuming $t = t_s = t_o = 365$. This leads us to find how Δk (assuming time invariance) changes as a function of Δp induced by time distortions, as shown in Figure 6.1(b). For these simulations, we assumed the later reward to equal 1.5 $\times$ the sooner reward. We vary the latter reward, making it 1.1 and 2 $\times$ the earlier reward, to test if these results hold up. These results are reported in the Robustness checks.

We find that Δp changes in a sigmoidal manner as a function of Δt. In Fig 6.1(a), the dotted line corresponding to $\Delta t = 0$ signifies subjective time being equal to the objective time, the negative x-axes signify the perceived shortening of time (i.e., time contraction), and the positive x-axes signify the perceived lengthening of time (i.e., time dilation). As time contracts ($\Delta t < 0$) and time dilates ($\Delta t > 0$), we see an increase ($\Delta p > 0$) and decrease ($\Delta p < 0$) in the choice probability for all values of prior probability p ranging

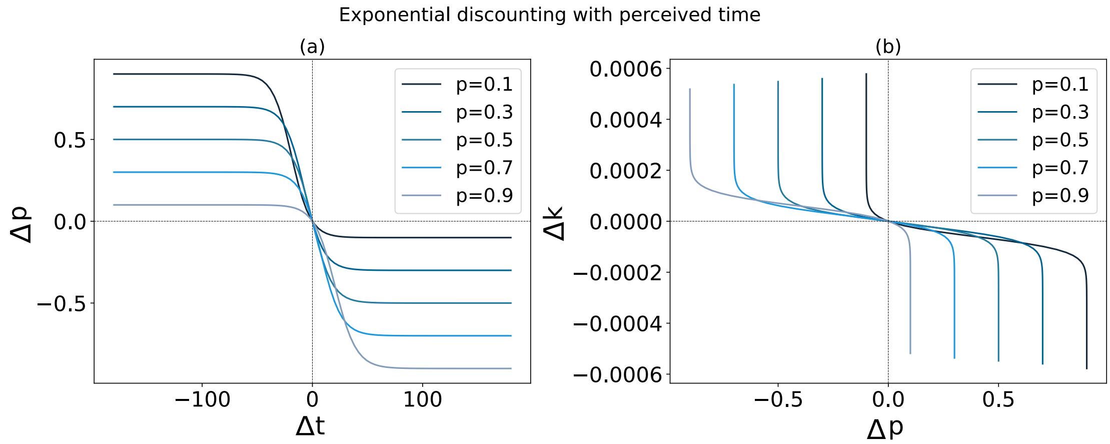


Figure 6.1: Figure (a) depicts how deviations in time Δt perturb the probability of choosing a later reward Δp when the future reward is discounted exponentially. We find that the probability of choosing the future outcome decreases as time dilates. When $\Delta t > 0$ such that perceived time $>$ objective time, we find $\Delta p < 0$ such that $p(l)$ at subjective time $< p(l)$ at the objective time. Figure (b) shows how discount rates Δk change as a result of observed shifts in preference Δp when psychological scaling of objective time is disregarded and instead clock time is considered. We find that for all prior probability values p, as the preference for the delayed rewards decreases, the discounting increases - when $\Delta p < 0$ (corresponding to $\Delta t > 0$), we find $\Delta k > 0$, that is, an increase in the discount rate and vice versa.

from 0.1 to 0.9. As time dilates, this fall in probability is maximum when the prior probability is high ($p = 0.9$) and minimum when it is low ($p = 0.1$), as shown in the fourth quadrant of Fig. 6.1(a).

Thus, our agent's preference for later rewards significantly falls when perceived time dilates compared to objective time. This fall is proportional to the prior probability of choosing the delayed reward. As the prior probability grows higher (p goes from 0.1 to 0.9), their shift in preference also grows steeper. This suggests that if one significantly prefers the delayed reward and the delay seems to be extending, the subjective valuation of the delayed outcome should decrease, leading to a drop in the choice probability. Thus, instead of waiting, they may reverse their preference later in time and choose the sooner reward.

Furthermore, as shown in Fig. 6.1(b), we find a corresponding change in discount rates when we plug the subjective time-based choice probability changes into exponential discounting. As the preference for later reward decreases ($\Delta p < 0$), the discount rate increases ($\Delta k > 0$) and vice versa. Thus, subjective expansion of time can lead to negative choice deviations, which can be interpreted as an increase in discount rates if one assumes time to be objective and invariant.

6.2 Subjective time in Hyperbolic model

We followed the same protocol as the previous section to evaluate how the probability of choosing later outcomes changes as a function of deviations in time using a hyperbolic discounting model instead of an exponential one. We also check if these choice deviations account for changes in discount rates when time is invariant.

6.2.1 Simulation procedure

We started with the same model parameters and prior probabilities of choosing the later reward $p(l)$ as before. This led us to the utility associated with the delayed reward $u(l)$ using Equation 6.2. With this $u(l)$, we derived our agent's discount factor k using hyperbolic discounting

$$u(l) = \frac{r_t}{1 + k \times t_o} \tag{6.11}$$

which leads us to

$$k = \frac{r_t - u(l)}{u(l) \times t_o} \tag{6.12}$$

Next, we incorporated subjective time t_s into Equation 6.12 such that perceived time is either greater or lesser than objective time to get the updated utility associated with the delayed reward $u(l)'$ given our discount rate k and time $= t_s$. Using this $u(l)'$, we find the new probability of choosing the later reward $p(l)'$ using Equation 6.6, which ultimately leads us to the changes in probability Δp and deviations in time Δt.

Lastly, we again check if these changes in probability brought about by deviations in time would also correspond to changes in discount rates. To do this, we plug the values of the updated utility of delayed reward $u(l)'$ into the standard hyperbolic discount function to derive the updated discount factor k', assuming time to be objective. Thus,

$$k' = \frac{r_t - u(l)'}{u(l)' \times t_o} \tag{6.13}$$

where time $t_s = t_o$. This leads us to check how Δk changes as a function of Δp induced by time distortions. For these simulations, we assumed the later reward to equal 1.5 $\times$ the sooner reward. We vary the later reward with respect to the sooner reward, making it 1.1 and 2 $\times$ the sooner reward, to test if these results hold up. These results are also reported in the Robustness checks.

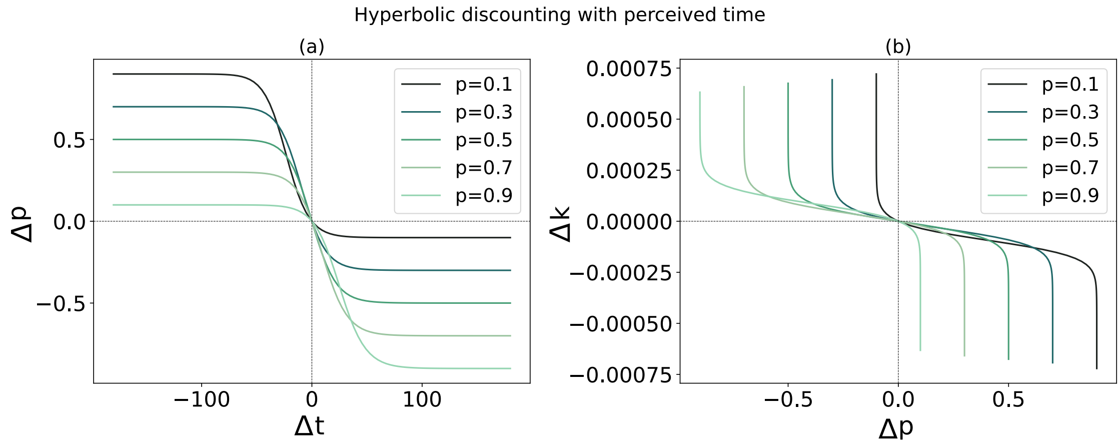


Figure 6.2: Figure (a) shows how changes in time Δt lead to shifts in the probability of choosing a delayed reward Δp when the reward is discounted hyperbolically. As time dilates (i.e., $\Delta t > 0$ such that subjective time > objective time), the probability of choosing the future outcome falls ($\Delta p < 0$) for all values of prior probability p. Figure (b) shows how discount rates change Δk as a function of shifts in preference Δp brought on by deviations in perceived time. For all values of prior probability p, as the preference for delayed rewards decreases, the discounting increases when time is objective and invariant.

6.2.2 Simulation results

Like the exponential discounting case, we find that as time dilates such that perceived time is longer than objective time, the probability of choosing the later reward decreases ($\Delta p < 0$) in hyperbolic discounting (as shown in Figure 6.2(a)). This descent was highest when the prior probability of choosing the later reward was high and vice versa. Similarly, as time contracts such that perceived time is smaller than clock time, the choice of the delayed reward increases ($\Delta p > 0$).

Changes in discount rates Δk as a function of shifts in probability Δp show comparable results as the exponential case, as shown in Fig. 6.1. A decrease in choice probability is accompanied by increases in discount rates and vice versa, as shown in Figure 6.2(b). Overall, these results align well with our intuition that underlying changes in preference brought on by time distortions may be measured as shifts in discount rates irrespective of the discounting model.

6.3 Discussion

In line with the newfound interest in the effects of subjective time on inter-temporal choices (Xu et al., 2020; Zauberman et al., 2009), we show using simulations that deviations from objective time may bring about similarly sized changes in time preferences usually attributed to shifts in discount rates in intertemporal choice experiments.

We started by manipulating time in exponential and hyperbolic discounting models to produce perceived time that is either greater or less than objective time. We found that when perceived time is greater than objective time or time dilates, our agent's probability of choosing later rewards decreases. However, choice probability increases when perceived time is smaller than objective time or time contracts. Thus, given the same discount rates and reward valuations, the chances of waiting for the future diminish if waiting for a year seems like a year and a half. However, if the same year feels like six months, the chance of delaying gratification increases.

Interestingly, these time-based shifts in the choice probability corresponded to changes in discount rates based on standard discounting models with objective time. A decrease in the probability of choosing delayed rewards caused by time dilation corresponded to an increase in discount rates, assuming time is invariant. Thus, changes in choice probability due to mental representations of clock time can explain discount-rate accounts of delay discounting. This theoretically adds support to our intuition that subjective time can bring about changes in choices which may be misconstrued as discount rate shifts.

6.4 Robustness checks

Now, to check the robustness of our results, we vary the value of the later reward in both exponential and hyperbolic discounting to see if we see the same results as we had seen before. In the model described above, we had taken the later reward to be 1.5 $\times$ the sooner reward. Here, we take the values of later rewards that are 1.1 and 2 $\times$ the sooner reward.

We found that our results held even though the later reward varied with respect to the earlier reward. As time dilates, the probability of choosing delayed rewards decreases when the later reward is 1.1 and 2 $\times$ the sooner reward (as shown in Figure 6.3(a) and (b)). Time contraction, i.e., perceived time being shorter than objective time, had the opposite effect. We also found that the slopes of this increase and decrease in choice probability were more prominent when the later reward was substantially larger than the earlier reward (as in Figure 6.3(b) compared to (a)). When the later reward was 1.1 $\times$ the sooner reward, we find the decrease in the probability of choosing a delayed reward was much more gradual when the prior probability was 0.9.

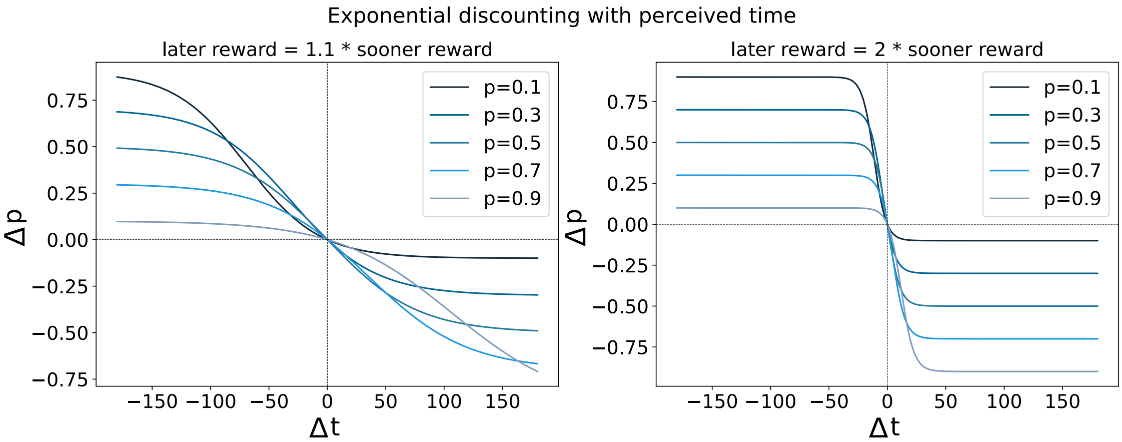


Figure 6.3: Figures (a) and (b) show how the probability of later reward changes as a function of perceived time in an exponential discount model when the later reward is 1.1 and 2 $\times$ the sooner reward. We find that our results hold even when the later reward is varied. As time dilates, the probability of choosing the later reward decreases and vice versa.

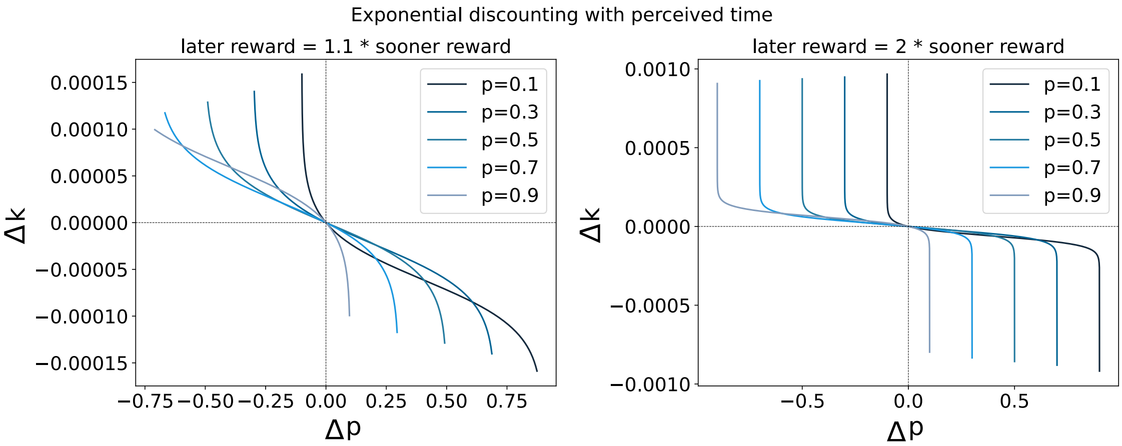


Figure 6.4: Figures (a) and (b) show how discount rates shift as a function of time-based changes in choice probability when the later reward is 1.1 and 2 $\times$ the sooner reward. We find that as the probability of choosing the later reward decreases, the discount rate increases and vice versa.

We also found that our results held for changes in the discount rate as a function of changes in choice probability brought on by time deviations. For both cases of the later reward being 1.1 and 2 $\times$ the sooner reward, we found that discount rates increased when subjective time induced choice deviations went negative and vice versa.

We do similar manipulations for hyperbolic discounting and find similar results as well. Changes in choice probability as a function of perceived time and changes in discount rates as a function of these perceived time-based changes in choice probability are plotted in

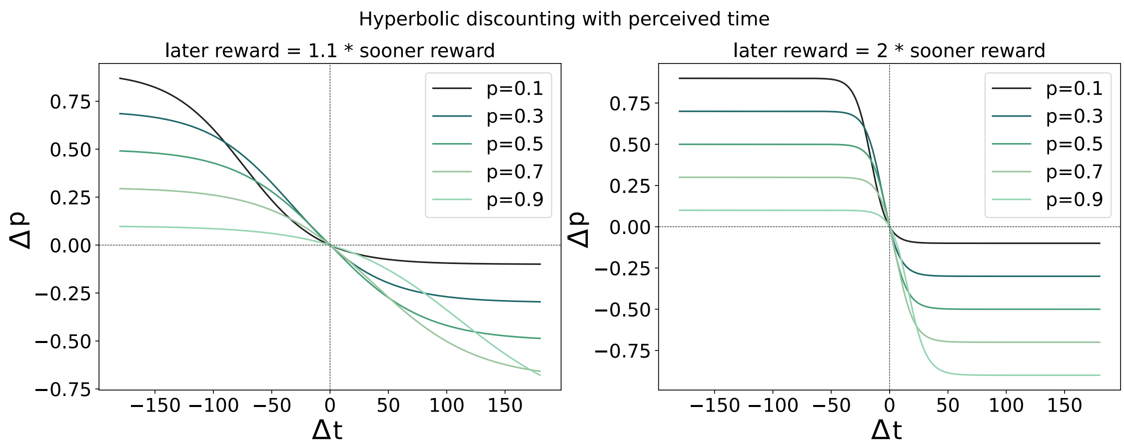


Figure 6.5: Figures (a) and (b) show how the probability of later reward changes as a function of perceived time in a hyperbolic discount model when the later reward is 1.1 and 2 $\times$ the sooner reward. We find that our results hold even when the later reward is varied. As time dilates, the probability of choosing the later reward decreases and vice versa.

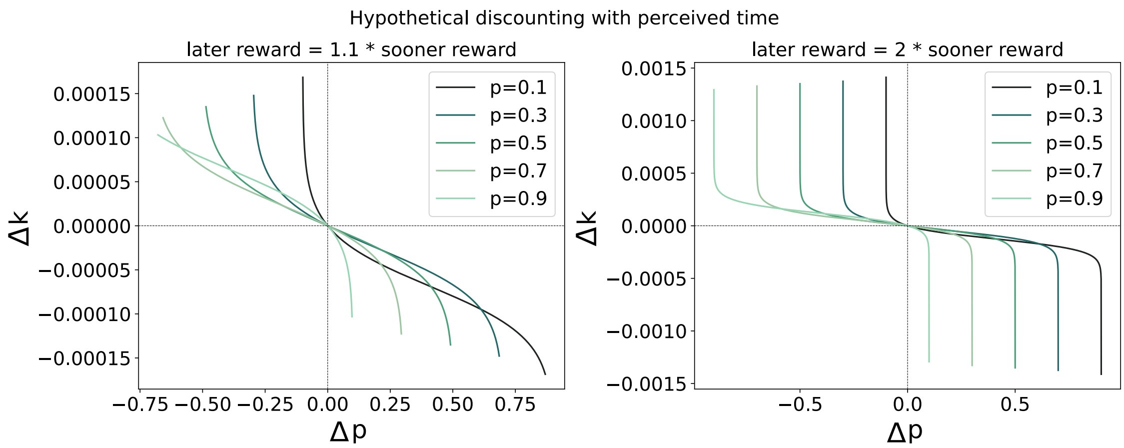


Figure 6.6: Figures (a) and (b) show how the probability of later reward changes as a function of perceived time in a hyperbolic discount model when the later reward is 1.1 and 2 $\times$ the sooner reward. We find that our results hold even when the later reward is varied. As time dilates, the probability of choosing the later reward decreases and vice versa.

Figure 6.5 and 6.6. For values of later reward $> 2\times$ the sooner reward, we find the same trend as when the later reward is $2 \times$ the sooner reward.

6.5 Summary and Looking ahead

We started by manipulating time in exponential and hyperbolic discounting models to produce perceived time that is either greater or less than objective time. We found that when perceived time is greater than objective time or time dilates, our agent's probability of choosing later rewards decreases. We also found that the choice probability increases when perceived time is smaller than objective time or time contracts. Thus, given the same discount rates and reward valuations, the chances of waiting for the future should diminish if one year seems like a year and a half. However, if the same year feels like six months, the chance of delaying gratification should increase.

Our simulation results also indicate that these time-based shifts in the probability of delayed rewards corresponded to changes in discount rates based on standard discounting models with objective time. A decrease in the probability of choosing delayed rewards caused by time dilation corresponded to an increase in discount rates, assuming time is invariant. Thus, preference shifts brought on by differential perceptions of time can be misconstrued as a loss of control using discounting models with linear objective time.

Now, standard models of intertemporal choice typically assume a stable representation of time, with discount rates reflecting assumed utility over delayed outcomes. The present framework relaxes this assumption by proposing that apparent shifts in discount rates may instead arise from systematic distortions in subjective time. This interpretation closely aligns with the reference-dependent valuation central to prospect theory, in which subjective distortions brought on by risky prospects drive choice behavior. In this sense, subjective time plays a role analogous to subjective value, providing a perceptual account of context-dependent impatience without requiring changes in underlying time preferences. In the following section, we investigate whether documented shifts in discount rates as a result of environmental shocks can be reinterpreted as time distortions and whether these distortions correlate with preference shifts empirically.

7

Precarity, subjective time and preference shifts

In the previous section, we manipulated time in exponential and hyperbolic discounting models and found that temporal distortions can lead to shifts in an individual's temporal preferences. Given the same discount rates and valuations of reward, the chances of waiting for the future should diminish if one perceives time to be extending and should increase if time seems to be shortening. We also found that these subjective-time-based shifts in the choice probability can be interpreted as changes in discount rates if one always considers time to be objective and invariant.

Now, our simulation and empirical studies have shown that people's preference for delayed rewards diminishes in the presence of budget-depleting unpredictable shocks. Shifts in discount rates have traditionally explained these choice deviations brought on by unpredictable variations in income or expenses. Standard discounting models assume some intrinsic utility of distal rewards, and subsequent changes in preferences are then explained by shifts in utility-based discount rates, offering a description rather than an explanation of the phenomenon. On the other hand, a time distortion account indicates a possible psychological mediator connecting environmental precarity to intertemporal decisions, which can be easily measured as deviations from an individual's sense of time or objective, clock time. Thus, a time distortion account opens up new scope for causal explanations of intertemporal preference changes without invoking shifts in discount rates.

As described in Chapter 2.5, studies across perceptual and decision literature suggest that - one, unpredictable stimuli distort duration judgments, two, environmental perturbations cause people to opt for sooner rewards, and three, perceived delay overestimation may lower future orientation. To our knowledge, no studies have attempted to theoretically or empirically connect these disjoint findings under one umbrella. In this section, we attempt to do so by - first, developing a theoretical framework to identify if duration distortions can explain deviations in preferences, second, identifying lab and field studies investigating the effects of unpredictable shocks on intertemporal decisions and reinterpreting the observed shifts in discount rates as time distortions using our conceptual framework and third, empirically verifying whether time distortions correlate with choice deviations.

7.1 Framework connecting discount shifts with time warps

While our previous exercise theoretically suggests that time distortions to discount rate shifts via choice deviations, it lacks a direct mathematical link that connects discount rate deviations with time distortions. To this effect, we develop a framework that reinterprets documented shifts in discount rates as estimates of temporal distortion.

To build that framework, we start by considering an individual whose choice of delayed reward changes by Δp as a result of an income or expense shock. If $p(l)$ and $p(l)'$ denote the choice probability of delayed rewards before and after shocks, then the change in choice probability can be denoted by $\Delta p = p(l)' - p(l)$. Consider that we know the value of the sooner r_0, the delayed reward r_t, and its intervening delay t.

Choice probabilities $p(l)$ and $p(l)'$ can be represented by a softmax function as:

$$p(l) = \frac{exp(u(l))}{exp(u(l)) + exp(u(s))}$$
$$p(l)' = \frac{exp(u(l)')}{exp(u(l)') + exp(u(s))}$$

where $u(s)$ denotes the utility of the sooner reward and is equal to its value r_0, $u(l)$ and $u(l)'$ denote the utility associated with the later reward before and after experiencing an income or expense shock.

Given that we know the choice probability of delayed rewards prior to and post-shock, we can derive the utility associated with it using

$$u(l) = ln\left(\frac{p(l) \times exp(u(s))}{1 - p(l)}\right)$$
$$u(l)' = ln\left(\frac{p(l)' \times exp(u(s))}{1 - p(l)'}\right)$$

7.1.1 Framework using exponential discounting

Assuming the delayed reward is discounted exponentially, $u(l)$ and $u(l)'$ is related to its value r_t by

$$u(l) = r_t \times exp(-k \times t)$$
$$u(l)' = r_t \times exp(-k' \times t)$$

where k and k' denote the discount rates before and after the shock, and t denotes the experienced delay between rewards. One can assume t to be equal to objective clock time or the individual's baseline subjective time.

Thus, using the previously obtained utility associated with the delayed reward before and after the shock, we can obtain k and k' using

$$k = \frac{1}{t} \times ln\left(\frac{r_t}{u(l)}\right)$$
$$k' = \frac{1}{t} \times ln\left(\frac{r_t}{u(l)'}\right)$$

Given values of delayed r_t and sooner reward r_0, delay between them t, and change in choice probability Δp as a result of income or expense shock, one can determine the change in discount rate Δk corresponding to Δp using

$$\Delta k = k' - k = \frac{1}{t}\left[ln\left(\frac{r_t}{u(l)'}\right) - ln\left(\frac{r_t}{u(l)}\right)\right] = \frac{1}{t}\left[ln\left(\frac{u(l)}{u(l)'}\right)\right]$$

Traditionally, researchers have studied changes in choice probability due to lab-induced instability or environmental perturbation in the framework of the discount rate. However, we aim to identify changes in perceived time that can correspond to reported changes in choice probabilities. Thus, if we assume that distortions in time bring about changes in choice probability instead of shifts in the discount rate, then $u(l)$ and $u(l)'$ would be noted by

$$u(l) = r_t \times exp(-k \times t)$$
$$u(l)' = r_t \times exp(-k \times t')$$

where t and t' represent the perceived delay duration before and after shocks.

Note that, compared to the traditional explanations, here we consider changes in perceived delay to bring about changes in utility post-shock while keeping the discount rate constant. Thus, one can obtain t and t' using $u(l)$ and $u(l)'$ by

$$t = \frac{1}{k} \times ln\left(\frac{r_t}{u(l)}\right)$$
$$t' = \frac{1}{k} \times ln\left(\frac{r_t}{u(l)'}\right)$$

Therefore, one can derive distortions in perceived time Δt using deviations in choice probability Δp using

$$\Delta t = t' - t = \frac{1}{k}\left[ln\left(\frac{r_t}{u(l)'}\right) - ln\left(\frac{r_t}{u(l)}\right)\right] = \frac{1}{k}\left[ln\left(\frac{u(l)}{u(l)'}\right)\right]$$

Considering the two derivations, we can say that

$$\boldsymbol{\frac{\Delta t}{t} = \frac{\Delta k}{k}} \tag{7.1}$$

This equation tells us that shifts in discount rate, scaled by an individual's discount rate before experiencing shocks, would equal time distortions scaled by the perceived delay between rewards before shocks. This also tells us that positive and negative changes in discount rates should correspond to time dilation and contraction in the context of unpredictable volatility.

7.1.2 Framework using hyperbolic discounting

Now, assuming the delayed reward to be hyperbolically discounted over time, utilities of the reward $u(l)$ and $u(l)'$ can be related to its actual value r_t using

$$u(l) = \frac{r_t}{1 + k \times t}$$

and

$$u(l)' = \frac{r_t}{1 + k' \times t}$$

where k and k' denote the discount rates before and after the shock, and t denotes the experienced delay. Again, one can assume t to be equal to objective clock time or the individual's baseline subjective time.

Using the previously obtained utility associated with the delayed reward before and after the shock, we can obtain k and k' using

$$k = \frac{1}{t} \times \left(\frac{r_t}{u(l)} - 1\right)$$
$$k' = \frac{1}{t} \times \left(\frac{r_t}{u(l)'} - 1\right)$$

Given values of delayed r_t and sooner reward r_0, delay between them t, and change in choice probability Δp as a result of income or expense shock, one can determine the change in discount rate Δk corresponding to Δp using

$$\Delta k = k' - k = \frac{1}{t}\left[\left(\frac{r_t}{u(l)'}\right) - \left(\frac{r_t}{u(l)}\right)\right] = \frac{r_t}{t}\left[\frac{1}{u(l)'} - \frac{1}{u(l)}\right]$$

For this exercise, we again assume that distortions in time bring about changes in choice probability instead of shifts in the discount rate. Therefore, $u(l)$ and $u(l)'$ would be denoted by

$$u(l) = \frac{r_t}{1 + k \times t}$$
$$u(l)' = \frac{r_t}{1 + k \times t'}$$

One can obtain t and t' using $u(l)$ and $u(l)'$ by

$$t = \frac{1}{k} \times \left(\frac{r_t}{u(l)} - 1\right)$$
$$t' = \frac{1}{k} \times \left(\frac{r_t}{u(l)'} - 1\right)$$

Assuming discount rates to be unchanged due to shocks, one can derive distortions in perceived time Δt using

$$\Delta t = t' - t = \frac{1}{k}\left[\left(\frac{r_t}{u(l)'}\right) - \left(\frac{r_t}{u(l)}\right)\right] = \frac{r_t}{k}\left[\frac{1}{u(l)'} - \frac{1}{u(l)}\right]$$

Again, we find that one can equate temporal distortions with respect to shifts in discount rate using

$$\frac{\boldsymbol{\Delta t}}{\boldsymbol{t}} = \frac{\boldsymbol{\Delta k}}{\boldsymbol{k}} \tag{7.2}$$

Thus, we find that scaled shifts in discount rates can be interpreted as scaled distortions in time using hyperbolic functional form as well. Overall, this exercise tells us that shifts in choice probability can be interpreted theoretically as delay distortions instead of changes in discount rate using both the exponential and hyperbolic frameworks.

7.2 Reinterpreting preference shifts as time distortions

In this section, we utilize our conceptual framework to investigate the order of time distortions corresponding to choice probability changes documented in lab and field studies. In these studies, variations in income or expenses are often formulated as narratives depicting a sudden loss in income (Bickel et al., 2016), as abrupt resource debits on an effortful task in the lab (Haushofer et al., 2013), or studied in the field as unpredictable environmental perturbations like rainfall anomalies (Falco et al., 2019). Given empirical reports of negative preference shifts caused by unpredictable shocks (shown in Table 7.1), we use our framework to derive the time distortions corresponding to such preference deviations.

Our primary criterion of choosing these articles was to interpret literature published within the last ten years that were conducted in diverse contexts using varied samples and employed diverse methods of shock formulation. Thus, we selected these five studies, which were conducted either in the lab or in the field, using different socio-economic samples, and examined real-life shocks (rainfall anomalies or droughts) or simulated ones.

7.2.1 Methods

Using data from studies mentioned in Table 7.1, we extracted choice probability shifts or changes in discount rates induced by income or expense shocks. For studies that report only Δp, we derived Δk using the procedure mentioned in the previous section. Next,

Table 7.1: Summary of studies examining the impact of negative income or expense shocks on temporal choices. The different columns denote the sample characteristics, observed effects and strength of the observed effects in terms of changes in discount rates. The final column shows the estimated time distortions (median and 95% CI) derived from observed changes in discount rates using our theoretical framework.

Study and sample	**Observed effects**	**Effect magnitude**	**Scaled time distortion**
Haushofer et al. (2013) 148 students (lab)	High-endowment group with a negative shock in a computerized task showed greater discounting than the low-endowment, no-shock group.	Negative income shock group showed lower indifference points than the poorly endowed ones ($d =$ -0.46).	med = 0.539 95% CI [0.469, 0.61]
Bickel et al. (2016) 599 individuals (MTurk)	Reading hypothetical negative income narratives increased discount rates more than neutral ones in both future gain and loss domains.	$\Delta \ln(k) = 1.29$ for a future gain scenario with a negative income shock vs. neutral narrative.	med = 3.37 95% CI [1.69, 6.08]
Falco et al. (2019) 1,160 farmers in Ethiopia	Increased rainfall anomalies led to increased income variation, resulting in higher subjective discount rates.	Rainfall anomalies reduced income ($\alpha = 0.66 \pm 0.33$) which increased discount rate ($\beta = -0.05 \pm 0.02$).	med = 0.326 95% CI [0.288, 0.366]
Meles et al. (2024) 5,600 rural households in Ethiopia	Income shocks (rainfall deviations and droughts) over two years increased impatience.	Preference for later rewards decreased with drought incidence ($\beta = -0.14 \pm 0.05$) and prior-year rainfall shortages ($\beta = -0.26 \pm 0.07$).	Droughts: med = 0.064 95% CI [0.056, 0.075]; Rainfall: med = 0.150 95% CI [0.135, 0.166]
Blain et al. (2025) 184 individuals (longitudinal data)	Income shocks, measured via subjective ratings, during the COVID-19 market crash (March–June 2020), increased preference for sooner rewards.	Discount rates increased with every unit increase in perceived shocks discount rates ($\beta = 0.14 \pm 0.06$).	med = 0.158 95% CI [0.135, 0.181]

using these Δk (difference in mean discount rates after and before shocks), we calculated scaled discount rate shifts $\Delta k/k$, which gave us the scaled time distortions $\Delta t/t$. For these computations, we considered subjective time at baseline t to be equal to objective clock time, since we did not have individuals' time estimates. Finally, we constructed a distribution of such scaled time distortions by bootstrapping 10000 samples from each dataset, giving us the median time distortion and its 95% confidence interval for each study (i.e., the 50th, 2.5th, and 97.5th percentile, respectively). Below, we discuss the methodology for each dataset in more detail before going on to the results.

7.2.1.1 Haushofer et al. (2013)

In this study, the authors investigated the effects of lab-induced income shocks on temporal discounting. They formulated a laboratory experiment where participants received high and low starting endowments and then performed an effortful task to earn money. Among these groups of high and low endowments, people either received a positive or a negative income shock such that their average incomes were equal at the end of the task. So, an individual in a high-endowment-negative-shock group would have his income equal to that of another in a low-endowment-no-shock group. The authors then tested future discounting using intertemporal choice tasks. They found that the negative-income-shock group exhibited higher discounting or lower indifference points (M = 16.43, 95%CI = [13.80, 19.07]) in the intertemporal tasks compared to the always-poor group (M = 19.43, 95%CI = [17.02, 21.85]).

For our computation, we used the 95% CI of indifference points reported in the paper for negative and no shock conditions to construct the range where k' and k may lie. Next, we drew n random samples of k' and k with replacement from this range (n = sample size in each group) and obtained the mean shift in discount rates using $\Delta k = k' - k$. Lastly, we obtained the scaled time distortion by dividing Δk by k. We did this 10000 times to get a bootstrapped distribution of $\Delta t/t$, giving us the median and 95% CI.

7.2.1.2 Bickel et al. (2016)

In this study, the authors manipulated income shocks to be negative, neutral, and positive using hypothetical narratives, and measured discount rates across future gain, future loss, past gain, and past loss monetary conditions. Furthermore, future discounting was measured using intertemporal tasks either by using the 'standard implicit' method ($X now vs. \$X+dx later) or by making the 'zero explicit' (\$X now and \$0 later vs. \$0 now and \$X+dx later).

For our time distortions calculation, we only take into account the effects of negative and neutral income shock narratives on the future gain option in the implicit standard framings. Reported discount rates of negative scenarios constituted post-shock conditions, and neutral scenarios were pre-shock conditions in our formulation. The authors calculated changes in discount rate by taking the log transform of discount rates k in their dataset. Following their footstep, we obtained the log-transformed discount rates associated with exposure to neutral and negative income shock narratives by randomly sampling from their dataset and then calculated the difference $\Delta ln(k)$. We derived scaled time distortion $\Delta t/t$ from $\Delta ln(k)$ using

$$
\begin{aligned}
&\Delta ln(k) = ln(k') - ln(k) \\
\implies &\Delta ln(k) = ln\left(\frac{k'}{k}\right) \\
\implies &\frac{k'}{k} = exp\left(\Delta ln(k)\right) \\
\implies &\frac{k'}{k} - 1 = exp\left(\Delta ln(k)\right) - 1 \\
\implies &\frac{\Delta k}{k} = exp\left(\Delta ln(k)\right) - 1 \\
\implies &\frac{\Delta t}{t} = exp\left(\Delta ln(k)\right) - 1 \qquad\qquad [\text{since } \frac{\Delta k}{k} = \frac{\Delta t}{t}]
\end{aligned}
$$

We do this 10000 times to obtain a bootstrapped distribution of scaled time distortions, which gave us the 50th (median) and its 95% confidence interval by taking the 47.5th percentile above and below the median.

7.2.1.3 Falco et al. (2019)

In this study, the authors investigated the effects of income variations on discounting among farming households in Ethiopia. They obtained farmers' discount rates using intertemporal tasks like 'Would you prefer a payment of 50 Ethiopian Birr today or 65 Ethiopian Birr after 12 months?' and reported a mean discount rate of 0.09 with a standard deviation of 0.04 among 651 farmers.

Income variations were measured using long-term rainfall anomalies, and subjective discount rates among farmers were studied as a function of these income variations. The authors found that farmers preferred smaller immediate rewards when they encountered adverse income shocks — farm income changed as a function of rainfall variations by 0.658 with a standard error of 0.328, and discount rates altered as a function of farm income by -0.0447 with a standard error of 0.0201 while controlling for other idiosyncratic shocks and demographic variables. Thus, increased rainfall anomalies reduced farm income, leading to discount rate increases.

To identify Δk, we randomly sampled from a 99% CI range of regression coefficients, which suggests changes in discount rate per unit decrease in rainfall. Discount rates k were also sampled similarly using the data from the experiment. Thus, we obtained n samples of Δk and k with replacement ($n =$ no. of farmers) and derived the scaled time distortion by dividing the mean Δk by the mean k. We did this 10000 times to construct a bootstrapped distribution of scaled time distortion $\Delta t/t$. We report the median time distortion and its 95% confidence interval by taking the 47.5th percentile above and below this median.

7.2.1.4 Meles et al. (2024)

In this study, the authors used household panel data from Ethiopia to investigate how risk and time preferences changed due to droughts and rainfall anomalies. Environmental shocks were measured using self-reports of droughts and rainfall shocks calculated as shortfalls relative to the long-term average during the primary rainy season. Discounting was measured similarly to Falco et al. (2019)'s study, where participants were asked to choose between 100 Birr today and 100+X Birr a month from today.

Discount rates and shocks were measured in 2010, 2012, and 2014. The authors report that 66%, 68.1%, and 86.6% of the participants chose the immediate reward for 2010, 2012, and 2014 (discount rates > 0.41). 10.9%, 10.6%, and 3.9% participants preferred the sooner option first and switched the delayed reward later (discount rates: from 0.22 to 0.41), and 23.1%, 21.2%, and 9.5% participants always preferred the delayed option (discount rates: 0 to 0.22) in 2010, 2012, and 2014, respectively.

The authors found that the mean preference for delayed reward decreased by $\alpha = 0.14$ with a standard error of 0.05 as a function of droughts and by $\beta = 0.26$ with a standard error of 0.07 as a function of rainfall anomalies. We utilize these preference changes to calculate our variable of interest - time distortions.

We began by simulating the distribution of discount rates (using data from all three waves), which led us to a metric of mean discount rates over time for 4326 households. Δp was constructed from the reported mean shifts in preference caused by droughts and rainfall shortfalls (α and β). Given these discount rates and measured change of preferences, we calculated p and $p' = p + \Delta p$, using our conceptual framework. This led us to t and t', which gave us scaled time distortions $\Delta t/t$ for our sample of 4326 households. We repeat this process 1000 times to estimate its bootstrapped distribution and report its median and 95% confidence intervals separately for droughts and rainfall anomalies.

7.2.1.5 Blain et al. (2025)

In this study, the authors investigated whether COVID-19 induced negative income shocks and negative affect affected future discounting. For our purposes, we were interested in seeing if discount rates varied due to income shocks experienced during the pandemic. The authors tested 1,145 individuals during the market crash in March 2020 and retested 200 during the market recovery in June 2020. Income shocks were measured using a subjective scale, where participants indicated the impact of COVID-19 on their income on a 6-point scale. Discount rates were calculated using Kirby and Petry (2004)'s scale, which made participants choose between a smaller, immediate, and a larger, delayed reward over multiple-choice trials. They found that temporal discounting rates were related to increases in perceived income shocks across individuals by $\beta = 0.14$ with a standard error of 0.06 while correcting for demographics.

Thus, for our computations, we assumed that most shifts in discount rates would lie in the 99.9% confidence interval of the β parameter. Since discount rates were not reported in the paper, we randomly sampled participants' hypothetical discount parameters from Kirby and Petry (2004)'s scale, where discount parameters vary from 0.00016 to 0.25. Similar to the previous study, we sampled discount rates and shifts in discount rate n times ($n =$ sample size) to calculate the mean discount rate and change in discount rate. Then, we constructed a bootstrapped distribution of scaled time distortions $\Delta t/t$ by iterating 10000 times and obtained its median and its 95% CI.

7.2.2 Results

As shown in Figure 7.1, we find that median scaled time distortions lie in the range of 0.064 to 0.539 for all studies except Bickel et al. (2016)'s study, which shows a median time distortion of 3.37 with its 95% CI [1.69, 6.08]. Thus, for a 1000-ms delay in future rewards, the median time distortions range between 64 ms and 539 ms across studies. Usually, in

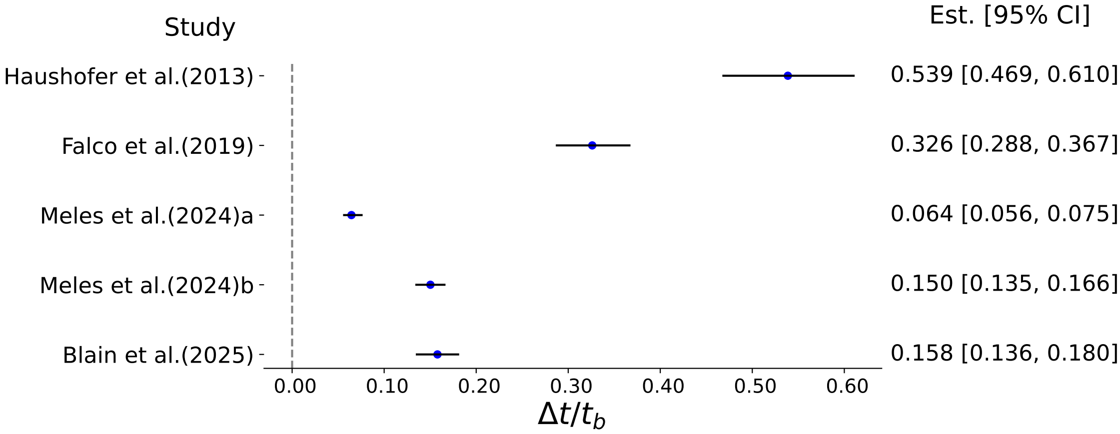


Figure 7.1: This figure shows the median scaled time distortions $\Delta t/t$ and its confidence intervals calculated from shifts in preference for studies reported in Table 7.1. The zero line depicts null time distortion caused by shock encounters (perceived time equal to clock time). Meles et al.(2024)a and b refer to the effects of droughts and rainfall shortfalls on shifts in preference separately.

perceptual studies, unpredictable stimuli are documented to cause temporal distortions of magnitudes from 5% (Ulrich et al., 2006), 12% (Pariyadath & Eagleman, 2007) to as high as 35% (Tse et al., 2004). Thus, for a 1000 ms standard duration, the estimated time distortions can vary in the range of 50 ms to 350 ms for perceptual studies, which seems to be reasonably aligned with our derived duration distortions.

We also find that time distortions show considerable heterogeneity across studies, which may have resulted from how income or expense shocks were operationalized in each experiment. While some have investigated income shock as abrupt hypothetical monetary debits (Haushofer et al., 2013), others have measured income shock subjectively (Blain et al., 2025) or using narrative depicting consequential adversity (Bickel et al., 2016). In Bickel et al. (2016)'s study, the negative income shock narrative is framed broadly as a sudden job loss, with being evicted and being unqualified for unemployment. Thus, the observed inflated time distortion may result from this broad framing encompassing detailed negative consequences of adversity. Overall, these results indicate that - first, increased temporal distortions can lead to negative shifts in preference if one considers discount rates invariant within individuals, and second, discount rate shifts assuming invariant time can be reinterpreted as time distortions.

7.3 Effects of lab-induced precarity on intertemporal choices

In this section, we investigate whether temporal distortions are related to preference shifts using our lab experiments. We calculate time distortions from deviations in choice probability and check whether we find similar results to those we had seen previously, using data from our Experiment 4. We also conduct a replication experiment with explicit felt time probes and a larger sample size to check whether our theoretical predictions hold empirically.

7.3.1 Estimating time distortions from Exp 4

In the Unpredictable arm of Experiment 4, we had simulated periods of stability and volatility using a farming game where participants earned money by growing and harvesting crops while navigating stable and turbulent farming conditions. During stability, participants saw minimal farming expenses, land rents, and crop losses. However, during precarious conditions, farming expenses and crop losses would unpredictably increase, resulting in an unforeseen drop in their income.

Intertemporal choices were designed in the game as three distinct crops (apple, rice, and teak), which systematically varied in their growth time (long-term and short-term) and profitability (risky and non-risky). Thus, participants could choose among non-risky long-term teak, non-risky short-term rice, and risky short-term apple. Our goal was to check whether individuals' preference for the long-term crop teak decreased and if estimated time distortions correlated with such preference shifts.

7.3.1.1 Methods

In our previous analysis, we had derived the mean number of crops planted in six trials before and after shocks and averaged it across all shocks to get a participant-level metric of preference shifts. For our current purpose, instead of calculating the mean number of crops, we calculated the probability of choice before $p(l)$ and after $p(l)'$ encountering shocks by dividing the total number of any particular crop planted on the field (e.g., teak) by the total number of crops chosen (teak+apple+rice). Using this $p(l)$ and $p(l)'$, we obtained the utility of choosing teak before $u(l)$ and after $u(l)'$ shocks.

To do these computations, we assumed the ratio of sooner and delayed rewards to equal the ratio of profits associated with the game's short-term and long-term crop choices. Thus,

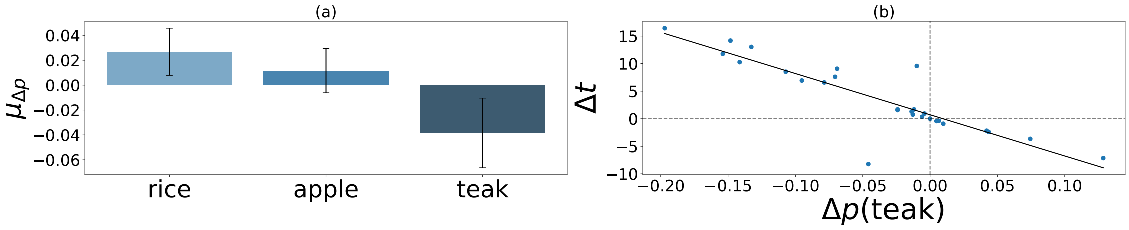


Figure 7.2: Figure (a) shows the mean change in choice probability ($\mu_{\Delta p}$) across crops as a result of lab-induced environmental precarity (n = 27). Error bars represent 95% CI. Figure (b) shows that the decreases in observed teak probability (Δp(teak)) are associated with increases in time distortions (Δt) estimated from the data (r = -0.87, $p < 0.001$).

the sooner reward r_0 was equal to 1, the delayed reward r_t was equal to 6.3, and the delay t was equal to 6 (ratio of the objective delay between fruition of teak and apple/rice). $u(l)$ led us to participant-specific measures of pre-shock discount rate k. Using this k, we derived pre- and post-shock time estimates t and t' corresponding to observed preference shifts $p(l)$ and $p(l)'$. These time estimates gave us our scaled time distortions $\Delta t/t$.

While time distortions can be measured as deviations from clock time or deviations from individuals' baseline subjective time, for this analysis, we calculated time distortions from objective time (i.e., $t = t_o$) since we did not have participants' time estimates. In Experiment 4, we excluded 2 participants based on 1.75*IQR exclusion criteria and obtained a sample size of 28 individuals in the 'Unpredictable' condition. In this analysis, we excluded one more individual with an extreme scaled discount rate distortion of -6.65, leading to a sample size $n = 27$.

7.3.1.2 Results

Figure 7.2(a) shows the mean choice probability deviations calculated as a function of shocks. Similar to our previous results, preference for the long-term crop teak decreased significantly after encountering shocks (M = -0.04, SD = 0.07, $t(27)$ = -2.83, p = 0.004, d = -0.54). Among the short-term crops, people preferred the non-risky choice option rice post shock (M = 0.03, SD = 0.05, $t(27)$ = 2.99, p = 0.006, d = 0.57). At the same time, no significant change was observed for the risky crop apple (M = 0.01, SD = 0.05, $t(27)$ = 1.14, p = 0.26, d = 0.22).

Traditionally, one can derive these shifts in preference as changes in discount rate. However, if one assumes discount rates to be subject-specific and invariant, changes in choice probabilities can also be construed as distortions in time. Equations 7.1 and 7.2 tell us that scaled distortions in time $\Delta t/t$ should be equal to scaled distortions in discount rates $\Delta k/k$. We found that to be the case with our data as well (M = 0.24, SD = 0.42).

Thus, our previously observed preference deviations can be interpreted as time distortions using our conceptual framework. Since each trial in our experiment was designed to last for 15 seconds (including trials on which participants experienced shocks), we calculated the estimated time distortions Δt using objective time $t = t_o$ = 15s and estimated $\Delta k/k$ from Δp using

$$\Delta t = \frac{t}{k} \times \Delta k \tag{7.3}$$

We found that Δt showed a right-skewed distribution with m = 3.6, med = 1.6, and sd = 6.35, suggesting a perceived time expansion at the group level. More importantly, the association between Δp and Δt (as shown in Figure 7.2(b)) suggests a strong negative correlation (r = -0.87, $p < 0.001$), indicating a potential association of time dilation with negative preference deviations at the individual level.

7.3.2 Exp 5: Validating preference shifts and time distortions

Overall, insights from lab and field studies (including our experiment 4) suggest a link between subjective time and present-focused behavior. However, whether such an association actually exists is unknown. In an attempt to answer the question, we ran a replication of the previous experiment with a larger sample size, where we asked individuals to denote their felt time estimates at different junctures in the game. Our main goal was to see whether participants shift away from long-term options as before and whether these preference shifts correlate with felt time distortions.

7.3.2.1 Methods

Design changes from Exp 4 Our overall design was similar to the previous one, where participants planted and harvested crops (apple, rice, and teak) to maximize their capital over time while navigating stable and volatile farming environments. However, we made two key changes in the current design:

- Stability post-volatility: In the previous experiment, the farming game ended with participants encountering 48 trials depicting volatility. Some participants had remarked that they did not choose teak in the last six trials as teak would not be ready to harvest by the time the game ends. This led to the exclusion of shock trials occurring in the last six trials from further analysis. In the current design, we added 12 trials of stable farming conditions to mitigate that effect. Thus, our experiment started with 24 trials of practice rounds, followed by 24 trials of stable farming conditions, then 48 trials of volatility, and ended with 12 trials of stability, increasing the total number of trials to 108 (from 96 in Experiment 4).

- Felt time measure: In the current design, we asked participants to denote the felt duration of the previous trial using a slider ranging from 1s to 60s at different points in the game. Each participant answered this question 9 times out of 108 trials - thrice during the first 24 trials of stability and six times during the following 48 turbulent trials. Within these 48 trials, we asked about felt time thrice immediately after a resource shock and thrice when there were no shocks.

The felt-time probes, as shown in Figure 7.4, were placed so that each participant faced these questions roughly at the beginning, middle, and end of the stable and volatile periods. For example, participants answered about their felt time during trials 25, 34, and 45 in the stable period, which lasted from trials 24 to 48. This pseudo-random design enabled us to get subjective time measures over the entire streamlined and turbulent period while making it impossible for participants to guess when the next probe would appear.

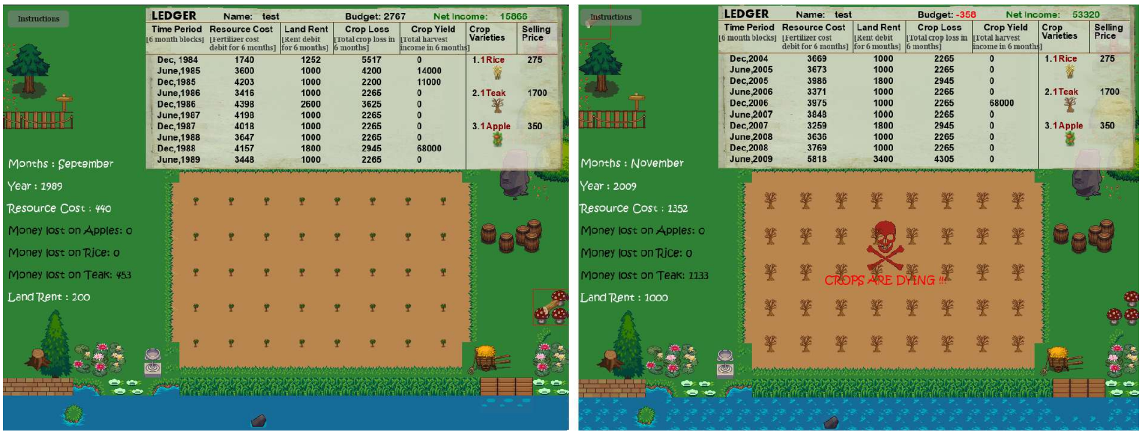


Figure 7.3: The first and second subplots display the game GUI of our farming experiment in stable and volatile farming conditions. In both images, the top of the GUI shows the 'Ledger,' which displays the trial-wise debits and credits of participants for the past ten trials and gets updated in real time. The left portion of the GUI displays the time (month and year), farming expenditures, and crop losses for each crop for the ongoing trial. Cumulative farming expenses, crop losses, and land rents are shown as 'Resource Cost,' 'Crop Loss,' and 'Land Rent' on the Ledger. The middle of the GUI shows the field plot where participants cultivate crops. Participants were notified that crop sowing patterns on the soil or time (month/year) did not affect crop losses or yields. The game can be played online here.

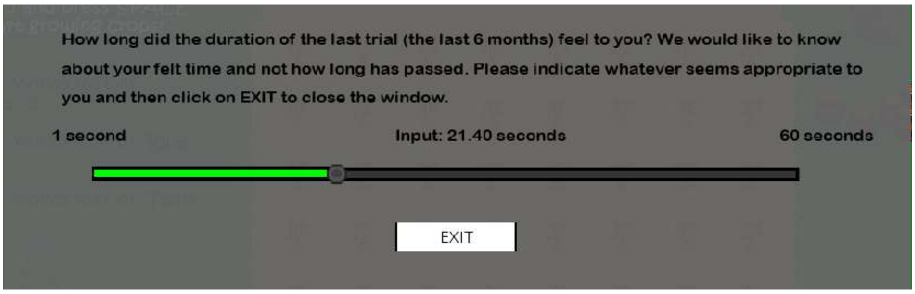


Figure 7.4: This figure displays the felt time question that participants responded to at different junctures in the game.

Participants This replication study was partly exploratory, as we did not have any estimates of how time distortions vary relative to preference deviations. Assuming a low correlation of -0.25, β = 0.80 and α = 0.05 in GPower (Faul et al., 2007b), we got a required sample size of 97. We collected data from 102 individuals, of which 6 participants were identified as outliers using a 1.75*IQR exclusion criterion similar to the one used in Mitra et al. (2025). Our final analysis was done with 96 participants (20 females, M_{age} = 21).

Analysis protocol Our analysis protocol was similar to the previous experiment. Participants' choice of crops was our measure of temporal preferences, and we hypothesized that preference for delayed reward would decrease as a result of shocks. Since the yield time for teak was six trials, we identified the preference shift over each shock by taking the average probability of crop choice six trials before and after each resource shock. Mathematically, it can be represented as:

$$\delta p = \frac{\sum_{t+1}^{t+6} p'}{6} - \frac{\sum_{t}^{t-5} p}{6}$$

where t is the trial on which resource shock occurs, p' and p are the probabilities of choosing each crop, which were calculated as

$$p' = \frac{n(c)'}{40} \text{and} \quad p = \frac{n(c)}{40}$$

c ∈[apples, rice, teak], $n(c)'$ and $n(c)$ denote the number of respective crops chosen post and pre-shock. 40 denotes the total number of crops that needs to planted on each trial i.e., the number of crop slots on the farmland. Thus, if a participant faced N resource

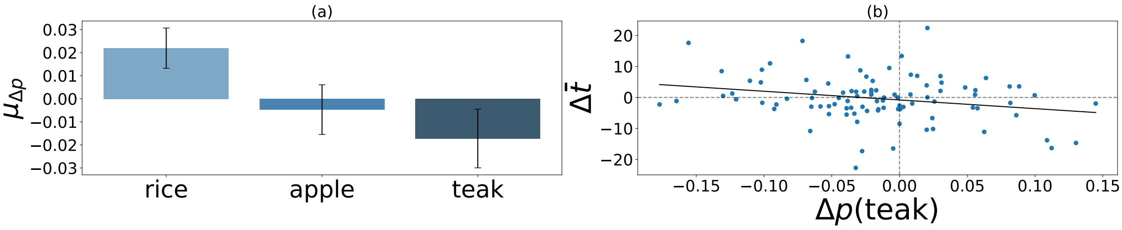


Figure 7.5: Figure (a) shows the mean change in probability of crop choice ($\mu_{\Delta p}$) as a result of lab-induced environmental precarity (n = 96). Error bars represent 95% CI. Figure (b) shows that the individuals who experienced time to be extending compared to their own baseline ($\Delta\bar{t}$) showed an increased fall in long-term preference (Δp(teak)) (r = -0.24, p = 0.008).

shock trials, shifts in preference Δp averaged over all such trials were obtained using

$$\Delta p = \sum \delta p / N$$

This Δp provided a participant-level metric of how crop preference shifted as a function of resource shocks in our experiment.

7.3.2.2 Results

As expected, we found that probability of choosing teak significantly decreased post shock across our sample of 96 individuals (M = -0.02, SD = 0.06, t(95) = -2.63, p = 0.005, 95 % CI [-0.03, -0.01], d = -0.27) as shown in Figure 7.5(a). Furthermore, among the short-term crops, rice preference increased (M = 0.022, SD = 0.044, t(95) = 4.9, $p < 0.001$, 95 % CI [0.01, 0.03], d = 0.50) and apple preference showed no change (M = -0.005, SD = 0.054, t(95) = -0.85, p = 0.396, 95 % CI [-0.02, 0.01], d = 0.087) as a result of experienced shocks. Thus, participants again preferred the low-risk short-term choice, rice, over the high-risk apple, when shifting their preference away from the long-term option, teak, as found in the previous experiment.

Instead of estimating felt time deviations using our conceptual framework, we calculated time distortions from the participants' data. As noted before, participants reported their subjective trial duration thrice during the stable period, thrice during non-shock turbulence, and thrice during shock-riddled turbulent trials. The average of these time reports constituted the baseline (t_{bs}), non-shock turbulent (t_{nst}), and shock turbulent (t_{st}) subjective time. Since each trial lasted for 15s, we also had a measure of objective, clock time t_o = 15 for reference. Thus, time distortions during volatility were calculated in three ways:

- Changes in felt time from baseline: $\Delta\bar{t} = t_{st} - t_{bs}$
- Changes in felt time within turbulence: $\Delta\acute{t} = t_{st} - t_{nst}$
- Changes in felt time from objective time: $\Delta\hat{t} = t_{st} - t_o$

The distribution details of all three estimates of time distortions are reported in Table 7.2. We found felt time distortions from individuals' baseline $\Delta\bar{t}$ and within turbulence $\Delta\acute{t}$ to be normally distributed. The distributions showed a minor underestimation of perceived time (since mean and median < 0), which was not statistically significant. On the other hand, felt time distortions from objective time $\Delta\hat{t}$ showed a right-skewed distribution (mean $>$ median) with statistically significant evidence for time overestimation ($t(95) = 2.7$, $p = 0.008$, $d = 0.27$, 95% CI [0.88, 5.8]). Interestingly, the average distortions $m_{\Delta\hat{t}} = 3.34$ closely match the estimated mean time distortion $m_{\Delta t} = 3.6$ we found previously. These results suggest that precarious conditions expanded subjective time relative to objective time but not from individuals' baseline perceptions at the group level.

Table 7.2: Summary statistics of time distortion distributions and their correlation with shifts in long-term teak preference. All correlations are Pearson's r, and bracketed values denote p-values.

Time Distortions	$\Delta\bar{t}$	$\Delta\acute{t}$	$\Delta\hat{t}$
Mean	-0.32	-0.11	3.34
Median	-0.295	-0.19	-0.39
SD	7.33	5.02	12.09
Corr with Δp(teak)	-0.24 (0.008)	-0.14 (0.09)	-0.11 (0.13)

Next, we ran correlations between shifts in teak preference and felt time distortions. Applying a Bonferroni correction for three comparisons, we found that shifts in probability of choosing teak Δp(teak) were significantly correlated with felt time distortions from individuals' baseline $\Delta\bar{t}$, as noted in Table 7.2. Subjective time distortions within turbulence $\Delta\acute{t}$ and from objective time $\Delta\hat{t}$ were also negatively correlated to teak preference shifts, but not statistically significant.

Overall, at the individual level, participants who reported expansion of delay durations during volatility compared to stable conditions were less likely to prefer long-term crops in the face of adversity. Individuals also reported time extension relative to clock time, and we found the effect of these time distortions on long-term plans to be small but directionally consistent.

Insights from this experiment reaffirm our previous intuition. Our conceptual framework suggested that deviations in long-term preference can be construed as shifts in subjective time if one considers discount rates to be invariant. Across lab and field studies and our previous experiment, we found that perceived temporal extension may contribute to increased short-term preference. Results from this experiment provide empirical validation that people perceive time differently during stability and turbulence, and these perceptual distortions are closely linked to their intertemporal decisions. Since all individuals in this experiment encountered the same number and magnitude of resource shocks, the variation in preference shifts can be attributed to their sense of time.

7.4 Summary and Discussion

Recent investigations highlight the need to move beyond standard explanations under the discounting framework and consider the role of time perception in intertemporal choices. Researchers have suggested that subjective time need not be equivalent to objective, clock time, and distortions in time can modulate people's preferences (Bradford et al., 2019; Zauberman et al., 2009). Furthermore, perceived time is often non-linear and logarithmic, which leads them to suggest losses in self-control may be understood in light of this non-linear time perception (Takahashi, 2016; Takahashi et al., 2008; Zauberman et al., 2009).

Indeed, the influence of subjective time on decisions can explain why people may prefer delayed rewards initially and defer them later, also known as preference reversals (Thaler, 1981). McGuire and Kable (2012) demonstrated that when the delay in intertemporal choices seems to increase over time (waiting for a phone call), people often prefer the delayed rewards initially and forgo them later. Indeed, some have suggested that the formulation of time-inconsistent, hyperbolic discounting stems from mischaracterizing subjective time as objective time in intertemporal decisions (Bradford & Doucette, 2023).

Here, we found that shifts in preference induced by unpredictable shocks can be interpreted as shifts in subjective time. Although subjective time estimates during volatile conditions increased compared to objective time in the replication study, we found a slight average underestimation from individuals' own perceptual baseline. Now, increased attention to an ongoing task (diverted from time) or increased working memory load is often known to shorten perceived time (Polti et al., 2018). Unpredictable exogenous shocks in our experiment may have played a similar role by diverting increased attention to ongoing turbulence, leading to the observed underestimation.

Furthermore, around one-third of our sample shows a negative time distortion and a negative shift in teak preference. This suggests that the influence of shocks on preferences may not be completely mediated by perceived time. Unpredictable perturbations can induce liquidity constraints on individuals, leading to an increased preference for short-term plans. Other cognitive mechanisms, such as increased attentional tunneling or cognitive load, may also be at play here.

While traditional theories have interpreted such preference shifts as shifts in discount rates (Haushofer et al., 2013; Meles et al., 2024), we suggest an alternative theory: that short-term preferences may arise from how time is perceived during precarity. Across multiple studies, we observe that time distortions reported in decision-making literature are of comparable magnitude to those reported in perceptual studies. Using our lab experiments, we reinterpreted discount rate shifts as distortions in felt time and verified that time distortions can account for preference shifts induced by precarity.

Insights from timing studies suggest that our perception of time is highly malleable to our lived experiences. Subjective time is often a function of attentional demands (Tse et al., 2004), information processing (Thomas & Weaver, 1975), or predictability of the stimuli (Pariyadath & Eagleman, 2007). In our context, environmental volatility may demand excessive attention to immediate troubles or impose the need to exercise high cognitive effort (Mani et al. (2013)'s attentional tunneling and high load). Such contextual factors may warp individuals' perception of time and how the future is visualized. Thus, environmental instability can affect mental time, affecting how far into the future one can afford to plan.

In a nutshell, a duration distortion account explains present-focused behavior by recognizing a subjective expansion or dilation of time, leading one to defer waiting, even though waiting is preferred initially. The novelty of our approach lies in unifying unpredictability, temporal distortions, and discounting under one overarching proposition, which enables us to understand how observed changes in the environment may cause a psychological drift that can lead to changes in decisions.

8

General Discussion and Conclusion

Psychological investigations of impatience came to the forefront with Walter Mischel's famous study, in which he presented kids with a marshmallow and asked them to wait fifteen minutes for a second marshmallow. They later found that children's ability to wait at four years of age predicted their SAT scores, planning ability, and executive control at fifteen years of age (Shoda et al., 1990). This sparked a widespread investigation into whether our intrinsic ability to control our impulses dictates our decisions and life trajectories.

Recently, this intuition has been challenged by numerous studies that underline the role of environmental factors on our ability to delay gratification. Kidd et al. (2013) replicated Mischel's study with a key manipulation - they either paired children with a reliable or unreliable experimenter in the marshmallow study. They found that children were much less likely to wait for the second marshmallow if their reward delivery agent was unreliable ($\sim$ 3 minutes) than children with reliable experimenters ($\sim$ 12 minutes). Other studies have also challenged Mischel's work, finding that children's ability to wait is not a strong predictor for future outcomes when early cognitive abilities, home environment, and socio-economic factors are considered (Watts et al., 2018). These studies tell us our impulse control may depend on the environment we are exposed to, and one may wait for a delayed reward if they find their environment reliable and trustworthy.

Identifying whether our intrinsic self-control or the environment governs our decisions is crucial because it is key to understanding why individuals living in precarious conditions often find themselves trapped in poverty. Early investigators pinpointed cultural factors as the reason for such outcomes, for instance, breakdown of family structures (Moynihan, 1965) or malformed societal and individual norms and values (Lewis, 1966) often passed down generationally. However, later on, researchers identified that fundamental structural inequalities and economic disparities, such as deindustrialization, job losses, and urban segregation of marginalized communities into ghettos, led to the formation and sustenance of deprivation (Ryan, 1976; Wilson, 2009, 2012).

Over the last seven decades, this debate of whether cultural or structural factors bind people into the poverty trap has been investigated by psychologists and economists who have investigated its causes and effects. These researchers have highlighted the role of environmental factors such as perceived mortality risks (Daly & Wilson, 2005a; Pepper & Nettle, 2017), lack of resources (Mani et al., 2013; Shah et al., 2012), and income uncertainty or shocks (Haushofer et al., 2013) on decisions and preferences across time. However, most of these studies are correlational, measured cross-sectionally between subjects, and with one-shot descriptive tasks. Thus, the precise mechanism of how living in precarious conditions leads to present-oriented behaviors was unclear.

Given these insights, we aimed to identify how living in precarious conditions or a state of uncertainty affects our decisions and preferences over time. Uncertainty inherent in making decisions about the future exposes people to various unpredictable events. Such unpredictable events, for example, job loss, eviction, or a prolonged illness, may drain people's saved resources (money or time) and present a more urgent immediate problem, making it difficult to plan for the future. In other words, unexpected expenses, disguised as unpredictable shocks, may deplete people's resources, leading them to forgo future goals and plan for the present. Now, if their initial resource pool is small, which is often the case for people living in poverty, such shocks may be more consequential. However, if substantial endowments may also get depleted given multiple unpredictable shocks, leading people to plan for *now*.

In this thesis, we computationally and empirically investigate how environmental and psychological factors lead people to act impatiently, choosing the smaller immediate reward instead of the larger delayed reward. We show using simulations that the utility of long-term plans diminish when observers face random shocks, making it optimal for them to plan for the short-term irrespective of initial endowment. Furthermore, the utility of long-term plans increases over time in the absence of shocks, suggesting people should plan for the future in stable environmental conditions, again irrespective of their starting endowments. Thus, while existing literature on the relationship between cognitive mechanisms and future discounting has little to say about the underlying reason, our 'resource shock' hypothesis places the mechanism front and center.

Next, we set out to empirically validate whether functioning under a limited budget with random, unpredictable expenses could induce future discounting within individuals. Instead of one-shot descriptive tasks, we designed a dynamic game environment where participants encountered intermittent periods of stability and volatility, and we measured the real-time evolution of their preferences. Using a lab experiment with students and a lab-in-the-field study with farmers, we showed that limited resources coupled with unexpected expenses push people to be more present-focused, irrespective of their socio-economic strata. However, as suggested by the simulation results, people learned to choose the long-term option more over time in the absence of such shocks. Interestingly, we also found that these preference shifts were driven primarily by expectation violations in the form of unpredictable shocks, and predictable shocks did not alter preference for the long-term. Thus, we identified the role of precarious environmental conditions on time preferences, fundamentally implicating the role of expectations in determining impatience.

Even though long-term planning is often construed as the rational choice, we show via simulations that moving to a shorter planning horizon is rational when one faces recurrent unforeseen expenses. This suggests that optimality is malleable and dynamic under environmental constraints, and rationality is contingent upon the ecological conditions one encounters. In other words, people's inter-temporal preferences are sensitive to the perturbations encountered in their environment, and they wax and wane based on these ecological constraints. Thus, our results align well with the 'ecological rationality' hypothesis (Todd & Gigerenzer, 2012) of temporal discounting and the 'resource rational' analysis (Bhui et al., 2021), which conceives context-dependent optimality arising from the interactions of the individual and their environment.

These insights lead us to explain the empirically documented co-occurrence of low socio-economic status and future devaluation, a critical sociological phenomenon (Haushofer & Fehr, 2014). We think that in a perfectly predictable world, having low resources would not affect intertemporal choices and people would still plan for the future. However, an unpredictable world filled with frequent over-the-budget expenses forces people to be present-focused. In other words, precarity makes it increasingly sub-optimal for individuals to make long-term plans, potentially leading them to prioritize short-term rewards. Thus, rather than conceptualizing impatience as a personality trait (Rowe & Rodgers, 1997) or cultural phenomenon (Lewis, 1966), we argue that it is a learned adaptive response to the socio-economic environment that individuals in poverty inhabit.

After identifying environmental precarity as a potential structural factor, we were interested in ascertaining how volatility may affect individuals psychologically, leading to switches in their preferences. The existing 'scarcity' literature suggests that the scarcity of essential resources (money or time) causes people to hyper-focus on immediate problems (Mani et al., 2013). This attentional tunneling exhausts mental resources required for individuals to think about their future (Shah et al., 2012). However, both attentional tunneling and reduced mental bandwidth have been criticized on methodological and empirical grounds. While it is unclear how short-term attentional shifts may affect intertemporal decisions spanning days or years, some studies have also not been able to replicate bandwidth effects in the field (Dalton et al., 2020). Furthermore, attentional tunneling in field tests has been measured using payday variations which capture liquidity constraints and not genuine income or expense shocks (de Bruijn & Antonides, 2021).

We proposed that environmental precarity may alter people's sense of time, and thus, if one perceives reward delay to be later than it actually is, they may choose to forego the delayed reward. This intuition comes from multiple lines of work. Evolutionary psychologists have long proposed that increased salience to mortality threat may be a viable cause for people living in lower socio-economic conditions not to invest in the future (Daly & Wilson, 2005b). Thus, people may perceive the future as increasingly distant or unreachable if the future feels uncertain. On the other hand, perceptual studies suggest that the perceived duration of an unexpected stimulus is often tied to encountered expectation violations (Pariyadath & Eagleman, 2007). Furthermore, recent developments in econophysics suggest that perceived time is often non-linear and logarithmic, which leads them to suggest losses in self-control may be understood in light of this non-linear time perception (Takahashi, 2016; Takahashi et al., 2008; Zauberman et al., 2009).

In line with this newfound interest in understanding future devaluation in terms of psychological time, we demonstrated using simulations how changes in time preference (conventionally attributed to changes in discount rates) may be produced by changes in time perception. Across both exponential and hyperbolic discounting models, we find a sigmoidal change in preference as a function of time deviations. When subjective time contracts, the probability of choosing the later reward increases, and when subjective time dilates, the choice probability decreases.

This seems intuitive - if one perceives a month to be a week, then waiting for a month seems easier and highly likely. However, if waiting for the same month seems like a year, then choosing to wait seems highly unlikely. We also found that these subjective time-induced choice probability shifts correspond to changes in discount rates if time is assumed to be objective and invariant. For both exponential and hyperbolic discounting, the decrease in the likelihood of choosing a later reward (corresponding to an increase in perceived time) translates to an increase in discount rates when time is considered objective and constant.

To pinpoint the relationship between discount rates and time, we developed a theoretical framework to reinterpret empirically documented deviations in discount rates as time distortions. Using this framework, we derived time distortions of varying magnitude across multiple lab and field studies investigating the effects of income or expense shocks on discount rates. These estimates were also consistent in size with time duration distortions reported in perceptual studies. Lastly, using our lab experiments, we empirically validated that felt time distortions induced by volatility correlate with preference shifts.

Despite facing the same number of shocks for the same duration, we found that people who felt time to be expanding during the shock lowered their preference for long-term rewards more. These insights theoretically and empirically validate our intuition that environmental precarity can warp an individual's perception of time, leading to a lowered preference for the delayed reward. Thus, a future investment of five years may feel like ten years to an individual living in poverty. Such experiences of time dilation may lead them to plan for *now* or next month and not think about the future or the next five years.

The idea of incorporating time distortion in discounting models has been introduced previously using time-scaled discount factors, where the time-scaling factor represents speeding up and slowing down of time (Andersen et al., 2014; Read, 2001). Time scaling makes similar predictions to our work — if the delay to a reward delivery seems to be extending, one will exhibit higher discounting, and may choose to forego the delayed reward.

Now, adopting a temporal distortion account of preference shifts offers several benefits from a theoretical perspective. For example, it avoids reliance on utility-based assumptions, which are difficult to apply to abstract goals like buying a house or landing a job. Second, it offers a natural reference point (for example, subjects' own baseline subjective time or clock time), allowing deviations to be measured, unlike discount rate accounts, which lack an objective measure (a 'true zero' point).

Standard economic theories often assume time preferences to be 'pure' and non-mutable and different from time discounting (Frederick et al., 2002). However, studies investigating the effect of shocks on preference have questioned this assumption, as discount rates increase proportionally with environmental perturbations. A time distortion perspective accommodates these findings by offering an alternative explanation where preference changes are caused by how time is perceived, keeping internal time preferences unperturbed.

These results demonstrate how a mental time narrative can explain discount rate accounts of time preference shifts. Initially, we had estimated time deviations from objective time from previous studies and lab experiments, which showed a group-level effect of time dilation and preference shifts. However, we observed a prominent individual-level effect of subjective time distortions from participants' baseline perceptions instead of objective time. This insight supports the necessity to incorporate subjective time in discounting models. While researchers often assume that time in intertemporal tasks is linear and objective, people may gauge time and calibrate future decisions with their own mental clock.

Understanding the mechanism of how precarious conditions alter temporal preferences and their interaction with perceived time yields important practical implications. The observed influence of precarity on decision-making suggests that effective welfare policies should not only alleviate material scarcity but also predictably buffer individuals against unexpected planning failures. By reducing exposure to unanticipated resource shocks, such policies can stabilize both objective budgets and subjective time horizons.

Interventions such as unconditional cash transfers or access to free healthcare are therefore likely to be particularly effective, as they directly support already constrained budgets while simultaneously reducing the cognitive and psychological burden associated with anticipating unforeseen expenses. In contrast, interventions focused primarily on liquidity such as debt relief or access to micro-credit may offer short-term economic relief without substantially altering the underlying mental constraints imposed by precarity. When future resource demands remain unpredictable, individuals may continue to adopt shortened planning horizons and present-focused strategies, even in the absence of immediate financial strain.

The proposed interplay of precarity, subjective time, and temporal preference is essential for understanding why people act impatiently. If internal time is malleable to our lived experiences, studying time preferences using this prism may yield an enhanced understanding of present-focused behavior in light of this psychological scaling of time, which offers similar explanations as lack of self-control without the moral judgment. Thus, a time distortion account paints delay discounting as an ecologically rational strategy - there is no point in waiting for tomorrow if tomorrow seems like forever.

8.1 Limitations & Future work

In our simulation connecting precarity with preference shifts, we found that the optimal planning duration lowers as a function of shocks in both low and high endowment conditions. Thus, optimal planning duration emerges as a function of shock frequency. While low resources may serve as a necessary condition for present-oriented behaviors, we think persistent, unpredictable shocks are sufficient to bring out shifts in planning horizons. Our farming game was designed to simulate these precise conditions in the lab, signifying the role of lived experiences of people in low socio-economic communities.

Now, the question arises as to what happens on the boundary conditions where endowments are critically low or enormously high. For example, if we consider an individual's endowment close to infinity, any number of unpredictable expenses may not deplete their budget and hence affect their planning duration. On the contrary, if one's endowment is close to zero, a single shock of comparable magnitude may deplete their resources. Thus, in these boundary conditions, the optimal planning duration becomes a function of both resource endowments and shock frequency.

Another question that arises is whether similar resource shocks affect individuals with different endowments differently. Our simulation results suggest that planning duration would shrink maximally for individuals with the lowest endowment, as smaller budgets would get depleted faster. We have not empirically validated such a claim, and future studies entail testing how preference shifts can vary as a function of endowment when controlling for shocks. In other words, how preferences may differ between individuals from low and high socio-economic backgrounds when both are exposed to similar unpredictable turbulence.

Now, if one thinks of these preference shifts in terms of the $\beta - \delta$ formulation, one question that naturally arises is whether precarity degrades general patience (δ) or amplifies the desire for immediate gratification (β) explicitly. We think a one-off, one-shot negative income or expense shock can temporarily lead one to focus on immediate gratification. However, prolonged or persistent exposure to such shocks can erode patience and lead one to consistently choose short-term outcomes over long-term ones. Prior work, such as

Haushofer et al. (2013), demonstrates that exposure to income shocks selectively increases β, capturing heightened present bias. A natural extension would be to investigate how β and δ modulate with shock frequency.

In our investigation of precarity-induced time distortions and preference shifts, we asked participants to denote duration estimates immediately after encountering the shock. We correlated these time deviations from their estimated during stability with participants' long-term crop choices. We found that variations in felt time during shock trials were negatively correlated with temporal preferences in the game. In other words, individuals who felt time to extend during shock subsequently choose fewer long-term crops.

Now, preference shifts may also correlate with mental simulations of future time or how long the future reward would take to deliver. For example, teak could be harvested after six trials in our farming game. If one imagines these six trials to last longer, they may choose fewer teaks because of perceived extension of future time or reward delivery.

Thus, in addition to temporal distortions experienced during shocks, deviations in mental simulations of future time may also affect intertemporal choices. For simplicity, one can assume that ongoing experiences of time distortions directly map onto future simulations of time. Thus, if one feels time to be extending right now, they may anchor on these perceptions and make judgments based on them. However, no empirical or theoretical grounding exists to connect how ongoing distortions map onto future simulations and how these may affect preferences, providing fertile grounds for future work.

An implicit assumption built into our theory is that individual's discount rates are constant. In addition to the formulation and measurement difficulties associated with discount rates, we think sensitivity to delayed outcomes may be a stable and pervasive individual characteristic as often demonstrated by studies which show positive correlations for discounting across domains and outcomes (Odum, 2011). Thus, we propose here that state-level changes in discount rates derived from observed shifts in preference can be attributed to subjective mental states such as time.

Since, we assumed discount rates to be invariant and interpreted preference shifts as resulting from changes in perceived time. However, people's ability to be patient may depend on how long they wait. In other words, if one has to wait an extended period, their ability to delay gratification may diminish, suggesting a relationship between discount rates and perceived time. Thus, intertemporal preferences induced by instability may be a function of discount rates, subjective time, and their interactions.

Now, we think the temporal distortion framework depends on the time scale of the decision, which can be reliably estimated. This includes durations that can be mentally simulated or perceived as a delay (from days or weeks to a few years). When the delay becomes extremely short (e.g., one hour) or extremely long (e.g., a decade), preferences are likely to be dominated by other cognitive mechanisms in addition to temporal distortion. For very short delays, subjective time will be nearly veridical, and changes in preference are likely to be driven by arousal or attention-based mechanisms. On the other hand, for very long delays, we think people would rely on semantic representations of time (such as "a long time from now") rather than continuous temporal simulation. In such cases, future valuation may be influenced by abstract beliefs about uncertainty or affective responses to instability rather than distortions in perceived duration.

Lastly, the effects of precarity on preferences through the lens of subjective time was quantified using the exponential and hyperbolic discounting models in Chapter 6. An promising path of investigation that can be followed up is through the β - δ discounting formulation. Prior work, such as Haushofer et al. (2013), demonstrates that exposure to income shocks selectively increases β capturing heightened present bias. A natural extension would be to examine whether similar effects emerge within the farming game paradigm. Beyond replication, an especially novel question concerns whether felt time correlates with β or δ. We believe that felt time would correlate with β (the need for immediate gratification), suggesting that, while individuals may have a general inclination to delay gratification, fluctuations in impatience (β) can be captured by time distortions.

8.2 Conclusion

This work advances the dialogue between computational cognitive science and behavioral economics by demonstrating how preferences and decision-making under constraints can be systematically modeled. By situating the findings within the framework of unpredictable ecological perturbations, we highlight how the inherent uncertainty in our lives shapes time, choice, and our future preferences. Our simulations and studies indicate that short-term plans are preferred when one encounters multiple unpredictable resource shocks that deplete their endowment, which we argue is sufficient to cause shifts towards the immediate. We complement the prevalent scarcity literature by suggesting that limited resources can be a necessary, but not a sufficient condition for bringing about such present-focused behavior. Together, these contributions enrich the theoretical accounts of human behavior and provide a structured basis for interpreting how real-world decision contexts influence choices and preferences.

In our introduction, I urged you to think about some questions, namely, what keeps the impoverished trapped in poverty and whether it can be construed as a lack of character or a reasonable response to their lived experiences. The other question that drives this work is whether we would behave similarly when exposed to these precarious conditions. Our simulated depiction of precarity showed that planning horizons are adaptive to environmental conditions. Even though people chose the delayed rewards during stability, short-term plans were preferred when they observed unpredictable expenses depleting their saved resources. This observation was true for the majority of our sample pool who belong to relatively affluent families (Kaur, 2021) and our farmer sample, most of whom have an average annual income of approximately Rs 1,20,000 $\sim$ USD 6000 (PPP adjusted) in a year (Satyasai & Bharti, 2016). From these results, several key insights emerge:

- Optimal planning durations shift to the short-term when resource shocks are frequent, with low and high initial endowments. Individuals, irrespective of their socio-economic strata, display this behavior in the lab and the field.
- Long-term planning is optimal when the environment is stable, which is also corroborated in the lab. This suggests an adaptive resource rational theory of impatience as a function of environmental constraints.
- While unpredictable shocks shorten planning horizons, predictable shocks do not. Thus, expectation-outcome mismatches (not liquidity constraints) drive impatience.
- Time distortions can bring about similar preference changes as documented by discount rate shifts. Thus, instead of loss of control, present-oriented behavior can be interpreted as a result of perceived time dilation.
- Individuals who felt time to extend during volatility, compared to their baseline perception during stability, chose short-term plans more. This suggests precarity can perturb our sense of time, leading to impatience.

In summary, this work paints impatience as an interaction of living experiences, sense of time and preferences across it. For individuals living in dire conditions with a lack of resources and buffers, the effects of precarity compound quickly. Mitigating other expenses then becomes a hardship, and their choices become susceptible to other perturbations, leading to behaviors that may look impatient but actually are a reasonable response to their conditions.

Impatience, thus, does not result from personal failings or cultural teachings, but rather from the inherent unpredictability in our physical and mental world. I hope this work has gone some distance in convincing you of the humane explanation for our seemingly irrational behaviors. While we often suffer from attribution errors, I hope this work nudges you to see impatience as a response to our shared human conditions, best captured in the African concept of *Ubuntu*:

> *A person is a person only through other persons, that my humanity is caught up in yours. I am fully me only if you are all you can be.* - Desmond Tutu

A

Turbulence, Crop Attributes, and Design Choices in Harvest Horizons

A.1 Determination of variance for volatility

As noted earlier, resource cost deductions were sampled from a normal distribution at the start of the trial which instantiated shocks, increased crop loss and land rents. To formulate these, trial-wise deductions were formulated in the following way:

in low variance blocks

$$\mu_L + 2\sigma_L \geq Budget \tag{A.1}$$

in high variance blocks

$$\mu_H + \sigma_H \geq Budget \tag{A.2}$$

where μ_L and μ_H indicate the mean of a normal distribution for low and high variance blocks, and σ_L and σ_H indicate the standard deviation of a normal distribution for low and high variance blocks.

Since the resource cost was drawn from a normal distribution, the area under the curve greater than 5000 was set to be around 5% and 33% for low and high variance blocks, respectively. Based on this, the Z-score for LV (low variance) blocks and HV (high variance) blocks were calculated to be 1.65 and 0.43, respectively. We assumed the mean for both LV and HV blocks to be the same $\mu_L = \mu_H = \mu$ and the cutoff to be equal to the budget 5000. Thus using z-score we got -

for *low variance* block:

$$\mu + 1.65\sigma_L = 5000 \tag{A.3}$$

for *high variance* block:

$$\mu + 0.43\sigma_H = 5000 \tag{A.4}$$

Taking the boundary conditions of equation A.1 and equation A.2, we assumed $\mu = 3750$. We used this mean in equations A.3 and equation A.4, which gave us:

$$\sigma_L = 760 \qquad \sigma_H = 2845 \tag{A.5}$$

Since resource cost deductions were shown monthly in the game in real-time, we used this formulation to sample monthly resource costs such that the sum of these monthly cost deductions equaled the total trial-level resource cost deduction. To make this happen, we applied similar calculations as above with the monthly budget 1000, the same Z-scores, and $\mu = 3750/5 = 750$, which got us to:

$$\sigma_L = 152 \qquad \sigma_H = 569 \tag{A.6}$$

In a nutshell, for LV blocks, resource cost deductions were sampled from a normal distribution of $N(3750, 760)$, and for HV blocks, they were sampled from $N(3750, 2845)$ on every trial. To simulate real-time monthly cost deductions, we sampled from a normal distribution $N(750, 152)$ for LV blocks and $N(750, 569)$ for HV blocks such that the sum of these monthly debits was equal to the trial-level cost deduction.

A.2 Determination of crop yields

We wanted to make the *effective profit* of Apple and Teak equal so that neither seems more lucrative. We implemented this in the following manner:

In case of *low variance* block:

$$x_a - ((p_L{}' * \rho' * x_a) + (p_L * \rho * x_a)) = x_t - ((p_L{}' * \eta' * x_t) + (p_L * \eta * x_t)) \quad \text{(A.7)}$$

In case of *high variance* block:

$$x_a - ((p_H{}' * \rho' * x_a) + (p_H * \rho * x_a)) = x_t - ((p_H{}' * \eta' * x_t) + (p_H * \eta * x_t)) \quad \text{(A.8)}$$

where: x_t = selling price of teak, x_a = selling price of apple, $p_L{}'$ = p(shock) in LV, p_L = p(no shock) in LV, $p_H{}'$ = p(shock) in HV, p_H = p(no shock) in HV, ρ' = apple loss factor|shock, ρ = apple loss factor|no shock, η' = scaled teak loss factor|shock, η = scaled teak loss factor|no shock.

We set $\rho = 0.3$, $\rho' = 0.8$, $\eta = 0.2$, and $\eta' = 0.5$ based on Table 4.1. Furthermore, based on 10000 iterations, we determined $p_L{}' = 0.05$, p_L as $1 - p_L{}' = 0.95$, $p_H{}' = 0.35$, and p_H as $1 - p_H{}' = 0.65$. Thus, we find

From equation A.7, in case of low variance block:

$$x_a - (0.05 * 0.8 * x_a + 0.95 * 0.3 * x_a) = 1/6(x_t - (0.05 * 0.5 * x_t + 0.95 * 0.2 * x_t)) \quad \text{(A.9)}$$

From equation A.8, in case of high variance block:

$$x_a - (0.35 * 0.8 * x_a + 0.65 * 0.3 * x_a) = 1/6(x_t - (0.35 * 0.5 * x_t + 0.65 * 0.2 * x_t)) \quad \text{(A.10)}$$

(**Note:** 1/6 accounts for the growth time of teak across six trials)

Ratio of x_t and x_a from Equation A.9 $\equiv$ 5.16 and the ratio of x_t and x_a from Equation A.10 $\equiv$ 4.53

Finally, the mean of the ratios = 4.85. Thus, since Apple's selling price was 350 coins, we set the selling price of teak at (4.85*350) = 1700 coins.

A.3 Design and Analysis choices for Harvest Horizons

The farming game was designed to expose participants to close-to-ideal randomized blocks of volatile and stable environments. Following a practice (P) block, participants encountered two randomized blocks each of volatility (V) and stability (S), resulting in block sequences such as P–V–S–V–V or P–S–S–V–V, among others. This design ensured substantial variability in environmental structure while avoiding systematic order effects. Within each block, resource debits were also randomized. Fertilizer costs, crop losses, and land rents were sampled in real time during game-play, such that participants could encounter environmental shocks on any trial and an arbitrary number of times throughout the game, subject to a predefined upper bound on the total number of shocks.

Since block order and trial sequences were randomized, there were no conditions in which stable environments systematically appeared first or volatile environments systematically appeared last. This design choice ensured that potential order effects due to learning or fatigue did not introduce systematic bias into the results. Consequently, each block type and each trial within a block were equally likely to occur at any position in the task. This procedure was implemented in Experiments 1 and 2. In Experiments 4 and 5, resource debits were prespecified rather than sampled in real time. This design ensured that each participant encountered an equal number of resource shocks, randomly distributed across the game. The pre-sampling procedure further minimized order effects by explicitly controlling the placement of shock trials within each volatile block.

Data exclusion was implemented in two stages - at the trial and participant levels. At the trial level, resource shocks occurring within the final six trials were excluded from the 'preference shift' computation, as participants were no longer motivated to grow teak toward the end of the game. At the participant level, extreme outliers (values exceeding 1.75 $\times$ IQR) were excluded, as these observations disproportionately skewed the distributions and biased mean estimates. Trial-level exclusions accounted for fewer than 5% of all trials, and participant-level exclusions accounted for fewer than 10% of the sample. For clarity and transparency, we also report all analyses including these trials and participants in the Robustness Checks section of each chapter.

B

Derivations used in Chapter 6

B.1 Deriving u(l) from p(l) using soft-max function

In Chapter 6, we used a model where we assumed that an agent has two choices - a smaller reward r_0 available now vs. a larger reward r_t available at an objective, calendar time t_o. Given probability of choosing the later reward $= p(l)$, we derived the utility $u(l)$ associated with it using a soft-max function

$$p(l) = \frac{exp(u(l))}{exp(u(l)) + exp(u(s))} \tag{B.1}$$

which yields

$$u(l) = ln\left(\frac{p(l) \times exp(u(s))}{1 - p(l)}\right) \tag{B.2}$$

where $u(s)$ is the utility of the smaller, immediate reward which is assumed to be equal to r_0.

Equation B.1 leads to Equation B.2 through the following steps:

$$\begin{aligned}
p(l) &= \frac{exp(u(l))}{exp(u(l)) + exp(u(s))} \\
\implies exp(u(l)) &= p(l) \times exp(u(l)) + p(l) \times exp(u(s)) \\
\implies exp(u(l)) \times (1 - p(l)) &= p(l) \times exp(u(s)) \\
\implies exp(u(l)) &= \frac{p(l) \times exp(u(s))}{1 - p(l)} \\
\implies u(l) &= ln\left(\frac{p(l) \times exp(u(s))}{1 - p(l)}\right)
\end{aligned}$$

Thus, given a shift in choice probability from $p(l)$ to $p(l)'$, the updated utility of the delayed reward $u(l)'$ can be derived in a similar fashion and would be noted by

$$\begin{aligned}
p(l)' &= \frac{exp(u(l)')}{exp(u(l)') + exp(u(s))} \\
\implies u(l)' &= ln\left(\frac{p(l)' \times exp(u(s))}{1 - p(l)'}\right)
\end{aligned}$$

B.2 Deriving k from u(l) using discounting models

B.2.1 Exponential discounting

Exponential discounting model suggests that the future reward will be discounted exponentially and thus the utility of delayed reward can be derived from

$$u(l) = r_t \times exp(-k \times t_o) \tag{B.3}$$

and our agent's discount factor k can be derived using objective time t_o by

$$k = \frac{1}{t_o} \times ln\left(\frac{r_t}{u(l)}\right) \tag{B.4}$$

Equation B.3 leads to Equation B.4 through the following steps:

$$
\begin{aligned}
& u(l) = r_t \times exp(-k \times t_o) \\
\implies & exp(-k \times t_o) = \frac{u(l)}{r_t} \\
\implies & k \times t_o = ln(\frac{r_t}{u(l)}) \\
\implies & k = \frac{1}{t_o} \times ln\left(\frac{r_t}{u(l)}\right)
\end{aligned}
$$

Thus, given a shift in future utility from $u(l)$ to $u(l)'$, the updated discount rate k' given objective invariant time t_o can be derived in a similar fashion and would be noted by

$$
\begin{aligned}
& u(l)' = r_t \times exp(-k' \times t_o) \\
\implies & k' = \frac{1}{t_o} \times ln\left(\frac{r_t}{u(l)'}\right)
\end{aligned}
$$

B.2.2 Hyperbolic discounting

Hyperbolic discount model says that the future reward will be discounted hyperbolically over time (time-inconsistent) and thus the utility of delayed reward $u(l)$ is given by

$$u(l) = \frac{r_t}{1 + k \times t_o} \tag{B.5}$$

which leads us to

$$k = \frac{r_t - u(l)}{u(l) \times t_o} \tag{B.6}$$

Equation B.5 leads to Equation B.6 through the following steps:

$$
\begin{aligned}
& u(l) = \frac{r_t}{1 + k \times t_o} \\
\implies & 1 + k \times t_o = \frac{r_t}{u(l)} \\
\implies & k \times t_o = \frac{r_t}{u(l)} - 1 \\
\implies & k = \frac{r_t - u(l)}{u(l) \times t_o}
\end{aligned}
$$

Thus, given a shift in future utility from $u(l)$ to $u(l)'$, the updated discount rate k' given objective invariant time t_o can be written as

$$u(l)' = \frac{r_t}{1 + k' \times t_o}$$
$$\implies k' = \frac{r_t - u(l)'}{u(l)' \times t_o}$$

C

Summary of statistical tests and effect sizes

Table C.1 summarizes the key statistical tests and outcomes used in the experiments, including outcome variables (their mean, SD, and 95% CIs), test type, sample size (N), and effect sizes (Cohen's d). Full methodological details are provided in the corresponding chapters.

- Experiment 1 - effects of precarity on inter-temporal preferences among students. δ_{teak} denotes the switch in long-term choice and δ_{apple} and δ_{rice} denotes the short-term choices.
- Experiment 2 - replication study demonstrating the effects of precarity on preferences among local farmers.
- Experiment 3 - effects of stable conditions on preference for delayed rewards.
- Experiment 4 - (a) replicates experiment 1 with pre-defined unpredictable shocks and (b) tests preference shifts with predictable turbulence.
- Experiment 5 - Replication of 4(a) along with perceived time estimates to measure the correlation between subjective time and inter-temporal preferences. $\Delta p(teak)$

denotes the change in probability of choosing the long-term choice and $\Delta p(apple)$ and $\Delta p(rice)$ denotes the change in probability of choosing the short-term choices.

Table C.1: Summary of statistical models and effect sizes.

Test	N	Outcome	Mean	SD	95% CI	Effect size
Experiment 1						
t	69	δ_{teak}	-0.34	1.39	[-0.62, -0.06]	-0.24
t	69	δ_{apple}	0.33	1.31	[0.01, 0.65]	0.25
t	69	δ_{rice}	0.01	1.18	[-0.27, 0.30]	0.01
Experiment 2						
t	70	δ_{teak}	-0.89	4.02	[-1.69, -0.09]	-0.22
t	70	δ_{apple}	-0.09	2.41	[-0.49, 0.67]	0.06
t	70	δ_{rice}	0.80	2.67	[0.16, 1.44]	0.30
Experiment 3						
t	19	δ_{teak}	0.19	0.22	[0.01, 0.28]	0.86
t	19	δ_{apple}	-0.11	0.17	[-0.19, -0.02]	-0.62
t	19	δ_{rice}	-0.08	0.09	[-0.13, -0.04]	-0.86
Experiment 4a						
t	28	δ_{teak}	-1.6	2.93	[-2.54, -0.65]	-0.54
t	28	δ_{apple}	0.42	1.87	[-0.33, 1.15]	0.22
t	28	δ_{rice}	1.19	2.06	[0.37, 2.0]	0.56
Experiment 4b						
t	30	δ_{teak}	0.25	1.83	[-0.32, 0.83]	0.14
t	30	δ_{apple}	-0.49	1.25	[-0.96, -0.02]	0.39
t	30	δ_{rice}	0.24	1.05	[-0.16, 0.63]	0.22
Experiment 5						
t	96	$\Delta p(teak)$	-0.02	0.063	[-0.03, -0.01]	-0.27
t	96	$\Delta p(apple)$	-0.005	0.054	[-0.02, 0.01]	0.087
t	96	$\Delta p(rice)$	0.022	0.044	[0.01, 0.03]	0.50

Bibliography

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2014). Discounting behavior: A reconsideration. *European Economic Review*, *71*, 15–33. https://doi.org/https://doi.org/10.1016/j.euroecorev.2014.06.009

Banerjee, A. V., & Duflo, E. (2007). The economic lives of the poor. *Journal of economic perspectives*, *21*(1), 141–168. https://doi.org/10.1257/jep.21.1.141

Bhui, R., Lai, L., & Gershman, S. J. (2021). Resource-rational decision making. *Current Opinion in Behavioral Sciences*, *41*, 15–21.

Bickel, W. K., Wilson, A. G., Chen, C., Koffarnus, M. N., & Franck, C. T. (2016). Stuck in time: Negative income shock constricts the temporal window of valuation spanning the future and the past. *PLOS ONE*, *11*, e0163051. https://doi.org/10.1371/JOURNAL.PONE.0163051

Blain, B., Globig, L. K., & Sharot, T. (2025). Adapting temporal preference to scarcity: A role for emotion? *Journal of Risk and Uncertainty*, *71*(1), 93–109. https://doi.org/10.1007/s11166-025-09453-x

Block, R. A., Hancock, P. A., & Zakay, D. (2010). How cognitive load affects duration judgments: A meta-analytic review. *Acta psychologica*, *134*(3), 330–343. https://doi.org/10.1016/j.actpsy.2010.03.006

Bradford, W. D., Dolan, P., & Galizzi, M. M. (2019). Looking ahead: Subjective time perception and individual discounting. *Journal of Risk and Uncertainty*, *58*(1), 43–69. https://doi.org/10.1007/s11166-019-09298-1

Bradford, W. D., & Doucette, M. H. (2023). Effect of a brief intervention on respondents' subjective perception of time and discount rates. *Journal of Risk and Uncertainty*, *66*(1), 47–75. https://doi.org/10.1007/s11166-022-09390-

Carvalho, L. S., Meier, S., & Wang, S. W. (2016). Poverty and economic decision-making: Evidence from changes in financial resources at payday. *American economic review*, *106*(2), 260–84. https://doi.org/10.1257/aer.20140481

Cocco, J. F., Gomes, F., & Lopes, P. (2016). *Expenditures and financial well-being* (tech. rep.). Queen Mary University of London. https://www.qmul.ac.uk/sef/media/econ/images/documents/20161205-joao-cocco.pdf

Colarieti, R., Mei, P., & Stantcheva, S. (2024, March). *The how and why of household reactions to income shocks* (Working Paper No. 32191). National Bureau of Economic Research. https://doi.org/10.3386/w32191

Dalton, P. S., Nhung, N., & Rüschenpöhler, J. (2020). Worries of the poor: The impact of financial burden on the risk attitudes of micro-entrepreneurs. *Journal of Economic Psychology*, *79*, 102198. https://doi.org/10.1016/j.joep.2019.102198

Daly, M., & Wilson, M. (2005a). Carpe diem: Adaptation and devaluing the future. *The quarterly review of Biology*, *80*(1), 55–60. https://doi.org/10.1086/431025

Daly, M., & Wilson, M. (2005b). Carpe diem: Adaptation and devaluing the future. *The Quarterly Review of Biology*, *80*(1), 55–60. https://doi.org/10.1086/431025

de Bruijn, E.-J., & Antonides, G. (2021). Poverty and economic decision making: A review of scarcity theory. *Theory and Decision*, 1–33. https://doi.org/10.1007/s11238-021-09802-7

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, *78*, 97–119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Dohmen, T., Enke, B., Falk, A., Huffman, D., Sunde, U., et al. (2015). Patience and the wealth of nations. *Unpublished Manuscript, University of Bonn*.

Droit-Volet, S., & Meck, W. H. (2007). How emotions colour our perception of time. *Trends in Cognitive Sciences*, *11*(12), 504–513. https://doi.org/https://doi.org/10.1016/j.tics.2007.09.008

Eagleman, D. M. (2004). Time perception is distorted during slow motion sequences in movies. *Journal of Vision*, *4*(8), 491. https://doi.org/10.1167/4.8.491

Falco, S. D., Berck, P., Bezabih, M., & Köhlin, G. (2019). Rain and impatience: Evidence from rural ethiopia. *Journal of Economic Behavior & Organization*, *160*, 40–51. https://doi.org/10.1016/J.JEBO.2019.02.016

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007a). G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007b). G*power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fayolle, S., Gil, S., & Droit-Volet, S. (2015). Fear and time: Fear speeds up the internal clock. *Behavioural processes*, *120*, 135–140.

Fehr, D., Fink, G., & Jack, K. (2019, October). *Poverty, seasonal scarcity and exchange asymmetries* (Working Paper No. 26357). National Bureau of Economic Research. https://doi.org/10.3386/w26357

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, *40*(2), 351–401.

Fu, Q., Hoijtink, H., & Moerbeek, M. (2021). Sample-size determination for the bayesian t test and welch's test using the approximate adjusted fractional bayes factor. *Behavior Research Methods*, *53*(1), 139–152. https://doi.org/10.3758/s13428-020-01408-1

Gibbon, J., Church, R. M., Meck, W. H., et al. (1984). Scalar timing in memory. *Annals of the New York Academy of sciences*, *423*(1), 52–77.

Griffiths, T. L., Lieder, F., & Goodman, N. D. (2015). Rational use of cognitive resources: Levels of analysis between the computational and the algorithmic. *Topics in cognitive science*, *7*(2), 217–229. https://doi.org/10.1111/tops.12142

Griskevicius, V., Tybur, J. M., Delton, A. W., & Robertson, T. E. (2011). The influence of mortality and socioeconomic status on risk and delayed rewards: A life history theory approach. *Journal of personality and social psychology*, *100*(6), 1015. https://doi.org/10.1037/a0022403

Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. *Science*, *344*(6186), 862–867. https://doi.org/10.1126/science.1232491

Haushofer, J., Schunk, D., & Fehr, E. (2013). Negative income shocks increase discount rates. *University of Zurich Working Paper*.

Hays, S. (2004). *Flat broke with children: Women in the age of welfare reform*. Oxford University Press. https://doi.org/10.4324/9780429494468-21

JASP Team. (2022). JASP (Version 0.16.4)[Computer software].

Kaur, R. (2021). Gendered parenting and returns from children in contemporary india: A study of iit students and their parents. *Current Sociology*. https://doi.org/10.1177/0011392121990022

Kidd, C., Palmeri, H., & Aslin, R. N. (2013). Rational snacking: Young children's decision-making on the marshmallow task is moderated by beliefs about environmental reliability. *Cognition*, *126*(1), 109–114. https://doi.org/10.1016/j.cognition.2012.08.004

Kirby, K. N., & Petry, N. M. (2004). Heroin and cocaine abusers have higher discount rates for delayed rewards than alcoholics or non-drug-using controls. *Addiction*, *99*(4), 461–471.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*(2), 443–478.

Lee, S., Kable, J. W., & Jung, W. H. (2025). Altering subjective time perception leads to correlated changes in neural activity and delay discounting. *NeuroImage*, *313*, 121244. https://doi.org/https://doi.org/10.1016/j.neuroimage.2025.121244

Lewis, O. (1966). The culture of poverty. *Scientific American*, *215*(4), 19–25.

Lichand, G., & Mani, A. (2020, February). *Cognitive droughts* (tech. rep. No. 341). https://doi.org/10.5167/uzh-185364

Ludwig, R. M., Flournoy, J. C., & Berkman, E. T. (2019). Inequality in personality and temporal discounting across socioeconomic status? assessing the evidence. *Journal of research in personality*, *81*, 79–87. https://doi.org/10.1016/j.jrp.2019.05.003

Malmendier, U. (2021). Experience effects in finance: Foundations, applications, and future directions. *Review of Finance*, *25*(5), 1339–1363. https://doi.org/10.1093/rof/rfab020

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty impedes cognitive function. *Science*, *341*(6149), 976–980.

Martinelli, N., & Droit-Volet, S. (2022). Judgment of duration and passage of time in prospective and retrospective conditions and its predictors for short and long durations. *Scientific Reports*, *12*(1), 22241. https://doi.org/10.1038/s41598-022-25913-9

Mazur, J. E. (1984). Tests of an equivalence rule for fixed and variable reinforcer delays [Cited by: 273]. *Journal of Experimental Psychology: Animal Behavior Processes*, *10*(4), 426–436. https://doi.org/10.1037/0097-7403.10.4.426

McGuire, J. T., & Kable, J. W. (2012). Decision makers calibrate behavioral persistence on the basis of time-interval experience. *Cognition*, *124*(2), 216–226. https://doi.org/https://doi.org/10.1016/j.cognition.2012.03.008

Meles, T. H., Abay, M. H., Berhane, G., & Taffesse, A. S. (2024). Shocks and stability of risk and time preferences among poor rural households in ethiopia. *Journal of African Economies*. https://doi.org/10.1093/JAE/EJAE005

Mereu, S., & Lleras, A. (2013). Feelings of control restore distorted time perception of emotionally charged events. *Consciousness and Cognition*, *22*(1), 306–314. https://doi.org/https://doi.org/10.1016/j.concog.2012.08.004

Mischel, W. (2014). *The marshmallow test: Understanding self-control and how to master it*. Random House.

Mitra, A., Srinivasan, N., & Srivastava, N. (2025). Present-focused behavior as a rational adaptation to precarity. *Open Mind*, *9*, 452–474.

Mitra, A., & Srivastava, N. (2024). Changes in time preference may simply be induced by changes in time perception.

Mitra, A., Srivastava, N., & Srinivasan, N. (2023). Unpredictability shortens planning horizons. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *45*, 540–547. https://doi.org/10.1093/cogsci/45.1.540

Moynihan, D. P. (1965). *The negro family: The case for national action*. US Government Printing Office.

Odum, A. L. (2011). Delay discounting: Trait variable? *Behavioural processes*, *87*(1), 1–9.

Ong, Q., Theseira, W., & Ng, I. Y. (2019). Reducing debt improves psychological functioning and changes decision-making in the poor. *Proceedings of the National Academy of Sciences*, *116*(15), 7244–7249. https://doi.org/10.1073/pnas.1810901116

Pampel, F. C., Krueger, P. M., & Denney, J. T. (2010). Socioeconomic disparities in health behaviors. *Annual review of sociology*, *36*, 349–370. https://doi.org/10.1146/annurev.soc.012809.102529

Pariyadath, V., & Eagleman, D. (2007). The effect of predictability on subjective duration. *PLOS ONE*, *2*, e1264. https://doi.org/10.1371/JOURNAL.PONE.0001264

Pepper, G. V., & Nettle, D. (2017). The behavioral constellation of deprivation: Causes and consequences. *Behavioral and Brain Sciences*, *40*. https://doi.org/10.1017/S0140525X1600234X

Polti, I., Martin, B., & van Wassenhove, V. (2018). The effect of attention and working memory on the estimation of elapsed time. *Scientific Reports*, *8*(1), 6690.

Poynter, W., & Homa, D. (1983). Duration judgment and the experience of change [Copyright: Copyright 2011 Elsevier B.V., All rights reserved.]. *Perception & Psychophysics*, *33*(6), 548–560. https://doi.org/10.3758/BF03202936

Read, D. (2001). Is time-discounting hyperbolic or subadditive? *Journal of Risk and Uncertainty*, *23*, 5–32. https://doi.org/10.1023/A:1011198414683

Riis-Vestergaard, M. I., & Haushofer, J. (2017). Stuff goes wrong, so act now. *Behavioral and Brain Sciences*, *40*, e340. https://doi.org/10.1017/S0140525X17001091

Rowe, D. C., & Rodgers, J. L. (1997). Poverty and behavior: Are environmental measures nature and nurture? *Developmental Review*, *17*(3), 358–375. https://doi.org/10.1006/drev.1997.0434

Ryan, W. (1976). *Blaming the victim* (Vol. 226). Vintage.

Satyasai, K. (2016). Farmer's income: Trend and strategies for doubling. *Indian Journal of Agricultural Economics*, *71*(3), None. https://doi.org/10.22004/ag.econ.302224

Satyasai, K., & Bharti, S. (2016). Doubling farmers' income: Way forward. *Rural Pulse*, *14*, 1–4.

Schilbach, F., Schofield, H., & Mullainathan, S. (2016). The psychological lives of the poor. *American Economic Review*, *106*(5), 435–40. https://doi.org/10.1257/aer.p20161101

Schönbrodt, F. D., Wagenmakers, E.-J., Zehetleitner, M., & Perugini, M. (2017). Sequential hypothesis testing with bayes factors: Efficiently testing mean differences. *Psychological methods*, *22*(2), 322. https://doi.org/10.1037/met0000061

Shah, A. K., Mullainathan, S., & Shafir, E. (2012). Some consequences of having too little. *Science*, *338*(6107), 682–685. https://doi.org/10.1126/science.1222426

Shah, A. K., Mullainathan, S., & Shafir, E. (2019). An exercise in self-replication: Replicating shah, mullainathan, and shafir (2012). *Journal of Economic Psychology*, *75*, 102127. https://doi.org/10.1016/j.joep.2018.12.001

Shoda, Y., Mischel, W., & Peake, P. K. (1990). Predicting adolescent cognitive and self-regulatory competencies from preschool delay of gratification: Identifying diagnostic conditions. *Developmental psychology*, *26*(6), 978.

Stefan, A. M., Gronau, Q. F., Schönbrodt, F. D., & Wagenmakers, E.-J. (2019). A tutorial on bayes factor design analysis using an informed prior. *Behavior research methods*, *51*(3), 1042–1058. https://doi.org/10.3758/s13428-018-01189-8

Stoet, G. (2010). Psytoolkit: A software package for programming psychological experiments using linux. *Behavior research methods*, *42*(4), 1096–1104. https://doi.org/10.3758/BRM.42.4.1096

Stoet, G. (2017). Psytoolkit: A novel web-based method for running online questionnaires and reaction-time experiments. *Teaching of Psychology*, *44*(1), 24–31. https://doi.org/10.1177/0098628316677643

Suo, T., Zhang, F., Zhao, G., & Li, H. (2014). The influence of time perception difference on intertemporal choice. *Acta Psychologica Sinica*, *46*(2), 165–173. https://doi.org/10.3724/SP.J.1041.2014.00165

Takahashi, T. (2016). *Loss of self-control in intertemporal choice may be attributable to logarithmic time-perception*. Springer.

Takahashi, T., Oono, H., & Radford, M. H. (2008). Psychophysics of time perception and intertemporal choice models. *Physica A: Statistical Mechanics and its Applications*, *387*(8-9), 2066–2074.

Tanaka, R., & Yotsumoto, Y. (2017). Passage of time judgments is relative to temporal expectation. *Frontiers in Psychology*, *8*, 187. https://doi.org/10.3389/fpsyg.2017.00187

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics Letters*, *8*(3), 201–207. https://doi.org/https://doi.org/10.1016/0165-1765(81)90067-7

Thomas, E., & Weaver, W. (1975). Cognitive processing and time perception. *Perception & Psychophysics*, *17*, 363–367. https://doi.org/10.3758/BF03199347

Todd, P. M., & Gigerenzer, G. E. (2012). *Ecological rationality: Intelligence in the world.* Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195315448.001.0001

Tomm, B. M., & Zhao, J. (2017). Scarcity impairs online detection and prospective memory. *Cognitive Science*. https://api.semanticscholar.org/CorpusID:39350748

Toren, I., Aberg, K. C., & Paz, R. (2020). Prediction errors bidirectionally bias time perception. *Nature Neuroscience*, *23*(10), 1198–1202.

Tse, P. U., Intriligator, J., Rivest, J., & Cavanagh, P. (2004). Attention and the subjective expansion of time. *Perception & Psychophysics*, *66*, 1171–1189. https://doi.org/10.3758/BF03196844

Ulrich, R., Nitschke, J., & Rammsayer, T. (2006). Perceived duration of expected and unexpected stimuli. *Psychological Research*, *70*, 77–87. https://doi.org/10.1007/s00426-004-0195-4

Underlid, K. (2007). Poverty and experiences of insecurity: A qualitative interview study of 25 long-standing recipients of social security. *International Journal of Social Welfare*, *16*, 65–74. https://doi.org/10.1111/j.1468-2397.2006.00439.x

Watts, T. W., Duncan, G. J., & Quan, H. (2018). Revisiting the marshmallow test: A conceptual replication investigating links between early delay of gratification and later outcomes. *Psychological science*, *29*(7), 1159–1177. https://doi.org/10.1177/0956797618761661

Wilson, W. J. (2009). *More than just race: Being black and poor in the inner city (issues of our time)*. WW Norton & Company.

Wilson, W. J. (2012). *The truly disadvantaged: The inner city, the underclass, and public policy*. University of Chicago Press.

Xu, P., González-Vallejo, C., & Vincent, B. T. (2020). Waiting in intertemporal choice tasks affects discounting and subjective time perception. *Journal of Experimental Psychology: General*, *149*(12), 2289–2313. https://doi.org/10.1037/xge0000771

Zauberman, G., Kim, B. K., Malkoc, S. A., & Bettman, J. R. (2009). Discounting time and time discounting: Subjective time perception and intertemporal preferences.

Journal of Marketing Research, *46*(4), 543–556. https://doi.org/10.1509/jmkr.46.4.543