Dynamic Optimization Meets Budgeting: Unraveling Financial Complexities

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May 21, 2025

Abstract

This paper explores sources of complexity in dynamic optimization, examining how individuals navigate variation in incomes, prices, and returns in ten-period consumption-saving decisions. Our findings reveal that dynamic optimization poses significant challenges, resulting in suboptimal choices even in straightforward scenarios with stable parameters, full information, no uncertainty, and opportunities to learn. These challenges intensify in scenarios involving complexities such as frequent price changes and compounding returns, characterized by a pronounced tendency to over-smooth consumption. Additionally, we introduce a novel budgeting calculator aimed to assist with consumption planning and to collect valuable non-choice data on subjects' planning strategies and horizons—an approach not previously utilized in studies of dynamic optimization. Participants' actual planning horizons tend to be longer than their consumption decisions would imply. Complete planning leads to better performance in more complex scenarios, even when people do not optimally utilize the calculator. However, there is little re-optimization after the first period and participants tend to stick with suboptimal plans for most of their life cycle. The decision to plan is less influenced by the complexity of the economic environment and more by the length of the planning horizon.

JEL classifications: C91, E21, E70

Keywords: consumption-saving decisions, dynamic optimization, laboratory experiment, budgeting tools, complexity, experimental macroeconomics

*Corresponding author: Luba Petersen (lubap@sfu.ca). We thank the Social Sciences and Humanities Research Council of Canada for generous financial support. We have benefited from valuable discussions and comments from Victor Aguiar, Mark Bils, Xavier Gabaix, Chenyu Hou, and Ryan Rholes. We thank Eric Fortier and Michael Mirdamadi for excellent research assistance.

1 Introduction

In the landscape of financial decision-making, dynamic optimization is a crucial element influencing choices for both individuals and institutions. This domain spans a broad spectrum of essential decisions, including investment strategies, hiring and supplying of labor, the formation of environmental policy, and especially, consumption and saving decisions. Economic theories often assume that agents are capable of navigating these complex situations effectively. However, empirical evidence suggests a contrasting reality. Many individuals encounter difficulties in planning over time—a challenge recognized early on by Strotz (1955), whose work introduced the notion of time inconsistency, highlighting that individuals may struggle to follow through on intertemporal plans. This foundational insight paved the way for later work on the cognitive and behavioral challenges of dynamic optimization, as emphasized in recent contributions by Enke et al. (2025) and Gabaix and Graeber (2024). But *what* makes dynamic optimization problems complex?

Our paper investigates how people navigate complexities in consumption-saving decisions, pinpointing five primary sources of complexity: shifts in the economic environment, the impact of compounding returns, the length of the planning horizon, computational challenges, and a lack of experience. To explore these elements, we conducted incentivized decision-making tasks where participants undertook a series of consumption-saving exercises over ten-period horizons with full information about all relevant future variables.

In our baseline scenario, ConstantYP, participants faced consumption decisions under conditions of constant and known incomes and prices, and without receiving interest on their savings. In this simplified setting, theoretically optimal behavior dictates spending one's entire income in each period. This design is intentionally simple, enabling us to detect patterns of random decision-making and any systematic biases.

Subsequent treatments systematically introduce complexities. The FluctY treatment fluctuates income between high and low levels, testing participants' ability to optimally smooth consumption over varying income. The FluctP treatment varies prices between two known levels, examining if participants properly factor price fluctuations and induced utility curvature into their spending decisions. Finally, in the PosIR treatment, we incorporate positive interest rates to analyze how compounding returns influence dynamic decisions. Across all treatments, sequential decision-making over the ten-period horizon allows us to assess how planning complexity increases with longer horizons.

Specifically, we examine whether participants are more likely to make larger planning errors conditional on their current savings at the start of their decision-making *life-cycle*.

Our experiments reveal that individuals frequently encounter significant challenges in optimizing their lifetime consumption plans, even in scenarios where income and prices are stable and savings yield no returns. In our ConstantYP treatment, the average inexperienced participant managed to attain only 76% of the unconditional optimal solution, measured in terms of per-period payoffs (i.e the optimal solution that does not account for current savings). This performance marginally improves to 82% by the third repetition of the optimization task, indicating limited learning through experience. These results underscore the inherent difficulty in dynamic optimization, even under simple environments.

Contrary to initial expectations, income fluctuations alone did not further reduce optimization accuracy. However, introducing fluctuating prices or compounding returns significantly impaired participants' optimization, reducing their performance to around 62–66%. This decline in performance persists as participants gain experience through the second and third iterations of the task. Interestingly, shortening the planning horizon is more effective in reducing optimization errors than simply gaining more experience. In the PosIR treatment, for example, participants improve their optimization performance by over 3 percentage points by reducing the planning horizon by just two periods, a level of improvement typically seen after repeating the full 10-period task twice. This finding is consistent with the well-documented pattern of exponential-growth bias (EGB), wherein individuals systematically underestimate the effects of compounding. Thus, truncating the horizon reduces the bite of the exponential curve.[1]

The nature of optimization errors varied according to the experimentally-induced complexity. In PosIR, participants typically undervalued early savings, reducing their available wealth for future consumption. Conversely, in FluctP, although participants recognized that spending more when prices were low was beneficial, they systematically underspent during these periods. Notably, our paper is the first to isolate and analyze the cognitive challenge of frequent price fluctuations independently from other factors such as income variability.

Given these cognitive hurdles, a key question arises: Are errors in dynamic opti-

[1] In particular, Levy and Tasoff (2016) show that an EGB leads individuals to underestimate future wealth and consequently under-save. Similarly, Stango and Zinman (2009) demonstrate that growth-biased households accumulate less wealth over time. Eisenstein and Hoch (2007) further show that even well-educated individuals routinely misjudge exponential processes.

mization primarily driven by miscalculations or by deeper difficulties in planning under complexity? To explore this, we introduce a second set of treatments where participants are provided with a budgeting calculator. Unlike basic tools or mental math, which may exacerbate the types of errors seen in the PosIR and FluctP scenarios, this device offers tailored assistance, helping users craft comprehensive spending plans while tracking all computations. By providing structured support, the calculator allows us to assess not only how thoroughly participants plan their spending, but also how their planning behavior adapts to changing economic conditions. Our novel approach, focusing on non-choice data, provides fresh insight into the depth of participants' dynamic planning and the influence of economic complexity on short-term decision-making. To our knowledge, this study is the first to leverage non-choice calculator data in the context of dynamic optimization, offering a unique perspective on the underlying processes that shape financial decisions, beyond just the outcomes themselves.

Our analysis of the budgeting calculator's effectiveness presents mixed outcomes. While we expected the calculator to streamline and facilitate decision-making, its actual impact was more nuanced. For instance, in the ConstantYP treatment, calculator access increased utility by eight to eleven percentage points compared to the unconditional optimal path and led to a 3.4% rise in normalized monetary rewards relative to the maximum possible payoff. In the PosIR treatment, the calculator improved optimization by five to six percentage points and increased normalized monetary payoffs by 4.4%. However, in the FluctY and FluctP treatments, the calculator's effectiveness was notably limited—its influence on utility was either minimal or indiscernible, suggesting that its benefits depend heavily on the structure and complexity of the environment.

The value of the budgeting tool in simplifying optimization tasks relies on participants' ability to use it proficiently. When used effectively, the calculator can boost unconditional optimization by 6 to 12 percentage points. In the PosIR setting —unlike in other treatments where problems can often be solved by focusing on one or two periods —calculator use plays a crucial role in addressing longer-horizon problems, which are otherwise too complex to compute manually.

Nevertheless, our findings demonstrate that even fully utilizing the calculator's capability—by entering data across the entire planning horizon—is insufficient on its own to guarantee optimal decision-making. A central contribution of our study is the direct observation and modeling of participants' planning horizons, an approach that distinguishes our work from previous studies relying solely on choice data. We refine the standard optimization model to explicitly incorporate varying planning horizons, showing that shorter horizons inherently lead to suboptimal outcomes.

Crucially, comparing model-implied horizons with empirical data on subjects' actual planning behavior (non-choice data) is essential. If our analysis had relied solely on consumption choices and assumed that subjects were perfect optimizers given their chosen horizons, any mismatch with the model's predictions would be absorbed into the error term. Instead, by directly observing participants' entries in the calculator, we are able to validate the model's predictions about planning horizons and assess the extent to which deviations arise from incorrect horizon assumptions versus execution errors.

Our empirical validation reveals that while the model accurately predicts the prevalence of one-period planners, it significantly underestimates the frequency of full-horizon planners and overestimates the incidence of intermediate horizons. Importantly, these discrepancies show that while selecting the longest possible planning horizon is necessary for making optimal consumption choices, it is not sufficient. In fact, there are significantly more participants who submit full 10-period plans than there are participants who make optimal consumption decisions—highlighting a clear gap between planning and successful execution.

Our experiment builds on the consumption-saving framework introduced by Hey and Dardanoni (1988) and closely relates to studies by Ballinger et al. (2011) and Gabaix and Graeber (2024), which also examine the role of environmental complexity. Table 1 summarizes the diverse experimental approaches within the broader *learning-to-optimize* literature (Duffy, 2016). Given that previous studies often introduce multiple complexities simultaneously—such as extended horizons, uncertainty, returns on savings, income fluctuations, and calculators—it can be challenging to isolate how each element impacts optimization. To address this, our parameterization, as detailed at the bottom of Table 1, introduces one feature of complexity at a time, allowing for a careful examination of each element's influence on optimization.

Although direct comparisons among these experiments are difficult due to their differing parameters and information sets, two key patterns consistently emerge in the existing research. First, participants struggle with dynamic planning. People often either consume too much or too little at the start of their life cycle and they neglect the long-term impacts of compounding returns. Second, challenges with dynamic planning are usually attributed to participants' limited planning horizons and attention, with background complexity playing an important role in shaping their decision-making and *inferred* planning horizons.

Our findings contribute to this literature by highlighting the additional optimization

Table 1: Related learning-to-optimize experiments

Paper	Uncertainty	Interest Rates (IR)	Fluctuating Variable	Borrowing Constraints	No. of Periods	No. of Sequences	Closed-Form Solution	Budgeting Calculator
Hey and Dardanoni (1988)	Yes	>0	Income	Yes	Indefinite	1	No	No[1]
Ballinger et al. (2003)	Yes	>0	Income	Yes	60	1[2]	No	1-period
Carbone and Hey (2004)	Yes	>0	Income	Yes	25	1	No	Unknown
Brown et al. (2009)	Yes	= 0	Income	Yes	30	7	No	1-period
Ballinger et al. (2011)	Yes	= 0	Income	Yes	20	5	No	Physical calculator
Carbone and Duffy (2014)	No	>0	Income	Yes	25	2	Yes	PC calculator
Luhan and Scharler (2014)	No	>0	Price and IR	Yes	2	20	Yes	PC calculator
Carbone and Infante (2015)	Yes	>0	Income	No	15	2	No	1-period
Levy and Tasoff (2016)	No	>0	Income and Interest Rate	Yes	5	4	Yes	Anything[3]
Meissner (2016)	Yes	= 0	Income	No	20	6	Yes	PC calculator
Yamamori et al. (2018)	No	= 0	Prices and Saving	Yes	20	1	Yes	Physical calculator
Duffy and Li (2019)	No	= 0	Income	Yes	25	2	Yes	PC calculator
Carbone et al. (2019)	Yes	>0	Income	No	15	2	No	1-period
Gechert and Siebert (2022)	Yes	= 0	Income	Yes	20	1	Yes	1-period
Lu (2022)	No	>0	Income	No	9	3	No	1-period
Miller and Rholes (2023)	Yes	>0	Income	No	20	2	No	1-period
Duffy and Orland (2023)	Yes	= 0	Income	Yes/No	3	15	No	1-period
Gabaix and Graeber (2024)	No	>0	Income	No	3	5	Yes	PC calculator
Duffy and Li (2024)	No	>0	Income	Yes	Indefinite	2	No	1-period / Tax-planning
This paper								
ConstantYP NoCalc	No	= 0	None	Yes	10	3	Yes	1-period
PosIR NoCalc	No	>0	None	Yes	10	3	Yes	1-period
FluctY NoCalc	No	= 0	Income	Yes	10	3	Yes	1-period
FluctP NoCalc	No	= 0	Price	Yes	10	3	Yes	1-period
ConstantYP Calc	No	= 0	None	Yes	10	3	Yes	$10-t$ periods
PosIR Calc	No	>0	None	Yes	10	3	Yes	$10-t$ periods
FluctY Calc	No	= 0	Income	Yes	10	3	Yes	$10-t$ periods
FluctP Calc	No	= 0	Price	Yes	10	3	Yes	$10-t$ periods

[1] Subjects could obtain information from the computer about the likely values of future incomes, the proportion of future token incomes greater than some specified value, and the proportion between two specified values.
[2] While participants completed one life-cycle task, they advised subsequent generations.
[3] Subjects were allowed the free use of tools such as spreadsheets, financial calculators, or the opportunity to seek advice from friends.

errors arising specifically from complexity due to compounding interest and price volatility—factors distinct from the income variability frequently studied in prior work. For instance, Carbone and Hey (2004) demonstrate that higher income volatility induces participants to adopt longer planning horizons, whereas lower volatility prompts short-term, hand-to-mouth decisions. Similarly, Luhan et al. (2014) and Yamamori et al. (2018) find that increased price variability leads to greater optimization errors, though in their settings, price changes were entangled with other macroeconomic variables. By explicitly isolating the effects of price changes, our study offers a clearer picture of how these predictable yet cognitively demanding elements independently impair decision-making. Additionally, Ballinger et al. (2011), in a 20-period savings experiment, link optimization performance to cognitive ability, noting that participants typically plan only about three periods ahead. The literature attributes such challenges in predictable environments to cognitive biases or limitations—such as overconfidence (Levy and Tasoff, 2016), rational inattention (Duffy and Li, 2019), and cognitive scarcity (Gabaix and Graeber, 2024).

Our paper provides the first concrete evidence regarding the extent to which individuals engage in long-horizon planning. We find that participants plan more extensively than previously estimated.[2] Non-choice data from our budgeting calculator treatments show that over 50% of participants initially formulate full-horizon, 10-period spending plans. However, despite extensive planning, their resulting decisions remain suboptimal and would have —without being able to observe their planning decisions —mistakenly classified them as short-horizon optimizers.

The main contribution of our paper lies in clearly demonstrating how environmental complexity influences individuals' dynamic optimization abilities. We also provide the first empirical documentation of the uptake and benefits of budgeting calculators in consumption-saving decisions. Crucially, we identify that significant barriers to optimal decision-making are driven not only by environmental complexity—such as compounding returns, the curvature of the objective function, and extended planning horizons—but also by motivational constraints. Although computational demands significantly amplify complexity, merely providing decision aids, such as budgeting calculators, does not guarantee improved outcomes. Rather, the effectiveness of these tools critically depends on how participants utilize them, highlighting the importance of both effective tool design and active user engagement in facilitating optimal financial decisions within complex

[2]Evidence from Carbone (2006) indicates that a substantial number of subjects plan over only a few periods—typically between 1 and 5—despite this being suboptimal in lifecycle consumption-saving decisions.

environments.

2 Theoretical Model and Experimental Design

The theoretical framework underpinning this study is a standard intertemporal model of life-cycle consumption and savings (See Modigliani and Brumberg, 1954). Our model is based on a finite-horizon and deterministic framework. Each consumer's goal is to

$$\max_{c_t} \sum_{t=1}^{T} k \left(\frac{1}{1-\sigma} \right) c_t^{1-\sigma} \tag{1}$$

subject to:

$$p_t c_t + s_t = y_t + (1+r) s_{t-1} \tag{2}$$

$$s_t \geq 0 : \forall t \quad \text{and} \quad s_0 = 0. \tag{3}$$

We assume a concave utility function, specifically a constant relative risk aversion (CRRA) with a parameter σ and a constant k. The variables y_t, s_t, and r represent the consumer's exogenous income, savings, and known and constant interest rate, respectively. The constraint $s_t \geq 0$ implies that borrowing is not allowed.

In this finite horizon model, the consumer faces no uncertainty regarding price and income processes. They make decisions about consumption, denoted as c_t, over T periods, considering their income, y_t, and implicitly decides how much to save at the interest rate r. The consumer pays a price p_t for each unit of consumption.

The optimal consumption path is given by $T-1$ Euler equations:

$$c_{t+1}^* = \left(\frac{p_t}{p_{t+1}} (1+r) \right)^{\frac{1}{\sigma}} c_t^* \tag{4}$$

These Euler equations relate consumption in period t to consumption in period $t+1$ and must be satisfied within the optimal consumption path. We use the lifetime budget constraint (Equation 5) to derive a system of T equations and T unknowns and then find the optimal consumption level c_t^* for $t \in [1, T]$.

$$\sum_{t=1}^{T} \frac{p_t c_t}{(1+r)^{t-1}} \leq \sum_{t=1}^{T} \frac{y_t}{(1+r)^{t-1}} \tag{5}$$

Solving the system of equations also yields the optimal level of consumption for period 1,

$$c_1 = \frac{\sum_{t=1}^{T} \frac{1}{(1+r)^{t-1}} y_t}{\left(p_1 + p_1^{\frac{1}{\sigma}} \left(\sum_{t=2}^{T} \left(\frac{p_t}{(1+r)^{t-1}}\right)^{\frac{\sigma-1}{\sigma}}\right)\right)} \tag{6}$$

2.1 Treatments

Our objective in designing the baseline experimental environment was to create a scenario simple enough for participants to solve without advanced budgeting tools.[3] To achieve this, we parameterized our baseline environment, named **ConstantYP**, with income and prices held constant throughout the entire consumption horizon. We chose a planning horizon of $T = 10$ periods—sufficiently long for meaningful forward planning and allowing us to clearly observe learning across stationary repetitions of the decision-making task. Incorporating repetitions is crucial in life-cycle experiments, as participants may not fully grasp how to manage the environment only partway through the sequence, leaving insufficient time to adjust earlier consumption choices. Each participant experienced three stationary repetitions of ten periods, with slight recalibrations to the environment across repetitions to create subtly varied optimization tasks.

We further designed three treatments using a between-subject approach, each introducing a distinct dimension of complexity to identify where and why decision-making errors occur. The first treatment, **FluctY**, varies participants' income predictably between high (y_H) and low (y_L) levels over the planning horizon. We set the initial-period income high enough so that the budget constraint would not bind under an unconditional optimal plan. Nevertheless, when considering the optimal consumption level conditional on current savings, the budget constraint may still bind. For example, if there are early deviations—especially if individuals overspend—the constraint might still bind taking as a reference the conditionally optimal consumption path. This treatment is particularly insightful, as it evaluates the participants' capability to smooth their consumption over time in the face of fluctuating income. The second treatment, **PosIR**, introduces

[3] We acknowledge that there are other ways to simplify the problem, such as the approach taken by Gechert and Siebert (2022), who impose a linear utility function instead of a concave one. Even though in their experiment income is randomly determined every period, given that the discount factor is less than one, the optimal prediction is no saving. However, just as Gechert and Siebert find that only half of their participants follow the optimal strategy, we also observe that many subjects in ConstantYP choose to save. This suggests that we cannot rule out that oversaving stems from cognitive limitations or unmodeled preferences, such as a preference for holding wealth, as they propose.

complexity relative to ConstantYP by providing positive interest ($r = 0.1$) on savings in each period. This modification allows us to investigate the cognitive challenges posed specifically by compounding returns. Lastly, the **FluctP** treatment introduces price fluctuations between high (p_H) and low (p_L) levels throughout the consumption horizon. Notably, this mirrors particular real-world scenarios, such as seasonal promotions on electronics at retailers like Costco, where dual pricing structures influence consumer decisions.[4] This variation enables us to determine if participants effectively account for the shape of their induced utility function—specifically, their valuation of additional consumption units—as prices change. Together, these treatments systematically add unique dimensions of complexity to our baseline optimization setting, allowing us to precisely dissect and understand the nuanced cognitive processes underlying dynamic decision-making.

To incentivize participants' optimization decisions, we induce a standard constant relative risk aversion (CRRA) per-period utility function:

$$u(c_t) = k\left(\frac{1}{1-\sigma}\right)c_t^{1-\sigma}.$$

Here, we set $\sigma = 0.5$ across all treatments. The parameter k is a scaling constant that does not affect the optimal consumption path. In the FluctP treatment, we assign the constant k a value of 2.65, and for the other treatments, we assign it a value of 3.35. This specific adjustment is made to ensure that the optimal life-cycle utility is equalized across all treatments, where the interest rate r is set to zero. The chosen value for σ is intended to create a sufficiently large intertemporal trade-off. Table 2 provides details on the income, price, and interest rate processes for each treatment. It is important to highlight the variations across repetitions: in the second repetition, income is doubled relative to the first. In the third repetition, both income and prices are doubled compared to the first repetition. Although the nominal variables change from the first to the last repetition, the real variables stay consistent, ensuring identical optimal solutions across these repetitions.

Figure 1 illustrates the optimal consumption paths for each treatment and repetition. Notably, despite different income processes, the optimal path is identical for the ConstantYP and FluctY treatments: consumers maximize utility by consuming 10 units

[4]We faced a tradeoff between creating a more realistic price path and ensuring that participants had the opportunity to identify the optimal path. We ultimately prioritized the latter, as this allowed subjects to apply a straightforward two-period optimization strategy to find the optimal consumption path.

Table 2: Treatment parameterization

Repetition	Period	Constant YP	PosIR	FluctY	FluctP
1	Odd	$y = 1,000$ $p = 100$ $r = 0$	$y = 1,000$ $p = 100$ $r = 0.1$	$y = 1,500$ $p = 100$ $r = 0$	$y = 1,200$ $p = 150$ $r = 0$
	Even	$y = 1,000$ $p = 100$ $r = 0$	$y = 1,000$ $p = 100$ $r = 0.1$	$y = 500$ $p = 100$ $r = 0$	$y = 1,200$ $p = 50$ $r = 0$
2	All	Compared to Repetition 1, y was doubled, and the other variables did not change.			
3	All	Compared to Repetition 1, y and p were doubled, and the other variables did not change.			

per period in Repetitions 1 and 3, and 20 units per period in Repetition 2. In the PosIR treatment, optimal consumption progressively increases due to positive interest and the absence of discounting. In the FluctP treatment, the optimal path follows a bi-periodic pattern—higher consumption at low prices and lower at high prices. Additionally, Figure 1 also shows the static consumption path $\frac{y_t}{p_t}$, reflecting a common heuristic of consuming one's entire income each period without considering intertemporal dynamics.[5]

In ConstantYP, the unconditional optimal solution matches the Hand-to-Mouth (H2M) strategy from the first period; however, if participants save initially, their conditional optimum diverges. In all other treatments, significant gaps exist between optimal and H2M paths.[6]

We further introduce a between-subject variation by manipulating participants' access to a budgeting calculator across treatments. In the **Calc** treatments, participants could optionally use a calculator to input hypothetical consumption plans across periods, based on given income, prices, and interest rates. Figure 2 (a) illustrates this interface.[7] In this example, participants could input a consumption plan for periods 6-10 and calculate the hypothetical per-period and accumulated points. Calculator use was voluntary and unrestricted, and upon decision submission, inputs reset while choice history remained accessible. The software recorded all plans after a participant clicked

[5]The ConstantYP treatment is an exception, as optimal consumption coincides exactly with this no-saving (Hand-to-Mouth) approach.

[6]See Appendix H for a detailed analysis.

[7]This is a modified screenshot created for illustrative purposes.

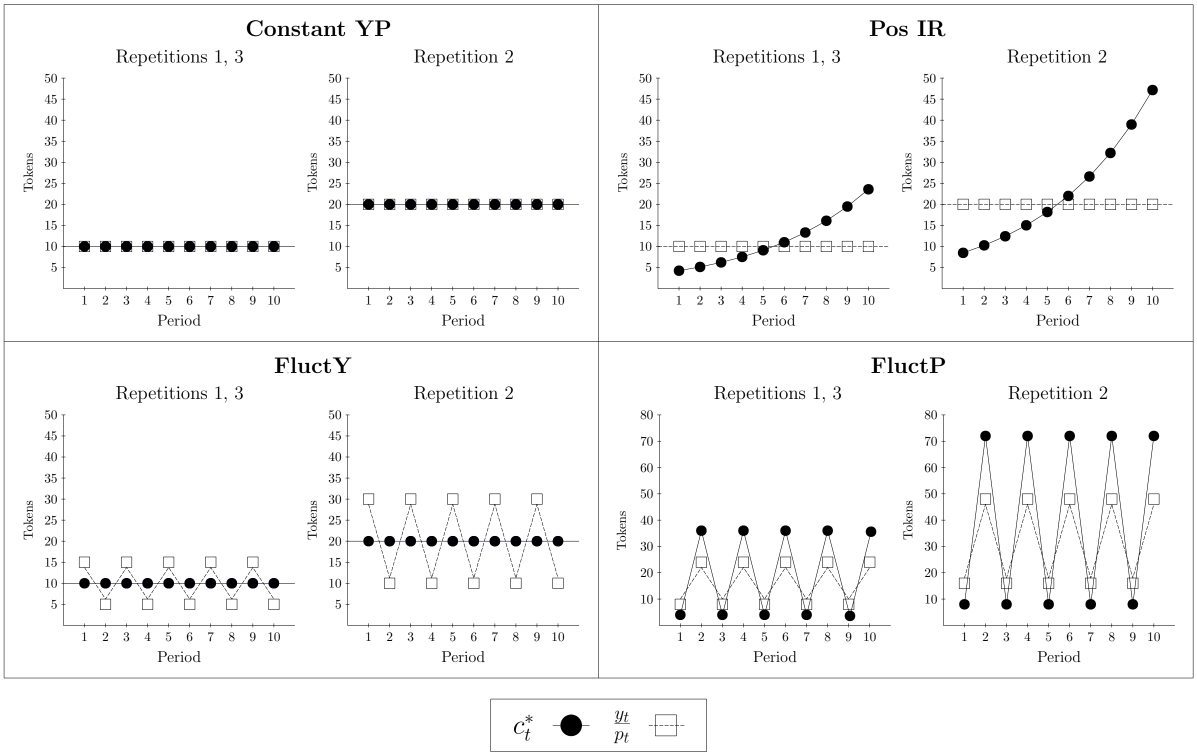

Figure 1: Theoretical predictions

the calculate button, providing valuable non-choice data that we utilize to evaluate participants' planning horizon and effort.[8]

Participants in the **NoCalc** treatments lacked calculator access. Their interface (Figure 2 (b)) allowed viewing past choices and future variables, but without structured financial planning support.[9] Participants in both groups had access to the standard Windows calculator, though these interactions were not recorded.[10]

2.2 Experimental Procedures

We recruited 326 undergraduate and graduate students from various disciplines, randomly assigning each participant to one of eight between-subject treatments. Sessions took place from July 2017 to March 2019 at two experimental laboratories (CRABE

[8]For a related application of non-choice data, see Fenig et al. (2022), who use it to study group dynamics in non-linear games.

[9]Our NoCalc treatment provides richer information than typical consumption-saving experiments, which often display limited data.

[10]Given limited recall and attention in household financial decision-making (D'Acunto and Weber (2022); D'Acunto et al. (2024)), our detailed informational setup likely represents an upper bound of participants' realistic optimization capabilities.

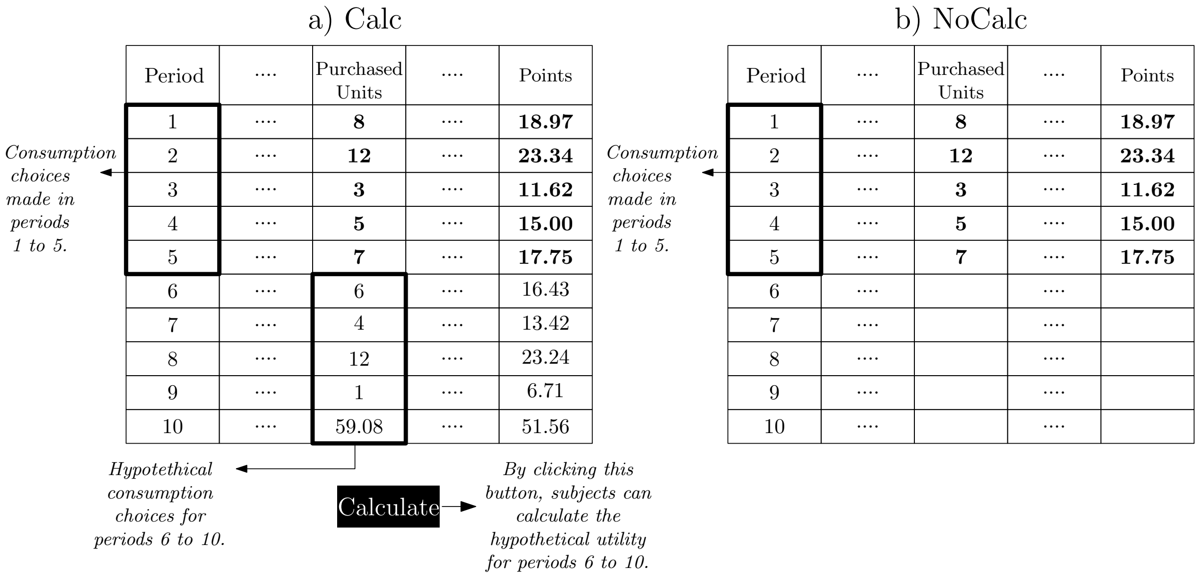

Figure 2: Screenshots for Treatments with a Budget Calculator and Treatments without a Budget Calculator

Laboratory at Simon Fraser University [SFU] and SSRL at University of Saskatchewan [UofS]), with participants nearly evenly split between the two institutions. Table 3 summarizes participant distribution by treatment. Experiments were computerized using z-Tree (Fischbacher, 2007).

Each session began with the experimenter reading aloud standardized instructions, followed by interactive computerized instructions and incentivized control questions to verify participants' understanding of key concepts. For example, to illustrate diminishing marginal utility, participants were required to identify that increasing consumption from 1 to 2 units yields a greater utility gain compared to increasing from 9 to 10 units. Participants earned points based on accuracy: four points per correct answer on the first attempt, three on the second, and two on the third. Participants had to answer all questions correctly to proceed. (Detailed instructions appear in Appendix J.)

Following this stage, participants faced three repetitions of the dynamic optimization tasks described in Table 2. They received tokens each period and chose how much output to purchase (with precision up to two decimal points), without time constraints. To aid decision-making, the main computer interface (Figure 3) provided visual tools displaying output-to-points relationships and, in Calc treatments, access to the budgeting calculator. Participants had all necessary information available simultaneously.[11]

[11] Participants could request pen and paper to perform additional calculations at any time.

Table 3: Number of subjects per treatment

Treatment	Budgeting Calculator	UofS	SFU	Total
ConstantYP Calc	Yes	22	22	44
ConstantYP No Calc	No	20	24	44
PosIR Calc	Yes	24	24	48
PosIR No Calc	No	22	21	43
FluctY Calc	Yes	28	20	48
FluctY No Calc	No	22	24	46
FluctP Calc	Yes	24	21	45
FluctP No Calc	No	24	24	48
Total		186	180	366

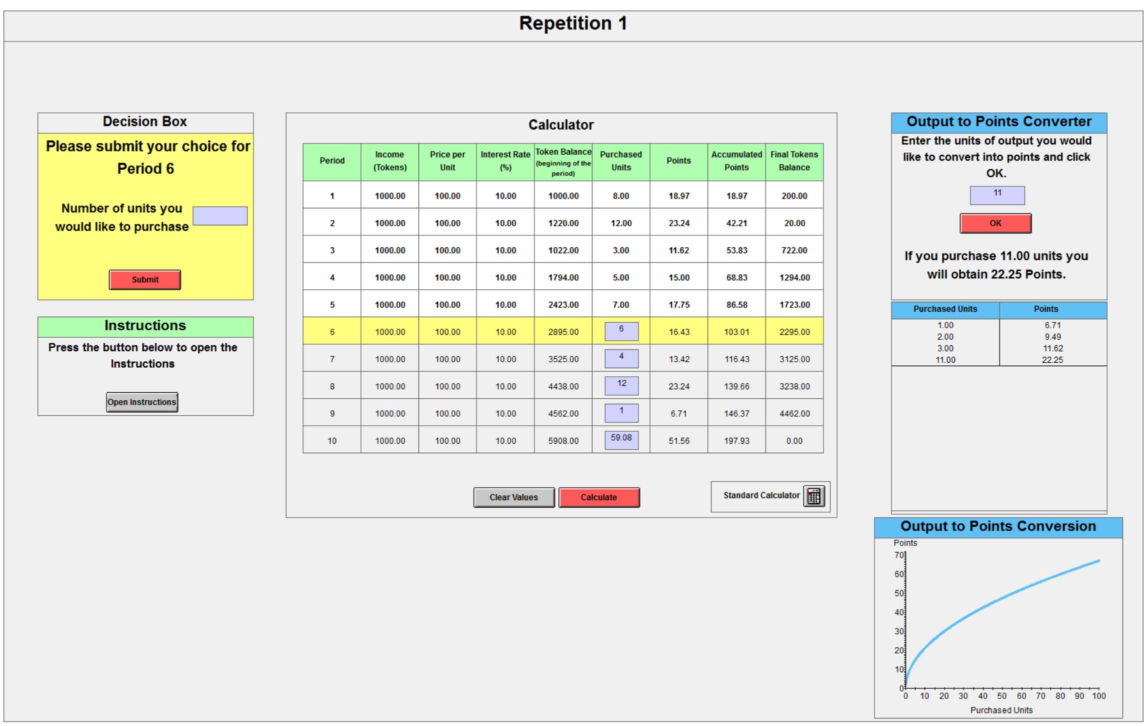

Figure 3: Screenshot of the experimental software for Stage 1

In the subsequent three stages, we measured participants along three dimensions: risk preferences, financial literacy, and backward induction ability. Stage 2 assessed risk preferences using a task adapted from Eckel and Grossman (2002), where participants chose among six 50/50 gambles (subsection K.2). Risk preferences serve as a fundamental control influencing economic decisions. Stage 3 evaluated financial literacy through five multiple-choice questions adapted from Lusardi and Mitchell (2007), with points awarded for correct first-attempt answers (subsection K.3). This measure captures participants' ability to effectively utilize financial planning tools, including consumption smoothing and compounding interest. Stage 4 tested backward induction skills using the "Race to 60" game from Bosch-Rosa et al. (2018), in which participants competed against a computer by selecting numbers from 1 to 10, attempting to reach or exceed 60 first (subsection K.4). This skill is critical as dynamic optimization models typically rely on backward induction. Finally, we collected demographic information on age, gender, education, and employment status.

Participant compensation included earnings from all four stages and the incentivized control questions. For Stage 1, we paid participants based on one randomly selected repetition. Payments were made in Canadian dollars at an exchange rate of 25 points = $1, plus a $7 show-up fee. Participants completed the experiment in approximately 40 minutes and earned an average of $21.39. Figure A.1 on the appendix provides a summary of the different stages of the experiment.

2.3 Hypotheses

Our analysis focuses on two metrics to measure participants' optimization ability. The first metric, the Unconditional Optimal Index, captures the relative difference between actual utility and the utility from the unconditional optimal solution, expressed as a percentage:

$$UncOptIndex_{i,q,r,t} = \gamma^U = 1 - \frac{|U_{i,q,r,t} - U^{unc}_{q,r,t}|}{U^{unc}_{q,r,t}} \tag{7}$$

where $U_{i,q,r,t}$ is participant i's utility from actual consumption in treatment q, repetition r, period t, and $U^{unc}_{q,r,t}$ is the unconditional optimal utility, identical for all participants within the same treatment, repetition, and period. This index equals 1 when the participant's choice matches the unconditional optimal level, computed prior to any participant decisions at the beginning of each repetition, given the known sequence of income, prices, and interest rates. The second metric, the Conditional Optimal Index, similarly quantifies deviations from each participant's conditional optimum, computed dynamically as the repetition progresses, based on their current cash balances and future income, prices and interest rates:

$$CondOptIndex_{i,q,r,t} = \gamma^C = 1 - \frac{|U_{i,q,r,t} - U^{cond}_{i,q,r,t}|}{U^{cond}_{i,q,r,t}} \tag{8}$$

where $U^{cond}_{i,q,r,t}$ is participant i's conditional optimal utility. Note that conditional and unconditional solutions coincide in the first period of each repetition.[12]

Participants in our experiment have complete information about future income, prices, and interest rates. According to rational-agent theory, informed individuals should initially follow the unconditional optimal consumption path and, after any deviations, adjust toward the conditional optimal path. Environmental complexity should not affect this ability, motivating our first hypothesis:

Hypothesis 1: (Un)conditional optimal consumption does not differ across environments or a presence of budgeting calculator: $\gamma^{ConstantYP} = \gamma^{FluctY} = \gamma^{FluctP} = \gamma^{PosIR}$.

However, extensive prior literature summarized in Table 1 documents substantial deviations from optimal paths, especially under greater complexity. To rank complexity across our treatments, we follow the approach of Gabaix and Graeber (2024), linearizing the optimal consumption in period 1 via a Taylor expansion (Equation 9). Complexity is measured by the number of non-zero terms required for optimal consumption decisions.

$$c_1 = \frac{y_1}{p_1} + \frac{1}{Tp_1}\sum_{t=2}^{T}(y_t - y_1) - \frac{y_1(T-1)}{2\sigma p_1}r + \left(\frac{1-\sigma}{\sigma}\right)\frac{y_1}{Tp_1^2}\sum_{t=2}^{T}(p_t - p_1) \tag{9}$$

The ConstantYP environment exhibits the lowest level of complexity. In this case, all terms in Equation 9 vanish except for the first one, since both prices and income remain constant across periods, and $r = 0$. Individuals simply need to divide their current income by the current price to determine optimal consumption. We normalize this scenario to zero complexity. In the FluctY treatment, the third and fourth terms of Equation 9 carry no weight because prices do not change and interest rates are zero. The

[12] Note that one of the advantages of our indices is that they account for the loss in payoffs (utility) when deviating from the unconditional and conditional paths, rather than just measuring deviations in terms of consumption values.

FluctY treatment is cognitively more challenging than ConstantYP as individuals must compute their permanent income over (T) periods and consume a fixed proportion in each period. In PosIR, the second and fourth terms of Equation 9 drop out of the expression. Focusing on the third term, determining optimal consumption requires individuals to consider three factors: the interest rate (r), the number of periods (T) in which interest can compound, and their intertemporal elasticity of substitution (σ). Finally, in FluctP, the second and third terms of Equation 9 vanish and individuals also have three separate factors to consider: they must account for adjustments in prices over time, their intertemporal elasticity of substitution, and their real income. Following Gabaix and Graeber, we evaluate the relative complexity of the treatments by comparing the number of factors or dimensions that the individual must consider when solving their consumption-saving problem.[13] Thus, we propose an alternative hypothesis reflecting this complexity ranking:

Alternative Hypothesis 1: (Un)conditional optimal consumption is ordered based on the complexity of the environment: $\gamma^{ConstantYP} > \gamma^{FluctY} > \gamma^{PosIR} = \gamma^{FluctP}$.

Given that all environments exhibit some inherent complexity, computing the optimal level of consumption becomes a challenging task. It is reasonable to anticipate that choices of individuals with access to a budgeting calculator would be closer to the optimal level of consumption than those without access to it. This motivates our second hypothesis, which posits that the availability of a budgeting tool significantly improves consumption decisions. Access to a budgeting calculator can be particularly helpful for individuals who struggle with computing the optimal level, even in less complex environments.

Hypothesis 2. The budgeting calculator improves (un)conditional optimal consumption: $\gamma^{j,Calc} > \gamma^{j,NoCalc}$ for environment $j \in \{ConstantYP, PosIR, FluctY, FluctP\}$.

By tracking the consumption decisions of participants over multiple repetitions, we can evaluate how experience contributes to improvements in their dynamic optimization skills. Evidence from Ballinger et al. (2003) suggests that participants learn from experience. Our experimental design can capture this learning clearly. Comparing the

[13] In the most basic cases, Gabaix and Graeber recommend using a Laplacian ignorance prior and posit that all micro-parts have the same complexity $c_i = \bar{c}$.

first and third repetitions, where changes are made only in nominal terms, the optimal consumption paths remain unaltered.

Hypothesis 3. Deviations of consumption from the (un)conditional optimal consumption paths decrease in later repetitions.

A fundamental distinction in calculating unconditional versus conditional optimal paths lies in the respective planning approaches. For the unconditional path, it is necessary to accurately determine the optimal consumption values for the entire horizon immediately in period 1. This task becomes increasingly challenging with a longer horizon. On the other hand, the conditional optimal path allows subjects to adjust their plans in response to unfolding events as each period progresses, making it easier to stay on or near the optimal path. Consequently, we hypothesize that as decision periods progress and the planning horizon shrinks, subjects are increasingly likely to make consumption choices that follow the conditional optimal path, driven by both a reduced complexity due to a shorter remaining horizon and a learning effect.

Hypothesis 4. Deviations of consumption from the conditional optimal consumption path decrease as the planning horizon becomes shorter.

3 Descriptive Optimization and Planning Patterns

We begin by examining optimization performance and calculator usage across treatments. Figure 4 shows median consumption paths for Repetitions 1 and 3, with white markers representing No Calculator conditions and black markers representing Calculator conditions. Vertical error bars indicate ±2 standard errors from 1,000 bootstrap samples. The red line represents the unconditional optimal path; regions above (green) indicate overconsumption, while those below (yellow) show underconsumption.[14] Notice that in period 10, the optimal consumption choice is relatively straightforward, as one should spend all the money in their bank account. To ensure that errors in this final period were not due to calculation mistakes, we displayed a message indicating the exact consumption amount needed to spend the entire balance. The vast majority followed

[14] Individual consumption time series are available in Appendix I.

this guidance. Across all subjects and repetitions, 90 percent of the cases ended with no cash remaining in the bank account.

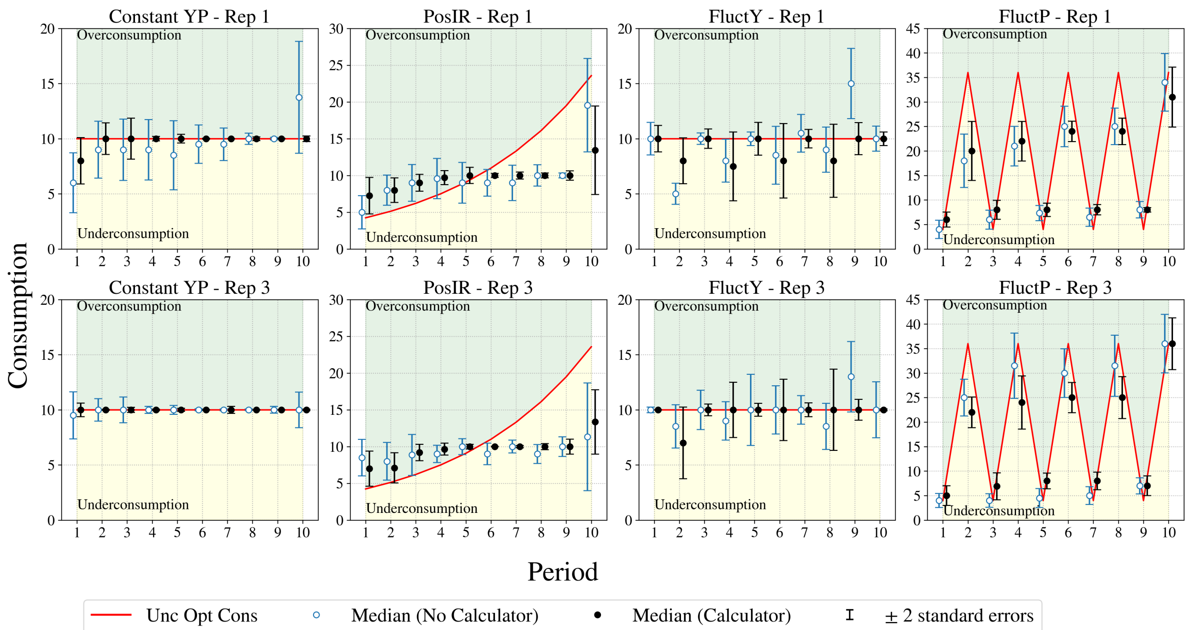

Figure 4: Median consumption per period and treatment (with ±2 SE from 1000 bootstrap samples)

Across treatments, clear differences emerge in optimization abilities. In ConstantYP, even the median inexperienced participant with calculator access closely follows the optimal consumption path. Conversely, in the PosIR treatment, participants underestimate the advantages of early savings, leading to initial overconsumption followed by underconsumption, with minimal improvement from experience.

In FluctY, optimal consumption is constant, requiring saving in odd-numbered periods to offset lower even-period incomes. Inexperienced participants exhibit a tendency to oversave early, leading to excessive consumption in Period 9. Experience and calculator access substantially mitigate these deviations.

In FluctP, optimal consumption requires saving during high-price (odd-numbered) periods and spending fully during low-price (even-numbered) periods. Participants tend to overly smooth their consumption, resulting in persistent overconsumption when prices are high and underconsumption when prices are low. While experience improves performance, the improvement between Repetitions 1 and 3 is more pronounced among participants without calculator access than among those with access.

Finally, regardless of the availability of a budgeting calculator, participants exhibit distinct consumption smoothing behaviors across different treatments. In simpler treatments like ConstantYP and FluctY, we observe a trend towards undersmoothing of consumption among experienced participants. On the other hand, in more complex treatments such as FluctP and PosIR, experienced participants demonstrate a tendency for oversmoothing. While undersmoothing is not necessarily surprising in ConstantYP and FluctY (this is the only direction suboptimal behavior can go in), it was ex-ante unclear how much participants would smooth their consumption in PosIR and FluctP. This pattern suggests that excess consumption smoothing represents a strategic response adopted by experienced individuals when navigating complex economic environments. It resonates with a 'wait-and-see' approach, indicating that in scenarios marked by uncertainty or complexity, the preferred strategy is to maintain the current course of action, rather than implementing significant changes in consumption behavior.

Figure 5 displays the median deviation of actual consumption from the conditional optimal level. Notably, in the early periods (1–5), deviations are often substantial—especially under the high-complexity treatments such as FluctP and PosIR—and there is a gap between the calculator and no-calculator groups. As we move into to later periods (e.g., 6–9), the magnitude of errors in complex treatments remains sizable. Taken together, the treatment-specific patterns of error reduction imply that experience and environmental complexity are key determinants of planning over time.

To complement this analysis, it is important to examine the full distributions of the UncOptIndex in order to more comprehensively assess the effect of the calculator. Figure 6 displays the cumulative distributions of γ^U (Unconditional Optimal Index) by treatment, for Repetitions 1 and 3.

These distributions reveal three preliminary observations. First, optimization errors persist across all treatments, even after extensive experience. Surprisingly, in the simplest environment (ConstantYP with calculator), one-fourth of participants still deviate from optimality by more than 10% in Repetition 3. In complex scenarios (PosIR, FluctP), deviations are more prevalent, and persistent across repetitions, regardless of calculator access. Similar patterns emerge when assessing conditional optimality (see Figure D.1 in Appendix D).

Second, experience notably enhances optimization, particularly in simpler environments. Between Repetitions 1 and 3, the share of participants achieving perfect optimization rises approximately 15 percentage points in ConstantYP and 10 percentage points in FluctY. Improvements in more complex environments (PosIR, FluctP) are comparatively modest.

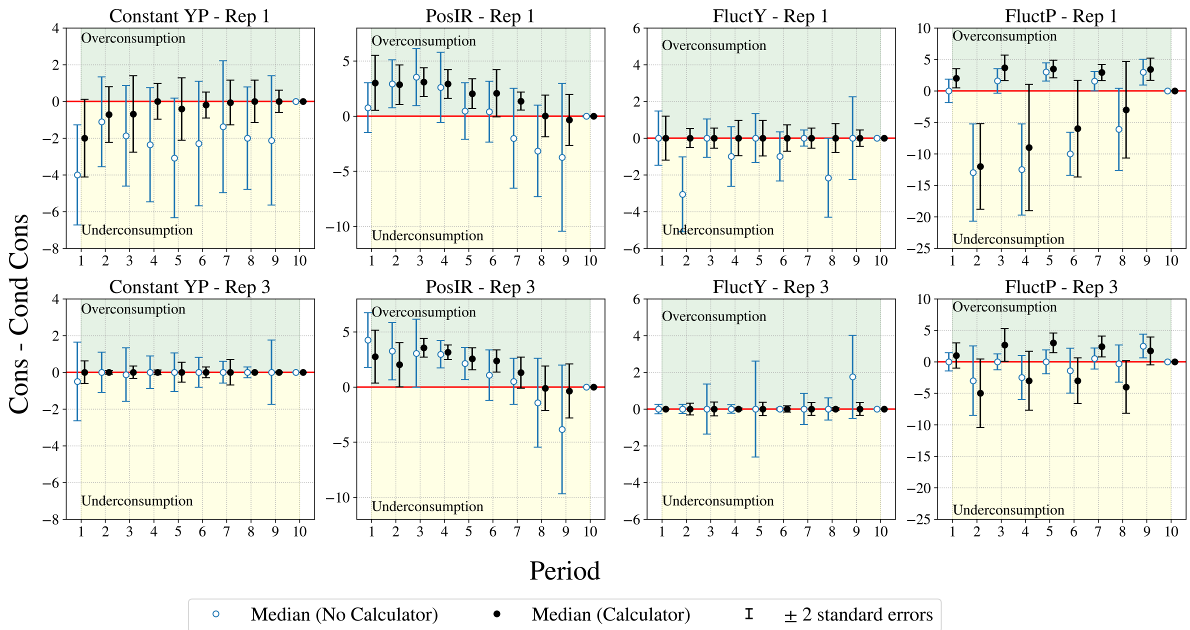

Figure 5: Median deviations from conditional optimal consumption per period and treatment (with ±2 SE from 1000 bootstrap samples)

Third, the budgeting calculator significantly improves outcomes mainly in the ConstantYP treatment, where it increases the proportion achieving perfect optimization by 14 percentage points. Its impact remains limited in more complex environments.

3.1 Planning with the Budgeting Calculator

To better understand the role of the budgeting calculator in shaping participants' decision-making, we turn to a descriptive analysis of how individuals engaged with the tool across treatments and over time. We recorded all participant entries into the calculator, allowing us to observe distinct patterns of interaction. In each period t, participants followed one of five approaches: *Complete*, where they entered values for all periods up to $T = 10$; *Sequential*, where they entered one period at a time, gradually extending their plan; *Partial*, where they entered fewer than $T - t + 1$ periods; *Current Period*, where they entered a value only for period t; and *No Input*, where they did not use the calculator at all.

A fully rational, forward-looking participant might not require the calculator. However, for those aware of the task's complexity, the tool provides support. We observed two main patterns: some participants filled in the entire plan before clicking *Calculate*,

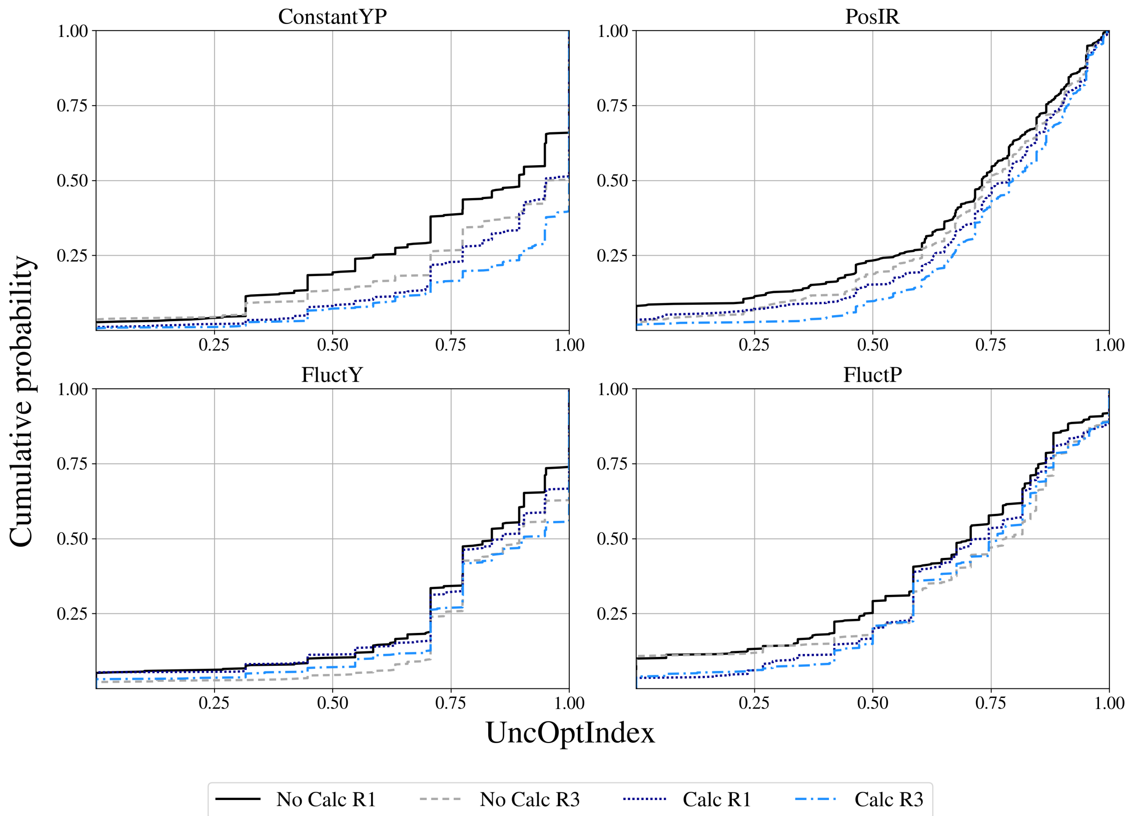

Figure 6: Cumulative Distribution Function of UncOptIndex

while others built their plan sequentially, period by period, observing how each decision affected that period's outcome. While both approaches require effort, sequential users likely sought a better understanding of intertemporal trade-offs. Participants entering fewer than the full horizon are categorized as *myopic planners*, focusing on a limited future.

Calculator use was optional and declined sharply after the first period of each repetition (see Figure 7). This trend may reflect several factors: first, participants did not need to recompute optimal plans each period, particularly in simpler environments; second, the extensive pre-experimental training may have built participant confidence; third, the minor differences across repetitions may have encouraged reliance on earlier experience; and fourth, some participants may have experienced fatigue or disengagement. Nonetheless, approximately half of participants consistently entered complete plans in the first period of each repetition, suggesting a clear understanding of the task's deterministic structure. A small but stable share (5–20%) entered only the current period's consumption, while sequential and partial usage remained less common.

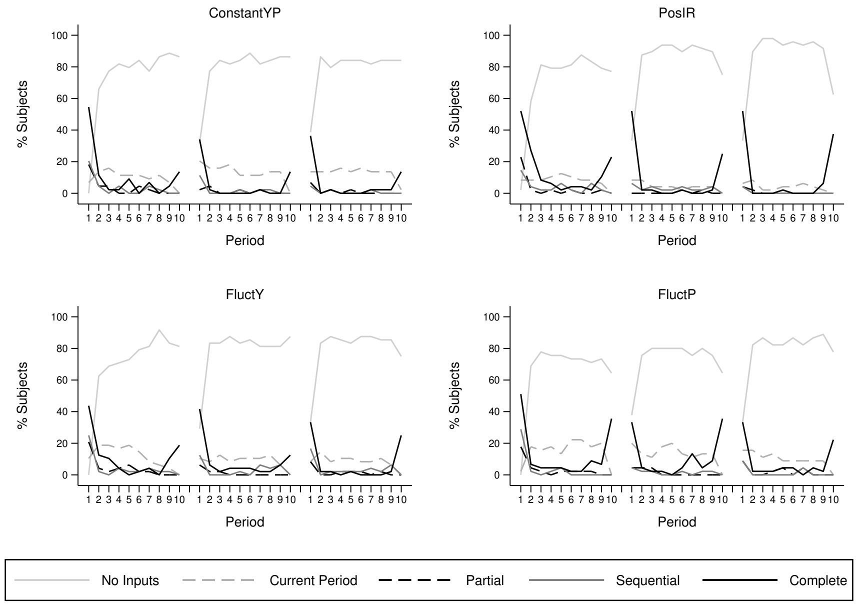

Figure 7: Budgeting calculator types over time

Because calculator use dropped sharply after the first period, we classify participants based on their calculator usage during the first period of each repetition. The distribution of usage types is shown in Figure E.1 in Appendix E.

4 Evaluation of hypotheses

Figure 8 presents the average Unconditional Optimal Index (γ^U) across treatments and repetitions, separated by calculator access (left panel: No Calculator; right panel: Calculator). Each bar corresponds to either Repetition 1 or 3, with the numerical average displayed at the base and vertical lines representing 95% confidence intervals. Statistical comparisons (from t-tests) are indicated by horizontal brackets above or below the bars. Standard errors are clustered at the subject level to account for repeated observations from the same individuals. The top brackets refer to differences across treatments within Repetition 3 (testing complexity effects), the middle brackets compare Repetitions 1 and 3 within each treatment (capturing learning effects), and the bottom brackets span both panels (evaluating calculator effectiveness). Asterisks denote significance levels.

We find evidence against Hypothesis 1, which predicts no differences in deviations from unconditional optimal consumption levels across economic environments. Specifically, when subjects have access to the budgeting calculator, deviations (γ^U) are lower in the ConstantYP environment relative to other treatments, with the difference between ConstantYP and FluctY statistically significant at the 10% level. Without the budgeting calculator, participants in ConstantYP perform better than those in FluctP and PosIR (consistent with Alternative Hypothesis 1) but show similar performance compared to FluctY. Moreover, optimization is significantly better in FluctY relative to PosIR and FluctP (for both Calculator and No Calculator). Notably, PosIR and FluctP treatments exhibit substantial similarities, especially when subjects lack the budgeting calculator. Overall, the observed ordering of treatment performance largely supports Alternative Hypothesis 1, reflecting differences in cognitive complexity across economic environments. Similar results are obtained using the *CondOptIndex*, as presented in Table C.1 of Appendix C.[15]

Result 1: The ability to (un)conditionally optimize differs across environments:
$\gamma^{ConstantYP} > \gamma^{FluctY} > \gamma^{PosIR} = \gamma^{FluctP}$.

Figure 8 also provides mixed support for Hypothesis 2 (bottom caparisons), which posits that access to the budgeting calculator significantly improves optimization for both unconditional and conditional consumption decisions. Across repetitions, access to the calculator reduces mean deviations from the unconditional optimal path by 7.7% in the ConstantYP treatment during the third repetition. Similarly, improvements in the conditional optimal path reach up to 6.6%, with these differences being statistically significant at the 10% level. In the PosIR treatment, access to the calculator results in a 5.9% improvement in both unconditional and conditional optimization in the third repetition, with these differences also significant at the 10% level. However, the evidence suggests that in the FluctY and FluctP treatments, the availability of the calculator does not significantly affect the optimization of either unconditional or conditional consumption decisions.

Result 2: Access to a budgeting tool does not consistently improve dynamic optimization across environments.

Our findings indicate a complex interaction between experience and the use of the

[15]Additionally, we compare the average time spent per period and the average number of plans per period, shown in Table C.1 on Appendix C, respectively

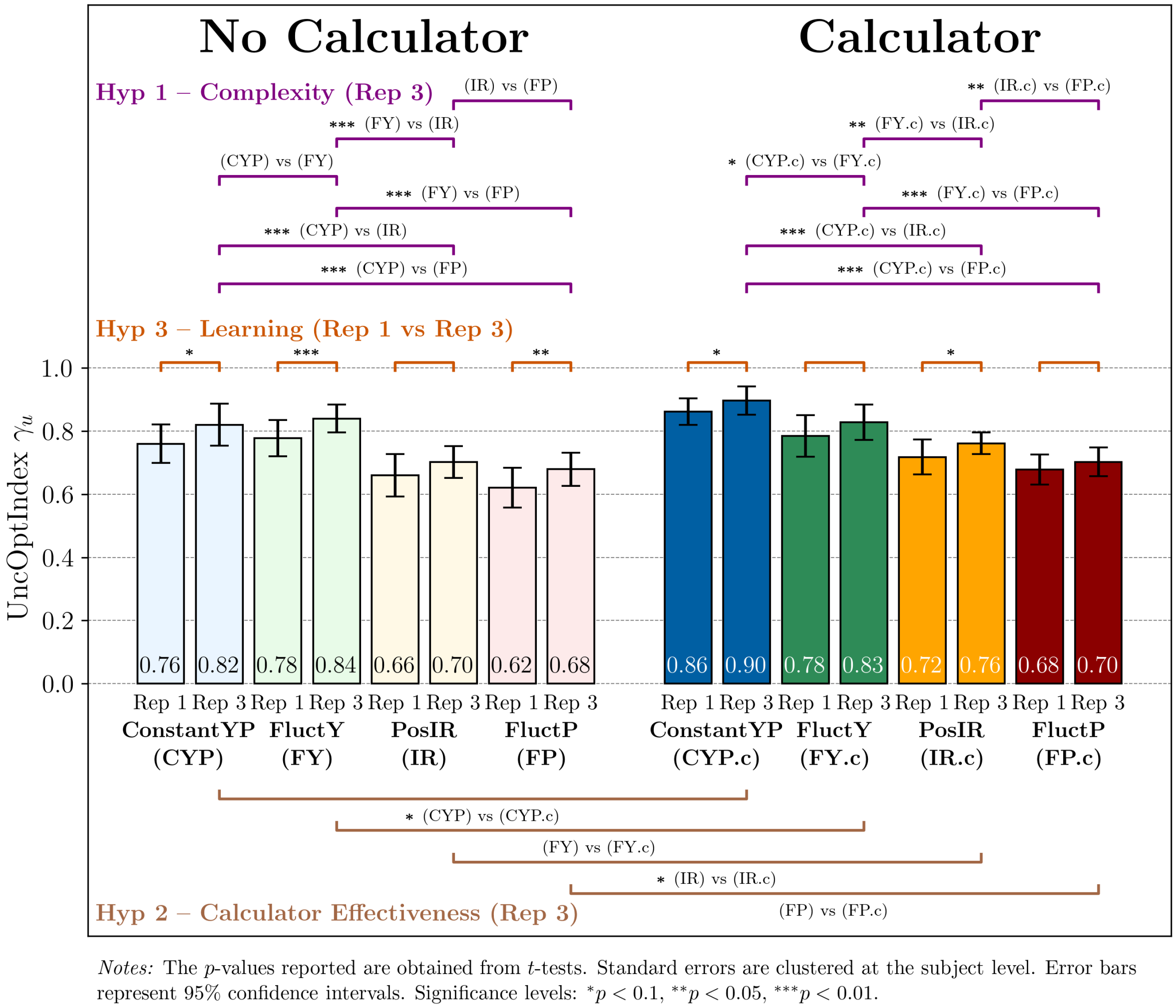

Figure 8: Mean Comparison of γ^U across Treatments

budgeting calculator in guiding subjects towards the unconditional and conditional optimal consumption paths. This observation challenges Hypothesis 3, which posits that deviations from these optimal paths should diminish in later repetitions. Our findings indicate that learning across repetitions appears to be limited as shown in Figure 8 (Comparisons at the middle of the figure); while improvements are observed in some treatments between earlier and later repetitions, there is no clear or consistent pattern. One conjecture with respect to the Calc treatments is that learning primarily occurs within each repetition. As subjects explore various plans during a repetition, their decision-making improves, but this improvement does not seem to carry over to subsequent repetitions. Interestingly, when comparing learning from Repetition 1 to Repetition 3, it appears to occur more frequently when subjects do not have access to the calculator, suggesting that reliance on external tools may hinder the retention of decision-making strategies across repetitions.

Result 3: Deviations in consumption from the unconditional and conditional optimal consumption paths do not consistently decrease with experience, particularly when subjects have access to a budgeting tool.

Next, we formally assess the efficacy of the budgeting calculator in improving consumer optimization for participant i in treatment q, repetition r, and period t. We examine the impacts of calculator access, its usage, learning dynamics, and demographic characteristics using the following comprehensive random-effects panel regression model, estimated separately for each environment:

$$\gamma^{U}_{i,q,r,t} = a + b_0\, Calculator_{i,q} + c_1 V_{i,q,r,t} + c_2 X_i + c_3 D_r + c_4 Period + \mu_i + \varepsilon_{i,q,r,t}. \quad (10)$$

Here, $Calculator$ is a binary variable equal to 1 in treatments where the budgeting calculator is available and 0 otherwise.

We include time-varying controls, denoted by $V_{i,q,r,t}$, which capture factors such as the number of minutes spent in each period. In addition, we include time-invariant demographic characteristics, X_i, to control for individual heterogeneity.[16]

To account for learning effects across repetitions, we include a vector of repetition fixed effects, D_r, representing dummy variables for Repetition 2 and 3. Additionally, to capture potential variation in optimization over time, we include a discrete variable for period number, $Period$. The subject-specific random effect is denoted by μ_i.

We estimate two additional model specifications. In the first, we go beyond calculator access and examine whether participants successfully used the tool. Specifically, we define a binary variable, $Calc\,\gamma^U$, which equals 1 if the participant's UncOptIndex reached at least 0.90 at any point up to period t, indicating successful optimization. In this specification, we replace the term $b_0\, Calculator$ from Equation 10 with $b_1\, Calc\,\gamma^U$, thus capturing the effect of successful use of the calculator rather than mere access to it.

[16] These include variables such as math background score (1–9), financial literacy score (0–4), backward induction ability (Race-to-60 wins, 0–8), gender, age, institution, education level, prior experimental experience, risk tolerance, years of education, and performance on control questions. The last variable captures accuracy and consistency on incentivized comprehension questions.

In the second specification, we focus more directly on calculator usage. Instead of a binary indicator for access, we introduce an interaction term $b_2\, Calculator \times CalcType^{t=1,j}_{i,q,r}$, where $CalcType^{t=1,j}_{i,q,r}$ is a dummy variable that equals 1 if participant i, in treatment q and repetition r, belongs to calculator usage type j as determined by behavior in period $t = 1$, and 0 otherwise. The variable $j \in \{1, 2, 3, 4\}$ indexes the four usage types described in Subsection 3.1, with the NoCalc group serving as the reference category.[17]

The estimated coefficient on the Calculator dummy variable, $\hat{b}_0$, presented in Columns (1), (4), (7), and (10) of Table 4, indicates how the presence of the calculator affects optimization. To further evaluate Hypothesis 2, we test whether $\hat{b}_0 > 0$ in each environment. We find that $\hat{b}_0$ is statistically significant only in the ConstantYP treatment, where having access to the calculator improves optimization by approximately 10 percentage points. In the other three environments, the estimated effects are smaller in magnitude and not statistically distinguishable from zero.

Columns (2), (5), (8), and (11) of Table 4 include the dummy $Calc\, \gamma^U$ to account for effective calculator use. The results show that effective usage improves performance by 6–12 percentage points for UncOptIndex, supporting a refined Hypothesis 2: effective use significantly reduces deviations from optimal consumption. Simply entering data is not enough—efficient calculations matter.

Now, discussing calculator usage in the simplest environment (Column 3), ConstantYP, entering values for only the first period improves unconditional optimization by approximately 8 percentage points (p.p.) compared to participants who do not activate the calculator. Sequential filling—entering values period by period—also helps, improving optimization by 5 p.p. Partial entry offers a stronger effect, increasing optimization by 12 p.p. Finally, complete usage is effective, increasing the optimal index by 9%. Notably, this does not provide an additional advantage to participants who found the optimal consumption using the calculator.

In the PosIR environment (Column 6), where savings accumulate with compounding interest, performance differences emerge across Calculator Types. Inputting only the current period's consumption does not enhance optimization. However, Partial Calculator users experience gains of 5 percentage points in unconditional optimization. Sequential completion yields no benefits for conditional optimization and may even negatively affect unconditional optimization. In contrast, complete usage improves unconditional

[17] Appendix D reports analogous regressions using conditional optimization as the dependent variable, $\gamma^C_{i,q,r,t}$, yielding similar results.

optimization by 9 percentage points for those with calculator access.

The efficacy of the calculator is less pronounced in the FluctY environment (Column 9). We do not observe consistent improvements in optimization for the Partial, Sequential, and Complete Calculator Types. In comparison to the NoCalc type, participants who only fill in the current period are 6 percentage points further from the optimal unconditional solution.

Lastly, in the FluctP environment (Column 12), the calculator benefits are confined to participants who complete it fully. The Complete Calculator Types are 8 percentage points closer to the optimal unconditional compared to those who did not use the calculator.

4.1 Experience and length of planning horizon

Our data provides strong support for Hypothesis 4, suggesting that conditional optimization improves as participants plan over shorter time horizons. As detailed in Table 5, we observe significant increases in $\gamma^c_{i,q,r,t}$ over time. In the absence of a calculator, participants in the ConstantYP and FluctY treatments exhibit improvements of 1.2 and 1.5 percentage points per period, respectively. This increase is even more pronounced in the PosIR and FluctP treatments, at 2.1 p.p. and 1.6 p.p. per period, respectively. These improvements in conditional optimization range from 11 p.p. to 19 p.p. when comparing the first and ninth periods.

Interestingly, the effects are less pronounced for subjects who have access to a calculator. This suggests that the calculator does not significantly aid subjects in correcting mistakes and approaching conditional optimization when the planning horizon is shorter and cognitive load is reduced. An exception to this trend is observed in the PosIR treatment, where within-repetition improvement is notable in the Calc treatment. In this case, there is an improvement of 24 p.p. from period 1 to period 9.

Another observation is that, in most treatments, the OptCondIndex improves in Repetition 3 compared to Repetition 1. However, in most cases, no such improvement is observed in Repetition 2. This is likely because Repetition 2 presents a slightly greater cognitive challenge than Repetition 3. While Repetition 3 closely resembles Repetition 1 in terms of the optimal consumption path, Repetition 2 introduces a slightly higher cognitive load, as income is the only variable that changes relative to Repetition 1.

Additionally, the interaction terms between Repetition 2 and Repetition 3 with Period are mostly insignificant, suggesting that per-period learning does not differ mean-

Table 4: Dependent variable: OptUncIndex

	Constant YP			**PosIR**			**FluctY**			**FluctP**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Calculator	0.101^{***}			0.050			0.002			0.046		
	(0.04)			(0.03)			(0.04)			(0.03)		
Calc γ^u		0.082^{***}			0.124^{***}			0.057^{***}			0.104^{***}	
		(0.02)			(0.02)			(0.02)			(0.02)	
Calculator Usage												
Current Period			0.080^{***}			-0.019			-0.056^{**}			0.007
			(0.03)			(0.03)			(0.03)			(0.03)
Partial			0.115^{***}			0.048^{*}			0.038			0.011
			(0.03)			(0.03)			(0.03)			(0.03)
Sequential			0.047^{*}			-0.081^{***}			0.011			0.003
			(0.03)			(0.03)			(0.02)			(0.03)
Complete			0.087^{***}			0.091^{***}			-0.033^{*}			0.078^{***}
			(0.02)			(0.02)			(0.02)			(0.02)
Constant	0.566^{*}	0.640^{**}	0.544^{*}	-0.384	-0.169	-0.274	0.298	0.294	0.334	0.822	0.860^{*}	0.852^{*}
	(0.31)	(0.30)	(0.30)	(0.32)	(0.31)	(0.33)	(0.37)	(0.35)	(0.36)	(0.50)	(0.49)	(0.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2640	2640	2640	2730	2730	2730	2820	2820	2820	2790	2790	2790
Overall R^2	0.11	0.12	0.12	0.09	0.12	0.08	0.05	0.08	0.05	0.07	0.09	0.08

Notes: This table displays the outcomes of a random effects panel regression analysis. The regression models incorporate demographic control variables, including gender, age, prior experimental experience, academic degree, affiliated institution, current year of study, and risk tolerance levels. Further controls include Period, Repetition, time spent, financial literacy, ability to backward induct, performance in control questions, and math level. Standard errors are presented in parentheses. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: Dependent variable: OptCondIndex

	Constant YP		PosIR		FluctY		FluctP	
	No Calc	Calc	No Calc	Calc	No Calc	Calc	No Calc	Calc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.714***	0.794***	0.565***	0.587***	0.746***	0.794***	0.605***	0.658***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Repetition 2	0.007	0.034*	0.024	-0.021	0.080***	0.011	-0.021	0.003
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)
Repetition 3	0.067**	0.083***	0.054*	0.009	0.098***	0.064***	0.009	0.009
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)
Period	0.012***	0.012***	0.021***	0.027***	0.015***	0.008***	0.016***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Repetition 2 x Period	-0.001	-0.004	-0.005	-0.000	-0.009**	-0.000	0.006	-0.001
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Repetition 3 x Period	-0.002	-0.007**	-0.005	0.004	-0.006*	-0.005	0.005	0.002
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	1320	1320	1290	1440	1380	1440	1440	1350
Overall R^2	0.03	0.02	0.04	0.12	0.03	0.01	0.04	0.03

Notes: This table presents the results of a random effects panel regression. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

ingfully across repetitions.

Result 4: As periods unfold and the planning horizon shrinks, deviations from the conditional optimal consumption path decrease, reflecting both the effects of learning over time and the simplification of the decision-making process.

In Appendix F, we describe the interaction between optimization abilities and demographic variables, and in subsection F.1, we examine which individual characteristics are associated with leaving money on the table in this experiment.

5 A Model of Short-Span Planning

One key factor contributing to suboptimal consumption paths is individuals' limited planning abilities. Individuals either refrain from planning altogether or formulate plans that extend only over a limited time frame. This often results in suboptimal decisions across the entire consumption sequence. Our study is among the first to offer direct evidence of individuals' planning abilities—or the lack thereof—through direct observation of their plans. This approach departs significantly from indirect methods, such as decision trees (see Hey 2002), which infer planning from decision outcomes rather than directly observing the planning process. In order to establish a benchmark for individuals who do not utilize the full planning horizon, we refine our existing optimization model. In this revised model, individuals aim to maximize

$$\max_{c_t} \sum_{t=1}^{H} k \left(\frac{1}{1-\sigma} \right) c_t^{1-\sigma} \tag{11}$$

subject to:

$$p_t c_t + s_t = y_t + (1+r) s_{t-1}, \tag{12}$$

where H is the horizon, ranging from 1 to 10. In this context, if $H = 10$, then the individual has complete foresight (which brings us back to the standard model), and if $H = 1$, the model predicts behavior that aligns with the Hand-to-Mouth heuristic, where individuals consume their income immediately without saving for the future. The implications of different planning horizons are presented in Table G.1 in the Appendix, which outlines the predicted consumption level in Period 1 by treatment and planning horizon.

Our focus here is on PosIR treatments because, in the rest of the treatments, the planning horizon does not significantly affect the optimal level of consumption. In ConstantYP, the optimal consumption level is unaffected by the planning horizon, while in FluctY and FluctP, the primary difference arises between individuals who plan exclusively for the current period and those who consider future periods. Additionally, if H is an even number, the optimal consumption in Period 1 aligns with the solution for a full-span planner.

We leverage our model's predictive power to ascertain a specific planning horizon for each subject based on their observed consumption decisions in the initial period of each repetition. This builds upon the assumption that an individual's consumption choice is influenced by their planning horizon and includes a random error component. The error component, ε, follows a normal distribution with mean zero and standard deviation σ. Then, by performing a maximum likelihood estimation, we can calculate the distribution of horizons in the sample and the standard deviation.[18]

The estimated parameters are shown in Table G.2 in the Appendix. We note that

[18] The details can be found in Appendix G.

close to 30% of the observations are not explained by short-span planning model. Among the 70% of observations that can be rationalized by the model, approximately 20% of them would correspond to 1-period planners, around 19% would correspond to individuals that plan for 2 or 3 periods in advance, over 10% would consider 8 periods, and close to 10% would use the full horizon.

Additionally, we can cross-validate these model predictions with the actual planning behaviors observed among the subjects in our experiment. This is possible because we have collected detailed planning data for each subject in every period, derived from the usage of the budgeting calculator. To directly compare this data, we examine each subject's planning horizon in the first period of each repetition by observing how many entries subjects filled out in the calculator during each of the trials. Note that they can fill out as few as one entry and as many as 10 periods (the full horizon).[19] Consequently, in Figure 9, we compare the distribution of planning horizons utilized by subjects against the model's predictions detailed in Table G.2.[20]

Figure 9 demonstrates that the model accurately forecasts the frequency with which a one-period planning horizon is employed. However, it underestimates the use of the full planning horizon; the model predicts its occurrence at around 10%, whereas, in reality, subjects choose this option nearly half of the time. Furthermore, the model's prediction of a 12% utilization rate for an 8-period planning horizon starkly contrasts with the actual trials, where this horizon is selected in less than 1% of instances. This notable discrepancy prompts a conjectural explanation: subjects who are aware of the benefits of compounding interest rates, but uncertain about the optimal savings amount, might resort to a straightforward heuristic. Such a heuristic might involve saving half of their income, yielding a consumption level of 5 units, closely aligning with the model's prediction of 5.13 units for an 8-period planner, as detailed in Table G.1.

Taken together, our findings suggest that while the short-span planning model captures certain patterns—particularly among one-period planners—it fails to account for

[19] In subsection G.2, we outline the procedure for filtering the planning data.

[20] Note that the first bar represents subjects who did not utilize the calculator for observed planning behavior and in terms of the Partial-Horizon model were not categorized. As a robustness check, we implemented an alternative method by taking consumption values from period 1 in each repetition and comparing them with ten possible consumption values based on the predictions of our model, each corresponding to a different planning horizon. For each horizon, we calculated the squared deviations between the observed consumption figures and the model's predicted values. The horizon with the smallest squared deviation was identified as the closest to the subject's observed consumption behavior. If these deviations fell below a certain threshold, the consumption pattern was classified as uncategorized. This approach's outcomes did not significantly differ from our main analysis findings.

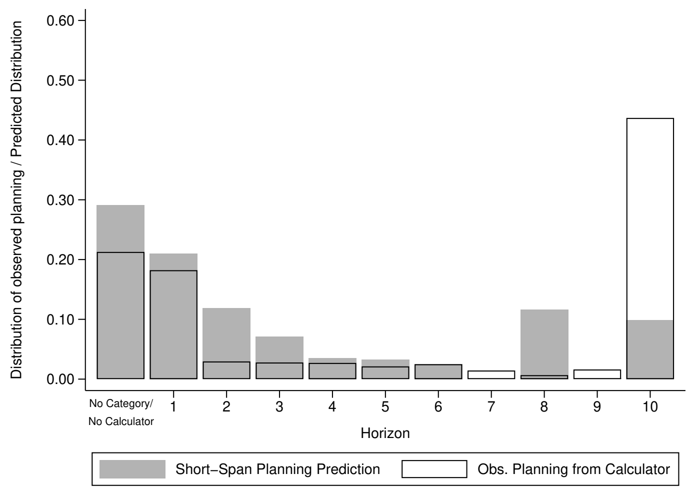

Figure 9: Comparison between the predicted and the observed horizon

the substantial proportion of participants who consistently use the full horizon. Importantly, many participants are making full-horizon plans but not implementing them effectively enough to appear as such in the data. As a result, they are misclassified by the model as having shorter planning horizons, highlighting a key limitation in using consumption choices alone to infer underlying planning behavior.

6 Discussion

Our study represents one of the first attempts to understand the role of environmental complexity in dynamic optimization, focusing on consumption smoothing. We uncover that different environments pose varying levels of challenges, some more demanding than others. Particularly, while the complexities associated with compounding interest rates on savings or fluctuating income are well-acknowledged, the challenges related to fluctuating prices have been less examined. Our research not only fills this gap but also presents new empirical evidence demonstrating that many individuals struggle with planning over extended periods, a fundamental yet often overlooked assumption of economic theory. Our findings resonate with existing literature on complexity, such as the works of Enke et al. (2025), Enke and Graeber (2023), and Gabaix and Graeber (2024), which conceptualize the mind as a cognitive economy faced with numerous decisions.

The theoretical perspective that helps interpret our findings is the concept of satisficing, originally proposed by Simon (1956) and further developed by Krosnick (1991). According to this framework, decision-making quality depends on anticipated task difficulty, motivation, and cognitive capacity. This notion is clearly reflected in our experimental results, where the non-choice data from Calculator treatments reveal patterns indicative of incomplete search processes and suboptimal planning. Our observations align closely with Caplin et al. (2011), who show that individuals faced with complex tasks often perform sequential searches and terminate upon reaching a reservation utility. Thus, despite providing decision-support tools like the budgeting calculator, participants experience only limited incremental gains in optimization, suggesting inherent constraints in cognitive processing and search behaviors.

These findings have significant implications for policymakers, educators, and financial practitioners seeking to enhance everyday financial decision-making. Even in controlled settings, individuals often display myopic planning and struggle with foundational concepts such as compound interest and price fluctuations. They rarely revise their initial plans, indicating a limited capacity to adapt as conditions change. This underscores the value of behavioral interventions that prompt individuals to revisit and adjust their plans—particularly in complex environments with intertemporal trade-offs.

Our results also show that budgeting calculators alone are not sufficient to overcome cognitive barriers. Instead, these tools may be more effective when combined with clear and accessible financial education that reinforces foundational principle. This integrated approach can improve individual outcomes and inform the design of smarter financial tools and policies.

From a policy perspective, our findings reveal that cognitive complexity—especially under fluctuating prices—introduces an additional layer of welfare loss, beyond standard concerns like menu costs or relative price dispersion. This suggests that cognitive limitations can amplify economic inefficiencies, highlighting the need to simplify financial decision environments and invest in financial literacy as a means to reduce these hidden costs.

Looking forward, our study opens several avenues for future research. Investigating dynamic optimization under diverse conditions such as uncertainty, social learning influences, expected liquidity constraints, and current binding constraints could enhance our understanding of decision-making complexities. Further studies on the effects of introducing and removing budget calculators and the sustained impact of financial literacy initiatives will provide deeper insights into how these tools and educational interventions affect consumer behavior.

7 Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4.0 in order to improve the readability of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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A Sequence of Events

Figure A.1 presents the sequence of events in the experimental sessions. Participants first received interactive instructions and completed 12 control questions to ensure comprehension. The experiment then proceeded through four main stages: a dynamic optimization game (Stage 1), a risk preference elicitation task (Stage 2), a financial literacy test (Stage 3), and a backward induction task (Stage 4). Stage 1 involved one of four possible environments, with or without access to a budgeting calculator, repeated over three rounds. The experiment concluded with a demographic questionnaire and final payment, which depended on participants' performance across all the stages.

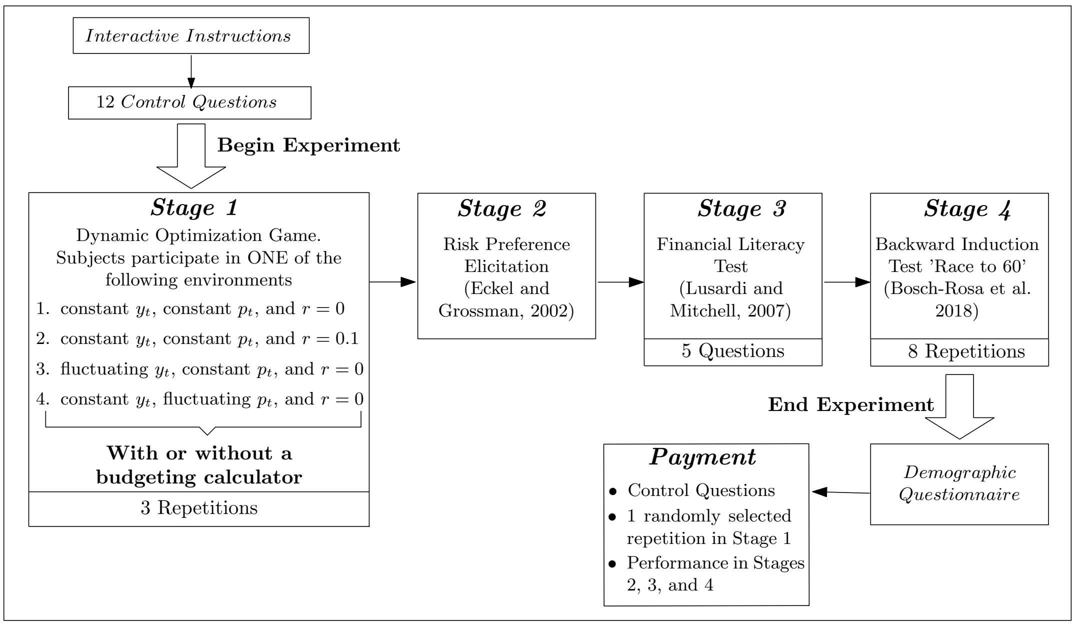


Figure A.1: Sequence of events in experimental sessions.

B Taylor Expansion for Optimal Choice

In this section, we apply a Taylor expansion to the optimal consumption choice for period 1, as specified in Equation 6. This analysis adheres to the methodology delineated by Gabaix and Graeber (2024) in their study of complexity. Let $\hat{y}_t = y_t - y_1$ and $\hat{p}_t = p_t - p_1$, and assume that $\hat{y}_t$ and $\hat{p}_t$ are negligibly small. Consequently, we can reformulate Equation 6.

$$c_1 = \frac{\sum_{t=1}^{T} \frac{y_1}{(1+r)^{t-1}} + \sum_{t=2}^{T} \frac{\hat{y}_t}{(1+r)^{t-1}}}{\left(p_1 + p_1^{\frac{1}{\sigma}} \left(\sum_{t=2}^{T} \left(\frac{\hat{p}_t + p_1}{(1+r)^{t-1}}\right)^{\frac{\sigma-1}{\sigma}}\right)\right)} \tag{13}$$

We begin by evaluating c_1 when $\hat{y}_t = 0$, $r = 0$ and $\hat{p}_t = 0$

$$c_1 = \frac{T y_1}{p_1 + p_1^{\frac{1}{\sigma}} \left((T-1)\, p_1^{\frac{\sigma-1}{\sigma}}\right)} = \frac{y_1}{p_1} \tag{14}$$

Then we calculate $\frac{\partial c_1}{\partial \hat{y}_t}$ and evaluate it when $\hat{y}_t = 0$, $r = 0$ and $\hat{p}_t = 0$

$$\begin{aligned}
\frac{\partial c_1}{\partial \hat{y}_t} &= \frac{\sum_{t=1}^{T} \left[\frac{1}{(1+r)^{t-1}}\right]}{\left(p_1 + p_1^{\frac{1}{\sigma}} \left(\sum_{t=2}^{T} \left(\frac{\hat{p}_t + p_1}{(1+r)^{t-1}}\right)^{\frac{\sigma-1}{\sigma}}\right)\right)} \\
&= \frac{1}{p_1 + p_1^{\frac{1}{\sigma}} \left(p_1^{\frac{\sigma-1}{\sigma}} (T-1)\right)} \\
&= \frac{1}{T p_1}
\end{aligned}$$

We then calculate $\frac{\partial c_1}{\partial r}$ and evaluate it when $\hat{y}_t = 0$, $r = 0$ and $\hat{p}_t = 0$

$$\frac{\partial c_1}{\partial r} = -\frac{\left(y_1 \sum_{t=1}^{T-1} t\right) T p_1 + \left(\left(\frac{1-\sigma}{\sigma}\right) p_1 \sum_{t=1}^{T-1} t\right) T y_1}{T^2 p_1^2} =$$

$$= -\frac{y_1 \sum_{t=1}^{T-1} t}{T p_1 \sigma}$$

$$= \frac{\frac{-y_1 (T-1)(T)}{2}}{T p_1 \sigma}$$

$$= -\frac{y_1 (T-1)}{2\sigma p_1}$$

Finally we calculate $\frac{\partial c_1}{\partial \hat{p}_t}$ and evaluate it when $\hat{y}_t = 0$, $r = 0$ and $\hat{p}_t = 0$

$$\frac{\partial c_1}{\partial \hat{p}_t} = -\frac{\left(\sum_{t=1}^{T} \frac{1}{(1+r)^{t-1}} (\hat{y}_t + y_1)\right) p_1^{\frac{1}{\sigma}} \left(\left(\frac{\sigma-1}{\sigma}\right) \left(\frac{\hat{p}_t + p_1}{(1+r)}\right)^{-\frac{1}{\sigma}}\right)}{\left(p_1 + p_1^{\frac{1}{\sigma}} \left(\sum_{t=2}^{T} \left(\frac{\hat{p}_t + p_1}{(1+r)^{t-1}}\right)^{\frac{\sigma-1}{\sigma}}\right)\right)^2}$$

$$= -\frac{T y_1 \left(\frac{\sigma-1}{\sigma}\right)}{T^2 p_1^2}$$

$$= \left(\frac{1-\sigma}{\sigma}\right) \frac{y_1}{T p_1^2}$$

Thus, the Taylor expansion is

$$c_1 = \frac{y_1}{p_1} + \frac{1}{T p_1} \sum_{t=2}^{T} \hat{y}_t - \frac{y_1 (T-1)}{2\sigma p_1} r + \left(\frac{1-\sigma}{\sigma}\right) \frac{y_1}{T p_1^2} \sum_{t=2}^{T} \hat{p}_t \tag{15}$$

C Mean Comparisons

Table C.1 complements Figure 8 by providing a detailed summary of treatment effects across all repetitions. While Figure 8 focuses on validating Hypotheses 1 through 3 using the Unconditional Optimization Index , this table expands the analysis by reporting two-sided t-tests for each repetition and including additional outcome variables. Specifically, it presents comparisons for the Conditional Optimization Index, time spent per period, and the number of plans entered per period across treatments. This broader view allows for a richer interpretation of behavioral patterns over time and across experimental conditions.

Table C.1: Summary of treatment effects

		Treatment				p-value of two sided t-test					
		Constant YP	Pos IR	Fluct Y	FluctP	[1] vs [2]	[1] vs [3]	[1] vs [4]	[2] vs [3]	[2] vs [4]	[3] vs [4]
Repetition 1											
γ^U	Calculator	0.862	0.718	0.785	0.678	0.000	0.056	0.000	0.130	0.281	0.012
	No Calculator	0.760	0.661	0.778	0.621	0.034	0.680	0.002	0.010	0.395	0.000
	Difference	0.102***	0.058	0.007	0.057						
γ^C	Calculator	0.859	0.734	0.839	0.741	0.000	0.580	0.000	0.006	0.822	0.006
	No Calculator	0.780	0.680	0.826	0.693	0.016	0.205	0.025	0.000	0.764	0.000
	Difference	0.079**	0.054	0.013	0.049						
Seconds/period	Calculator	35.569	51.951	37.822	60.284	0.059	0.723	0.013	0.066	0.436	0.014
	No Calculator	35.301	38.615	30.600	47.383	0.648	0.355	0.052	0.209	0.229	0.001
	Difference	0.268	13.336	7.221*	12.901						
No. Sim/period	Calculator	3.705	5.046	4.060	4.162	0.112	0.594	0.534	0.226	0.309	0.885
Repetition 2											
γ^U	Calculator	0.868	0.701	0.794	0.680	0.000	0.055	0.000	0.027	0.596	0.004
	No Calculator	0.761	0.673	0.822	0.649	0.060	0.165	0.008	0.001	0.553	0.000
	Difference	0.107**	0.028	-0.028	0.031						
γ^C	Calculator	0.869	0.713	0.849	0.736	0.000	0.585	0.000	0.000	0.527	0.001
	No Calculator	0.780	0.677	0.858	0.705	0.019	0.052	0.052	0.000	0.454	0.000
	Difference	0.089**	0.035	-0.008	0.031						
Seconds/period	Calculator	21.792	37.784	25.208	34.988	0.029	0.321	0.001	0.096	0.715	0.023
	No Calculator	17.506	18.736	18.925	31.530	0.696	0.632	0.001	0.948	0.002	0.001
	Difference	4.286	19.048**	6.283*	3.458						
No. Sim/period	Calculator	1.316	2.621	2.108	1.573	0.024	0.127	0.578	0.461	0.113	0.382
Repetition 3											
γ^U	Calculator	0.897	0.761	0.829	0.703	0.000	0.063	0.000	0.047	0.046	0.001
	No Calculator	0.820	0.702	0.840	0.680	0.007	0.638	0.002	0.000	0.548	0.000
	Difference	0.077*	0.059*	-0.011	0.023						
γ^C	Calculator	0.902	0.766	0.875	0.760	0.000	0.402	0.000	0.000	0.801	0.000
	No Calculator	0.836	0.708	0.888	0.728	0.001	0.140	0.007	0.000	0.568	0.000
	Difference	0.066*	0.059*	-0.013	0.032						
Seconds/period	Calculator	20.146	29.726	22.263	29.771	0.054	0.578	0.043	0.113	0.993	0.095
	No Calculator	13.118	15.518	16.821	21.637	0.244	0.073	0.000	0.556	0.012	0.047
	Difference	7.028**	14.209***	5.442*	8.134*						
No. Sim/period	Calculator	1.395	2.075	1.785	1.478	0.217	0.479	0.861	0.617	0.237	0.542

p-value of two sided t-test (comparisons across repetitions)

		Calculator				No Calculator			
		Constant YP	Pos IR	Fluct Y	FluctP	Constant YP	Pos IR	Fluct Y	FluctP
γ^U	Rep1 vs Rep 2	0.720	0.422	0.689	0.949	0.968	0.714	0.094	0.224
	Rep1 vs Rep 3	0.081	0.102	0.107	0.259	0.091	0.254	0.010	0.024
	Rep2 vs Rep3	0.070	0.019	0.060	0.221	0.029	0.170	0.365	0.087
γ^C	Rep1 vs Rep 2	0.591	0.239	0.555	0.777	0.992	0.918	0.173	0.521
	Rep1 vs Rep 3	0.024	0.140	0.129	0.347	0.078	0.382	0.004	0.109
	Rep2 vs Rep3	0.027	0.024	0.100	0.133	0.023	0.107	0.112	0.137
Seconds/period	Rep1 vs Rep 2	0.009	0.040	0.000	0.002	0.000	0.000	0.000	0.000
	Rep1 vs Rep 3	0.003	0.003	0.000	0.001	0.000	0.000	0.000	0.000
	Rep2 vs Rep3	0.576	0.246	0.222	0.199	0.004	0.031	0.181	0.006
No. Sim/period	Rep1 vs Rep 2	0.000	0.001	0.000	0.000				
	Rep1 vs Rep 3	0.000	0.000	0.000	0.000				
	Rep2 vs Rep3	0.818	0.294	0.233	0.766				

Notes: The p-values reported are obtained from t-tests. The standard errors hare clustered at the subject level. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

D Distribution and Predictors of the Conditional Optimal Index

Figure D.1 serves as a complement to Figure 6, which presents the cumulative distributions of the Unconditional Optimization Index (UncOptIndex). In this figure, we show the corresponding cumulative distribution functions for the Conditional Optimization Index (CondOptIndex) across environments and calculator treatments for Repetitions 1 and 3. The observed patterns are similar to those in Figure 6, suggesting that the impact of calculator access and experience across repetitions is consistent under both unconditional and conditional measures of optimization. Additionally, Table D.2 presents the regression results using the CondOptIndex as the dependent variable and serves as the counterpart to Table Table D.2. The patterns observed in Table D.2 closely mirror those in Table D.2, further reinforcing the robustness of our findings across both optimization measures.

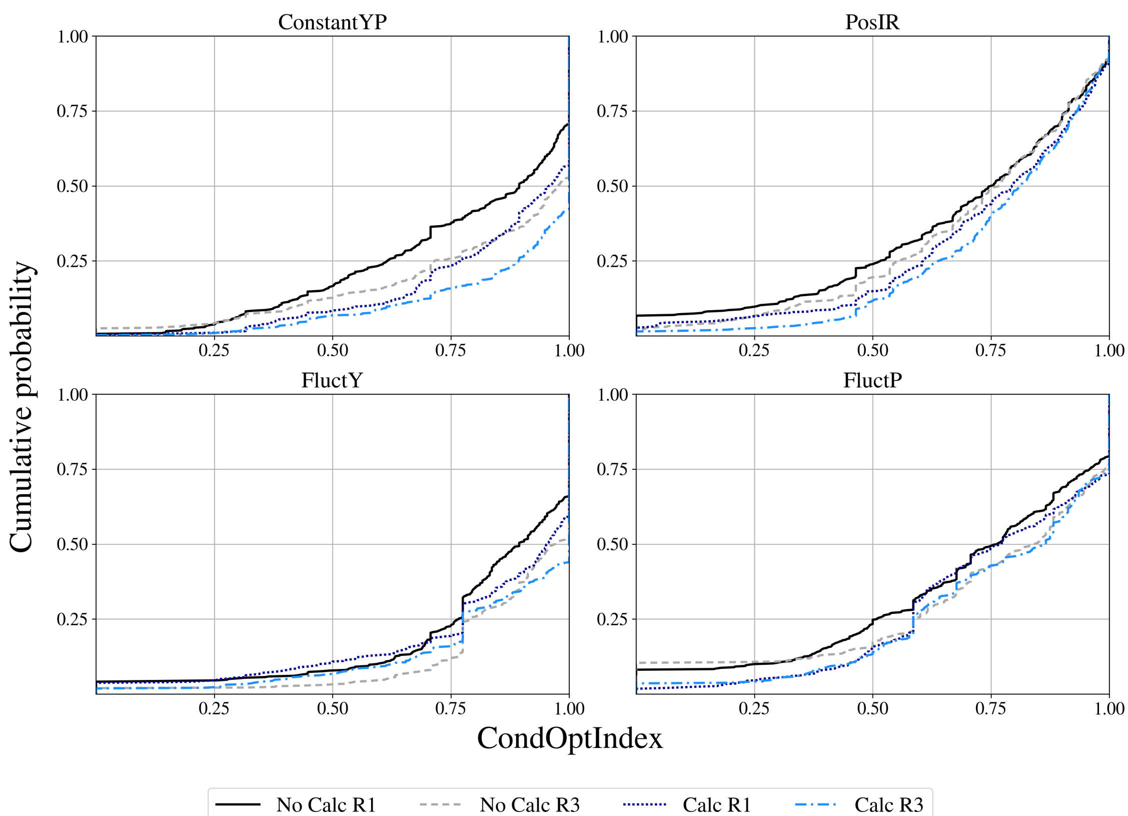


Figure D.1: Cumulative Distribution Function of CondOptIndex

Table D.2: Dependent variable: OptCondIndex

	Constant YP			**PosIR**			**FluctY**			**FluctP**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Calculator	0.083^{**}			0.048			0.005			0.046		
	(0.04)			(0.03)			(0.04)			(0.03)		
Calc γ^C		0.087^{***}			0.065^{***}			0.019			0.058^{***}	
		(0.01)			(0.02)			(0.01)			(0.02)	
Calculator Usage												
Current Period			0.077^{***}			0.007			-0.050^{**}			0.005
			(0.02)			(0.03)			(0.02)			(0.03)
Partial			0.108^{***}			0.051^{**}			0.022			-0.012
			(0.02)			(0.02)			(0.02)			(0.03)
Sequential			0.024			-0.047			0.014			0.019
			(0.02)			(0.03)			(0.02)			(0.03)
Complete			0.066^{***}			0.087^{***}			-0.022			0.077^{***}
			(0.02)			(0.02)			(0.02)			(0.02)
Constant	0.364	0.378	0.328	-0.513^{*}	-0.453	-0.410	0.326	0.333	0.355	0.812^{*}	0.793^{*}	0.856^{*}
	(0.28)	(0.27)	(0.28)	(0.30)	(0.30)	(0.30)	(0.31)	(0.30)	(0.30)	(0.45)	(0.44)	(0.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2640	2640	2640	2730	2730	2730	2820	2820	2820	2790	2790	2790
Overall R^2	0.14	0.17	0.15	0.15	0.16	0.15	0.06	0.07	0.06	0.10	0.10	0.11

Notes: This table displays the outcomes of a random effects panel regression analysis. The regression models incorporate demographic control variables, including gender, age, prior experimental experience, academic degree, affiliated institution, current year of study, and risk tolerance levels. Further controls include Period, Repetition, time spent, financial literacy, ability to backward induct, performance in control questions, and math level. Standard errors are presented in parentheses. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

E Calculator Types

Figure E.1 complements Figure 7 by showing the distribution of subjects across calculator usage types for each repetition, broken down by treatment. This figure highlights shifts in the frequency of each usage type—from no inputs to complete planning—across Repetitions 1 to 3 in each environment.

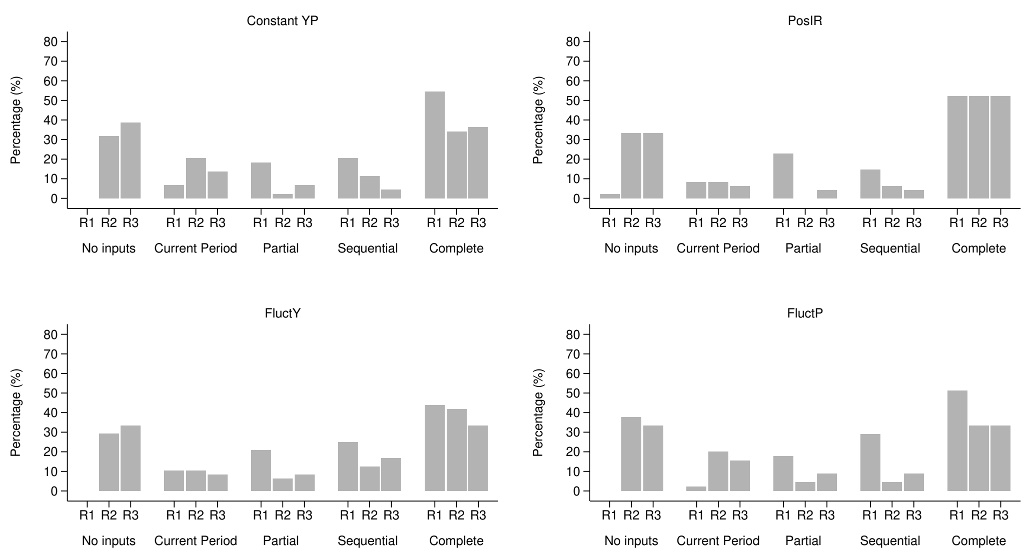


Figure E.1: Budgeting calculator usage types, by treatment and repetition

F Demographics

Mathematical training and financial literacy are key factors associated with financial sophistication (Lusardi and Mitchell, 2011; Van Rooij et al., 2012). It is natural to believe that individuals with mathematical proficiency would excel in sequential calculations and logical reasoning, crucial for formulating optimal consumption plans. Financial literacy may complement this by offering a practical framework for applying such calculations to real-world financial decisions, such as assessing future costs and benefits and understanding the time value of money. These combined skills are presumed to significantly aid individuals in solving intertemporal consumption problems, particularly through the cognitive process of backward induction, which we explicitly elicited in our study.

In Tables F.1 and F.2, we examine each treatment individually to identify whether the presence of the calculator interacts with demographic characteristics. Our results provide little support for our prior. Our findings indicate that individual characteristics do not consistently affect subjects' ability to solve intertemporal consumption problems. No significant effects were observed based on other demographic variables such as gender or age. Higher financial literacy leads to a large and significant improvement in optimization in ConstantYP-NoCalc (8-9 p.p. improvement per correct answer), but not in any other treatment. Stronger backward-induction skills are associated with better *unconditional* optimization in ConstantYP-Calc, but no improvements elsewhere.

Finally, mathematical training has quite a large effect on FluctP-Calc respondents' unconditional and conditional optimization. Unconditional optimization is 3.5 p.p. higher for each additional level of mathematical training. We observe a $3.5 \times 8 = 28$ p.p. difference between those studying in the most mathematically-intensive degrees and those with the least mathematically-intensive degrees (there are 9 categories, so a difference of 8 math levels). In terms of conditional optimization, we observe a $2.8 \times 8 = 22.4$ p.p. difference. Again, this trait does not lead to significantly higher levels of optimization in other treatments.

We are also left intrigued by the finding that mathematical training does not significantly influence optimization in the PosIR treatment. This is at odds with previous literature that underscores the correlation between mathematical skill and the ability to compute compounding returns.An explanation for the inconsistent demographic effects could be the leveling effect of our extensive training phase before the experiment, which included a thorough 30-minute instruction session. This training may have equalized the playing field among subjects with varied backgrounds.

Table F.1: Dependent variable: OptUncIndex

	Constant YP			**Pos IR**			**FluctY**			**FluctP**		
	No Calc	Calc	Calc	No Calc	Calc	Calc	No Calc	Calc	Calc	No Calc	Calc	Calc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No of Calculations			-0.001			-0.001			-0.001			0.001
			(0.00)			(0.00)			(0.00)			(0.00)
Calc γ^U			0.093***			0.213***			0.115***			0.105***
			(0.02)			(0.02)			(0.02)			(0.02)
Minutes Spent	-0.037***	-0.012***	-0.010*	-0.008	-0.009***	-0.005	-0.011	-0.014***	-0.007	0.011	-0.000	-0.002
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Repetition 2	-0.010	0.036***	0.038***	0.010	-0.019	-0.019	0.042***	0.007	0.023*	0.031*	0.005	-0.001
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Repetition 3	0.047***	0.065***	0.069***	0.038***	0.037**	0.025*	0.059***	0.035***	0.047***	0.063***	0.029	0.018
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Period	-0.010***	0.001	0.001	-0.006***	0.000	-0.000	-0.003*	-0.009***	-0.009***	0.006**	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Math Level	0.040	0.009	0.007	0.007	-0.015	-0.016*	-0.005	0.004	0.005	0.015	0.041***	0.035**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Backward Induction	-0.001	0.042**	0.036*	-0.015	0.015	0.005	0.024	-0.004	-0.007	-0.002	0.027	0.028
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Financial Literacy	0.092**	-0.018	-0.017	0.022	-0.013	-0.020	0.034	-0.012	-0.013	0.021	-0.012	-0.011
	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)
Control Questions	-0.003	0.005	0.003	0.013	0.021**	0.020***	0.007	0.012	0.014	0.006	0.002	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Calculator Usage												
Current Period		0.074***	0.075***		-0.028	-0.006		-0.068**	-0.049*		-0.002	0.013
		(0.02)	(0.02)		(0.03)	(0.03)		(0.03)	(0.03)		(0.03)	(0.03)
Partial		0.122***	0.102***		0.035	0.052**		0.016	0.038		-0.007	-0.003
		(0.02)	(0.03)		(0.03)	(0.03)		(0.03)	(0.03)		(0.03)	(0.03)
Sequential		0.051**	-0.000		-0.089***	-0.176***		-0.005	-0.056**		-0.022	-0.063*
		(0.02)	(0.03)		(0.03)	(0.03)		(0.02)	(0.02)		(0.03)	(0.03)
Complete		0.088***	0.029		0.081***	-0.086***		-0.048**	-0.099***		0.053*	0.013
		(0.02)	(0.02)		(0.02)	(0.03)		(0.02)	(0.03)		(0.03)	(0.03)
Constant	0.677	0.601	0.662*	-0.122	-0.360	-0.203	0.267	0.432	0.266	0.311	0.358	0.526
	(0.48)	(0.44)	(0.40)	(0.73)	(0.39)	(0.24)	(0.51)	(0.53)	(0.52)	(1.10)	(0.68)	(0.67)
Observations	1320	1320	1320	1290	1440	1440	1380	1440	1440	1440	1350	1350
Overall R^2	0.15	0.16	0.21	0.05	0.14	0.26	0.10	0.05	0.14	0.07	0.14	0.16

Notes: This table displays the outcomes of a random effects panel regression analysis. The regression models incorporate demographic control variables, including gender, age, prior experimental experience, academic degree, affiliated institution, current year of study, and risk tolerance levels. Additionally, we control for participants' comprehension of the instructions, by adding the participants' performance in the control questions. Standard errors are presented in parentheses. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table F.2: Dependent variable: OptCondIndex

	Constant YP			**Pos IR**			**FluctY**			**FluctP**		
	No Calc	Calc	Calc	No Calc	Calc	Calc	No Calc	Calc	Calc	No Calc	Calc	Calc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No of Calculations			-0.001			0.001			-0.001			0.001
			(0.00)			(0.00)			(0.00)			(0.00)
Calc γ^C			0.112***			0.052***			0.032*			0.057***
			(0.02)			(0.01)			(0.02)			(0.02)
Minutes Spent	0.002	-0.005*	-0.004	0.008	0.000	-0.003	-0.006	-0.005	-0.001	0.019***	0.002	-0.001
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Repetition 2	0.001	0.034***	0.062***	-0.000	-0.014	-0.005	0.031***	0.008	0.014	0.017	0.005	0.017
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Repetition 3	0.057***	0.067***	0.080***	0.031**	0.037***	0.044***	0.061***	0.030**	0.030**	0.043***	0.030*	0.041**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Period	0.011***	0.007***	0.006***	0.018***	0.028***	0.028***	0.009***	0.006***	0.005***	0.022***	0.016***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Math Level	0.041*	0.012	0.012	0.006	-0.012	-0.010	-0.008	-0.003	-0.004	0.013	0.035***	0.031***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Backward Induction	0.001	0.036	0.026	-0.009	0.011	0.009	0.014	-0.009	-0.008	-0.005	0.021	0.023
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Financial Literacy	0.084**	-0.009	-0.009	0.027	-0.020	-0.019	0.038	-0.004	-0.003	0.020	-0.009	-0.009
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Control Questions	0.000	0.006	0.006	0.011	0.022***	0.021***	0.006	0.014*	0.014	0.002	0.000	0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Calculator Usage												
Current Period		0.074***	0.008		0.004	0.003		-0.062**	-0.075***		-0.001	-0.025
		(0.02)	(0.02)		(0.03)	(0.03)		(0.02)	(0.03)		(0.03)	(0.03)
Partial		0.116***	0.050**		0.048*	0.043*		0.000	-0.025		-0.021	-0.022
		(0.02)	(0.02)		(0.03)	(0.03)		(0.03)	(0.03)		(0.03)	(0.03)
Sequential		0.028	-0.043*		-0.049	-0.058*		-0.001	-0.013		0.006	0.009
		(0.02)	(0.02)		(0.03)	(0.03)		(0.02)	(0.02)		(0.03)	(0.03)
Complete		0.069***	-0.003		0.084***	0.075***		-0.039*	-0.057**		0.061**	0.051*
		(0.02)	(0.02)		(0.02)	(0.02)		(0.02)	(0.02)		(0.03)	(0.03)
Constant	0.285	0.481	0.468	-0.159	-0.557	-0.517	0.388	0.340	0.357	0.473	0.447	0.440
	(0.42)	(0.47)	(0.45)	(0.68)	(0.36)	(0.36)	(0.43)	(0.44)	(0.44)	(0.99)	(0.56)	(0.53)
Observations	1320	1320	1320	1290	1440	1440	1380	1440	1440	1440	1350	1350
Overall R^2	0.19	0.17	0.21	0.08	0.24	0.26	0.09	0.09	0.10	0.10	0.17	0.18

Notes: This table displays the outcomes of a random effects panel regression analysis. The regression models incorporate demographic control variables, including gender, age, prior experimental experience, academic degree, affiliated institution, current year of study, and risk tolerance levels. Additionally, we control for participants' comprehension of the instructions, by adding the participants' performance in the control questions. Standard errors are presented in parentheses. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F.1 Why Do Participants Leave Money on the Table?

Table F.3 reports regression results examining why some subjects left money on the table in the final period of the repetitions. The dependent variable measures the number of repetitions (ranging from 0 to 3) in which participants left money on the table. This occurs when a subject finishes the experiment with sufficient funds to purchase more than one consumption unit, excluding minor rounding errors.

Among the 366 participants, 13 left money on the table in one repetition, 11 in two repetitions, and 13 in all three repetitions. The remaining 90% never left money on the table.

The regression results indicate that performance on the incentivized control questions (ranging from 36 to 48 points), administered before the experiment, strongly predicts whether a participant left money on the table. Specifically, the coefficient for control question performance is -0.084 and highly significant (p-value < 0.01), suggesting that a 12.5-point decrease in control question performance is associated with an increase of approximately one repetition in which a participant left money on the table. Since answering the control questions correctly required understanding how to interpret the experiment's information, this finding supports the conjecture that participants who left money on the table did so due to distraction or a lack of comprehension.

Additionally, subjects in the PosIR condition were significantly more likely to leave money on the table, though this effect was mitigated when they had access to a calculator. The negative coefficient on the interaction term between Calculator and PosIR suggests that the budgeting calculator access helped counteract the tendency to leave money on the table in this condition.

Table F.3: OLS Regression. Dependent Variable: Number of Repetitions Subjects left Money on the Table

Variable	**Coefficient (SE)**
Math Level	-0.013 (0.02)
Race Wins	-0.007 (0.02)
Financial Literacy	-0.049 (0.04)
Risk Preferences	0.022 (0.02)
Female	-0.003 (0.07)
Degree	-0.036 (0.06)
Age	0.000 (0.01)
SFU	0.006 (0.07)
Years of Education	-0.008 (0.03)
Experience in Experiments	-0.025 (0.08)
Control Questions	-0.084*** (0.02)
Calculator	0.132 (0.14)
PosIR	0.520*** (0.18)
FluctY	0.021 (0.09)
FluctP	-0.011 (0.08)
Calculator × PosIR	-0.467* (0.24)
Calculator × FluctY	-0.103 (0.16)
Calculator × FluctP	-0.114 (0.15)
Constant	4.264*** (0.95)
Observations	366
R-squared	0.21

Notes: Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G Short-Span Planning Model's Estimation

Our methodology relies on the notion that an individual's initial consumption choice is influenced by their planning horizon and includes a random error component. This error component, denoted as ε, follows a normal distribution with a mean of zero and a standard deviation of σ. Therefore, the actual consumption choice for a specific planning horizon, denoted by c_H, is given by: $c_H = c_H + \varepsilon$, where H varies from 1 to 10 and c_H represents the theoretically optimal consumption level in Period 1 for the respective H. Additionally, we consider the possibility that a subset of subjects may make their consumption choices randomly. We model this by assuming that these subjects' decisions follow a uniform distribution ranging from 0 to 10. As a result, our model considers the population to comprise $H+1$ distinct planner types, each characterized by a proportion p_h for h in the range of [0,10].

To define a log-likelihood function, we integrate these proportions with the corresponding conditional densities. This methodology enables the computation of the sample log-likelihood for the n observations in our dataset. The log-likelihood function is expressed as follows:

$$\text{LogL} = \sum_{i=1}^{n} \ln \left[\frac{\hat{p}_0}{100} + \sum_{h=1}^{10} \hat{p}_h \frac{1}{\sigma} \phi \left(\frac{c_{i,R} - c_H^*}{\hat{\sigma}} \right) \right],$$

where $c_{i,R}$ represents the actual consumption of subject i in repetition R. The next step involves determining the proportions $\hat{p}_h$ and the standard deviation $\hat{\sigma}$ that maximize this log-likelihood function.

Table G.1: Optimal consumption level in Period 1, c_H

H	ConstantYP	PosIR	FluctY	FluctP
1	10.00	10.00	15.00	8.00
2	10.00	9.09	10.00	4.00
3	10.00	8.26	11.67	4.80
4	10.00	7.51	10.00	4.00
5	10.00	6.83	11.00	4.44
6	10.00	6.21	10.00	4.00
7	10.00	5.64	10.71	4.31
8	10.00	5.13	10.00	4.00
9	10.00	4.67	10.56	4.24
10	10.00	4.24	10.00	4.00

Table G.2: Parameter estimation results of short-span planning model

Parameter	Coefficient	Standard Error
$\hat{p}_1$	0.21^{***}	0.034
$\hat{p}_2$	0.118^{***}	0.028
$\hat{p}_3$	0.071^{***}	0.022
$\hat{p}_4$	0.035^{**}	0.016
$\hat{p}_5$	0.032^{**}	0.015
$\hat{p}_6$	0.025^{*}	0.014
$\hat{p}_7$	0	NA
$\hat{p}_8$	0.116^{***}	0.027
$\tilde{p}_9$	0.001	0.021
$\hat{p}_{10}$	0.099^{***}	0.031
Uncategorized	0.291^{***}	0.04
$\hat{\sigma}$	0.162^{***}	0.013

Note: p_7 was set to 0 because otherwise the function did not converge. Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

G.1 Distribution of Estimated Horizons: With and Without the Calculator

Examining the estimated horizon among participants with access to the calculator compared to those without reveals that access to the calculator tends to result in a longer implied horizon. This is illustrated in Figure G.1, which shows the cumulative distributions of the implied horizons for both groups —those with and without access to the calculator. Importantly, while the presence of the calculator appears to nudge participants to plan further ahead, the majority of PosIR-Calc subjects' decisions do not align with a full-horizon plan.

G.2 Ensuring Balanced Representation in Planning Data

In our analysis, we make two adjustments when examining the panning data data. The first is that we omit intermediate plans for sequential users: if a subject incrementally increases the planning horizon by clicking the *Submit* button each time they enter an additional consumption value, we only retain the final (longest) plan. The second adjustment recognizes that in a single period, subjects may use the calculator to test various

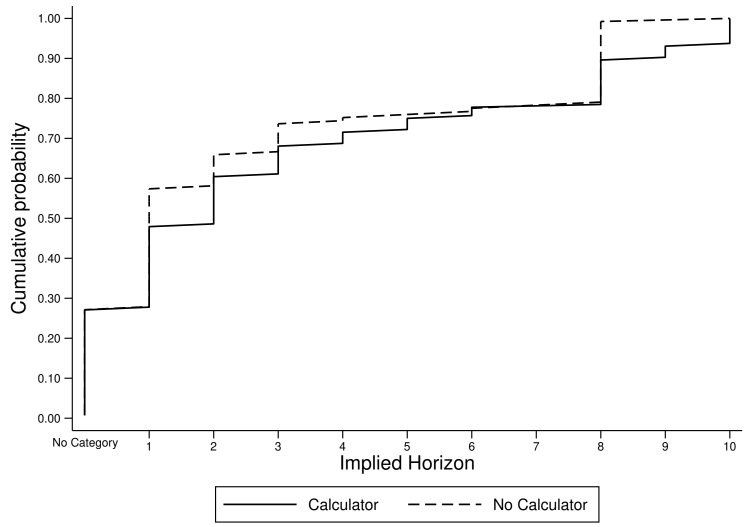


Figure G.1: CDF of Implied Horizon

potential plans, complicating the analysis as it is unclear which plan they intend to implement. These plans may even differ in their time horizons. To ensure a balanced evaluation, we assign equal weight to each participant using the budgeting calculator in each repetition. This means that every individual's plan contributes equally to the overall distribution. However, the weight of a specific plan is inversely proportional to the frequency of calculator usage by that subject. This approach mitigates the potential overrepresentation of subjects who are simply exploring the payoff space, preventing their exploratory attempts from disproportionately affecting the distribution.

G.3 Individual-Level Analysis

To assess the model's predictions against actual planning horizons on an individual basis, we employ $\hat{\sigma}$ to establish a range for c_H for each participant, thereby facilitating the assignment of corresponding planning horizons. Figure G.2 illustrates this detailed examination. The x-axis shows the horizon predicted by the short-span planning model, whereas the y-axis presents the mode of the horizons used by subjects with the budgeting calculator during the first period of each repetition. Notably, the patterns observed herein provide further insight: the actual planning horizons are typically more extended than those predicted by the short-term horizon model. Moreover, in over 25 percent of cases, the model either fails to categorize an individual or predicts a horizon of 1, while subjects opt for the full horizon. Conversely, subjects adhere to the model's full-horizon prediction in only 3 percent of cases. Nevertheless, in approximately 3 percent of instances, the model forecasts full horizon usage, yet individuals select a shorter horizon.

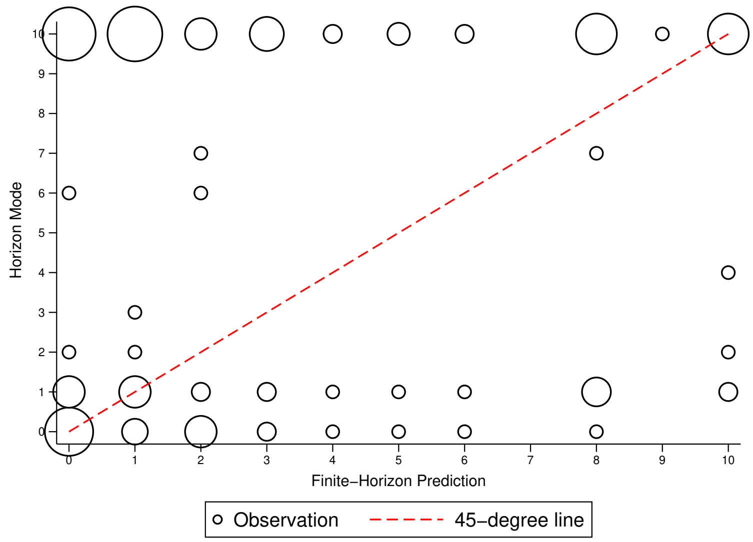


Figure G.2: Comparison between the predicted and the observed horizon at the individual level

G.4 Utility Performance Across Planning Horizons

Figure Figure G.3 compares the predicted utility generated by the Short-Span Planning Model with the achieved utility of subjects using a calculator, across planning horizons and repetitions. This analysis is restricted to period 1 of each repetition, which is why the horizons range from 1 to 10. Each panel represents a different repetition. The bars are divided into two sections: the lower portion (grey shade) reflects the average per-period utility achieved by participants from period 1 to the selected horizon, while the upper portion (white bars) corresponds to the predicted utility based on the model.

Contrary to the hypothesis that subjects perform better when planning with short horizons, the figure shows that achieved utility increases with a longer planning horizon. This pattern can likely be explained by two factors: (1) most participants tend to plan using the full horizon (58% of all plans), and (2) subjects may be using shorter-horizon plans (particularly those spanning 1–2 periods) to explore and familiarize themselves with the utility function, rather than optimizing in strict alignment with the short-span planning model.

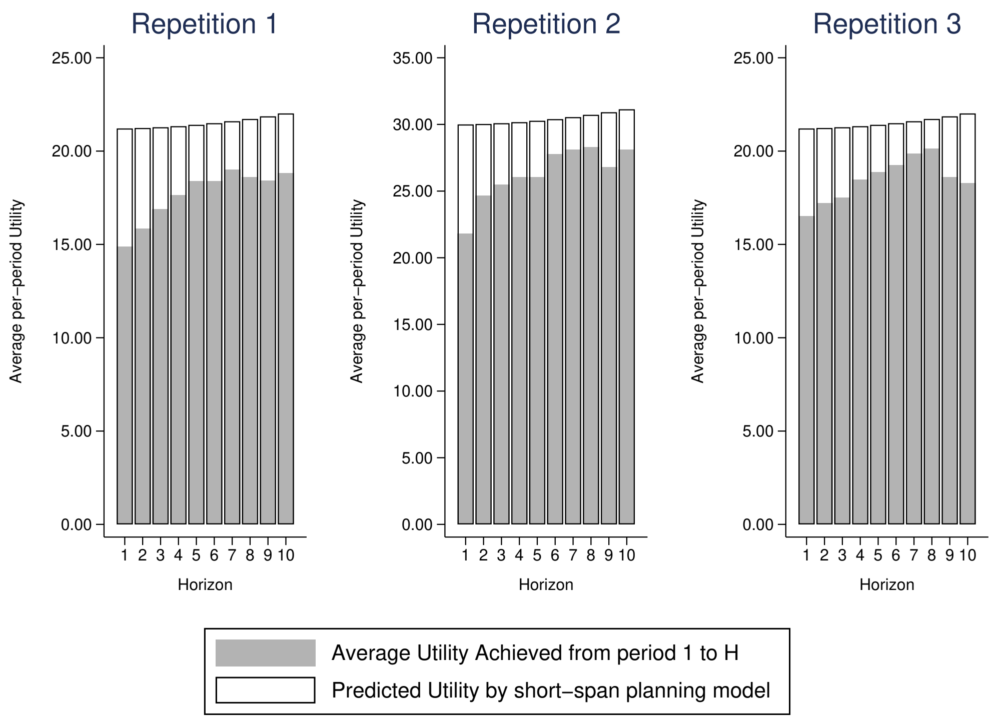


Figure G.3: Predicted Utility by the Short-Span Planning Model vs. Achieved Utility by Horizon

H Hand-to-Mouth Heuristic

One evident heuristic that subjects may adopt to circumvent complexity is the "hand-to-mouth behavior (H2M)," where they expend all their available cash each period. Yet, this approach comes with the cost of potential utility loss. When subjects refrain from saving in any period, they incur a utility reduction of 3.6% in PosIR and 3.4% in both FluctP and FluctY, relative to the optimal path.[21] In the ConstantYP treatment, the optimal consumption path inherently involves zero savings per period. However, even in this treatment, we can examine the adoption of this heuristic by observing deviations from the unconditionally optimal consumption in at least one period. Two relevant questions arise: Does this heuristic become more prevalent as complexity increases, and does access to the calculator limit its usage?

To address these questions, Figure H.1 displays the percentage of subjects using the H2M heuristic across various treatments and over time. In the ConstantYP, FluctY, and FluctP treatments, subjects who chose not to save, given that not saving was the implied optimal choice for that specific period, are excluded from the analysis. The figure demonstrates that the adoption of this heuristic varies across treatments.

In the ConstantYP treatment, the percentage of subjects employing the H2M heuristic is small, accounting for less than 10 percent of the periods. Furthermore, there is no discernible distinction between subjects with calculator access and those without in this treatment.

In the FluctY treatment, subjects display the correct intuition by employing the H2M heuristic when their income is low, aligning with consumption smoothing principles. Here, the heuristic was utilized in 21.99 percent of the periods when the calculator was present and in 19.08 percent of the periods when it was absent.[22]

In the context of complex environments, starting with the PosIR treatment, the absence of a calculator led to a higher incidence of the Hand to Mouth (H2M) heuristic. The H2M heuristic was utilized in 12.03 percent of the periods when the calculator was available, and in 16.02 percent of the periods when it was not (across all repetitions). This pattern underscores the potential utility of the calculator in mitigating reliance on H2M behavior. Notably, there were 6 subjects who consistently used this heuristic from the beginning to the end of Repetition 3 when the calculator was not enabled, which is

[21] In 9% of the repetitions, participants used this heuristic in all periods.

[22] Running a test on the equality of proportions at a 95% significance level, we do not find a statistically significant difference between the two calculator conditions ($p = 0.0699$).

double the number observed when the calculator was available.

In the FluctP treatment, the H2M heuristic was employed in 22.46 percent of the periods with calculator access, and in 17.05 percent of periods without it, across all repetitions.[23] Notably, within this treatment, the proportion of subjects utilizing the heuristic increases during periods of low prices, reflecting their awareness of the benefits of purchasing more units at lower costs, though they often exceed optimal consumption levels. Furthermore, considering participants who consistently applied the heuristic throughout Repetition 3, only three subjects did so with the calculator enabled, compared to seven without calculator access.

[23]We reject the null hypothesis of equality of proportions ($p = 0.0006$). A plausible explanation for this behavior in the FluctP treatment is that employing the H2M heuristic requires more complex arithmetic operations—specifically, dividing numbers by 50 or 150—compared to other treatments, which typically involve divisions by 100. The budgeting calculator may encourage the adoption of the H2M heuristic by simplifying these arithmetic challenges.

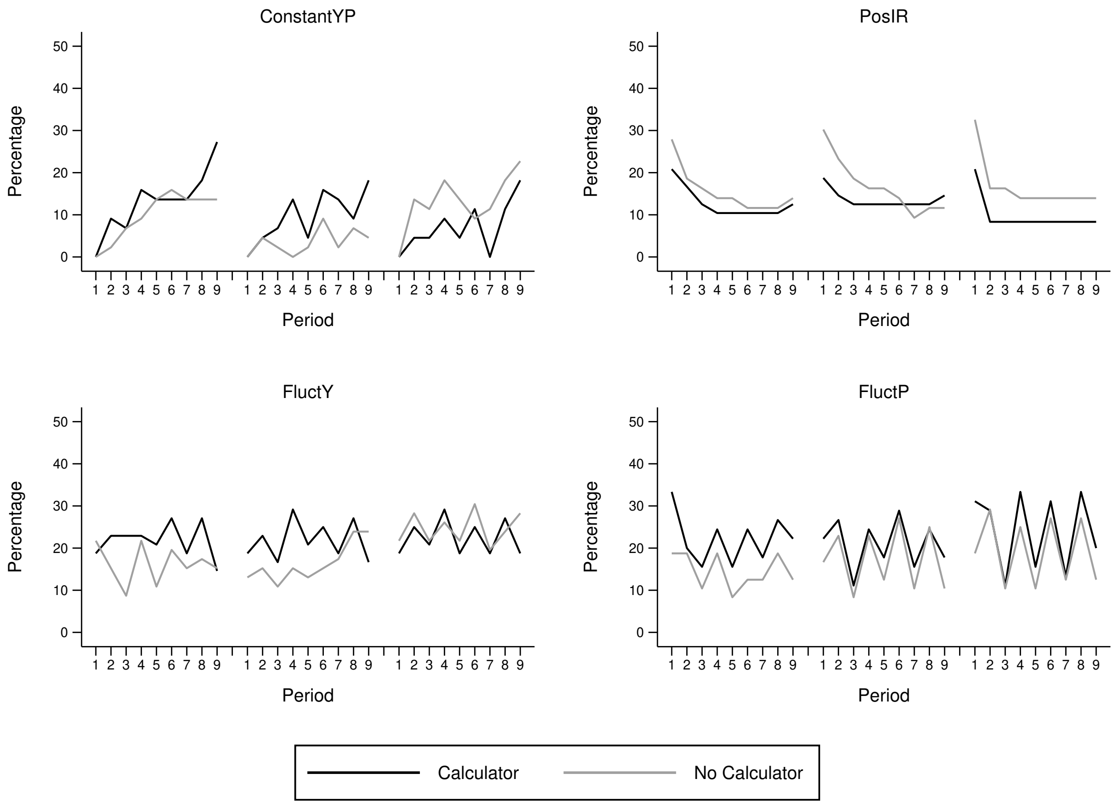


Figure H.1: Percentage of subjects using the hand-to-mouth heuristic

I Individual Time Series

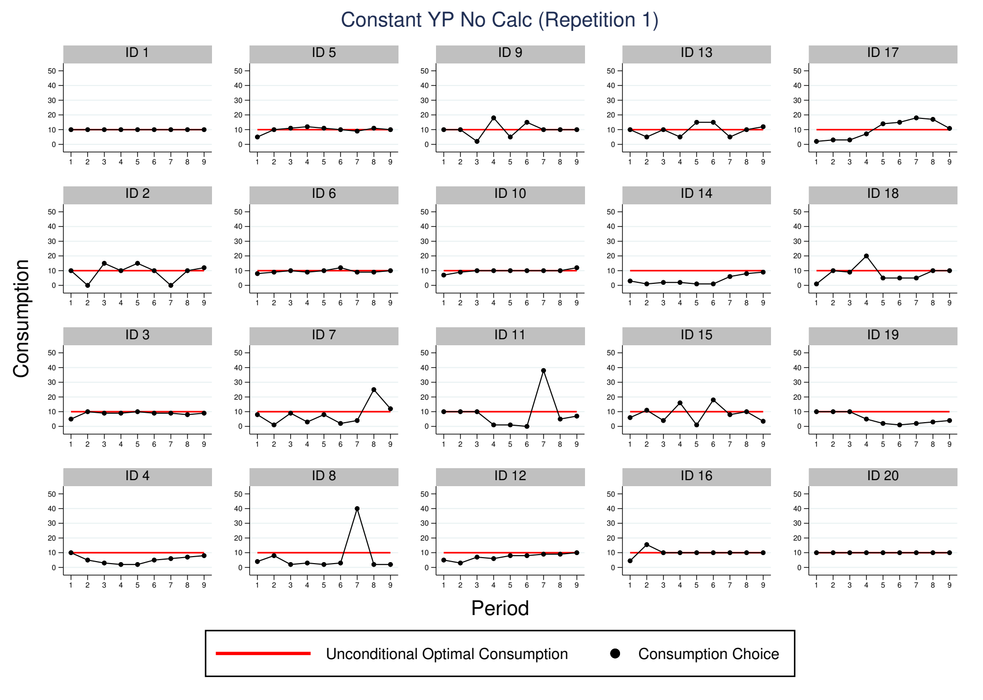


Figure I.1: Constant YP No Calc, Repetition 1 (Session 1)

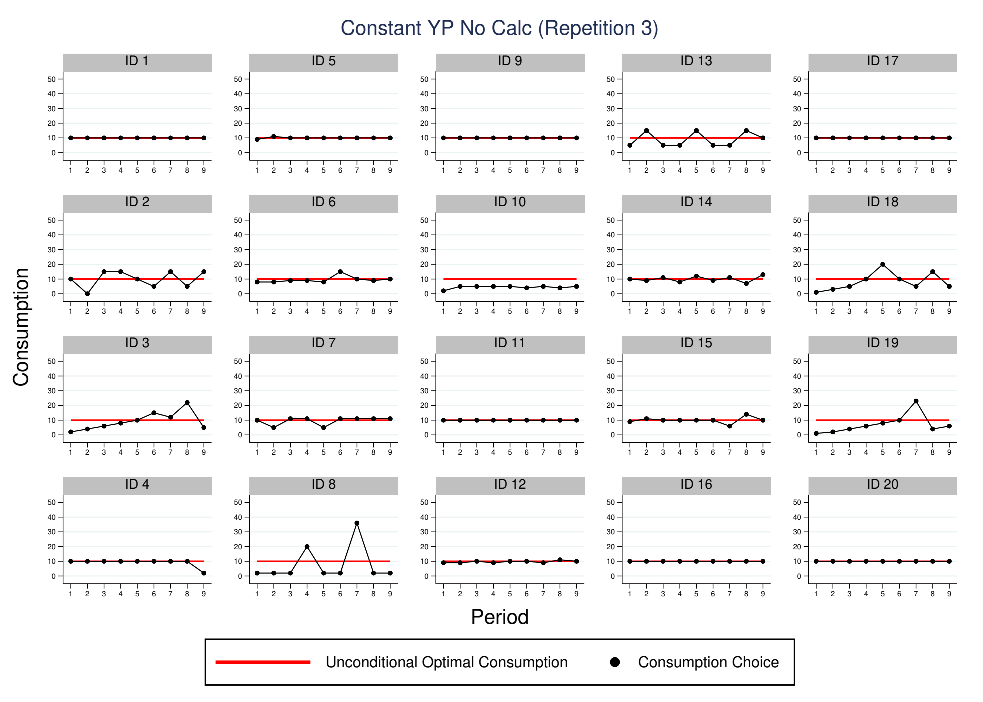


Figure I.2: Constant YP No Calc, Repetition 3 (Session 1)

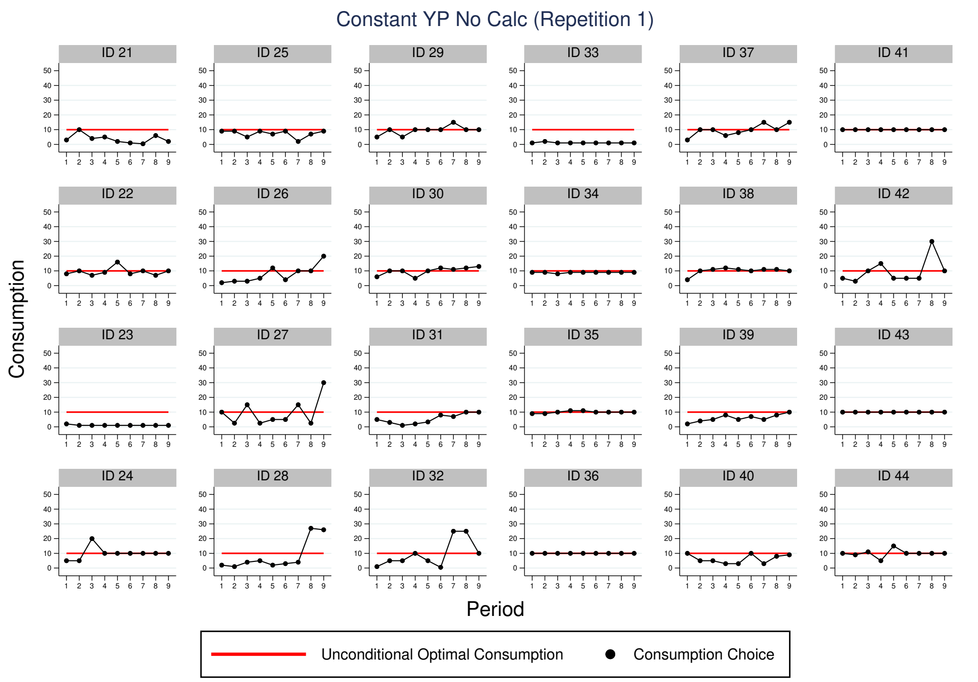


Figure I.3: Constant YP No Calc, Repetition 1 (Session 2)

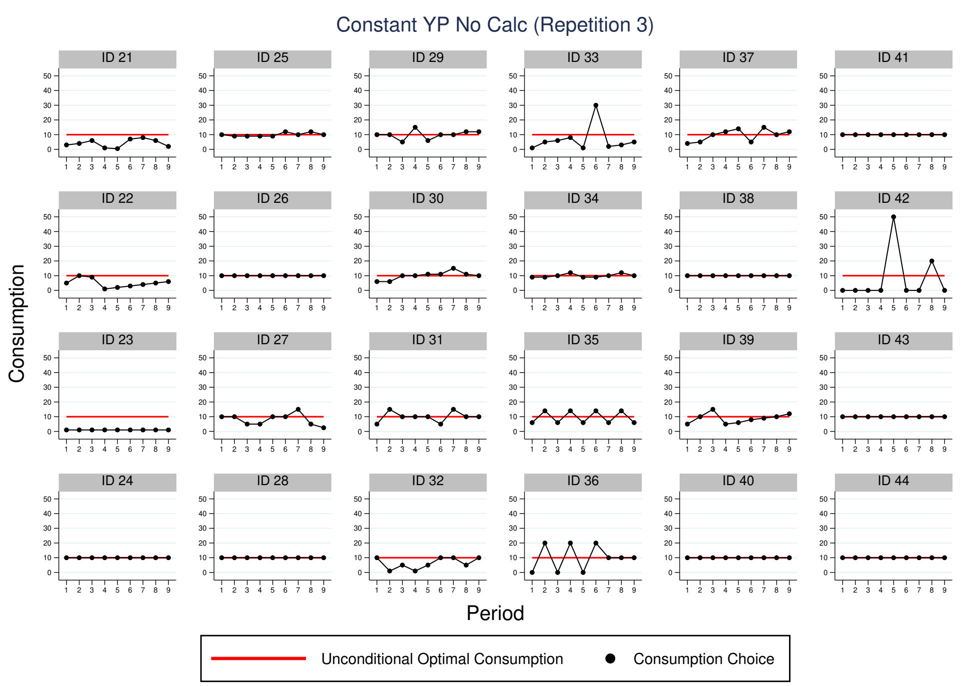


Figure I.4: Constant YP No Calc, Repetition 3 (Session 2)

Figure I.5: Constant YP Calc, Repetition 1 (Session 1)

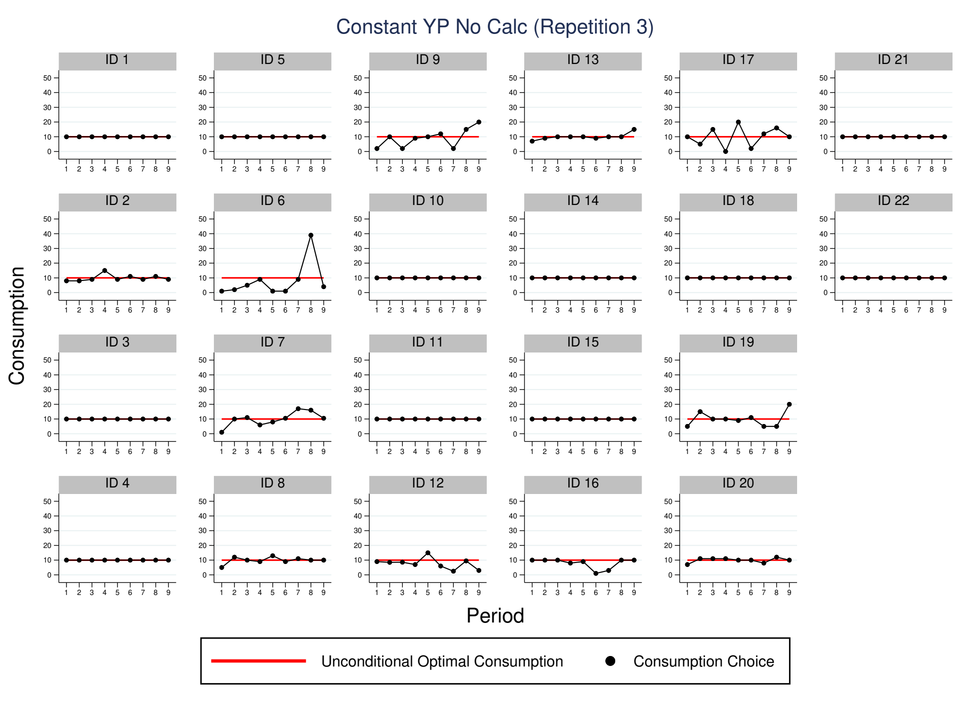


Figure I.6: Constant YP Calc, Repetition 3 (Session 1)

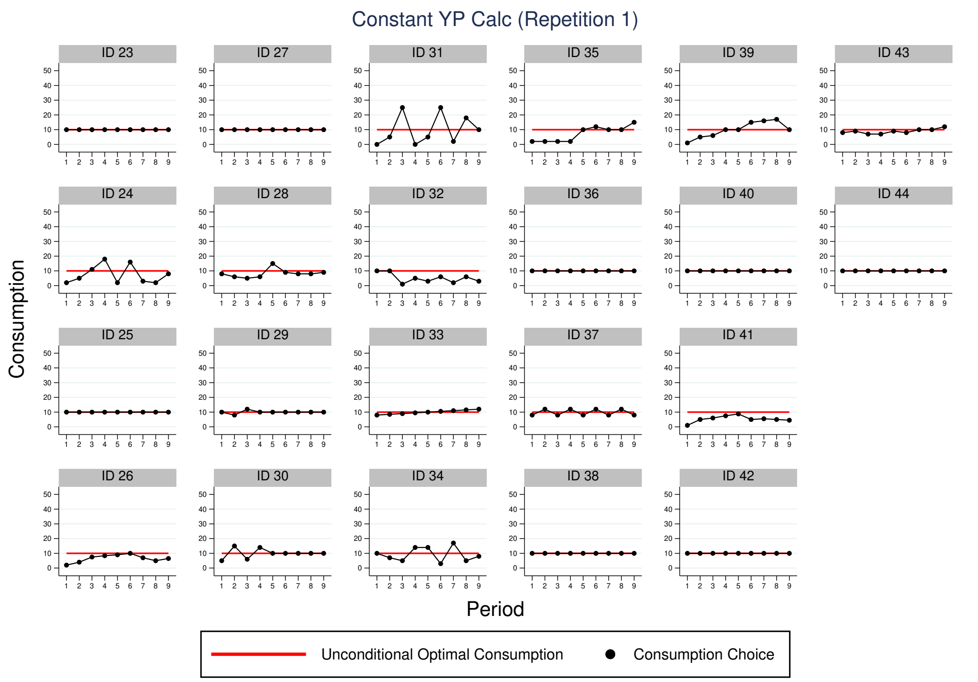


Figure I.7: Constant YP No Calc, Repetition 1 (Session 2)

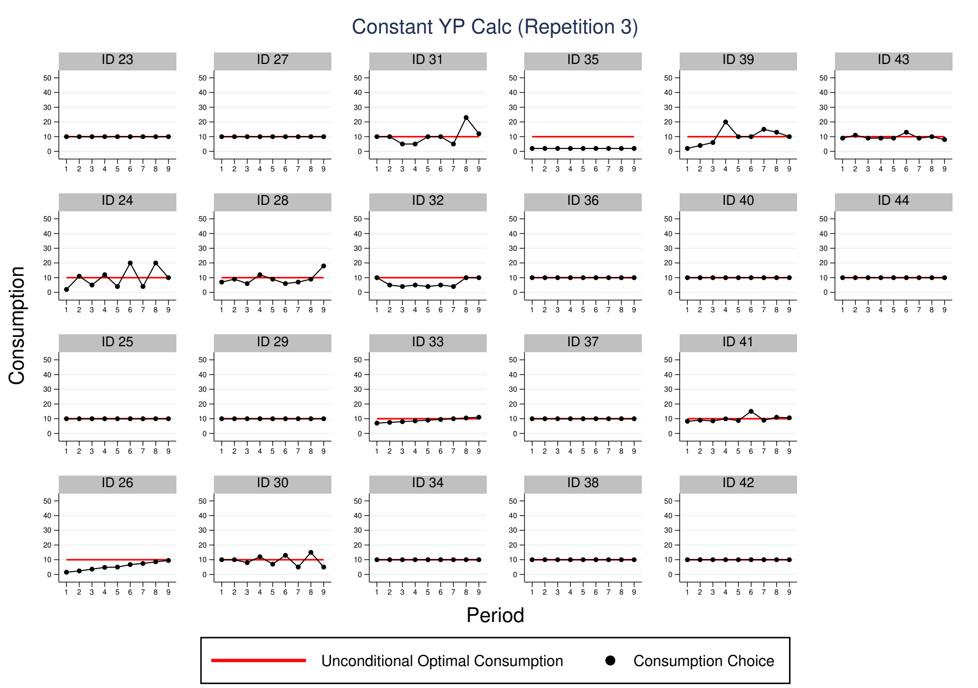


Figure I.8: Constant YP Calc, Repetition 3 (Session 2)

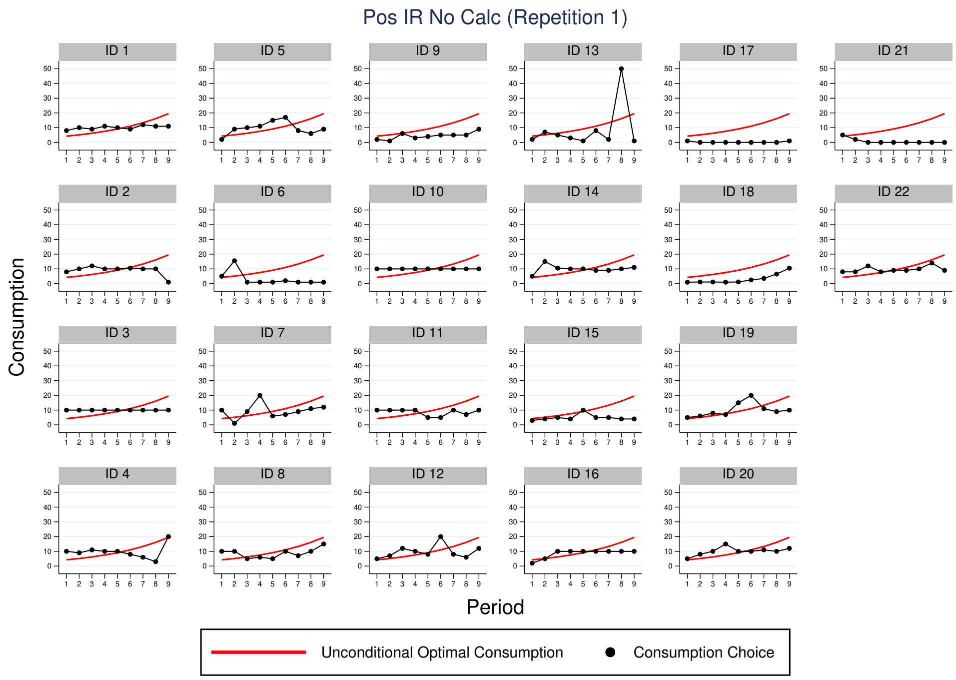


Figure I.9: Pos IR No Calc, Repetition 1 (Session 1)

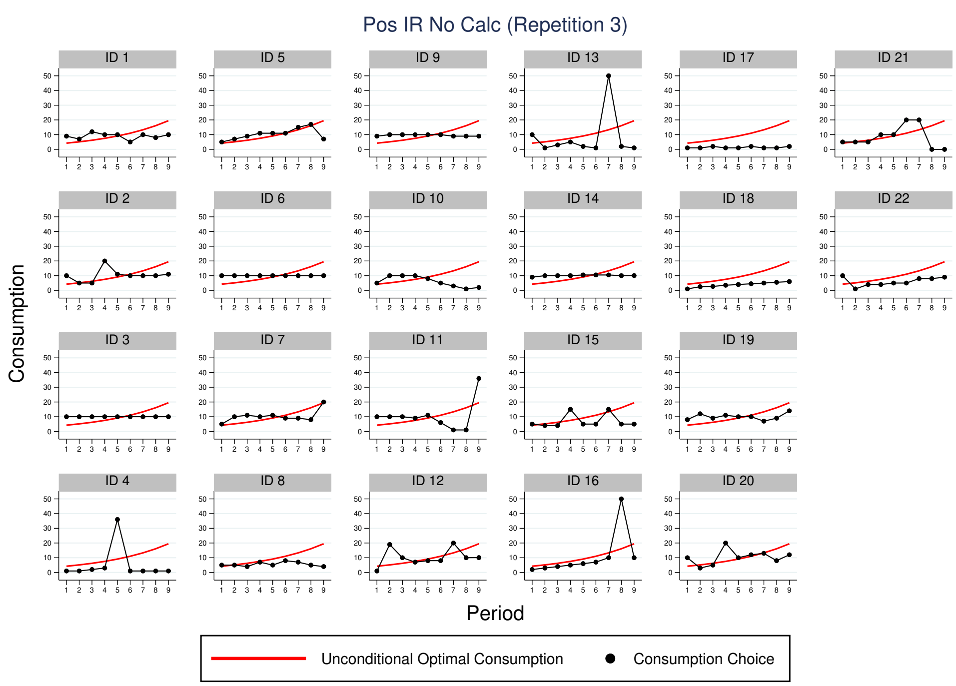


Figure I.10: Pos IR No Calc, Repetition 3 (Session 1)

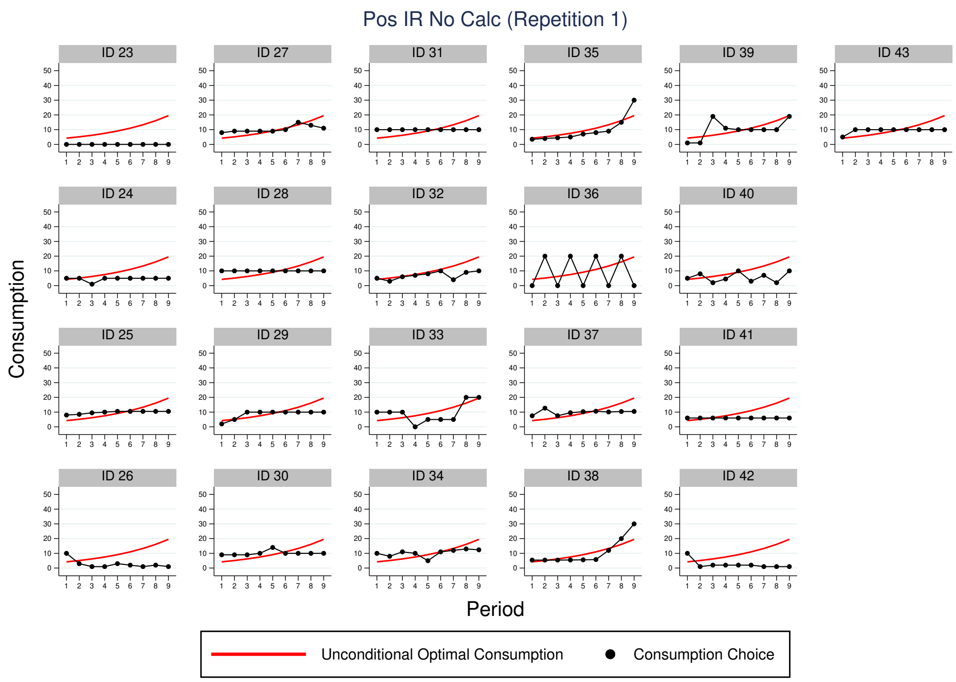


Figure I.11: Pos IR No Calc, Repetition 1 (Session 2)

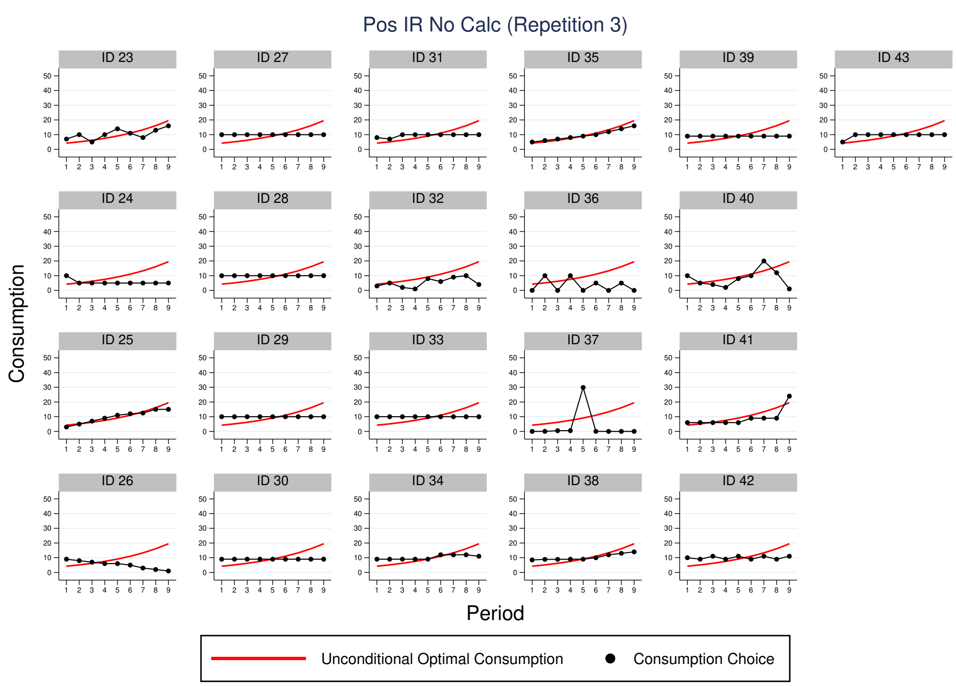


Figure I.12: Pos IR No Calc, Repetition 3 (Session 2)

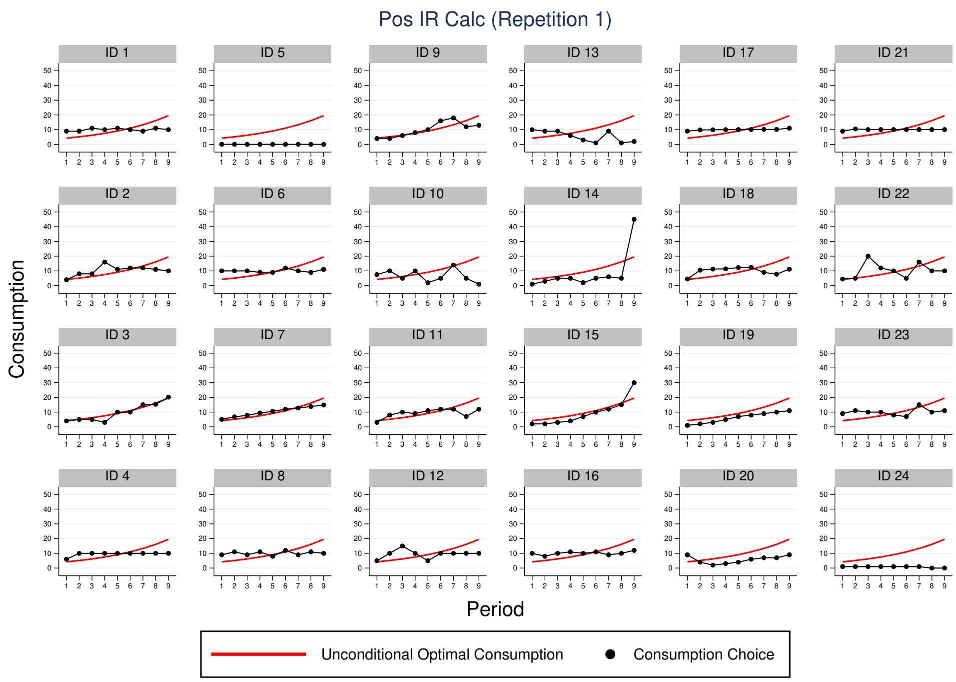


Figure I.13: Pos IR Calc, Repetition 1 (Session 1)

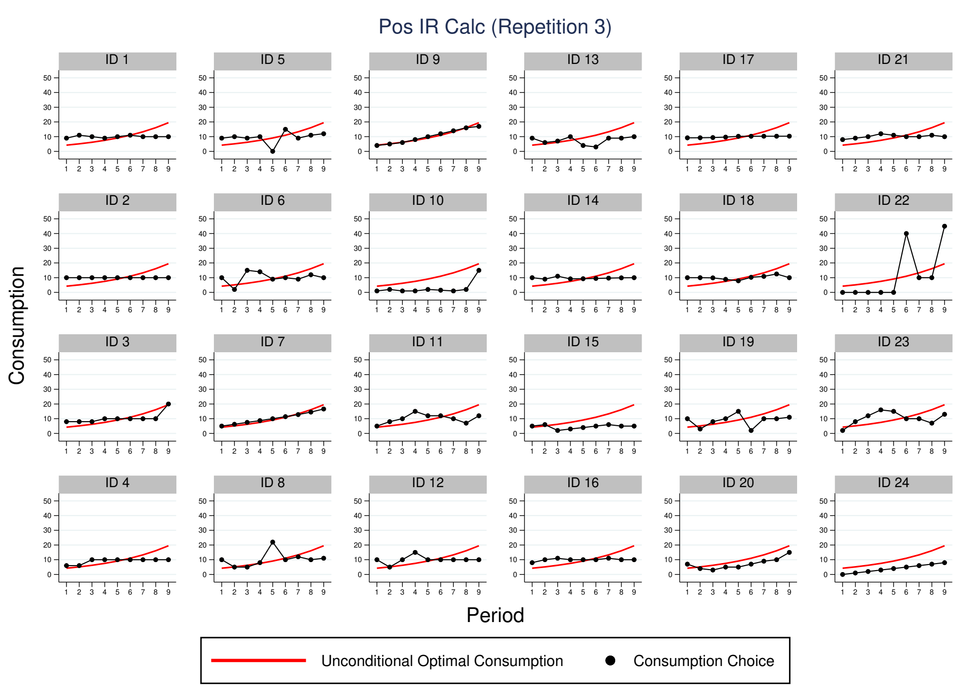


Figure I.14: Pos IR Calc, Repetition 3 (Session 1)

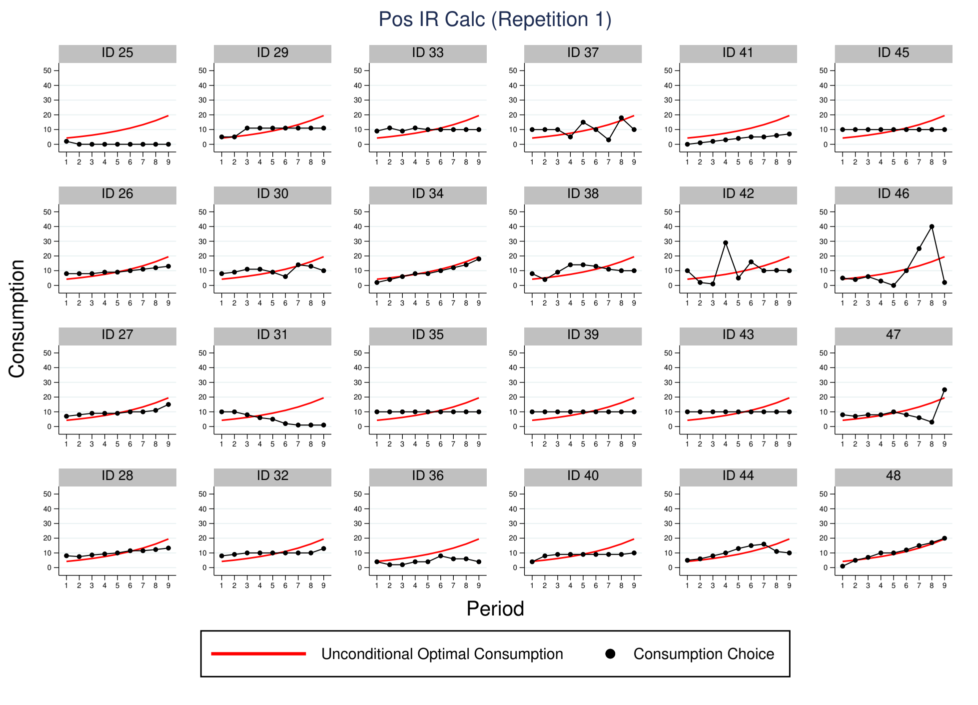


Figure I.15: Pos IR No Calc, Repetition 1 (Session 2)

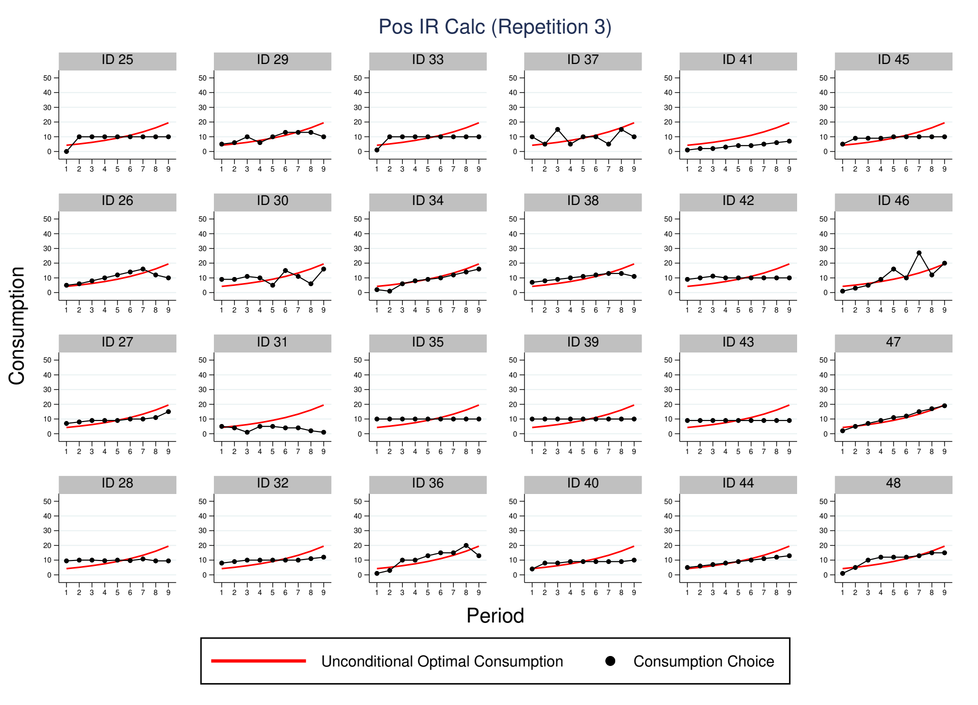


Figure I.16: Pos IR Calc, Repetition 3 (Session 2)

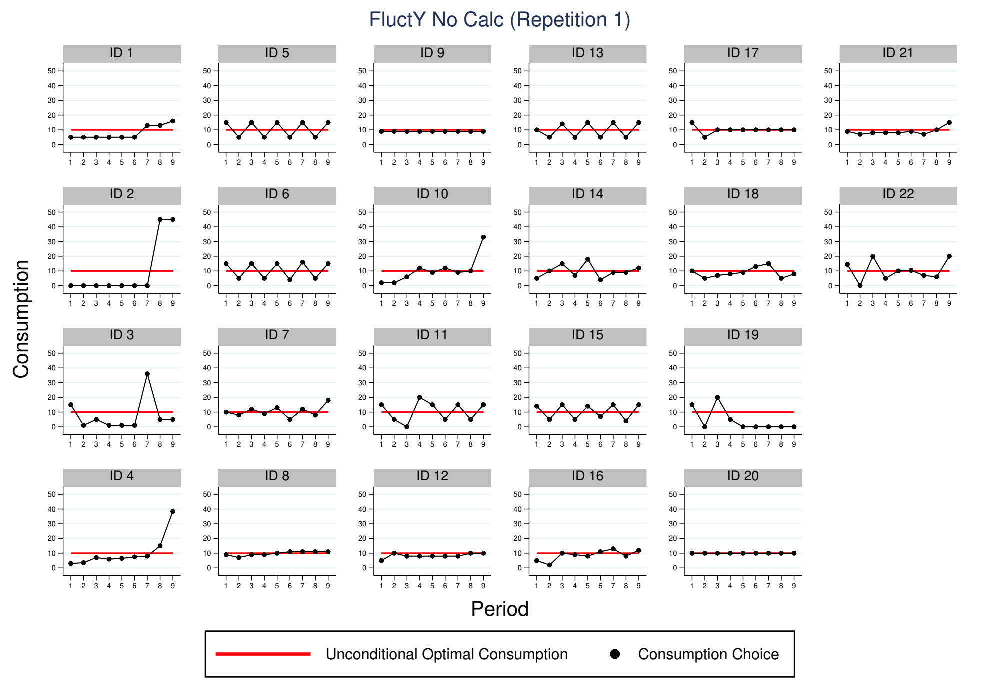


Figure I.17: FluctY No Calc, Repetition 1 (Session 1)

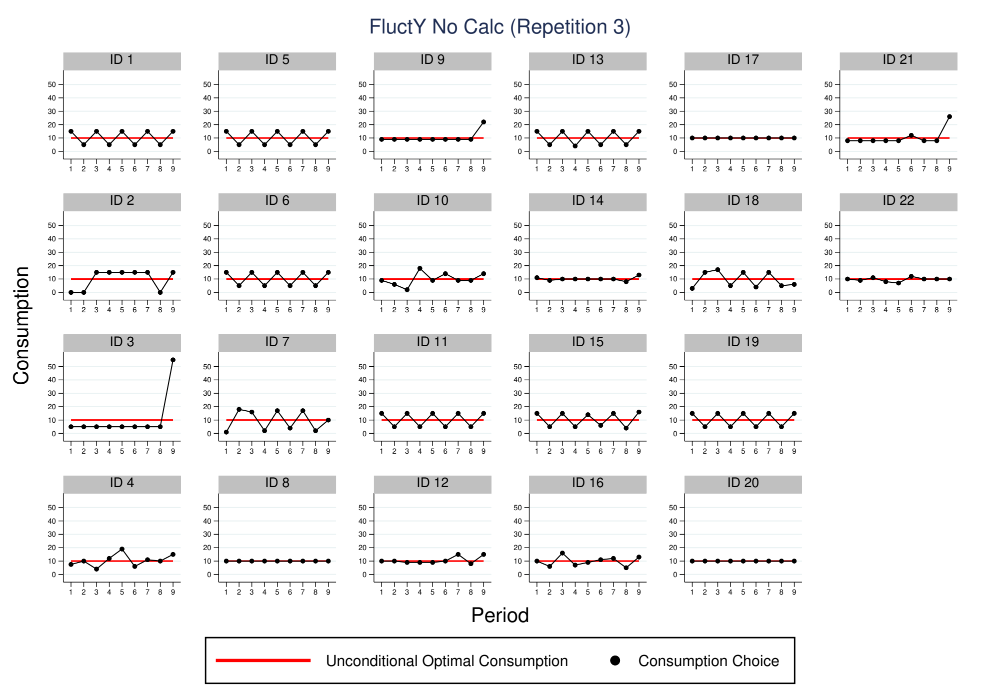


Figure I.18: FluctY No Calc, Repetition 3 (Session 1)

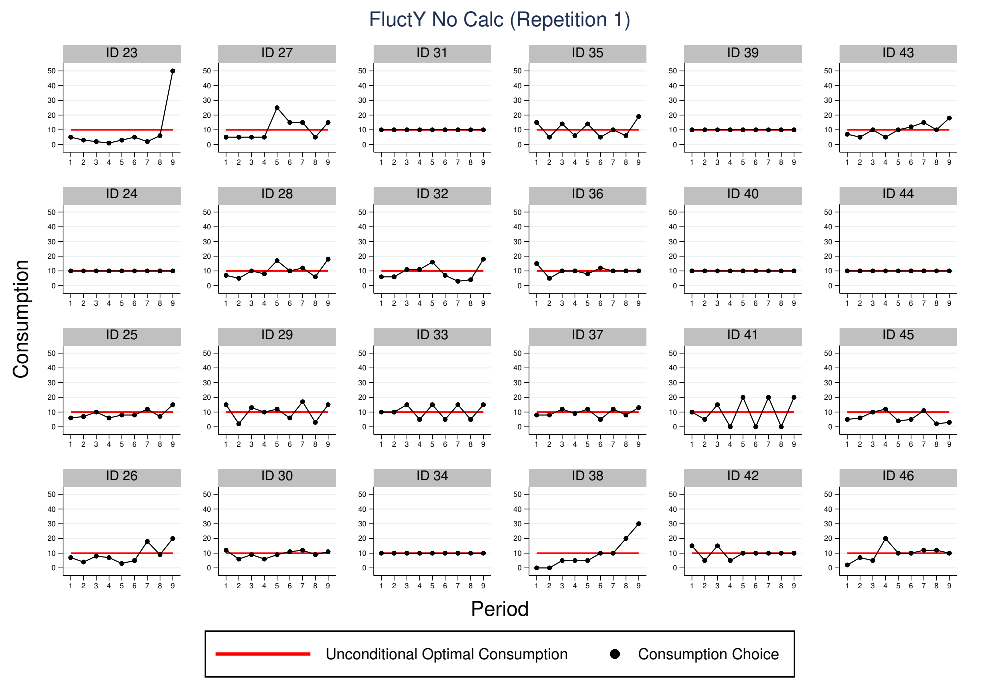


Figure I.19: FluctY No Calc, Repetition 1 (Session 2)

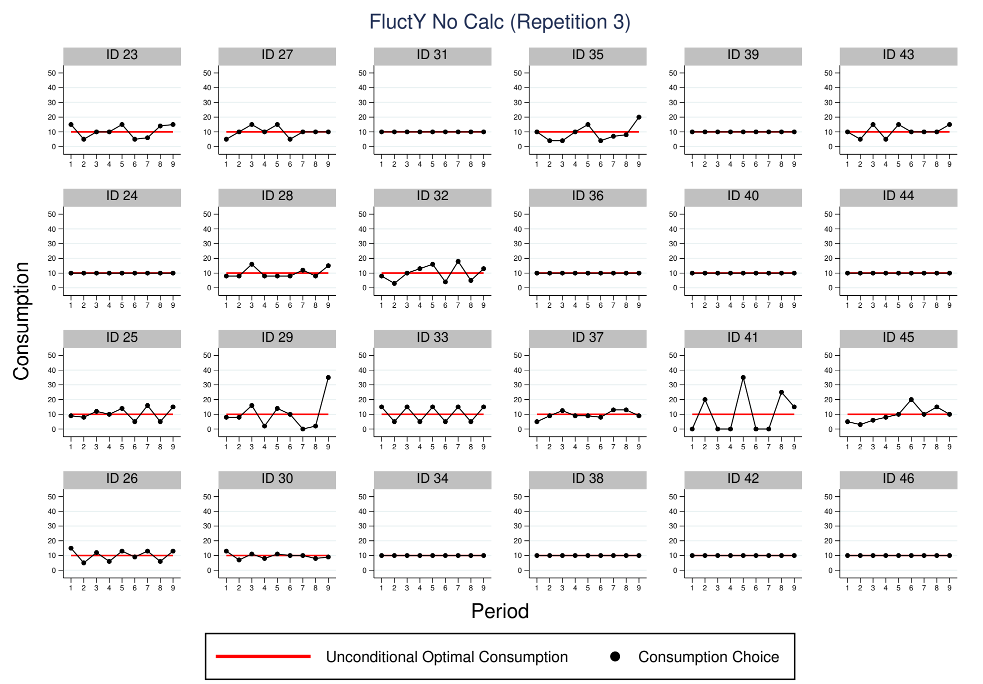


Figure I.20: FluctY No Calc, Repetition 3 (Session 2)

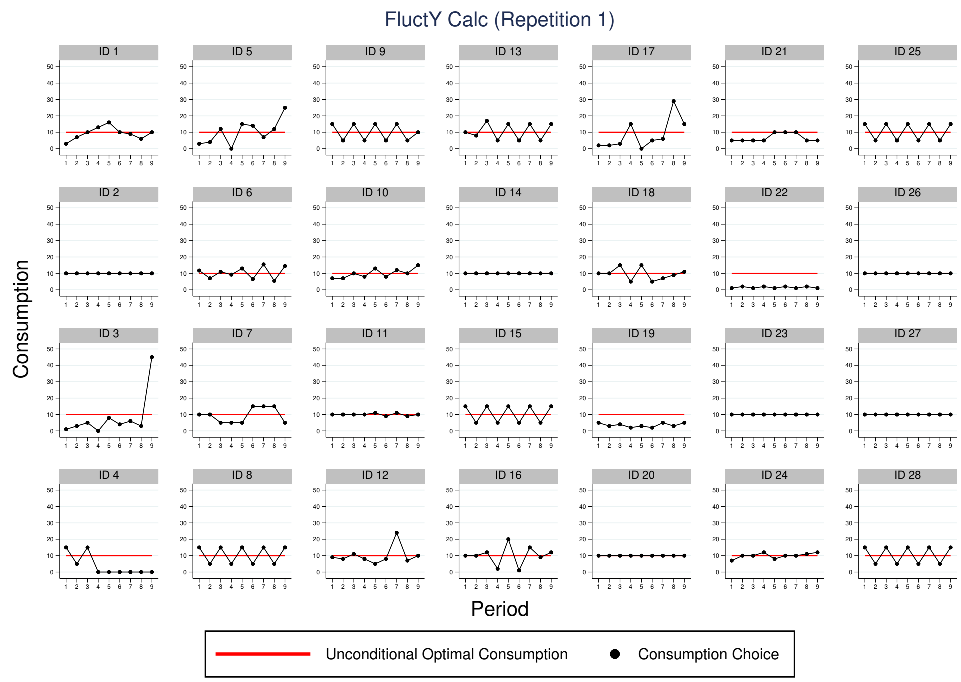


Figure I.21: FluctY Calc, Repetition 1 (Session 1)

Figure I.22: FluctY Calc, Repetition 3 (Session 1)

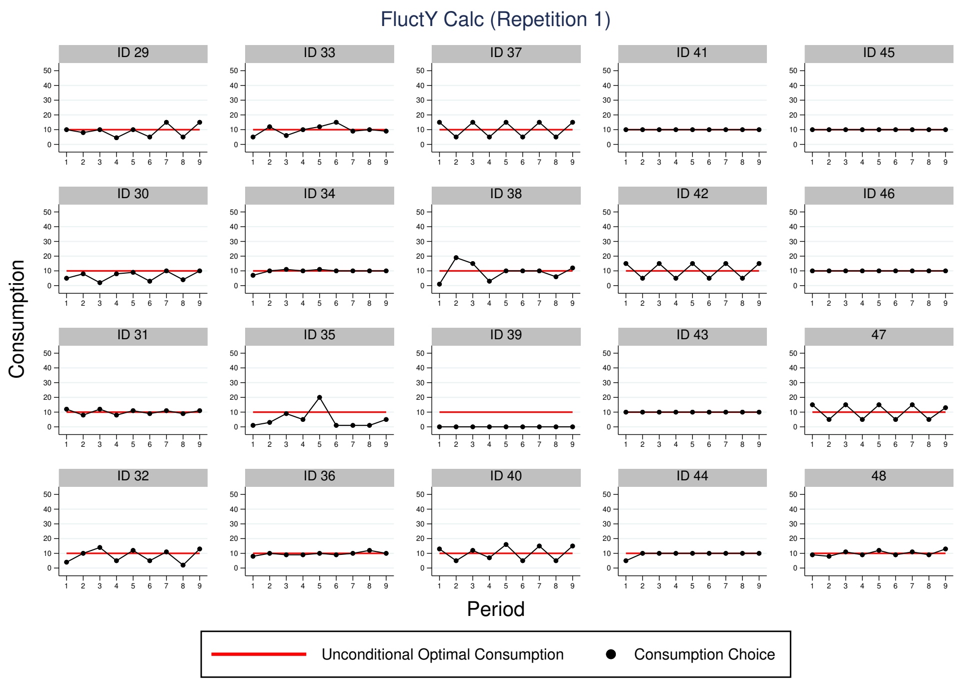


Figure I.23: FluctY No Calc, Repetition 1 (Session 2)

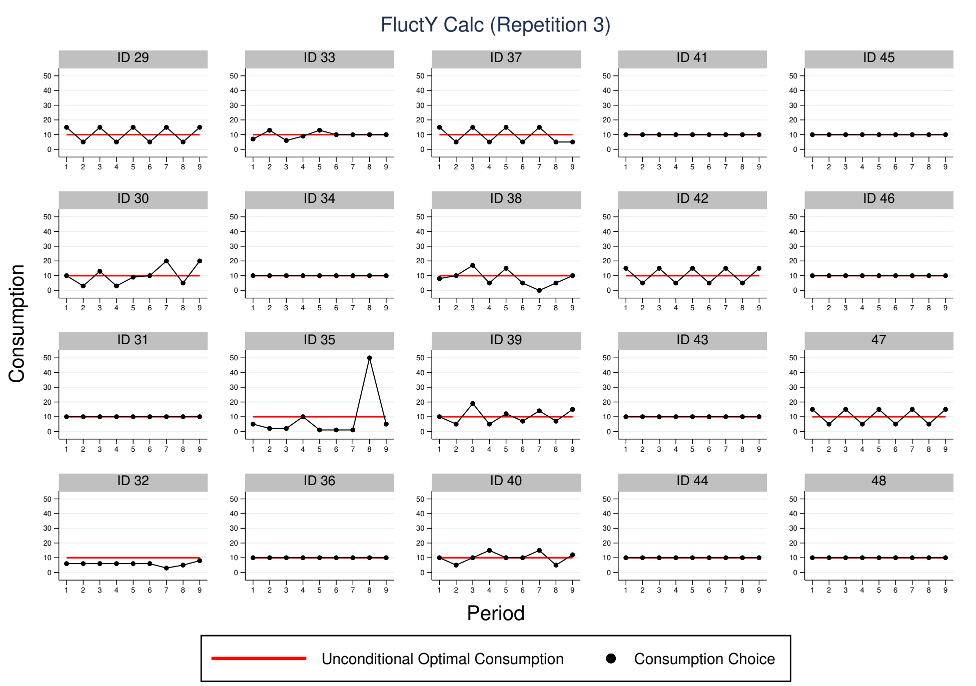


Figure I.24: FluctY Calc, Repetition 3 (Session 2)

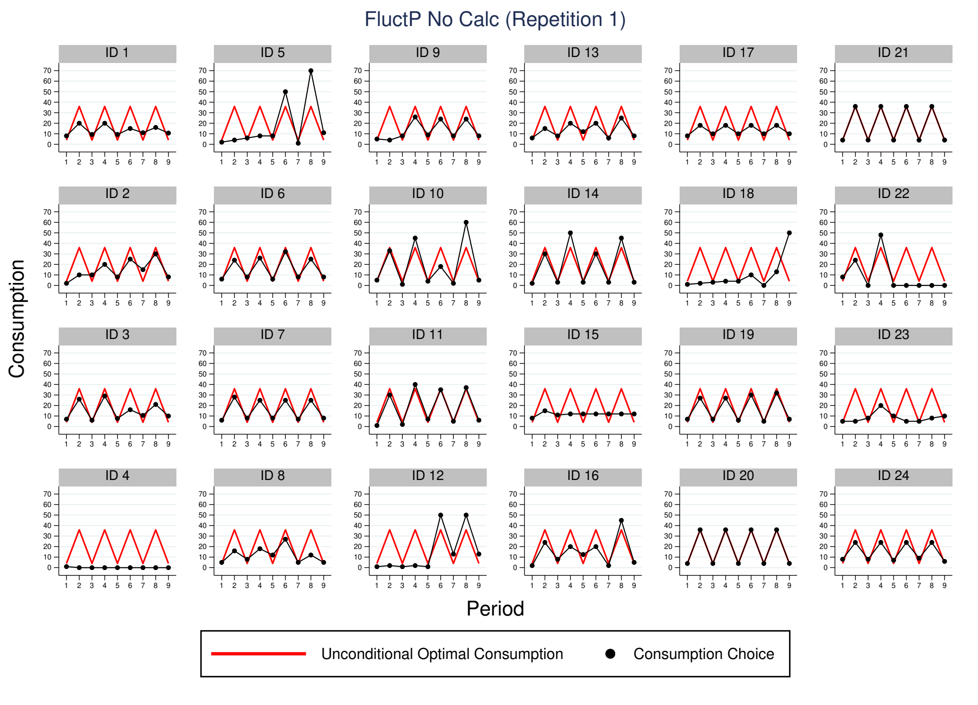


Figure I.25: FluctP No Calc, Repetition 1 (Session 1)

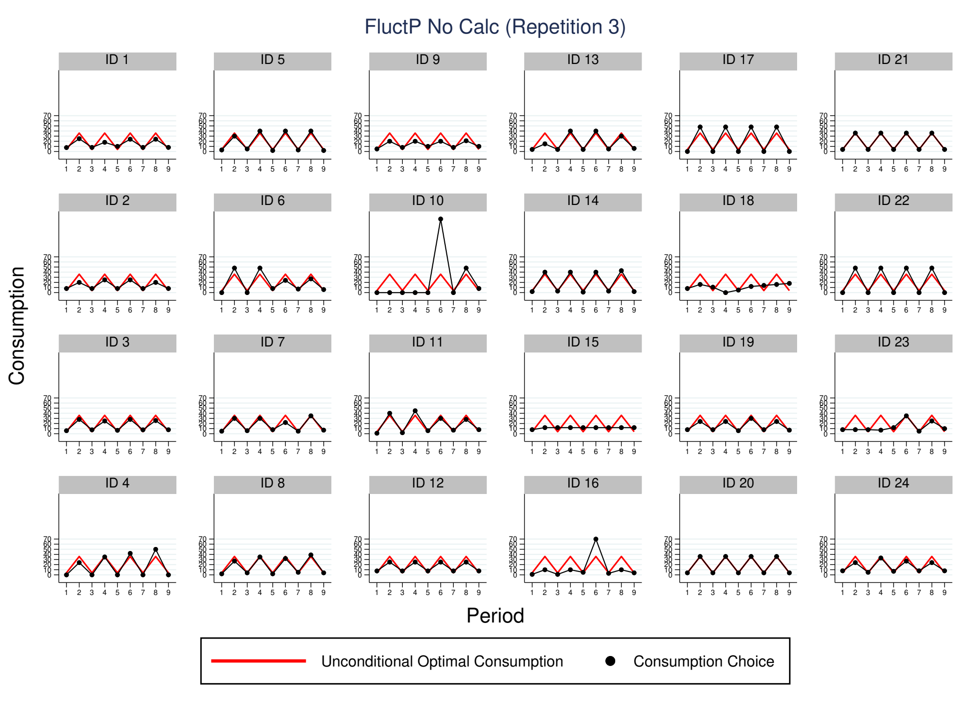


Figure I.26: FluctP No Calc, Repetition 3 (Session 1)

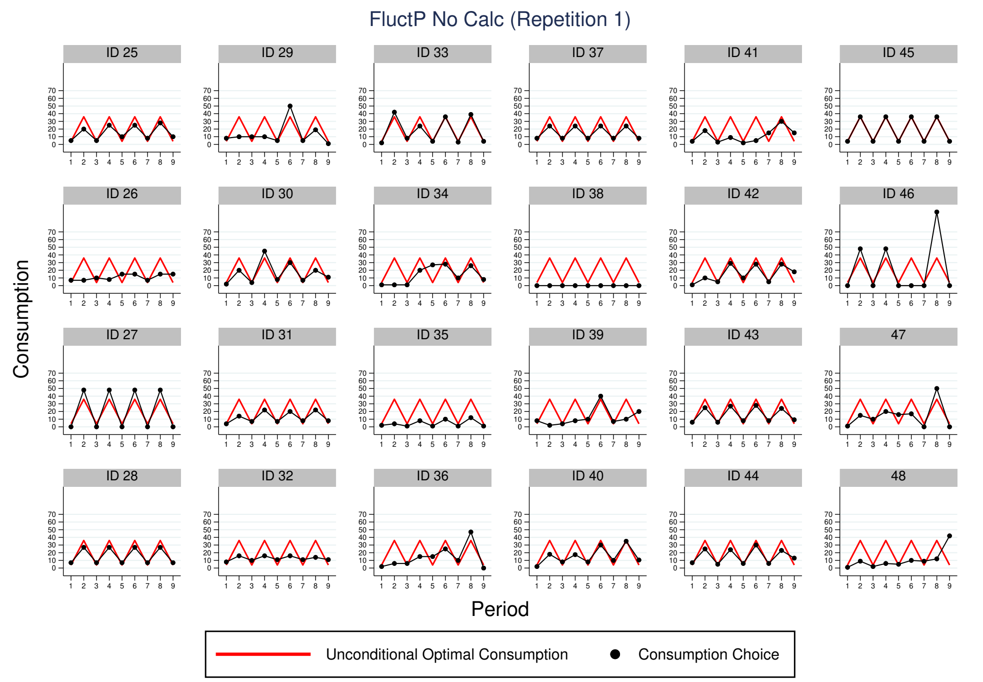


Figure I.27: FluctP No Calc, Repetition 1 (Session 2)

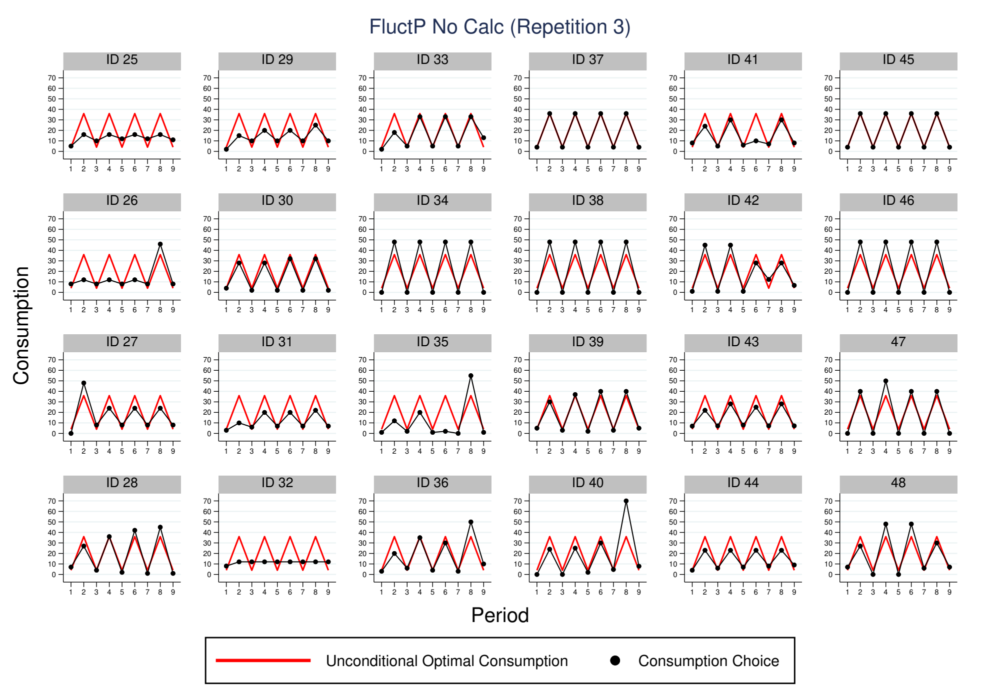


Figure I.28: FluctP No Calc, Repetition 3 (Session 2)

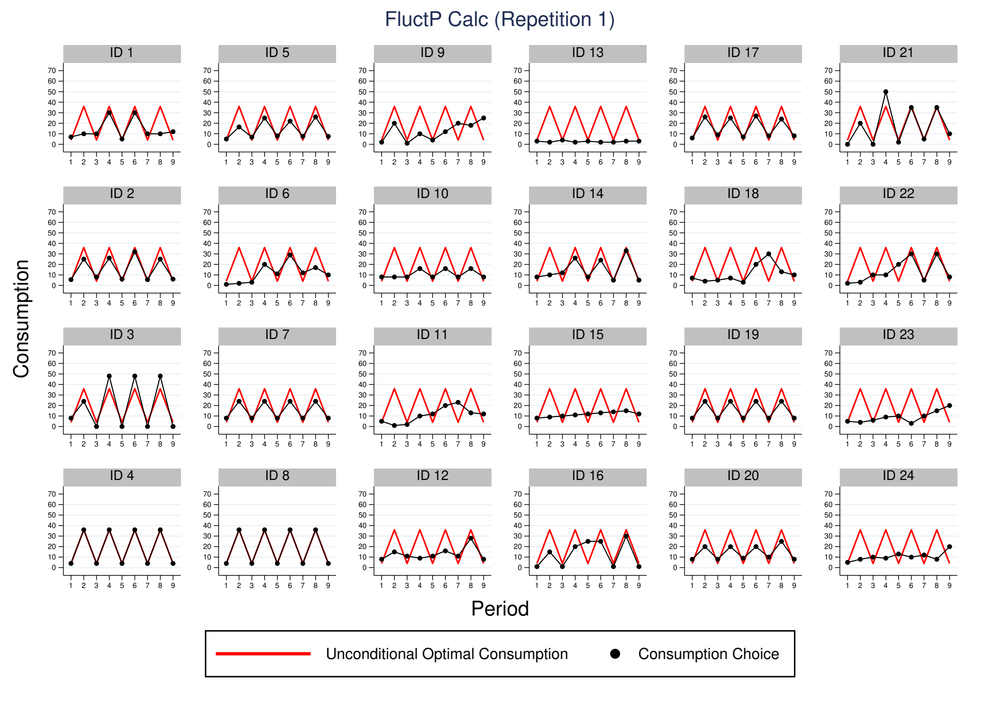


Figure I.29: FluctP Calc, Repetition 1 (Session 1)

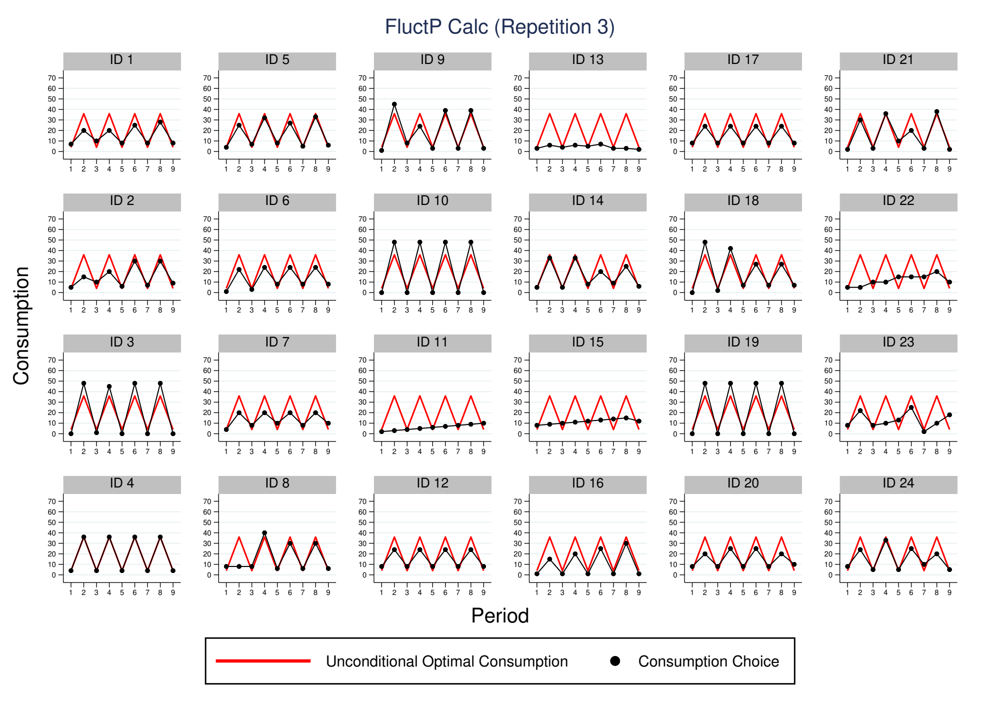


Figure I.30: FluctP Calc, Repetition 3 (Session 1)

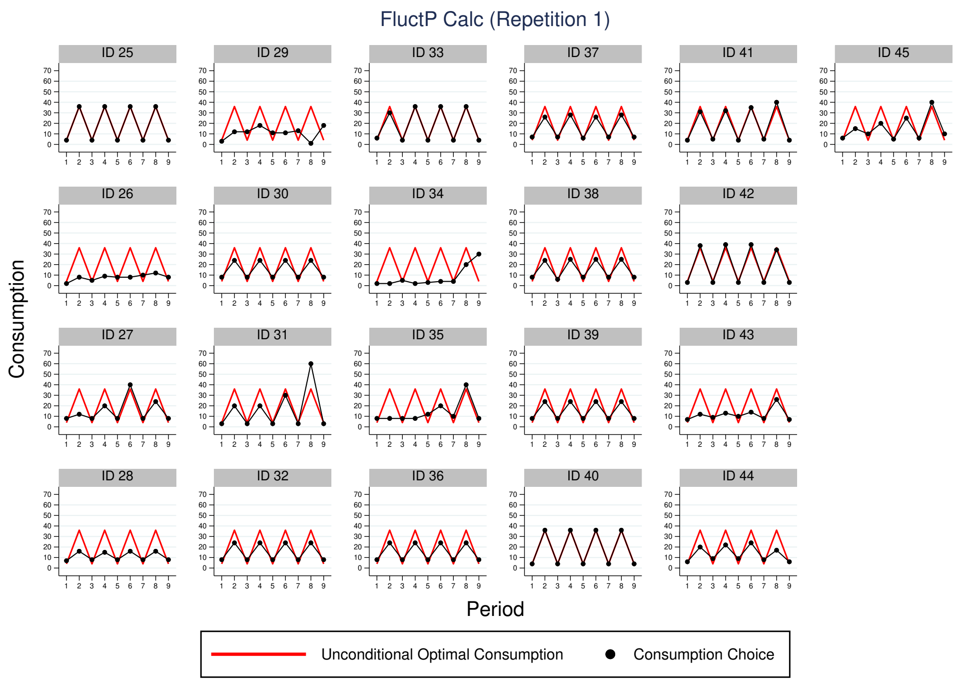


Figure I.31: FluctP No Calc, Repetition 1 (Session 2)

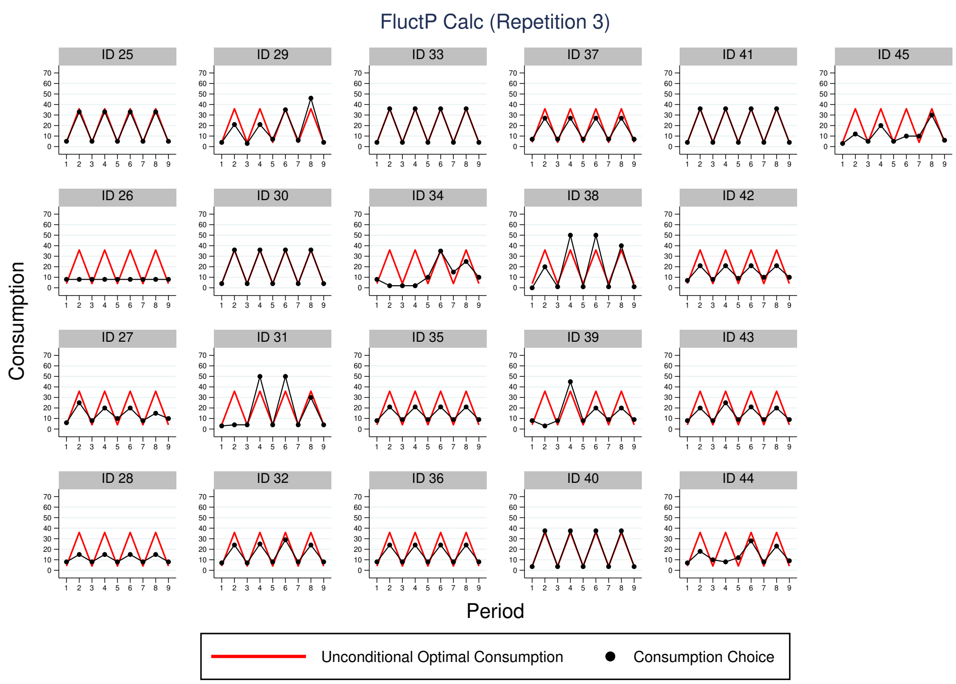


Figure I.32: FluctP Calc, Repetition 3 (Session 2)

J Instructions

J.1 Main Instructions

J.1.1 Calc Sessions

The instructions distributed to subjects in treatments where the calculator was enabled are reproduced on the subsequent pages. All subjects received identical instructions, with the exception of those in the PosIR treatment, where minor adjustments were made to incorporate interest rates.

CRABE Lab
Centre for Research in Adaptive Behaviour in Economics

Participant Instructions

You are taking part in an economics experiment in which you will be able to earn money. Your earnings will depend on your decisions. It is therefore important to read these instructions with attention. During the experiment you are not allowed to communicate with any other participant. If you do not follow these instructions you will be excluded from the experiment and receive only the show-up payment of $7.

The experiment consist of **4 PARTS**. <u>These instructions are for the first part only</u>. After completing each part of the experiment, you will receive instructions for each subsequent part. The earnings you accumulate will be added up at the end of the experiment, and converted to Canadian dollars. Specifically, for every **25 points** you accumulate, you will obtain **$1**. You will also receive a $7 show-up payment (if you arrived on time). Before you leave the lab, you will sign a receipt and will be paid in cash privately.

First Part

In the first part of this experiment, you will be making decisions on how much to save and spend over a number of periods.

There are two objects of interest in this experiment, **<u>tokens</u>** and **<u>points</u>**. The total number of points you accumulate in a repetition will determine your monetary payoff.

You will participate in 3 repetitions of the exact same experiment, each consisting of 10 periods.
In every repetition, at the beginning of each period, you will receive some tokens. In addition to these tokens, you may have additional tokens saved from previous periods.

<u>Purchase Decision</u>

Each period, after viewing the total number of tokens you have available, you must decide how many units of output you would like to buy using tokens. When you submit your purchases orders you can use up to two decimal places (the minimum you can buy is 0). Output is sold at a certain price per unit. The output you buy will be transformed into points. The more output you acquire in a period, the higher will be your points earnings for that period. Importantly, as you purchase more output in a single period, you will earn fewer and fewer additional points. Your first unit will be worth the most, and each subsequent point will be worth less.

After submitting your purchase order, the computer will calculate your expenditure as following:

Expenditure = Number of units purchased x Price per unit.

This expenditure will be deducted from your token balance. If, at a certain period, you do not have enough tokens to buy output, you will not be able to complete your order. You may not spend more than your token balance.

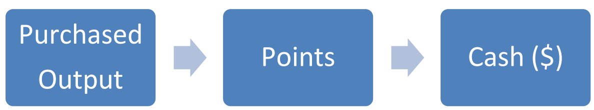
Your token balance at the start of each period is given by the following:

Tokens at the beginning of current period = Tokens from previous period + Current income

<u>Compensation</u>

The points will be converted into Canadian dollars at the end of the experiment. You will be compensated according to the following rules:

1. The game will be repeated 3 times. At the end of the experiment, the computer will randomly select one of the repetitions for payment. That is, there is an equal chance that any repetition will be the one that counts for payment.
2. The diagram below shows the relation between purchased output, points, and cash ($).



3. The amount of points you earn in the randomly selected repetition will be converted into CAD at the rate:

25 points = $1

4. Any tokens held at the end of a repetition are worthless.
5. Additionally, you will receive 4 points for every control question you answer correctly in the first attempt; 3 points for every question you answer correctly in the second attempt; and 2 points for every question you answer correctly in the third attempt.

<u>Information</u>

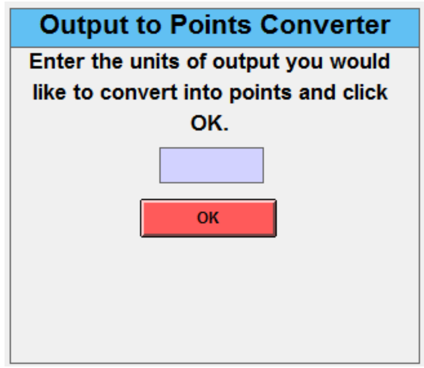
You will be provided precise information about the income and prices you will face in all 10 periods of each repetition. That is, there is no uncertainty about these variables. You will also have information about your previous decisions and economic variables. <u>Please note that prices and income may vary from repetition to repetition.</u>

<u>Repetitions</u>

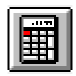
The experiment will consist of 3 repetitions of 10 periods each. After a repetition is completed, you will see a Review Screen that will display your total points from that repetition. There will be no carryover of tokens or points between repetitions. When a new repetition begins, all token balances and points will be reset to zero.

Output to Points Converter

Throughout the experiment, you will have access to an Output to Points Converter that you may use to help you make decisions. To use the Output to Points Converter, you will need to enter the number of units of output you wish to convert to points. After clicking the OK button, the computer will display the points associated with the output you entered.



Standard Calculator

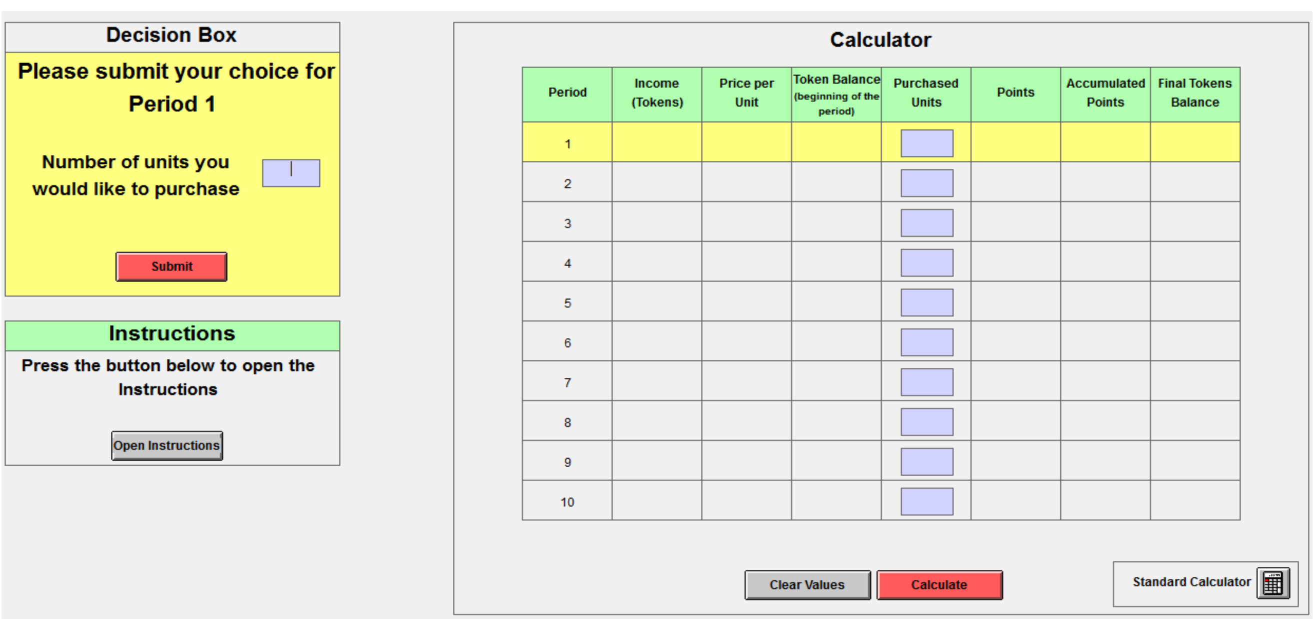
You may use a standard calculator by clicking on 

Payoff Calculator

Throughout the experiment, you will have access to a calculator that you may use to help you make decisions.

To use the calculator, you will need to fill in hypothetical values for your purchase decisions in the current and future periods. After all your hypothetical decisions have been submitted, you will be able to see what your points and tokens balance would be. You can consider as many hypothetical combinations as you want before making each decision.

Before the experiment starts you will learn how to use the calculator; you will be able to practice with it; and finally, you will have to answer some paid control questions.



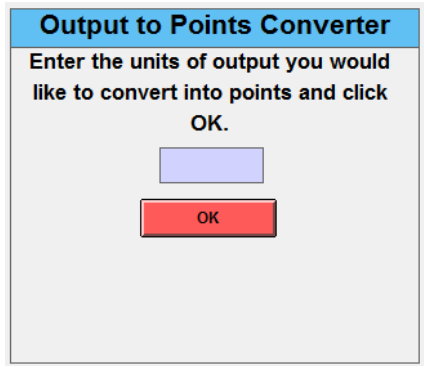
Remember that your actual purchase decision has to be entered on the left hand side of the screen.

J.1.2 No Calc Sessions

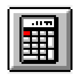
For the sessions in which the budgeting calculator was not enabled the third page of the instructions was adapted as shown below.

Output to Points Converter

Throughout the experiment, you will have access to an Output to Points Converter that you may use to help you make decisions. To use the Output to Points Converter, you will need to enter the number of units of output you wish to convert to points. After clicking the OK button, the computer will display the points associated with the output you entered.

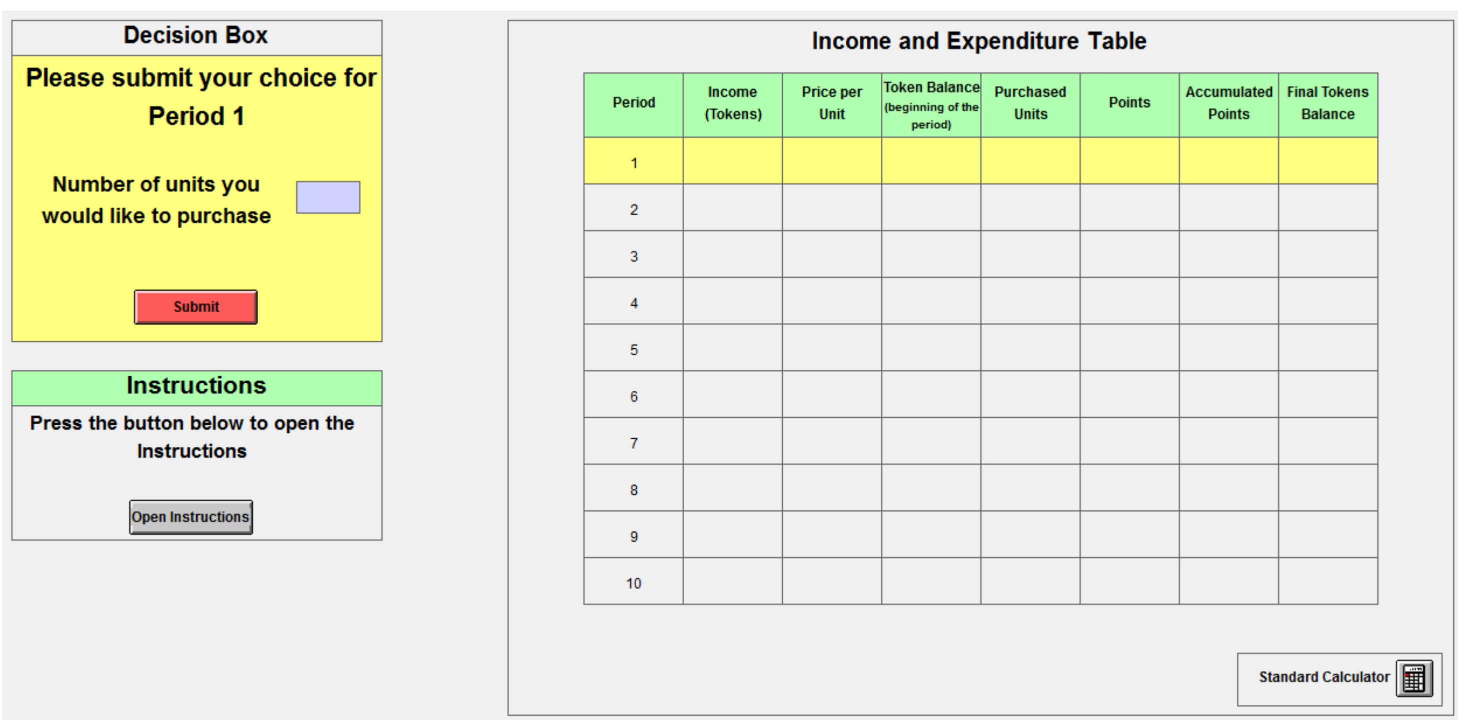


Standard Calculator

You may use a standard calculator by clicking on 

Income and Expenditure Table

Throughout the experiment, you will have access to an Income and Expenditure Table that you may use to help you make decisions.
Each period, you will be able to see what your points and tokens balance are.
Before the experiment starts, you will learn how to read the table. You will also have to answer some paid control questions in which you will be able to put to the test your ability to read the table.



Remember that your actual purchase decision has to be entered on the left hand side of the screen.

J.2 Interactive Instructions

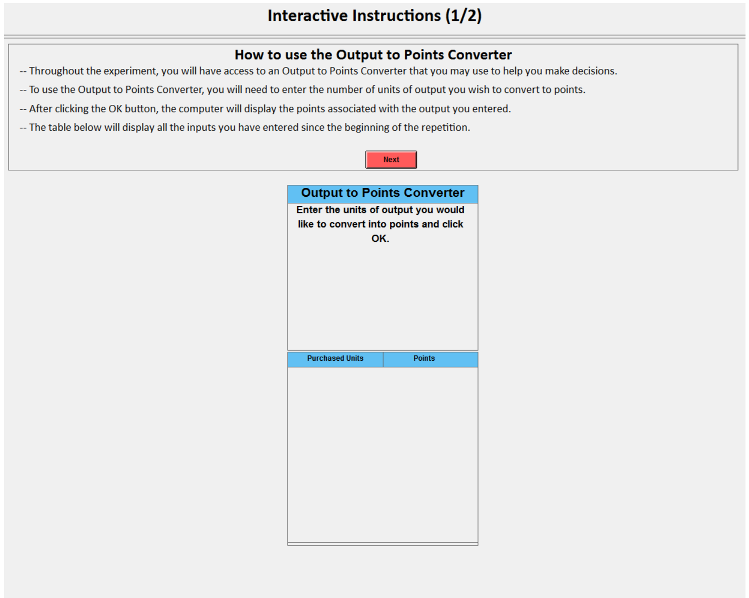


Figure J.1: Screenshot for interactive instructions 1

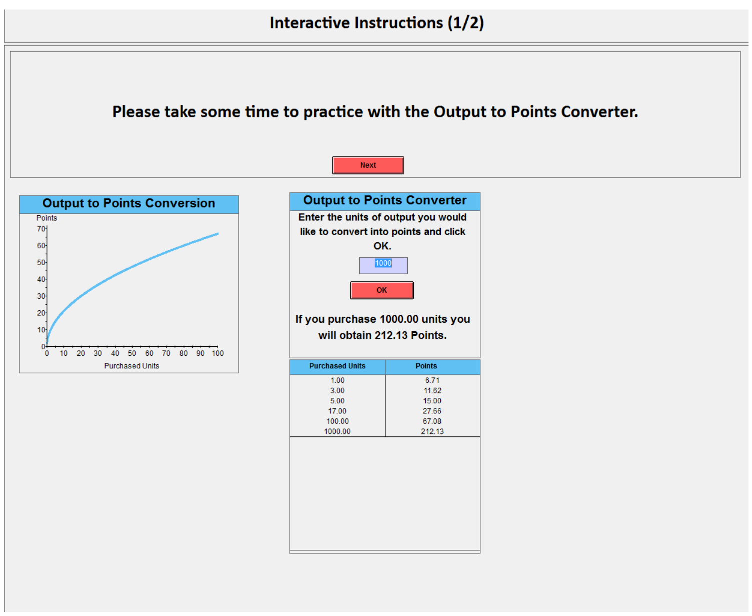


Figure J.2: Screenshot for interactive instructions 2

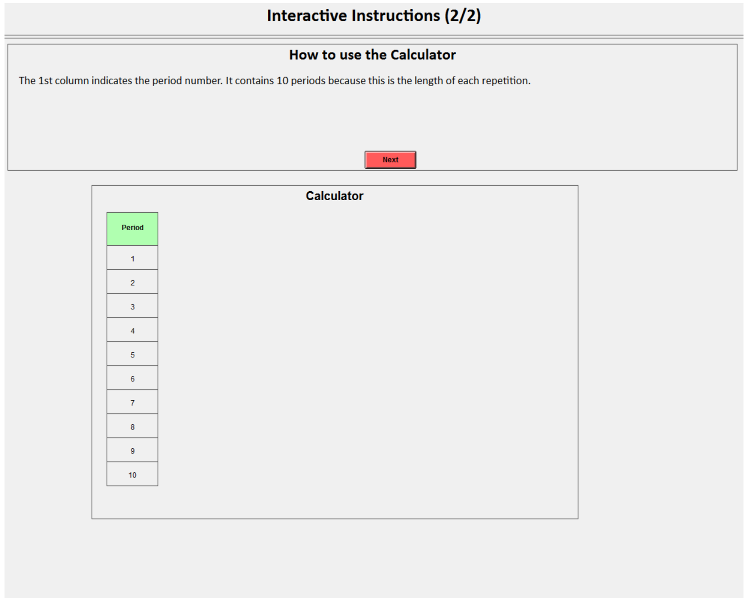


Figure J.3: Screenshot for interactive instructions 3

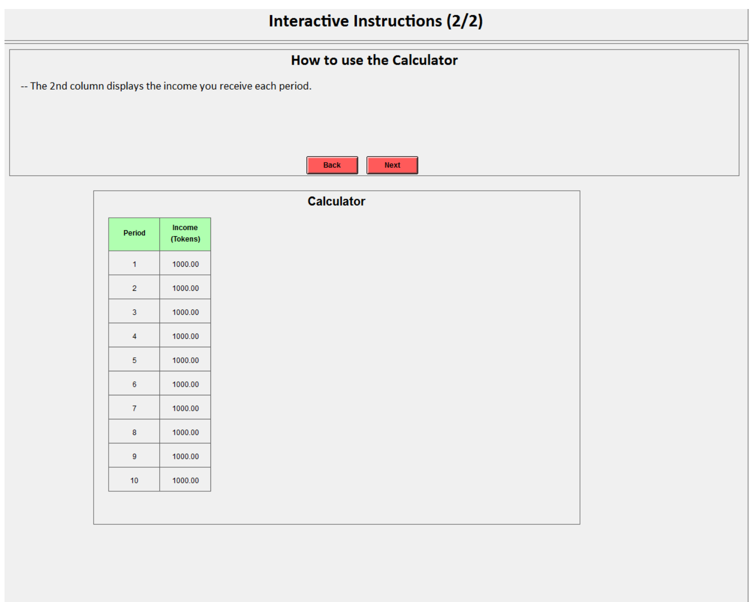
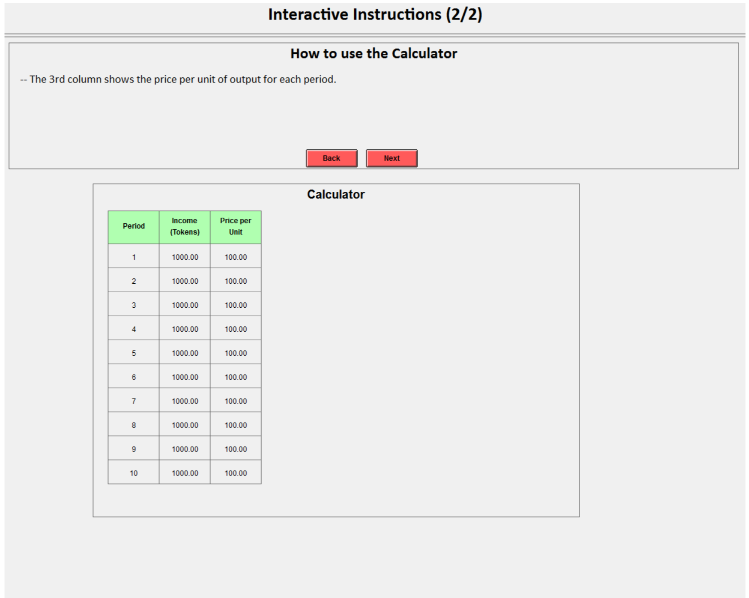
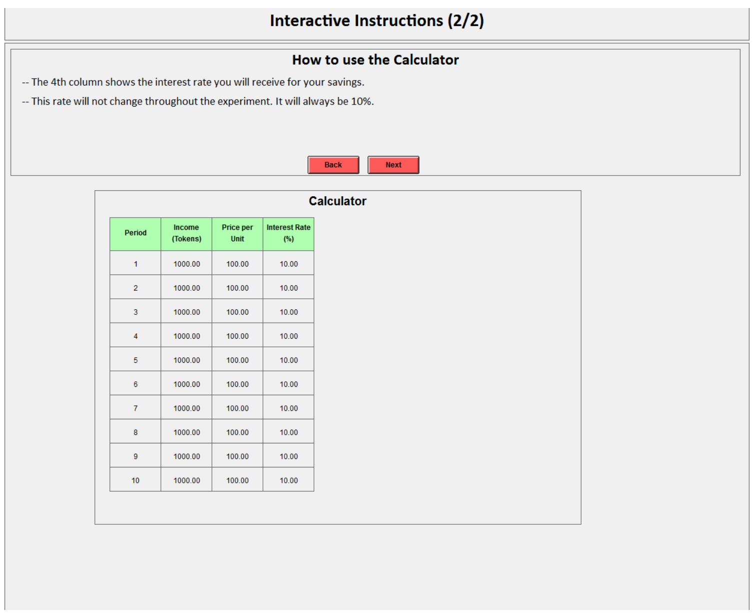


Figure J.4: Screenshot for interactive instructions 4



Period	Income (Tokens)	Price per Unit
1	1000.00	100.00
2	1000.00	100.00
3	1000.00	100.00
4	1000.00	100.00
5	1000.00	100.00
6	1000.00	100.00
7	1000.00	100.00
8	1000.00	100.00
9	1000.00	100.00
10	1000.00	100.00

Figure J.5: Screenshot for interactive instructions 5



Period	Income (Tokens)	Price per Unit	Interest Rate (%)
1	1000.00	100.00	10.00
2	1000.00	100.00	10.00
3	1000.00	100.00	10.00
4	1000.00	100.00	10.00
5	1000.00	100.00	10.00
6	1000.00	100.00	10.00
7	1000.00	100.00	10.00
8	1000.00	100.00	10.00
9	1000.00	100.00	10.00
10	1000.00	100.00	10.00

Figure J.6: Screenshot for interactive instructions 6

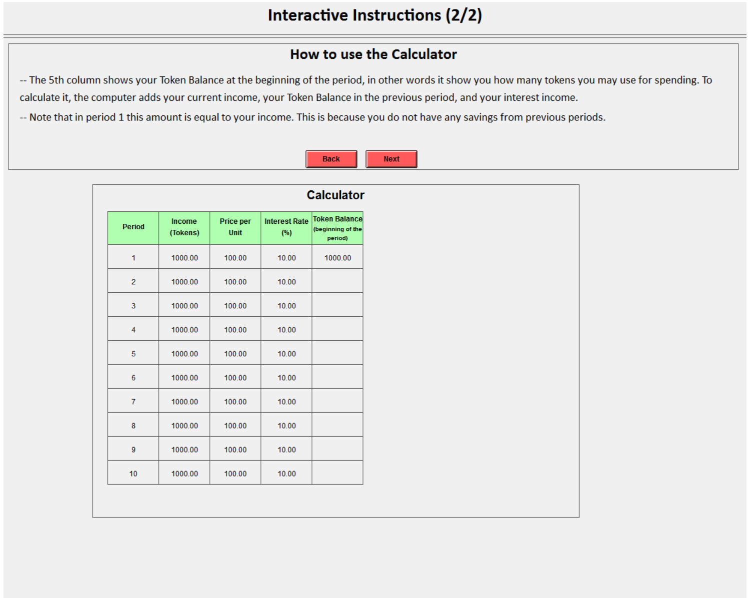


Figure J.7: Screenshot for interactive instructions 7

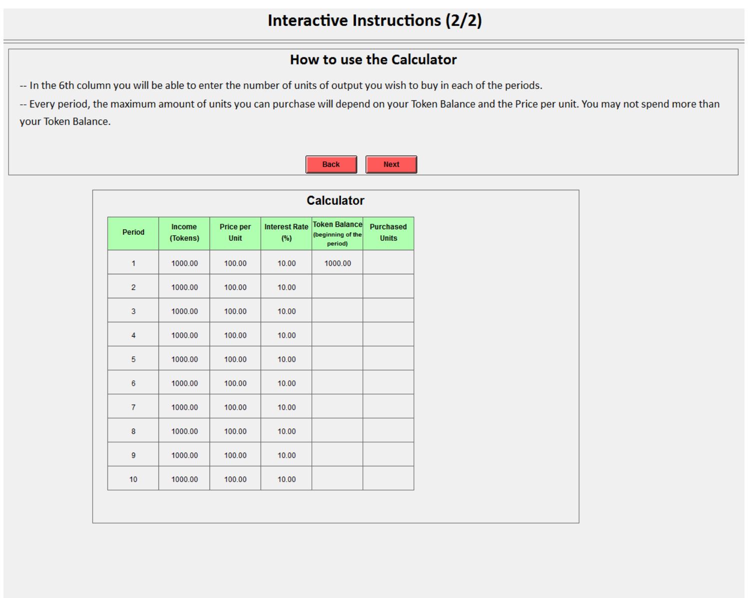


Figure J.8: Screenshot for interactive instructions 8

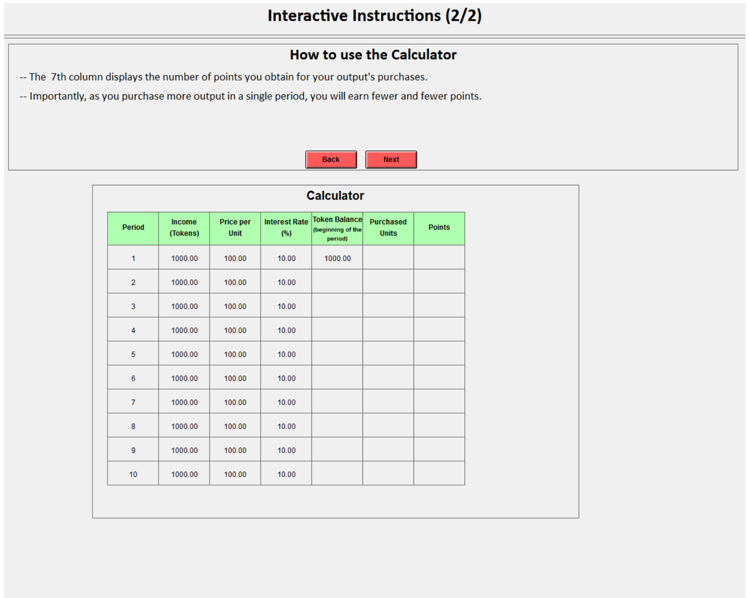


Figure J.9: Screenshot for interactive instructions 9

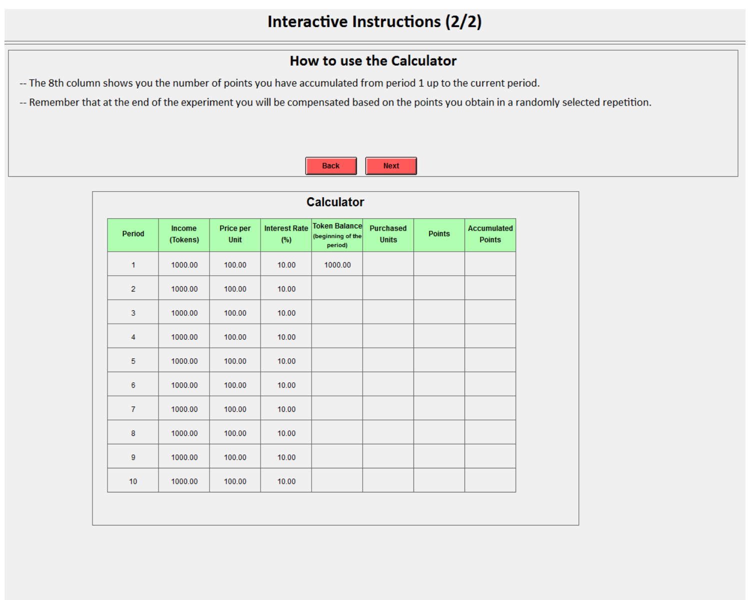
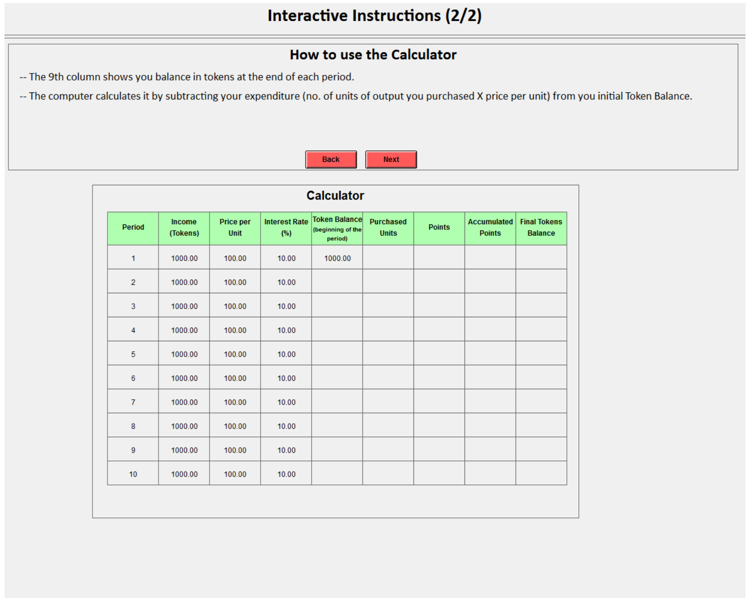
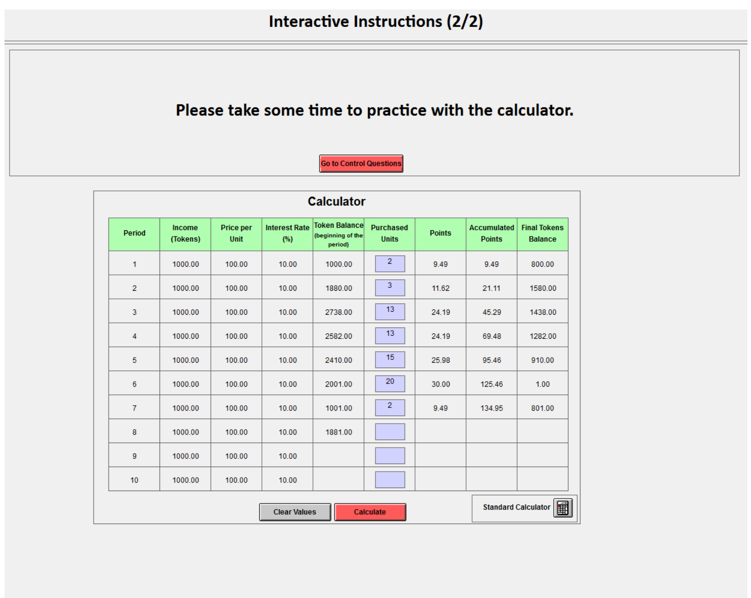


Figure J.10: Screenshot for interactive instructions 10



Period	Income (Tokens)	Price per Unit	Interest Rate (%)	Token Balance (beginning of the period)	Purchased Units	Points	Accumulated Points	Final Tokens Balance
1	1000.00	100.00	10.00	1000.00				
2	1000.00	100.00	10.00					
3	1000.00	100.00	10.00					
4	1000.00	100.00	10.00					
5	1000.00	100.00	10.00					
6	1000.00	100.00	10.00					
7	1000.00	100.00	10.00					
8	1000.00	100.00	10.00					
9	1000.00	100.00	10.00					
10	1000.00	100.00	10.00					

Figure J.11: Screenshot for interactive instructions 11



Period	Income (Tokens)	Price per Unit	Interest Rate (%)	Token Balance (beginning of the period)	Purchased Units	Points	Accumulated Points	Final Tokens Balance
1	1000.00	100.00	10.00	1000.00	2	9.49	9.49	800.00
2	1000.00	100.00	10.00	1880.00	3	11.62	21.11	1580.00
3	1000.00	100.00	10.00	2738.00	13	24.19	45.29	1438.00
4	1000.00	100.00	10.00	2582.00	13	24.19	69.48	1282.00
5	1000.00	100.00	10.00	2410.00	15	25.98	95.46	910.00
6	1000.00	100.00	10.00	2001.00	20	30.00	125.46	1.00
7	1000.00	100.00	10.00	1001.00	2	9.49	134.95	801.00
8	1000.00	100.00	10.00	1881.00				
9	1000.00	100.00	10.00					
10	1000.00	100.00	10.00					

Figure J.12: Screenshot for interactive instructions 12

K Computer Interface

K.1 Control Questions

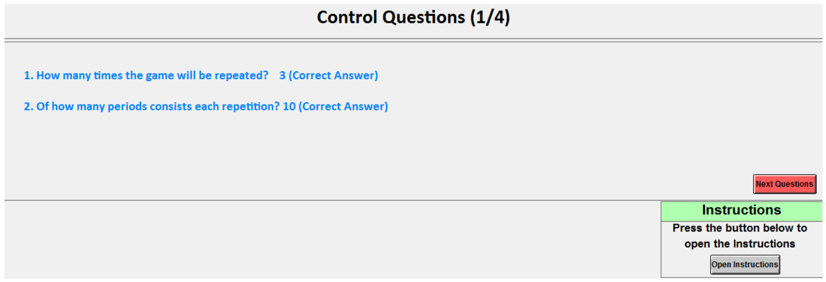


Figure K.1: Screenshot for Control Question 1

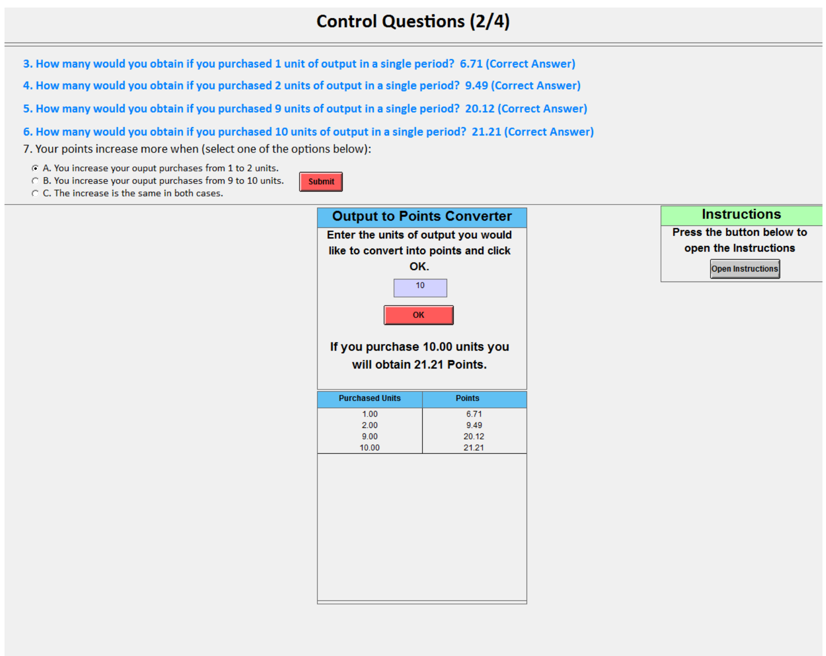
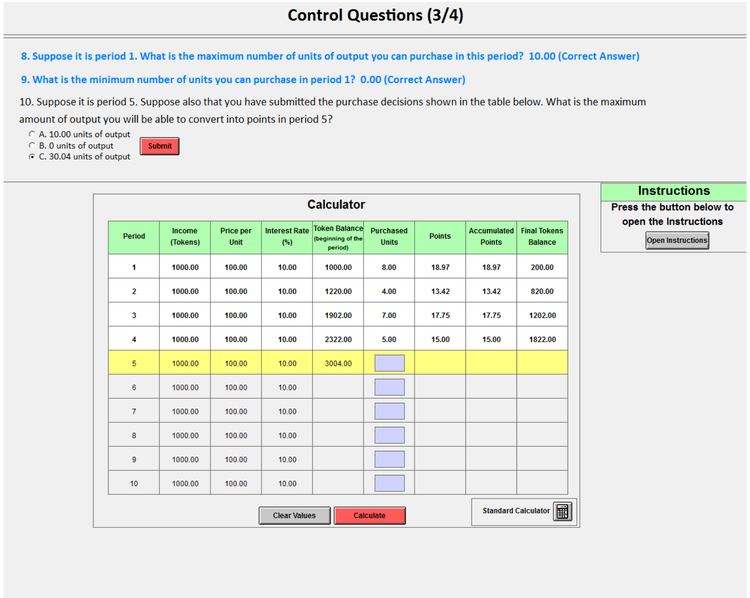
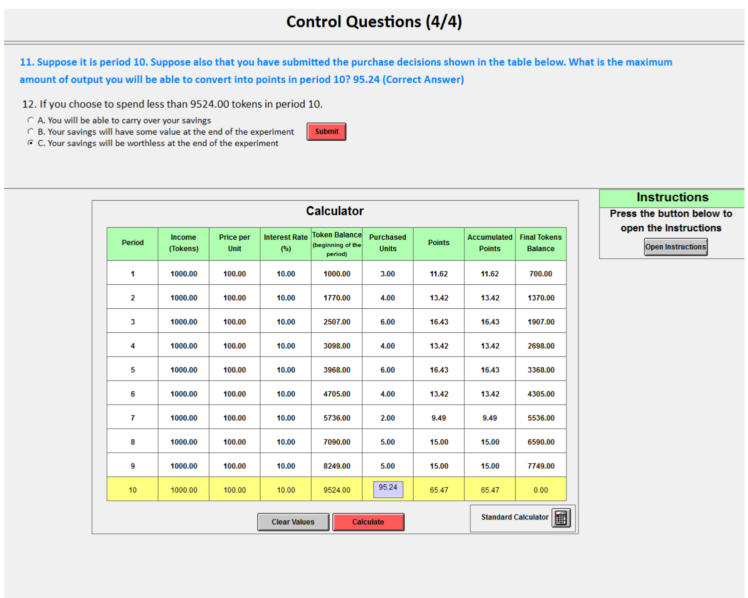


Figure K.2: Screenshot for Control Question 2



Period	Income (Tokens)	Price per Unit	Interest Rate (%)	Token Balance (beginning of the period)	Purchased Units	Points	Accumulated Points	Final Tokens Balance
1	1000.00	100.00	10.00	1000.00	8.00	18.97	18.97	200.00
2	1000.00	100.00	10.00	1220.00	4.00	13.42	13.42	820.00
3	1000.00	100.00	10.00	1902.00	7.00	17.75	17.75	1202.00
4	1000.00	100.00	10.00	2322.00	5.00	15.00	15.00	1822.00
5	1000.00	100.00	10.00	3004.00				
6	1000.00	100.00	10.00					
7	1000.00	100.00	10.00					
8	1000.00	100.00	10.00					
9	1000.00	100.00	10.00					
10	1000.00	100.00	10.00					

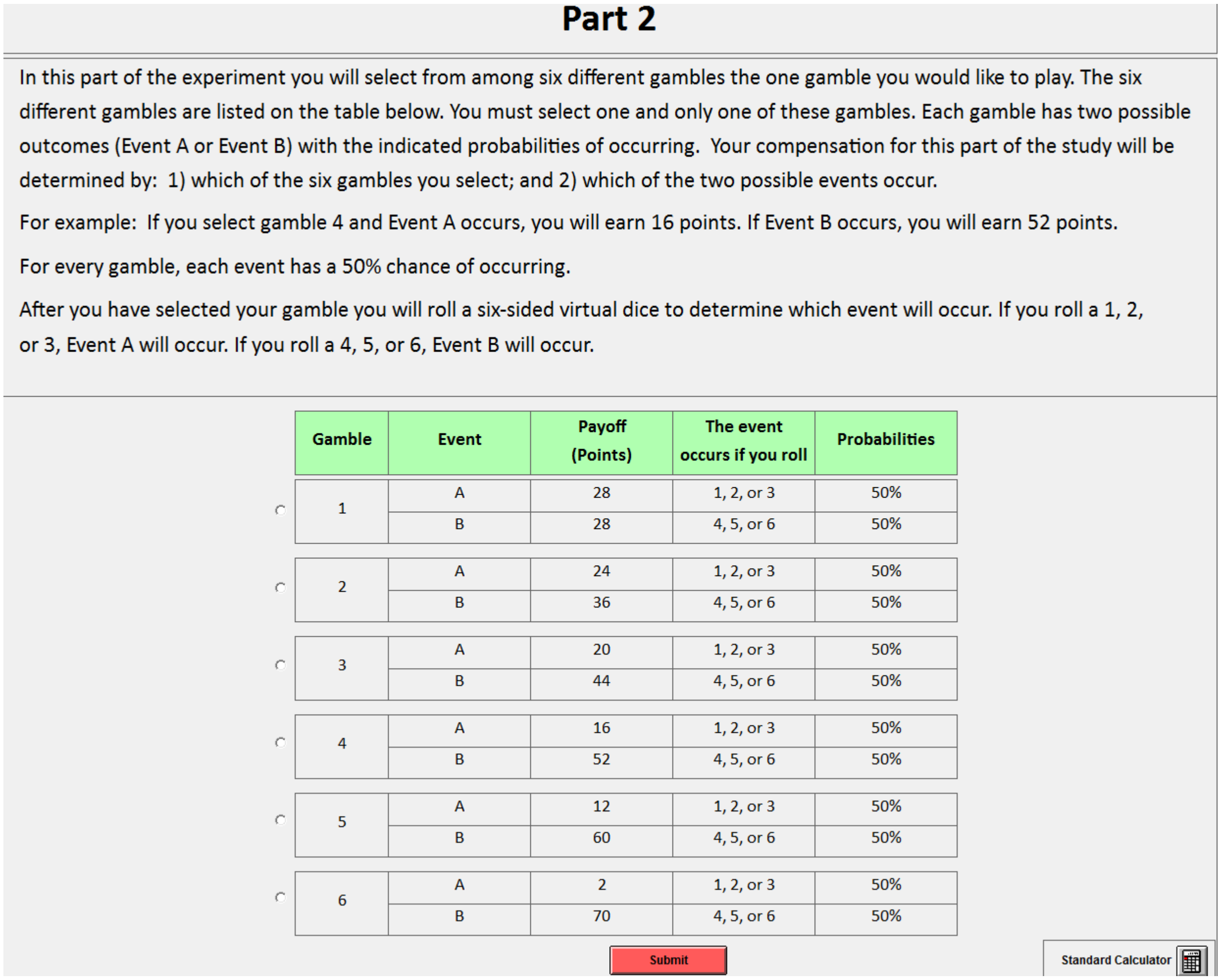
Figure K.3: Screenshot for Control Question 3



Period	Income (Tokens)	Price per Unit	Interest Rate (%)	Token Balance (beginning of the period)	Purchased Units	Points	Accumulated Points	Final Tokens Balance
1	1000.00	100.00	10.00	1000.00	3.00	11.62	11.62	700.00
2	1000.00	100.00	10.00	1770.00	4.00	13.42	13.42	1370.00
3	1000.00	100.00	10.00	2507.00	6.00	16.43	16.43	1907.00
4	1000.00	100.00	10.00	3098.00	4.00	13.42	13.42	2698.00
5	1000.00	100.00	10.00	3968.00	6.00	16.43	16.43	3368.00
6	1000.00	100.00	10.00	4705.00	4.00	13.42	13.42	4305.00
7	1000.00	100.00	10.00	5736.00	2.00	9.49	9.49	5536.00
8	1000.00	100.00	10.00	7090.00	5.00	15.00	15.00	6590.00
9	1000.00	100.00	10.00	8249.00	5.00	15.00	15.00	7749.00
10	1000.00	100.00	10.00	9524.00	95.24	65.47	65.47	0.00

Figure K.4: Screenshot for Control Question 4

K.2 Risk Preferences Elicitation



Part 2

In this part of the experiment you will select from among six different gambles the one gamble you would like to play. The six different gambles are listed on the table below. You must select one and only one of these gambles. Each gamble has two possible outcomes (Event A or Event B) with the indicated probabilities of occurring. Your compensation for this part of the study will be determined by: 1) which of the six gambles you select; and 2) which of the two possible events occur.

For example: If you select gamble 4 and Event A occurs, you will earn 16 points. If Event B occurs, you will earn 52 points.

For every gamble, each event has a 50% chance of occurring.

After you have selected your gamble you will roll a six-sided virtual dice to determine which event will occur. If you roll a 1, 2, or 3, Event A will occur. If you roll a 4, 5, or 6, Event B will occur.

Gamble	Event	Payoff (Points)	The event occurs if you roll	Probabilities
1	A	28	1, 2, or 3	50%
	B	28	4, 5, or 6	50%
2	A	24	1, 2, or 3	50%
	B	36	4, 5, or 6	50%
3	A	20	1, 2, or 3	50%
	B	44	4, 5, or 6	50%
4	A	16	1, 2, or 3	50%
	B	52	4, 5, or 6	50%
5	A	12	1, 2, or 3	50%
	B	60	4, 5, or 6	50%
6	A	2	1, 2, or 3	50%
	B	70	4, 5, or 6	50%

Submit

Standard Calculator

Figure K.5: Screenshot for Stage 2

K.3 Financial Literacy

Part 3

1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- A. More than $102
- B. Exactly $102
- C. Less than $102

Submit

Standard Calculator

2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account?

- A. More than today
- B. Exactly the same as today
- C. Less than today

Submit

Standard Calculator

3. Do you think that the following statement is true or false? "Buying a single company stock usually provides a safer return than a stock mutual fund."

- A. True
- B. False
- C. There is not enough information

Submit

Standard Calculator

4. Do you think the following statement is true or false: A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest over the life of the loan will be less?

- A. True
- B. False
- C. There is not enough information

Submit

Standard Calculator

5. If interest rates rise, what will typically happen to bond prices?

- A. They will rise
- B. They will fall
- C. They will stay the same
- D. There is no relationship

Submit

Standard Calculator

Figure K.6: Screenshot for Stage 3

K.4 Race to 60

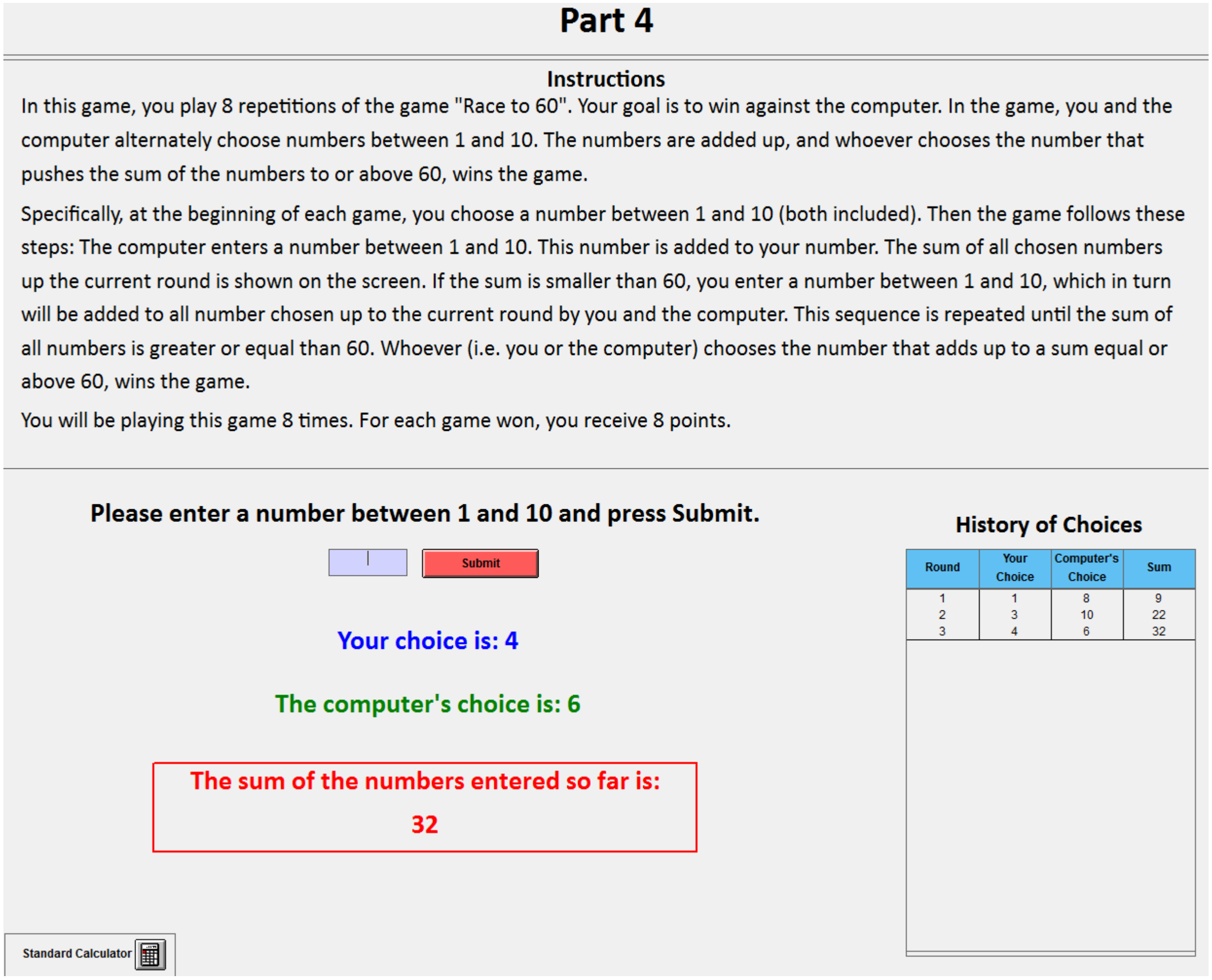


Figure K.7: Screenshot for Stage 3