Dynamic Optimization Meets Budgeting: Unraveling Financial Complexities

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Abstract

This paper explores the complexities of dynamic optimization in consumption and savings decisions, examining how individuals navigate economic variables such as fluctuating incomes, variable prices, and interest rates. Our findings indicate that optimization is challenging, leading to suboptimal choices even in straightforward scenarios with stable parameters, full information, and no uncertainty. These challenges escalate in more complex situations involving factors like inflation and compound interest on savings, where we observed a pronounced tendency towards over-smoothing consumption. Additionally, we introduce a novel experimental tool: a budgeting calculator designed to assist with consumption planning. While its use did not consistently improve decision-making performance, it provided valuable insights by collecting non-choice data, including subjects' planning strategies and horizons – an approach not previously utilized in studies of dynamic optimization. Some participants effectively used the calculator to devise and execute optimal consumption strategies across various scenarios, spanning the full duration of the experiment. However, those who made only partial plans struggled to identify optimal paths in more complex situations. The study also highlights the cognitive challenges posed by extended planning horizons, suggesting that shortening decision-making periods could be more beneficial for optimization than experiential learning.

JEL classifications: C92, E13, H31, H4, E62

Keywords: Consumption-Saving Decisions · Dynamic Optimization · Laboratory Experiment · Budgeting Tools · Complexity.

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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, labor markets, environmental policy formation, and especially, the dynamics of saving and consumption. Economic theories often suggest 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 emphasized by recent research (Gabaix and Graeber, 2023; Oprea, 2022). 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 the effects of inexperience. To explore these elements, we conducted incentivized decision-making tasks where participants undertook a series of consumption-saving exercises. In these tasks, participants were required to make sequential spending choices over ten-period horizons with full information about all relevant future variables.

In our baseline scenario, participants faced ten periods of consumption decisions under conditions of constant and known incomes and prices, and without getting interest on their savings. In such a simplified setting, the theoretically optimal behavior is to spend the entire income in each period. This design is strategically simple, enabling us to detect patterns of random decision-making and any consistent systematic biases.

We then introduce various facets of complexity within the optimization problem to better understand the common pitfalls in decision-making. In the FluctY treatment, we alter participants' income between two predictable levels, high and low. This variation helps us determine if participants can grasp the concept of smoothing out their consumption over time, despite income changes. The FluctP treatment involves changing prices between high and low levels. This change allows us to observe whether participants take into account the shape of their utility function—that is, how they value each additional unit of consumption—when they decide how much to spend. In the PosIR treatment, we add a new element to our basic setting by introducing positive interest on savings. This helps us assess how the complexity of decision-making is affected when participants need to consider the effects of compounding returns. Furthermore, across all treatments, participants make spending decisions sequentially over a ten-period horizon. This sequential approach to decision-making lets us, at the subject-level, the additional complexity associated with lengthier planning horizons. Specifically, we look at 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 achieving optimal outcomes, even in scenarios where income and prices are stable and savings yield no returns. These results underscore the inherent difficulty of optimization decisions, even under the simplest environments. In our ConstantYP treatment, the average inexperienced participant managed to attain only 76% of the unconditional optimal solution (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 a slight learning effect over time.

Contrary to our expectations, introducing complexity by altering income levels does not hinder participants' performance. However, the introduction of more complex elements like compounding interest on savings or fluctuating prices significantly impacts participants' ability to optimize unconditionally. In such complex scenarios, inexperienced participants' optimization efficiency falls to 66% and 62%, respectively. This decline in performance is persistent, even 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.[1]

[1] 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 10-period task twice.

Furthermore, the nature of the errors varies with the type of complexity introduced. In the PosIR scenario, a common oversight is the undervaluing of early savings, leading to diminished wealth for later consumption. On the other hand, the FluctP scenario reveals a different challenge: while most recognize the advantage of spending more when prices are low, their spending often falls short of the optimal level. This is the first study to analyze the complexity of decision-making in the context of inflation in isolation, i.e., when all variables except prices remain constant. It highlights the increased cognitive challenges involved in making optimal decisions under such inflationary conditions.[2]

To further investigate the impact of these complexities on decision-making, our study also considers the tools individuals commonly use for planning consumption and savings. Typically, people rely on basic tools like simple calculators or their own mathematical abilities, which leads us to an important question: are the common errors in optimization primarily due to calculation mistakes? In an effort to address this, our study introduces a second set of treatments where participants use a budgeting calculator. This device goes beyond basic calculations, offering tailored assistance for creating comprehensive spending plans. It also tracks all computations, allowing us to analyze how extensively participants plan their spending and whether their planning behavior changes depending on the economic conditions they face. This innovative approach, focusing on non-choice data, provides a unique lens to assess the the depth of people's dynamic planning and the impact of economic complexity on their short-sightedness. To our knowledge, this study is the first to utilize calculator data in the context of dynamic optimization. By analyzing this data, we gain insights into the decision-making process that go beyond just the final decisions made by participants.[3] Furthermore, we examine the role of experience in mitigating cognitive complexity by having participants repeat the decision-making exercise three times, each spanning ten periods, under similar conditions.

[2]While the experiments conducted by Luhan et al. (2014) and Yamamori et al. (2018) have analyzed dynamic optimization under fluctuating prices, they simultaneously alter other macroeconomic variables. In Luhan et al. (2014) experiment, interest rates are positive, and in Yamamori et al. (2018), savings fluctuate in tandem with prices. This complicates the evaluation of how subjects' behavior changes due to purely inflationary factors.

[3]An example of how this type of data can be used is found in Fenig et al. (2022), who apply it to study group dynamics in non-linear games.

Our analysis into the budgeting calculator's effectiveness yields mixed results. While we anticipated that the calculator would streamline the decision-making process, the actual impact was nuanced. In the ConstantYP treatment, for instance, calculator access resulted in an 8 to 11 percentage point increase in selecting the unconditional optimal path. In the PosIR treatment, the calculator's assistance boosted optimization by 5 to 6 percentage points, but in FluctY and FluctP, its influence was minimal or indiscernible.

It is important to note that the effectiveness of the budgeting tool in simplifying optimization tasks depends on the participants' effective usage. Successful use of the calculator can improve unconditional optimization by 10 to 20 percentage points. To better understand how to use this tool effectively, it is crucial to identify two sources of complexity where the calculator aids in simplification. These are: (i) transforming units of consumption into utility levels, which is far from trivial for non-linear functions, and (ii) projecting long-term consumption plans. Interestingly, in our setting, short-term planning is not an obstacle in finding the optimal path in ConstantYP and only causes minor deviations in FluctP and FluctY. On the other hand, full-horizon planning is crucial in finding the optimal path in PosIR due to the impact of interest rates on the growth of savings. To account for this, we extend our main model to incorporate short-span planning. However, our findings suggest that short-term planning alone does not fully explain deviations from the optimal path.

Overall, we find strong support to models positing that complexity hinders dynamic optimization (Gabaix and Graeber, 2023; Woodford, 2019). The most substantial barriers to optimal decision-making include the objective function's curvature, the impact of compounding returns, and the length of the planning horizon. Our research indicates that while varying income alone does not exacerbate decision-making challenges, the presence of numerical calculations can significantly contribute to the complexity of the task. It is imperative to recognize that the presence of a decision-aid tool like a budgeting calculator does not automatically translate to improved outcomes. However, when used effectively, it can be a powerful aid in navigating complex financial decisions.

The structure of the paper is as follows. Section 2 provides a summary of the literature most relevant to this paper. Section 3 presents the theoretical model, describes the different treatments, outlines the experimental design, and lists the main hypotheses. Section 4 offers an overview of the main results. In Section 5, we employ econometric techniques to more formally demonstrate the treatment effects of environmental complexity and the use of the budgeting calculator. In Section 6 we extend our model to allow for short-span planning. Finally, Section 7 concludes the paper.

2 Related Literature

In this subsection, we explore two distinct yet interconnected bodies of research. The first pertains to the complexities inherent in decision-making, while the second focuses on learning-to-optimize experiments within the specific domain of consumption and saving decisions. These two areas of study provide critical insights that inform our understanding of the challenges and behaviors observed in financial decision-making processes.

Many researchers have theorized about the difficulties agents face in dynamically optimizing. A common theme is the inattention to key variables in optimization problems, as detailed in studies by Schipper (2014), Sims (2003), Maćkowiak and Wiederholt (2015), and Gabaix (2014). These works suggest that agents might either neglect important variables or focus on a limited subset due to the costs of processing information. Mis-specified preferences also contribute to what appears to be optimization errors. Contrary to the commonly assumed exponential discounting in many intertemporal planning models, substantial evidence suggests that individuals tend to discount future utility in a hyperbolic manner (Loewenstein and Prelec, 1992; Laibson, 1997; O'Donoghue and Rabin, 1999).

The literature also highlights the numerical challenges in dynamic optimization. Even the authors of this paper admit to finding the mathematical aspects of extended multi-problem constrained optimization daunting. Simple three-period problems, which might seem elementary, can still pose significant hurdles for many (Gabaix and Graeber, 2023).

Emphasizing the importance of this, Lusardi and Wallace (2013) highlight that a firm grasp on quantitative literacy is a cornerstone of financial literacy.

In the context of financial planning over lengthy horizons, Ilut and Valchev (2023) develop a model in which agents, despite perceiving all objective variables relevant to their payoff, encounter subjective uncertainty about optimizing their actions in the given state. This necessitates engaging in costly learning processes to determine the optimal course of action. Our experimental design reflects this situation: participants are fully informed of all relevant variables, yet they face challenges in effective problem-solving. Our findings align with the dual reasoning model proposed by these authors. Initially, agents tend to rely on cognitive planning (System 2). However, as they progress through their life cycle, many switch to using intuitive heuristics (System 1). Interestingly, towards the end of their life cycle, as the planning horizon becomes shorter, some agents appear to revert to cognitive planning (System 2). In our study, the budgeting calculator serves as a supportive tool, providing participants with an intuitive interface to manage and adjust their financial decisions, effectively bridging the gap between complex data and practical decision-making.

Significantly, the complexity of the economic environment and its impact on optimization is a focal point in the literature. Enke et al. (2023) assert that such complexity plays a role in the emergence of hyperbolic discounting and present bias, notably by causing a reduced sensitivity to changes in time intervals. Additionally, Gabaix and Graeber (2023) investigate a three-period consumption-saving scenario, uncovering that tasks with fluctuating endowments and positive, compounding interest are viewed by subjects as more challenging, leading to increased errors and longer decision times.

A strategy to decrease cognitive demands is to condense the timeframe for planning. For example, the findings from Carbone (2006) emphasize that subjects often exhibit a preference for very short planning horizons in financial decisions. This idea is further supported by Caliendo and Aadland (2007) research on short-term planning and life-cycle consumption. Their model accounts for heterogeneity in planning horizons, with perfect-foresight and hand-to-mouth individuals representing the extreme cases. These studies highlight the realistic nature of truncated planning approaches in complex decision-making. Hence, the combination of limited planning horizons and insufficient effort in finding an optimal solution—a behavior known as 'satisficing'—means that budgeting calculators offers limited average benefits.

Dynamic optimization problems are inherently complex. The challenges stem from various factors: the extended planning horizons, a wide array of choice variables, the options to borrow or save at differing interest rates, and the unpredictability of future events. Such a diverse range of considerations often leads to decision overload for individuals, nudging them towards simpler heuristics or fallback options in an attempt to manage the overload.

The controlled environment of a laboratory is instrumental in unraveling how individuals approach optimization amidst the variability of economic conditions. Table 1 provides an insightful overview by compiling various learning-to-optimize experiments. The table indicates that, in most experiments, participants obtain interest from their savings. Moreover, there is a prevalent uncertainty about future variables, with income being the variable that most frequently changes. The most common planning horizon across these studies is 20 periods, and it is notable that most experiments do not provide closed-form solutions. The co-occurrence of intricate elements within these experiments—such as extended horizons, uncertainty, returns on savings, and income fluctuations—poses a challenge in discerning the impact of different complexity elements on optimization behaviors. To address this, our parameterization, as detailed at the bottom of the table, introduces one complexity feature at a time, allowing for a meticulous examination of each element's influence on optimization.

Table 1: Related learning-to-optimize experimental literature

Paper	Uncertainty	Interest Rates (IR)	Fluctuating Variable	Borrowing Constraints	No. of Periods	Closed-Form Solution
Hey and Dardanoni (1988)	Yes	>0	Income	Yes	Random	No
Ballinger et al. (2003)	Yes	>0	Income	Yes	60	No
Carbone and Hey (2004)	Yes	>0	Income	Yes	25	No
Brown et al. (2009)	Yes	= 0	Income	Yes	30	No
Ballinger et al. (2011)	Yes	= 0	Income	Yes	20	No
Carbone and Duffy (2014)	No	>0	Income	Yes	25	Yes
Luhan et al. (2014)	No	>0	Price and IR	Yes	5	Yes
Carbone and Infante (2015)	Yes	>0	Income	No	15	No
Meissner (2016)	Yes	=0	Income	No	20	Yes
Duffy and Li (2019)	No	=0	Income	Yes	25	Yes
Yamamori et al. (2018)	No	= 0	Prices	Yes	20	Yes
Carbone et al. (2019)	Yes	>0	Income	No	15	No
Lu (2022)	No	>0	Income	No	9	No
Miller and Rholes (2023)	No	>0	Income	No	20	No
Duffy and Orland (2023)	Yes	= 0	Income	No	3	No
Gabaix and Graeber (2023)	No	> 0	Income	No	3	No
This paper						
ConstantYP	No	= 0	None	Yes	10	No
PosIR	No	> 0	None	Yes	10	No
FluctY	No	= 0	Income	Yes	10	No
FluctP	No	= 0	Price	Yes	10	No

Although direct comparisons among these experiments are complex due to their differing parameters and information sets, two key patterns consistently emerge in the research. First, there is a noticeable struggle with dynamic planning – individuals often either consume too much or too little, neglecting the long-term impacts of compounding returns. Second, the tendency to optimize decisions appears to enhance as the planning horizon becomes shorter. Echoing this, Ballinger et al. (2011) observed that subjects typically anticipate only up to three periods ahead, underscoring the cognitive limits in longer-term financial planning.

3 Theoretical Model and Experimental Design

The theoretical framework underpinning this study is a standard intertemporal 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,

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

3.1 Treatments

Our objective in designing the baseline environment was to create a setting that enables participants to solve the dynamic decision problem without the need for advanced budgeting tools. Therefore, we parameterized our baseline environment, named **Constant YP**, to maintain income and prices constant throughout the entire consumption horizon. We selected a planning horizon of $T = 10$ periods, which is sufficiently long for participants to plan ahead and also provides ample time for us to observe their learning through stationary repetitions of the environment. Including stationary repetitions is critical in life-cycle experiments because some participants may only understand how to overcome the difficulties of the environment halfway through the sequence, making it impossible for them to adjust their previous consumption choices. Each participant encounters three repetitions of ten periods, and we re-calibrate the environment across repetitions to generate slightly different optimization problems.

We designed and implemented three additional treatments, each introducing a distinct dimension of complexity to understand where and why errors occur in decision-making. The first treatment, **FluctY**, varies participants' income between two predictable levels, high (y_H) and low (y_L), throughout the horizon. By ensuring that a higher income is received in the first period, we prevent the budget constraint from binding for an optimizing participant, and even for individuals who tend to over-consume compared to the unconditionally optimal solution. 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**, adds a layer of complexity by introducing a positive interest rate ($r = 0.1$) on savings in every period of each of the three repetitions. This approach allows us to observe the cognitive challenges associated with compounding returns on savings decisions. Lastly, in the **FluctP** treatment, we introduce price fluctuations between two values, high (p_H) and low (p_L), for the entire horizon. This treatment is designed to see if participants consider the shape of their utility function, i.e., how they value each additional unit of consumption, in their spending decisions, especially when prices vary. These three treatments, by adding different complexity dimensions to the basic optimization setting, help us dissect the nuances of decision-making under varied economic conditions.

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

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

Here, we parameterize $\sigma = 0.5$ for all treatments, and we set the constant k to 2.65 in the FluctP treatment and 3.35 for the other treatments. This specific adjustment of k is made to ensure that the optimal life-cycle utility is equalized across all treatments where the interest rate r is set to 0. The chosen value for σ is intended to create a sufficiently large intertemporal tradeoff. 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 there are changes in the nominal variables from the first to the last repetition, the real variables remain consistent, ensuring that the optimal solution is identical across these two repetitions.

Table 2: Parameters of Treatments

			Treatment			
			Constant YP	PosIR	FluctY	FluctP
Repetition 1	y_t	$t \in \{1,3,5,7,9\}$	1000	1000	1500	1200
		$t \in \{2,4,6,8,10\}$	1000	1000	500	1200
	p_t	$t \in \{1,3,5,7,9\}$	100	100	100	150
		$t \in \{2,4,6,8,10\}$	100	100	100	50
	r		0	0.1	0	0
Repetition 2	y_t	$t \in \{1,3,5,7,9\}$	2000	2000	3000	2400
		$t \in \{2,4,6,8,10\}$	2000	2000	3000	2400
	p_t	$t \in \{1,3,5,7,9\}$	100	100	100	150
		$t \in \{2,4,6,8,10\}$	100	100	100	50
	r		0	0.1	0	0
Repetition 3	y_t	$t \in \{1,3,5,7,9\}$	2000	2000	3000	2400
		$t \in \{2,4,6,8,10\}$	2000	2000	3000	2400
	p_t	$t \in \{1,3,5,7,9\}$	200	200	200	300
		$t \in \{2,4,6,8,10\}$	200	200	200	100
	r		0	0.1	0	0

Figure 1 displays the optimal consumption path corresponding to each treatment and repetition. Notably, despite the differences in the income process, the optimal consumption path remains the same for the Constant YP and FluctY treatments. In this frameworks, consumers maximize utility by consuming 10 units per period in Repetitions 1 and 3, and 20 units per period in Repetition 2. In the PosIR treatment, the optimal consumption path increases over time as there is no discounting. Finally, under the FluctP treatment, the optimal consumption level varies in response to price changes: it increases when the price is low and decreases when high, following a bi-periodic pattern. Additionally, Figure 1 illustrates the consumption path $\frac{y_t}{p_t}$, representing an agent's mistaken static optimization approach, where the entire income is consumed each period without considering the intertemporal dynamics.[4]

[4] The exception is the ConstantYP treatment, in which the optimal unconditional consumption path implies not saving.

In the ConstantYP treatment, the unconditional optimal solution aligns with the 'Hand-to-Mouth' (H2M) strategy in the first period. Should a participant choose to save any income during this period, the conditionally optimal consumption path would deviate from the H2M heuristic. Conversely, in all other treatments, there is a noticeable divergence between the optimal and H2M consumption paths.[5]

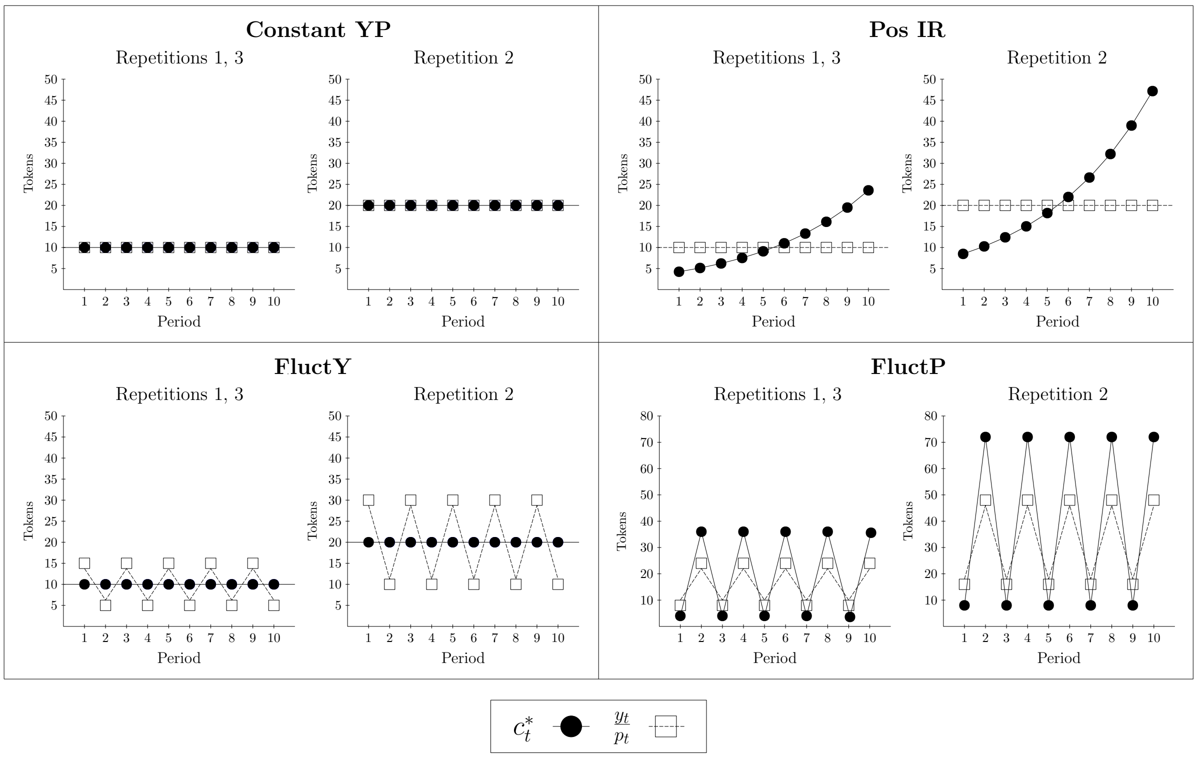


Figure 1: Theoretical Predictions.

We introduce a second treatment variation to our study by varying participants' access to a budgeting calculator across each of the four parameterizations. In the **Calc** treatments, subjects were given the option to use a budgeting calculator where they could enter hypothetical consumption choices for the current and future periods based on the given income, prices, and interest rates. Figure 2(a) shows a screenshot of the budgeting calculator. In this example, participants could input a consumption plan for periods 6-10 and calculate the hypothetical per-period and accumulated points. They were free to use the calculator as much as they wanted, and there was no requirement

[5]We analyze this strategy in Appendix D.

to use it at all. After submitting their decisions, participants could view the history of their consumption choices and corresponding saving balances. The software recorded all plans after a participant clicked the calculate button.However, each time subjects submitted their consumption choices, the calculator was cleared.

In contrast, in the **NoCalc** treatment, participants did not have access to the budgeting calculator. Figure 2(b) displays a screenshot of the NoCalc interface. While participants could not use the tool to make financial plans, they could still view the history of their past choices and all future incomes, prices, and interest rates. Participants in both treatments were allowed to use the Windows calculator to make their decisions, but these inputs were not recorded.[6]

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

3.2 Experimental Procedures

The study recruited undergraduate and graduate participants from various academic disciplines, resulting in a total of 326 subjects who participated in one of eight treatments.[7] Table 3 shows the number of participants per treatment. The experiment was

[6]It is important to note that our No Calc treatments offer more detailed and easily accessible information compared to standard experiments in consumption smoothing. In these standard experiments, subjects sometimes only see their current income and accumulated savings, based on which they have to make their current consumption decisions.

[7]The experiments were conducted at two distinct locations: the CRABE Laboratory at Simon Fraser University (SFU) and the SSRL at the University of Saskatchewan (UofS). Our participant sample was

computerized and programmed using z-Tree Fischbacher (2007).

Table 3: Number of Subjects per Treatment

Treatment	Budgeting Calculator	Number of Subjects
ConstantYP Calc	Yes	44
ConstantYP No Calc	No	44
PosIR Calc	Yes	48
PosIR No Calc	No	43
FluctY Calc	Yes	48
FluctY No Calc	No	46
FluctP Calc	Yes	45
FluctP No Calc	No	48

At the beginning of each session, the experimenter read aloud the written instructions given to the participants. Afterward, the participants completed an interactive computerized instruction phase and answered incentivized control questions. The control questions are available in Appendix F and ensured that participants understood the main features of the dynamic optimization experiment and the tools provided to them. Participants earned points based on their performance in the control questions: four points for each correct answer on the first attempt, three points for the second attempt, and two points for the third attempt. No additional points were awarded for more than three attempts. Participants had to answer all questions correctly before they could proceed.

After completing these questions, participants proceeded to Stage 1. This stage involved three repetitions of one of the dynamic optimization environments shown in Table 2. Figure 3 displays a screenshot of the main computer interface. [8] At the

nearly evenly split between individuals from SFU and UofS. We do not find any meaningful differences in behavior between participants from both institutions.

[8]There was no time limit for completing any stage of the experiment. In Stage 1, which consisted of three repetitions, subjects spent between 3 and 85 minutes in total.

beginning of each period, participants were given an income (y_t) in tokens and asked to decide how many units of output they wanted to purchase. To aid in their decision-making, they could consult the plot that associated output to points located at the bottom right corner of the screen. Alternatively, they could use the Output to Points converter at the upper right corner of the screen to better understand the properties of the utility function. In the Calc sessions, participants could also use the budgeting calculator located on the right-hand side of the screen to explore different consumption paths and their implications for their savings and points (utility) before submitting their final choices on the left-hand side of the screen, as shown in Figure 3. Our interface design aimed to ensure that participants had all relevant information readily accessible on one screen.[9]

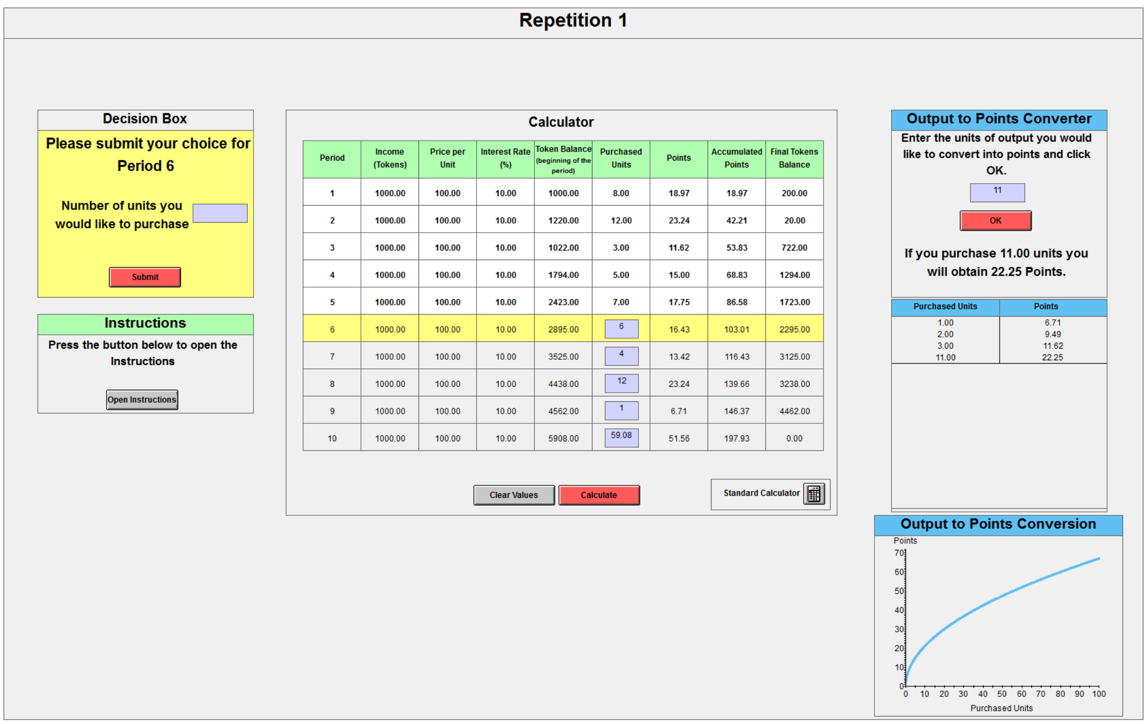


Figure 3: Screenshot of the Experimental Software for Stage 1

In the following three stages of the experiment, we collected variables that distinguish participants across three different dimensions: risk preferences, financial literacy,

[9]Participants who requested it were provided with pen and paper to write down calculations, which could be used at any point during the experiment.

and ability to use backward induction. Stage 2 focused on assessing risk preferences through a task adapted from Eckel and Grossman (2002), where participants chose between six different 50/50 gambles (see Appendix G.2 for a screenshot). In Stage 3, participants' financial literacy was measured using a method adapted from Lusardi and Mitchell (2007), involving five multiple-choice questions with points awarded for correct first-attempt answers (screenshot in Appendix G.3). Stage 4 assessed the ability to use backward induction through the Race to 60 game, as proposed by Bosch-Rosa et al. (2018). In this game, participants competed against a computer, selecting numbers between 1 and 10 to reach or exceed 60 first, with eight points awarded for each win (refer to Appendix G.4 for a screenshot). The experiment concluded with a demographic questionnaire gathering information on participants' age, gender, education, and employment status.

To calculate participants' payment, we added up the points they earned in all four stages and from correctly answering the control questions. For Stage 1, participants were paid for one randomly selected repetition. Payment was made in Canadian dollars (CAD) at an exchange rate of 25 points = \$1. In addition, participants received a show-up fee of \$7. On average, participants completed the experiment in 40 minutes, and the average payment was \$21.39. Figure 4 provides a summary of the different stages of the experiment.

3.3 Hypotheses

We focus our analysis on two metrics when measuring participants' ability to optimize. The first metric is the Unconditional Optimal Index, which computes the relative disparity between the actual utility and the utility associated with the unconditional optimal solution, represented 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 $U_{i,q,r,t}$ represents the utility associated with the actual consumption choice made in

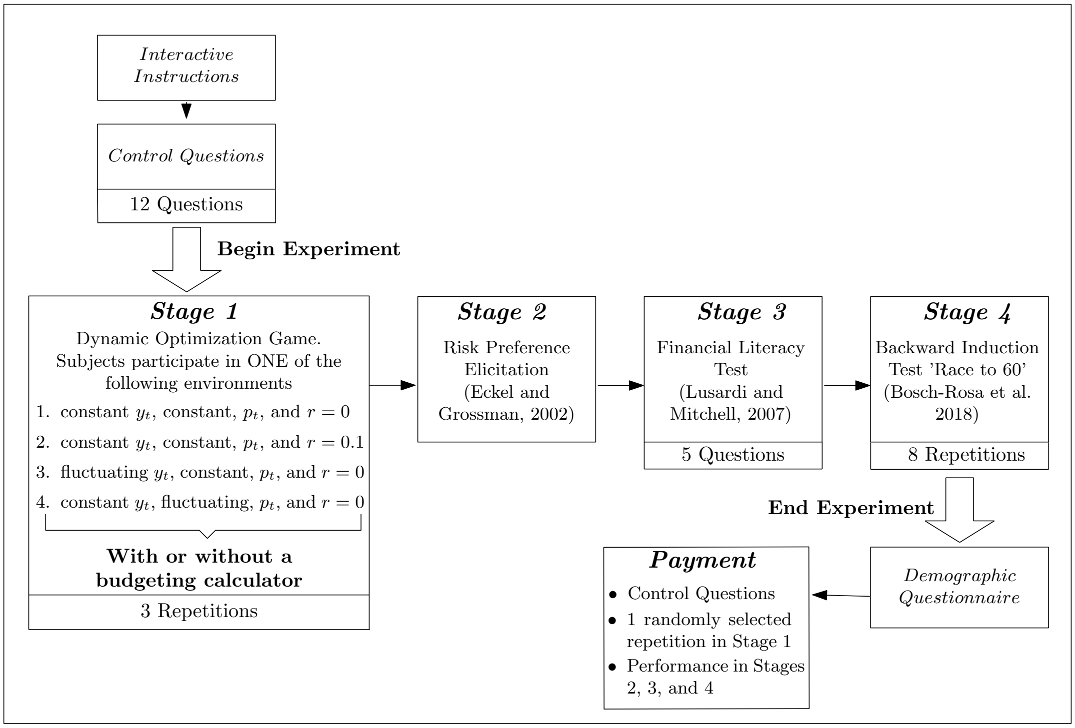


Figure 4: Sequence of Events in Experimental Sessions.

treatment q, repetition, r, period t by participant i, while $U^{unc}_{q,r,t}$ represents the treatment-repetition-period utility associated with unconditionally optimal consumption. Note that $U^{unc}_{q,r,t}$ is the same for all participants of the same treatment, repetition and period. The index takes a value of 1 when a subject selects a consumption level identical to the unconditional optimal. The calculation of the unconditional optimal level of consumption is determined at the beginning of the repetition before participants have made any consumption decisions and is based on the complete stream of income, prices, and interest rates in a given repetition. The second measure is the Conditional Optimal Index that computes the relative disparity between the actual utility and the utility linked to participant i's conditional optimal solution, also represented as a percentage:

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

where $U^{cond}_{i,q,r,t}$ represents the utility associated with subject i's conditionally optimal consumption in treatment q, repetition r, and period t. The conditional optimal level of consumption is calculated each period as the repetition evolves and depends on the entering balances of participant i and the future stream of incomes, prices, and interest rates. The conditional and unconditional optimal solutions coincide in the first period of each repetition.[10]

In our experiment, participants have complete information about the lifetime stream of income, prices, and interest rates they will encounter in each sequence. Standard rational-agent economic theory would predict that, for agents who understand how to solve a constrained optimization problem, it is feasible that they would be able to make spending decisions that align with the *unconditional* optimal consumption path. Should they happen to temporarily deviate from that optimal consumption path, they should continue to form *conditionally* optimal decisions thereafter. The features and complexity of the economic environment should not affect ability to optimize. This serves as the basis of 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, there is ample evidence from research presented in Table 1 demonstrating that people deviate significantly from the (un)conditionally optimal consumption path when making spending decisions. Related work by Gabaix and Graeber (2023) and Enke et al. (2023) highlight the role that complexity plays in behavioral biases and optimization errors. They show that people optimize better in environments that are relatively less complex. We can identify and rank the complexity of economic environments by using the model of Gabaix and Graeber (2023) for assessing complexity within an intertemporal consumption framework. We begin by linearizing Equation 6 through the implementation of a Taylor expansion:[11]

[10]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.

[11]Appendix A shows the derivation of the Taylor expansion.

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

For simplicity, each element of the problem is assumed to have the same level of complexity, $\bar{c}$. Following Gabaix and Graeber (2023), we assess that our ConstantYP environment exhibits the least amount of complexity (normalized to zero complexity). The FluctY treatment entails a complexity level of $\bar{c}$, as individuals need to consider the horizon when calculating optimal choices. Finally, FluctP and PosIR are predicted to have a complexity level of $2\bar{c}$, as individuals now need to consider the interaction between the horizon and the elasticity of substitution, σ. This leads to our alternative hypothesis that the relative complexity across environments determines the relative ordering of optimization errors.

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

Knowing that all environments, except for ConstantYP, have some inherent level of complexity, computing the optimal level of consumption presents a challenging task. It is reasonable to anticipate that 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 assess the extent to which experience leads 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 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 key distinction between calculating unconditional and conditional optimal paths lies in the planning approach. 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 with a shorter horizon for optimization, subjects are more likely to make consumption decisions that align with the conditional optimal path, as the reduced planning horizon simplifies the task.

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

Our final hypothesis relates individual characteristics to dynamic optimization skills. To dynamically optimize, a participant must not only complete complex financial calculations but also consider their future decisions. We predict that mathematical skills, financial literacy, and the ability to backward induct will be positively correlated with dynamic optimization skills (see Lusardi and Wallace, 2013). Participants who possess these skills may be better equipped to understand the budgeting tool and apply it effectively, resulting in greater consistency with the optimal consumption paths.

Hypothesis 5. Dynamic optimization is positively correlated with mathematical training, financial literacy, and backward-induction skills.

4 Overview of experimental results

We begin with an overview of optimization performance and calculator usage across the different treatment.

4.1 Average consumption decisions

Figure 5 presents the mean consumption decisions over time for Repetitions 1 and 3 for each treatment, represented by solid black lines. The gray area indicates the 95% confidence intervals. The optimal consumption path is denoted by red dashed lines. We only include periods 1 to 9 because the consumption decision in Period 10 was trivial; to maximize their current utility, subjects had to spend all the available cash in their bank account.[12]

Across different treatments, there are noticeable disparities in participants' optimization abilities. In the ConstantYP treatment, even in the initial repetition, the mean participant with access to the budgeting calculator consistently selects a consumption path that is nearly optimal.

In other treatments, deviations from optimality exhibit distinct patterns. In the PosIR treatment, the optimal path involves saving a relatively larger share of income in early periods to take advantage of the compounding return. Participants tend to underestimate the benefits of saving early in their life-cycle, resulting in overconsumption in earlier periods and underconsumption in later periods. Their ability to optimize does not appear to improve with experience.[13]

[12]To make sure participants had no calculation errors, we displayed a message indicating the exact consumption amount they needed to enter to spend it all. The vast majority followed this guidance. Across all subjects and all repetitions, in 90 percent of the cases, they finished the repetition with no cash remaining in their bank account.

[13]We also investigate a scenario where subjects perceive an increase in savings following a simple

In the FluctY treatment, the optimal consumption path is flat. Optimizing participants should save a portion of their income in odd-numbered periods to offset lower income in even-numbered periods. In Repetition 1, less experienced participants often under-consume in periods with lower income, leading to excessive saving and consumption in Period 9. However, with increased experience, this tendency to oversave diminishes, particularly when participants have access to the budgeting calculator.

In the FluctP treatment, the optimal plan involves setting aside some income during odd-numbered periods when prices are relatively high and utilize their entire wealth during even-numbered periods. While the average participant demonstrates a general understanding of how consumption should vary with prices, there is an evident inclination to smooth consumption excessively. This leads to heightened consumption in odd-numbered periods and inadequate consumption in even-numbered periods relative to the unconditionally optimal decision. This behavior remains up to Repetition 3. However, experience leads to notable improvements in optimization, especially for those participants who do not have access to a budgeting calculator.

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 is a strategic response employed by experienced individuals when navigating complex economic environments. It resonates with the '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

interest rate model. This implies that each saved token is believed to grow to an amount represented by $1 + \sum_{s=t}^{T} r_s$ by the end of a specified time horizon. Nonetheless, the data from PosIR cannot be explained by individuals employing this heuristic.

than implementing significant changes in consumption behavior.

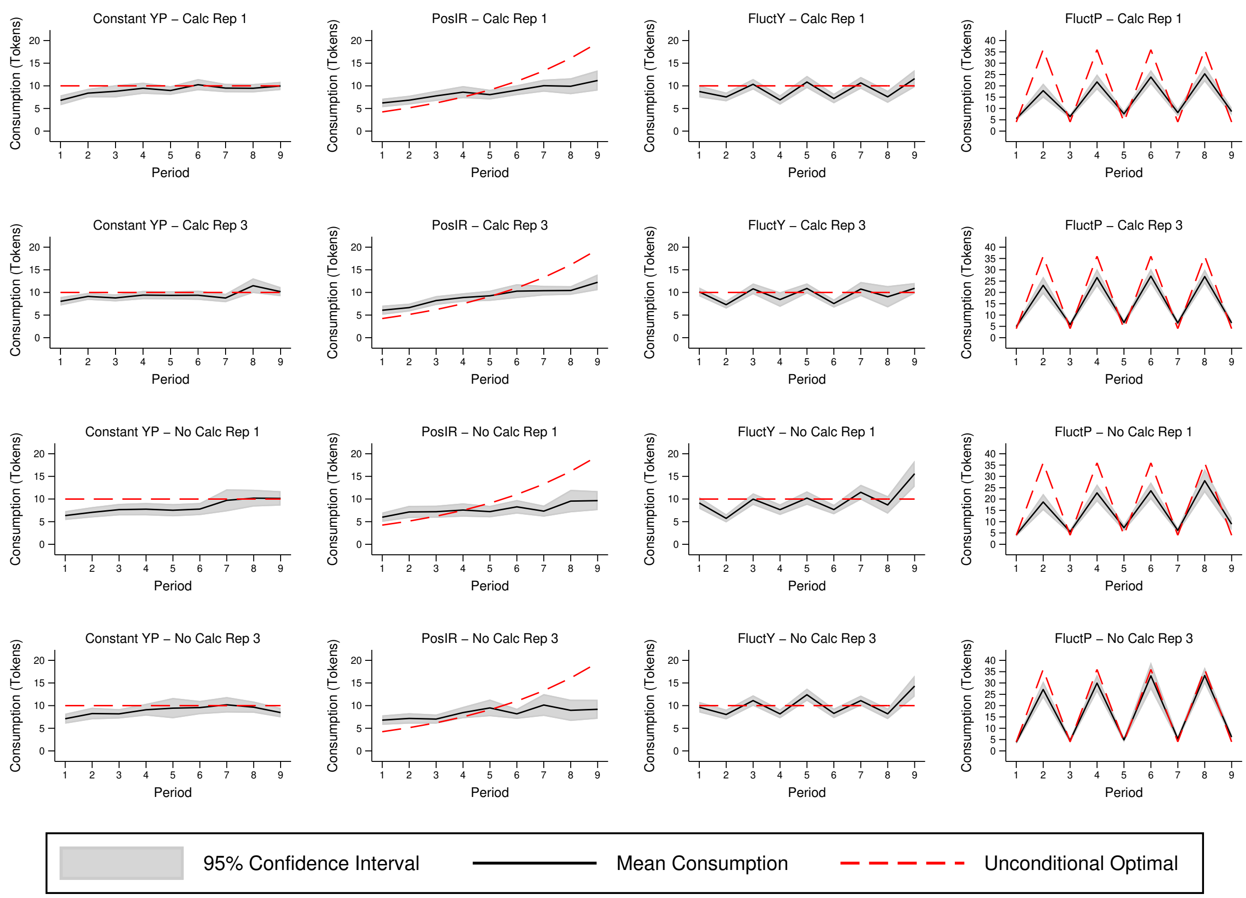


Figure 5: Average consumption per period and treatment

4.2 Measuring Optimization Abilities: Unconditional and Conditional Optimal Index

The distributions of γ^U and γ^C are presented in Figure 6 and Figure 7. The distributions are broken down by repetition and treatment. We separate the 90 to 95 percentage and 95 to 100 percentage bins to highlight participants' ability to nearly perfectly optimize, while allowing for the possibility of rounding.

The histograms highlight three initial findings. First, there is significant optimization errors across all of our treatments, even after significant experience. In the simplest

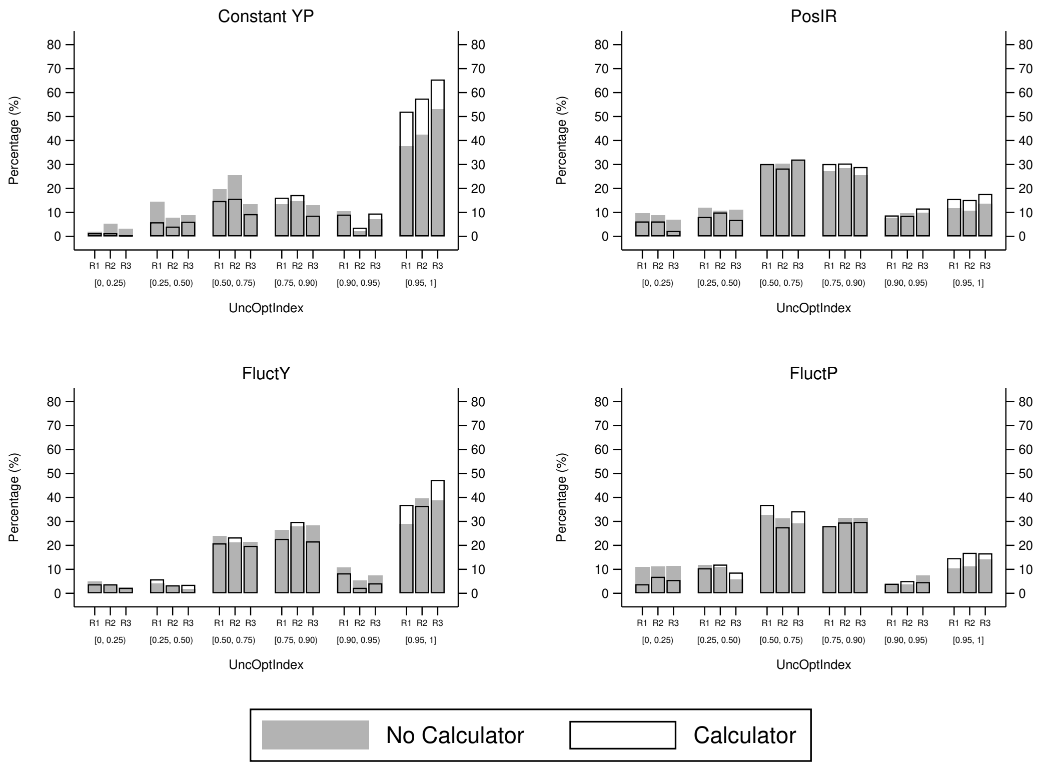


Figure 6: Histogram of UncOptIndex

environment, where incomes and prices are constant and participants have access to a budgeting calculator, one-quarter of the individuals deviate from the optimal path by more than 10 percent in Repetition 3. And in more complicated environments like PosIR and FluctP, deviations are significantly more substantial and persistent, regardless of calculator accessibility. Surprisingly, this pattern does not change much for deviations from the conditional optimal, as shown in Figure 7.

Second, we find that for those at the top of the distribution, the ability of participants to dynamically optimize both unconditionally and conditionally improves with experience, particularly in relatively simple environments such as ConstantYP and FluctY. This improvement is partly attributed to subjects who already had a good understanding of the problem in the first repetition, as they further improved their optimization skills by the third repetition. Notably, between the first and third repetitions, we observe

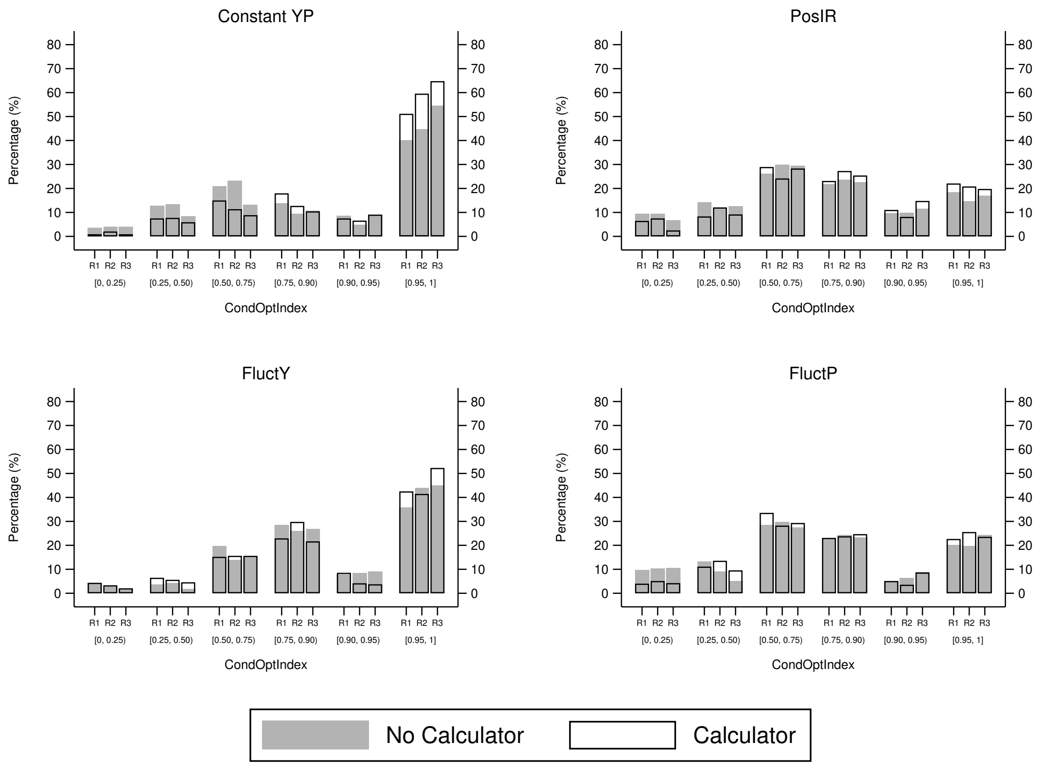


Figure 7: Histogram of CondOptIndex

a significant increase of approximately 15 percentage points in the proportion of participants achieving perfect optimization in ConstantYP, and a 10 percentage point increase in FluctY. However, in more complex environments like PosIR and FluctP, where the optimization challenge is greater, the observed effects are comparatively smaller.

Third, the availability of a budgeting calculator significantly impacts optimization in the ConstantYP and FluctY environments compared to PosIR and FluctP, particularly for participants at the top of the distribution. This effect is less obvious for participants in the middle or bottom of the distribution. In the ConstantYP environment, the presence of the budgeting calculator shifts the distribution towards the right, resulting in a 14 percentage point increase in the proportion of participants who achieve perfect optimization. However, the benefits provided by the calculator are less pronounced in the other three environments.

4.3 Evaluation of hypotheses

Table 4 presents the mean deviation of the *UncOptIndex* (γ^U) and *CondOptIndex* (γ^C), measured at the session level for each treatment and repetition. Additionally, we report the mean deviations for time spent and the number of calculations attempted in the Calculator treatments. Differences within and across treatments are documented, with corrections applied for multiple hypothesis (List et al., 2019).

We find compelling evidence to reject Hypothesis 1, which predicts that there should be no difference in deviations from both the unconditional and conditional optimal levels of consumption across different environments. When holding access to the budget calculator held constant, we observe that both γ^u and γ^c are significantly higher in the ConstantYP environment compared to other treatments in the majority of repetitions. Participants also appear better optimize, both unconditionally and conditionally, in the FluctY environment than in either PosIR or FluctP. Notably, PosIR and FluctP exhibit marked similarities, especially when participants do not have access to a budgeting calculator. From a broader perspective, the treatment ordering aligns with Alternative Hypothesis 1 that considers the cognitive complexity present within the economic environment.

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

Our findings present mixed evidence in support of Hypothesis 2, which predicts that access to the budgeting calculator significantly enhances the optimization of both unconditional and conditional consumption decisions. In Repetition 1 and Repetition 3, access to the calculator leads to reductions in mean deviations from the unconditional optimal path by 10.2% and 7.7% in ConstantYP and by 5.8% and 5.9% in PosIR, respectively. Correspondingly, the improvements in the conditional optimal path are 7.9%

Table 4: Summary of treatment effects

		Treatment				p-value of two sided t-test					
		Constant YP [1]	Pos IR [2]	Fluct Y [3]	FluctP [4]	[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	0.000	0.000	0.000	0.117	0.000
	No Calculator	0.760	0.661	0.778	0.621	0.000	0.721	0.000	0.000	0.318	0.000
	Difference	0.102^{***}	0.058^{**}	0.007	0.057^{*}						
γ^C	Calculator	0.859	0.734	0.816	0.724	0.000	0.016	0.000	0.000	0.784	0.000
	No Calculator	0.780	0.680	0.809	0.680	0.000	0.311	0.000	0.000	0.999	0.000
	Difference	0.079^{***}	0.054^{**}	0.006	0.044						
Seconds/period	Calculator	35.569	51.951	37.822	60.284	0.220	0.752	0.159	0.272	0.851	0.209
	No Calculator	35.301	38.615	30.600	47.383	0.850	0.647	0.052	0.653	0.664	0.000
	Difference	0.268	13.336	7.221	12.901						
No. Sim/period	Calculator	3.875	5.252	4.202	4.291	0.871	0.966	0.953	0.944	0.958	0.922
Repetition 2											
γ^U	Calculator	0.868	0.701	0.794	0.680	0.000	0.000	0.000	0.000	0.624	0.000
	No Calculator	0.761	0.673	0.822	0.649	0.000	0.000	0.000	0.000	0.584	0.000
	Difference	0.107^{***}	0.028	-0.028	0.031						
γ^C	Calculator	0.869	0.713	0.823	0.720	0.000	0.008	0.000	0.000	0.903	0.000
	No Calculator	0.780	0.677	0.843	0.690	0.000	0.000	0.000	0.000	0.863	0.000
	Difference	0.089^{***}	0.035	-0.020	0.029						
Seconds/period	Calculator	21.792	37.784	25.208	34.988	0.352	0.759	0.033	0.536	0.770	0.182
	No Calculator	17.506	18.736	18.925	31.530	0.856	0.830	0.000	0.942	0.002	0.011
	Difference	4.286	19.048	6.283	3.458						
No. Sim/period	Calculator	1.316	2.623	2.119	1.578	0.510	0.459	0.961	0.986	0.790	0.920
Repetition 3											
γ^U	Calculator	0.897	0.761	0.829	0.703	0.000	0.000	0.000	0.000	0.000	0.000
	No Calculator	0.820	0.702	0.840	0.680	0.000	0.567	0.000	0.000	0.602	0.000
	Difference	0.077^{***}	0.059^{***}	-0.011	0.023						
γ^C	Calculator	0.902	0.766	0.852	0.742	0.000	0.000	0.000	0.000	0.369	0.000
	No Calculator	0.836	0.708	0.864	0.716	0.000	0.225	0.000	0.000	0.688	0.000
	Difference	0.066^{***}	0.059^{***}	-0.011	0.027						
Seconds/period	Calculator	20.146	29.726	22.263	29.771	0.386	0.784	0.269	0.422	0.994	0.352
	No Calculator	13.118	15.518	16.821	21.637	0.526	0.144	0.000	0.733	0.023	0.138
	Difference	7.028	14.209	5.442	8.134						
No. Sim/period	Calculator	1.395	2.077	1.790	1.482	0.910	0.910	0.974	0.976	0.944	0.972

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	0.985	0.741	0.797	0.941	0.998	0.707	0.052	0.692
	Rep1 vs Rep 3	0.104	0.036	0.110	0.677	0.019	0.191	0.000	0.067
	Rep2 vs Rep3	0.230	0.000	0.199	0.647	0.024	0.556	0.657	0.561
γ^c	Rep1 vs Rep 2	0.935	0.650	0.639	0.913	0.986	0.888	0.150	0.891
	Rep1 vs Rep 3	0.009	0.207	0.132	0.738	0.020	0.616	0.000	0.449
	Rep2 vs Rep3	0.093	0.011	0.194	0.685	0.005	0.470	0.449	0.677
Seconds/period	Rep1 vs Rep 2	0.215	0.613	0.139	0.299	0.000	0.113	0.000	0.000
	Rep1 vs Rep 3	0.210	0.081	0.039	0.137	0.000	0.080	0.000	0.000
	Rep2 vs Rep3	0.957	0.755	0.762	0.776	0.246	0.696	0.748	0.100
No. Sim/period	Rep1 vs Rep 2	0.007	0.032	0.012	0.006				
	Rep1 vs Rep 3	0.008	0.010	0.000	0.009				
	Rep2 vs Rep3	0.965	0.865	0.914	0.823				

Notes: The p-values reported are obtained from t-tests and have been corrected for multiple hypothesis testing (List et al., 2019). Significance levels are denoted as follows: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

and 6.6% in ConstantYP, and 5.4% and 5.9% in PosIR for Repetitions 1 and 3. All these differences are statistically significant at the 5% level. However, the evidence indicates that in the FluctY and FluctP treatments, the calculator's availability does not significantly impact the optimization of either unconditional or conditional consumption.

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 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 analysis, particularly in comparing γ^U and γ^C across various treatments and between repetitions, reveals an inconsistency in the calculator's effects. PosIR Calc is the only that consistently demonstrates improvements over time. For subjects with access to the calculator in ConstantYP and FluctY, experience does not significantly enhance performance. As previously shown, experience appears to primarily benefit those who were already close to the optimal paths in the first repetition. The limited learning observed over time in calculator treatments may be attributed to subjects gathering most of their learning during the first repetition. While the calculator appears to be useful in exploring various plans and improves learning within a single repetition, this improvement does not seem to carry over to subsequent repetitions.

On the other hand, in situations where participants do not have access to a calculator, there is evidence of learning occurring across multiple repetitions, with the PosIR treatment again being a notable outlier. This finding is significant for experimental designs where subjects accumulate interest on savings. Our results show that without the aid of a calculator, learning from stationary repetitions is limited, emphasizing the crucial role the budgeting tools can play in enhancing learning.

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 calculator.

Our remaining hypotheses related to the planning horizon and demographic characteristics are explored in the following sections where we exploit our experiments' panel data structure. Before we discuss our final hypothesis tests, we divert our attention to a brief analysis of participants' usage of the budgeting calculator.

4.4 How Participants Use the Budgeting Calculator

All calculations computed in the budgeting calculator were recorded. This data enables us to evaluate how participants engaged with the calculator and whether the nature of engagement had an effect on decision-making. We observe five distinct patterns in how participants filled in the budgeting calculator in period t.

1. Complete: All entries between t and $T = 10$ are inputted in each calculation.
2. Sequential: Entries and calculations are conducted sequentially. Subjects compute Period t calculations first, followed by Periods t and $t+1$, and again t, $t+1$, $t+2$, until they reach T.
3. Partial: Less than $T - t + 1$ periods are entered into the calculator.[14]
4. Current Period: Only Period t consumption is inputted.
5. No Inputs: No calculations are made.

How should a fully-forward looking, perfectly optimizing agent use the calculator? If they understand how to solve the optimization problem, they should not spend time

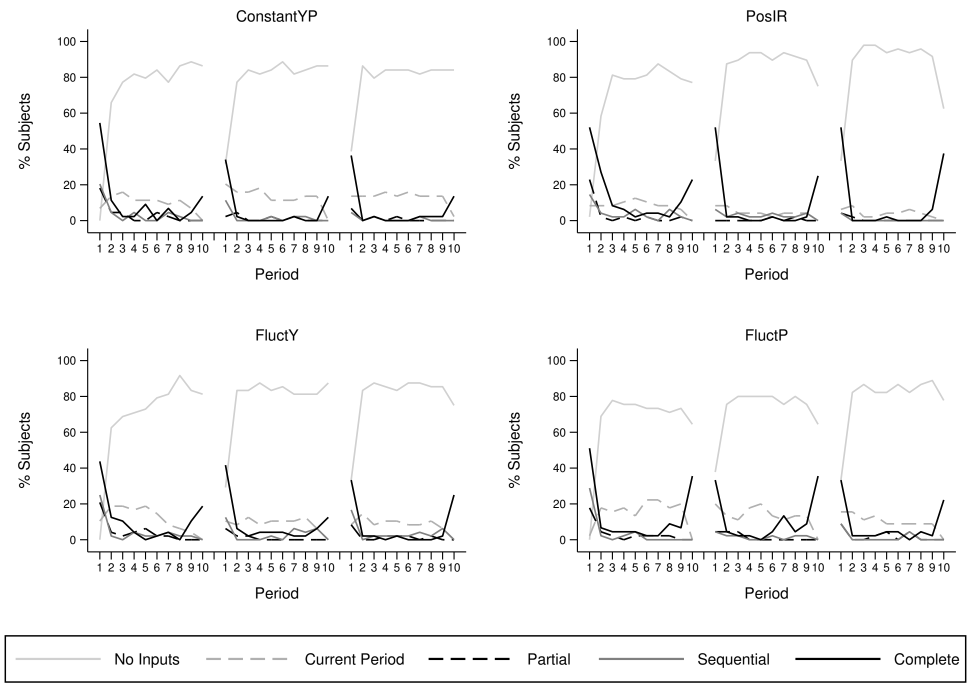
[14] This type of behavior has been modeled by Caliendo and Aadland (2007). In their model, forward-looking individuals solve partial-horizon models. They speculate that such behavior in individuals stems from factors including "...lack of self-control, financial illiteracy, distaste for contemplating old age, or to avoid financial planning costs in an uncertain environment, among others."

doing any calculations. On the other hand, if they are forward-looking but have difficulty with the computational aspect of the problem, they should submit a complete set of entries before making their spending decisions. We observe participants *complete* the calculator in two ways: either immediately filling in the calculator entirely, or sequentially with at least $T - t + 1$ calculations, inputting and calculating one period at a time. This latter approach takes more time but provides participants an opportunity to saliently observe the impact of each period's consumption-saving decision. Participants who input less than $T - t + 1$ periods of the calculator are labeled as *Partial* or *Current-Period* and who we will also refer to as *myopic* planners.

It is important to note that the subjects in the Calculator treatments are not required to use the budgeting calculator when making their spending decisions. As shown in Figure 8, the percentage of subjects who do not activate the calculator increases over time. There are several reasons for this trend: (i) Subjects do not need to make calculations every period to determine the optimal consumption path, especially in simple environments, (ii) subjects underwent an extensive tutorial and practice period before starting the experiment, (iii) minor changes in the environments between repetitions may allow subjects to rely on past repetitions to approximate the optimal approach, and (iv) subjects may experience fatigue after a few periods. Despite this, roughly one-half of the subjects submit complete sequences of consumption values at the beginning of each repetition. This is consistent with subjects understanding that the environment is deterministic, and in order to calculate the unconditional optimal, they must submit full sequences. Note that if subjects wish to calculate the conditional optimal solution, they may use the calculator in periods 2 to 10, but there is little evidence of that. Furthermore, there is a constant share of subjects using the calculator to enter consumption values for the current period (between 5% and 20% depending on the treatment), with only a few subjects partially or sequentially using the calculator over time.

Considering the notable decrease in calculator usage observed after the initial period of each repetition, we assign participants to a specific Calculator Type based solely on their calculator usage during the first period. The distribution of types is summarized

Figure 8: Budgeting Calculator Types Over Time



in Figure 9.

5 Evaluation of optimization

In this section, we assess the effectiveness of the budgeting calculator more formally. We evaluate the impacts of the calculator, its usage, learning, and demographics using the following comprehensive random-effects panel regression specification for each respective environment:

$$\begin{aligned}\gamma_{i,q,r,t} =& a + b_0 Calculator + b_1 Calculator \times CalculatorType^{t=1}_{i,q,r} \\ &+ b_2 V_{i,q,r,t} + b_3 X_i + b_4 Period + b_5 Repetition + \mu_i + error_{i,q,r,t},\end{aligned}$$

here, $\gamma_{i,q,r,t}$ represents either $UncOptIndex_{i,q,r,t}$ or $CondOptIndex_{i,q,r,t}$. The variable $Calculator$ is a dummy variable that takes the value of 1 in treatments where the

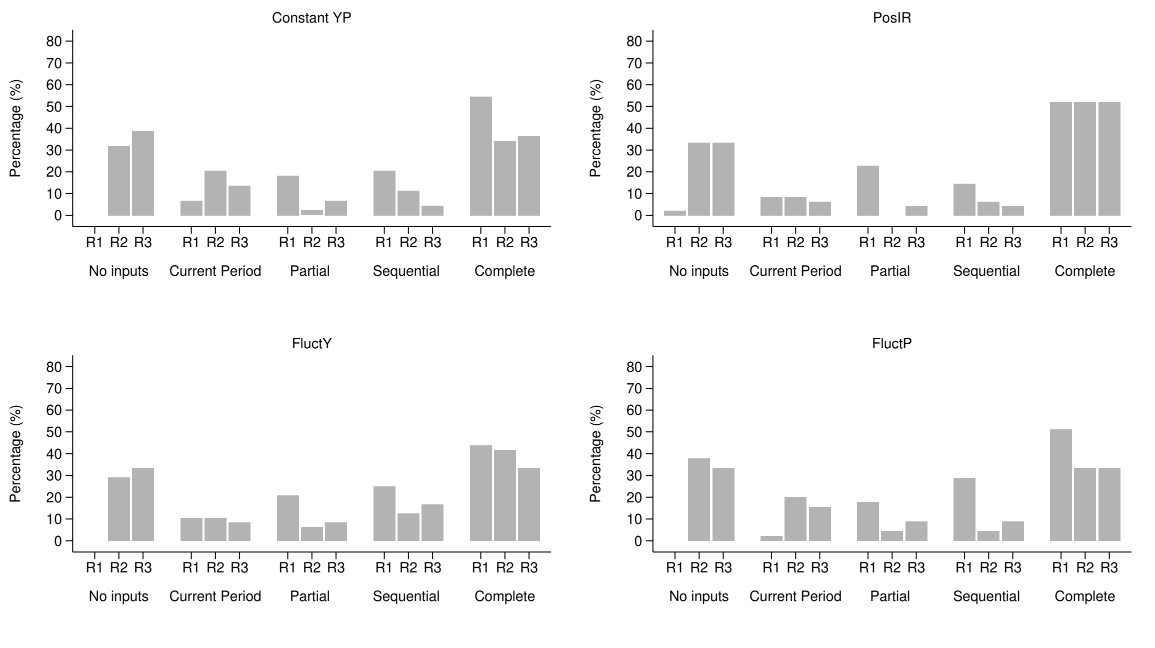


Figure 9: Budgeting calculator usage types, by treatment and repetition

budgeting calculator is present, and 0 otherwise. Additionally, $CalculatorType_{i,q,r}^{t=1}$ is a categorical variable that assigns participants to one of the five calculator usage types, with the baseline category being the NoCalc type.

We include time-varying controls denoted as $V_{i,q,r,t}$, which capture various factors such as the amount of time spent in a given period t (denoted as *Minutes Spent)* and the cumulative count of calculations performed by the participant since the beginning of Repetition 1 (denoted as *No. of Calculations)*. It is important to emphasize that participants who chose to use the budgeting calculator had the freedom to either search for the optimal levels or enter any desired consumption values. Therefore, it is crucial to distinguish between participants who effectively used the calculator to find the optimal levels and those who did not. We define a participant as able to find the optimal consumption if, when using the calculator, their UncOptIndex and CondOptIndex are equal to or greater than 0.90 at any point up to period t within the repetition. Thus, we introduce the binary variables Calc UncOpt and Calc CondOpt, which take the value of 1 if subjects were able to calculate the optimal consumption levels or 0 otherwise.

Furthermore, time-invariant demographic controls denoted as X_i are incorporated to account for participant characteristics unrelated to decisions made in the experiment. These include variables such as math background score (ranging from 1 to 9), financial literacy score (ranging from 0 to 4), backward induction ability (number of wins in Race-to-60, ranging from 0 to 8), gender, age, institution, level of education, experience in previous experiments, risk tolerance, the number of years as a student, and performance on control questions. This last variable measures the accuracy and consistency of responses to a set of incentivized control questions designed to assess understanding of the experimental setup and procedures.

$Repetition = \{Rep2, Rep3\}$ is a vector of dummy variables that captures the effects of learning from experience. $Period = t$ is a discrete variable that evaluates how the length of the planning horizon affects optimization. Finally, the subject-specific random effect is denoted as μ_i.

The estimate $\hat{b}_0$ presented in Columns (1), (4), (7), and (10) of Tables 5 and 6 indicates how the presence of the calculator affects optimization. To further evaluate Hypothesis 2, we test whether $\hat{b}_0 > 0$ for each environment. For both unconditional and conditional optimization, we find that $\hat{b}_0$ is very small, ranging between 0-4 p.p. and not statistically different from zero in any environment.

5.1 Impact of Calculator Usage on Dynamic Optimization

During the first period, participants can significantly enhance their ability to dynamically optimize by using the calculator. In the simplest environment, ConstantYP, filling in the calculator with only the current period (first period), either partially or completely, improves unconditional optimization by approximately 7 to 11 percentage points (p.p.) and conditional optimization by around 6 to 11 p.p. compared to participants who do not activate the calculator.

Sequential completion of the calculator resulted in a less sizeable and significant effect. On average, there is only a 4 percentage point improvement for unconditional optimization and a 2 percentage point improvement for conditional optimization. These improvements are not statistically significant. By contrast, Complete types experience a 8 p.p.(6 p.p.) improvement in (un)conditional optimization.

In the PosIR environment where participants face compounding interest on their saving, we observed more notable differences in performance across the Calculator Types. When participants only complete the consumption decision for the current period, there is no improvement in optimization. However, the Partial and Complete Calculator Types show improvements of 5 and 9 percentage points, respectively, in their optimization. Moreover, imperfectly using the calculator still leads to significant improvements in conditional optimization (Column 6).

Sequential completion does not result in any improvement in conditional optimization, and it can actually have a negative impact on unconditional optimization. On average, participants who sequentially optimize in the first period PosIR end up 8 percentage points further away from the optimal unconditional solution compared to those who did not use the calculator during the experiment.

The effectiveness of the calculator is less pronounced in the FluctY environment. We do not consistently observe 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 and 4 percentage points further from the optimal conditional solution.

Finally, in the FluctP environment, we find that the calculator only benefits participants who fill it in completely. The Complete Calculator Types are 7 percentage points closer to both the optimal unconditional and conditional decisions compared to those who did not use the calculator. Even if a subject fails to find the optimal solution using the calculator, she still improves her conditional optimization by 5 p.p. by filling the calculator in completely.

The estimates presented in columns (3), (6), (9), and (12) of Tables 5 and 6 demonstrate that using the calculator significantly improves subjects' performance by 10 to 20 percentage points for the UncOptIndex and 9 to 16 percentage points for the CondOptIndex. These results provide strong support for a modified version of Hypothesis 2 that utilizing a calculator *effectively* reduces deviations from both unconditional and conditional optimal consumption paths. Moreover, the results highlight the importance of carrying out calculations efficiently. Simply entering information into the calculator or doing so incompletely does not guarantee optimization improvements.

5.2 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 7, which breaks down our results by treatment, we observe that $\gamma^c_{i,t}$ increases significantly over time. Without access to a calculator, participants in the ConstantYP and FluctY treatments improve by 1.1 percentage points (p.p.) each period. This increase is even more pronounced in the PosIR and FluctP treatments, at 1.8 p.p. and 2.1 p.p. per period, respectively. These improvements in conditional optimization range from 9 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, except in the Pos IR treatment, where within-repetition improvement is notable. In this case, there is an improvement of 25 p.p. from period 1 to period 9. This suggests that the calculator does not significantly aid subjects in correcting mistakes and approaching conditional optimization when the horizon is shorter and there is a reduced cognitive burden. The exception is in the PosIR treatment, a relevant finding since this type of experiment is commonly conducted. Here, the calculator makes a difference both for within-repetition and between-repetition learning.

Result 4: Deviations from the conditional optimal consumption path diminish as the planning horizon shortens. However, this effect is less pronounced when participants use a calculator. The notable exception to this trend is observed in the Pos IR treatment.

Table 5: Dependent Variable: OptUncIndex

	Constant YP			POS IR			FluctY			FluctP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Calculator	0.043			0.006			0.013			0.014		
	(0.04)			(0.04)			(0.04)			(0.04)		
No. of Calculations		-0.000			-0.001			-0.000			0.001	
		(0.00)			(0.00)			(0.00)			(0.00)	
Calc γ^U			0.094***			0.194***			0.118***			0.105***
			(0.03)			(0.03)			(0.02)			(0.03)
Minutes Spent	-0.018***	-0.018***	-0.019***	-0.009***	-0.006*	-0.010***	-0.012***	-0.011**	-0.012***	0.002	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Repetition 2	0.013	0.014	0.014	-0.004	-0.004	-0.005	0.027***	0.027***	0.034***	0.022*	0.023*	0.019
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Repetition 3	0.056***	0.058***	0.059***	0.039***	0.039***	0.033***	0.050***	0.050***	0.055***	0.049***	0.050***	0.044***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Period	-0.004***	-0.004***	-0.004***	-0.003**	-0.003**	-0.003**	-0.006***	-0.006***	-0.006***	0.004**	0.004**	0.004**
	(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	0.017	0.013	0.013	0.006	0.006	0.003	0.006	0.006	0.008	0.024***	0.024***	0.022**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Backward Induction	0.016	0.015	0.013	0.008	0.008	0.003	0.003	0.002	0.004	0.013	0.013	0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Financial Literacy	0.015	0.013	0.013	0.003	0.003	0.000	0.008	0.008	0.005	0.000	-0.001	0.001
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Control Questions	0.004	0.005	0.004	0.018***	0.018***	0.016***	0.009	0.009	0.010	-0.006	-0.006	-0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Calculator Usage												
Current Period	0.071**	0.080***	0.077***	-0.022	-0.020	-0.015	-0.057**	-0.056**	-0.043	0.003	0.006	0.018
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Partial	0.108***	0.115***	0.090***	0.047*	0.049*	0.061**	0.038	0.038	0.045*	0.007	0.011	0.013
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sequential	0.040	0.047*	-0.009	-0.084***	-0.080**	-0.179***	0.011	0.011	-0.054**	-0.001	0.002	-0.039
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Complete	0.079***	0.087***	0.023	0.090***	0.093***	-0.056*	-0.032	-0.033*	-0.097***	0.073***	0.076***	0.036
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Constant	0.545*	0.544*	0.589**	-0.321	-0.321	-0.178	0.347	0.334	0.286	0.832	0.853*	0.813
	(0.31)	(0.31)	(0.30)	(0.33)	(0.33)	(0.30)	(0.34)	(0.36)	(0.35)	(0.51)	(0.51)	(0.50)
Observations	2640	2640	2640	2730	2730	2730	2820	2820	2820	2790	2790	2790
Overall R^2	0.12	0.12	0.14	0.08	0.08	0.13	0.05	0.05	0.09	0.08	0.08	0.09

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: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

5.3 Demographics

Mathematical training and financial literacy are frequently highlighted for enhancing financial sophistication (Lusardi and Mitchell, 2011; Van Rooij et al., 2012). In Hypothesis 5, we anticipated that individuals with mathematical proficiency would be better at sequential calculations and logical reasoning, essential for devising optimal consumption

Table 6: Dependent Variable: OptCondIndex

	Constant YP			**POS IR**			**FluctY**			**FluctP**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Calculator	0.037			0.001			-0.000			0.012		
	(0.04)			(0.04)			(0.04)			(0.03)		
No. of Calculations		-0.001			-0.001			-0.000			0.000	
		(0.00)			(0.00)			(0.00)			(0.00)	
Calc γ^C			0.095***			0.070***			0.060***			0.091***
			(0.02)			(0.02)			(0.02)			(0.02)
Minutes Spent	-0.003	-0.001	-0.003	0.001	0.003	0.000	0.001	0.002	0.001	0.007***	0.006*	0.006**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Repetition 2	0.015*	0.016*	0.017**	-0.008	-0.008	-0.005	0.024***	0.024***	0.026***	0.011	0.012	0.019
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Repetition 3	0.059***	0.060***	0.061***	0.033***	0.033***	0.036***	0.047***	0.047***	0.045***	0.036***	0.037***	0.041***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Period	0.009***	0.009***	0.009***	0.023***	0.023***	0.023***	0.010***	0.010***	0.009***	0.020***	0.020***	0.019***
	(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	0.017	0.014	0.014	0.005	0.005	0.006	0.004	0.004	0.004	0.019**	0.019**	0.018**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Backward Induction	0.017	0.016	0.012	0.007	0.007	0.006	0.001	0.001	0.002	0.010	0.010	0.010
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Financial Literacy	0.018	0.016	0.018	0.002	0.002	0.004	0.010	0.010	0.012	0.003	0.002	0.003
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Control Questions	0.006	0.007	0.006	0.018***	0.018***	0.016**	0.010*	0.010	0.010*	-0.007	-0.007	-0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Calculator Usage												
Current Period	0.071***	0.077***	0.061***	0.006	0.006	0.001	-0.043*	-0.044*	-0.046**	-0.000	0.003	0.005
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Partial	0.103***	0.110***	0.083***	0.051**	0.052**	0.044*	0.038	0.036	0.031	-0.020	-0.017	0.000
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Sequential	0.019	0.025	-0.030	-0.049	-0.047	-0.074**	0.015	0.014	-0.002	0.009	0.012	0.017
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Complete	0.060***	0.067***	0.008	0.087***	0.089***	0.067***	-0.015	-0.017	-0.046**	0.072***	0.075***	0.052**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Constant	0.328	0.328	0.404	-0.448	-0.449	-0.403	0.227	0.226	0.217	0.835*	0.852*	0.802*
	(0.28)	(0.28)	(0.27)	(0.31)	(0.31)	(0.31)	(0.29)	(0.31)	(0.30)	(0.45)	(0.45)	(0.44)
Observations	2640	2640	2640	2730	2730	2730	2820	2820	2820	2790	2790	2790
Overall R^2	0.16	0.16	0.18	0.15	0.15	0.15	0.07	0.07	0.10	0.12	0.12	0.13

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: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

plans. Financial literacy augments this by providing a practical framework for applying these 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

Table 7: Dependent Variable: OptCondIndex

	Constant YP		Pos IR		FluctY		FluctP	
	No Calc	Calc	No Calc	Calc	No Calc	Calc	No Calc	Calc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.720***	0.815***	0.583***	0.580***	0.748***	0.771***	0.565***	0.631***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Repetition 2	0.000	0.010	-0.003	-0.021*	0.033***	0.007	0.010	-0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Repetition 3	0.056***	0.043***	0.028*	0.032***	0.054***	0.037***	0.036**	0.018
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Period	0.011***	0.008***	0.018***	0.028***	0.011***	0.008***	0.021***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1320	1320	1290	1440	1380	1440	1440	1350
Overall R^2	0.03	0.02	0.04	0.12	0.03	0.02	0.04	0.04

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

elicited in our study.

In Tables 8 and 9 we examine each treatment individually to identify whether the presence of the calculator interacts with demographic characteristics. Our results provide little support for Hypothesis 5. We find that individual characteristics do not consistently influence the ability of subjects 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, 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 empahsizes the correlation of mathematical skill and 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.

Result 5: Individual and demographic characteristics, including financial literacy, show no correlation with the ability to find optimal plans in intertemporal consumption frameworks, with the exception of a minor effect in mathematical training.

6 A Model of Short-Span Planning

One of the primary reasons individuals may stray from an optimal consumption plan is due to their shorter planning horizons compared to the entire span of the experiment. This phenomenon can be thoroughly investigated by refining our existing economic model. In this modified model, individuals aim to maximize

$$\max_{c_t} \sum_{t=1}^{H} k \left(\frac{1}{1-\sigma} \right) c_t^{1-\sigma} \tag{10}$$

subject to:

$$p_t c_t + s_t = y_t + (1+r) s_{t-1}, \tag{11}$$

where H is the horizon, it ranges from 1 to 10. In this context, if $H = 10$, then the individual has full 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 10 in the Appendix, which outlines the predicted consumption level in Period 1 by treatment and planning horizon.

Our focus here is on PosIR 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.

In PosIR, the model suggests that individuals maximize the benefits of interest rates by extending the planning horizon. Notably, as the planning horizon lengthens, consumption in Period 1 decreases, emphasizing the importance of saving in the early periods. We leverage our model's predictive power to determine a specific planning horizon for each subject based on their observed consumption decisions in the first period during each repetition. This builds upon the notion 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.[15]

The estimated parameters are shown in Table 11 in the appendix. In this table, we note that close to 30% of the observations are not explained by short-span planning model. Among the 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 predictions with the actual planning behavior of the subjects in our experiment. This is possible because we have collected detailed

[15] The details can be found in Appendix C

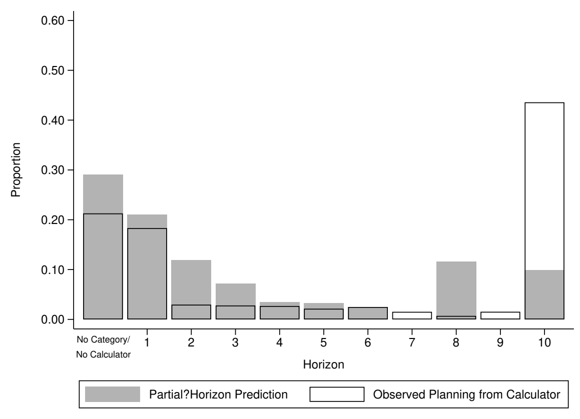


Figure 10: Comparison between the predicted and the observed horizon

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 the 10 periods (the full horizon).[16] Thus, in Figure 10,[17] we compare the proportion of different horizons used by subjects to the predictions of the model shown in Table 11.[18]

[16] In our analysis, we make two adjustments when examining the data. The first is that we omit intermediate plans for sequential users. To elaborate, 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 acknowledges that within a single period, subjects may employ various plans, sometimes even different horizons. To ensure a fair assessment, we assign equal weight to each participant who uses the budgeting calculator within a 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.

[17] 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.

[18] 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 10 reveals that the model accurately predicts the frequency of a one-period planning horizon being employed. However, it underestimates the use of the full planning horizon; the model predicts its occurrence at around 10%, while in reality, subjects opt for the full horizon close to half of the time. Moreover, the model's prediction of a 12% usage rate for an 8-period planning horizon stands in stark contrast to what we observe in actual trials, where this horizon is chosen in less than 1% of cases. This notable discrepancy leads us to 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 could be saving half of their income, resulting in a consumption level of 5 units, which is close enough to the model's prediction of 5.13 for an 8-period planner, as shown in Table 10.

7 Discussion

Our study represents one of the first attempts in understanding the role of environmental complexity in dynamic optimization, with a focus 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 are well-acknowledged, the intricacies related to fluctuating income and prices have been less examined. Our research fills this gap, providing critical insights into how these environmental complexities influence dynamic optimization. In exploring these complexities, our experiments reveal that individuals frequently encounter significant hurdles in achieving optimal outcomes, even in seemingly straightforward scenarios. These challenges are not merely due to the variability of economic conditions but also stem from cognitive limitations and numerical challenges inherent in dynamic decision-making. Our findings resonate with existing literature on complexity, such as the works of Oprea (2022), Enke and Graeber (2019), and Gabaix and Graeber (2023), which conceptualize the mind as a cognitive economy faced with numerous decisions. Another key aspect of our study is the potential role of a meticulously designed budgeting calculator in aiding decision-making. Our results indicate that the mere availability of such a tool does not guarantee its effective use. The effectiveness of a budgeting tool depends largely on how individuals choose to utilize it. This observation is crucial, as it highlights that providing tools for financial planning is beneficial, but their impact hinges on the user's engagement and understanding. Moreover, by analyzing non-choice data from the budget calculator, we gain deeper insights into the strategies, preferences, and decision-making horizons of individuals. This novel approach of examining life-cycle consumption experiments through the lens of calculator inputs opens new frontiers in financial decision-making research.

Crucially, our paper makes a significant contribution by directly examining individuals' capacity for planning, a core assumption in economic theory often taken for granted. Standard economic models assume that agents can plan effectively, even for long horizons, which is essential for making optimal present choices. However, empirical evidence supporting this assumption, particularly from laboratory experiments, is scarce.[19] Our work stands as one of the first to provide concrete evidence of individuals' planning abilities—or the lack thereof—by directly observing their plans. This approach differs markedly from indirect methods using decision trees (see Hey 2002), which infer planning from decision outcomes. Expanding upon this concept, we can even compare observed planning-horizons to implied horizons from a short-span horizon model. This analysis leads us to rule out the short-span model in positive interest rate environments, pointing towards a broader issue in achieving optimal paths than just the incapacity for long-term planning.

Looking forward, there are numerous avenues for future research. Investigating dynamic optimization under various conditions such as uncertainty, the impact of social learning, expected liquidity constraints, and current binding constraints can provide further valuable insights. Additionally, a within-subject analysis of the effects of introducing and removing a budget calculator, as well as the lasting impact of financial

[19] One exception is planning in the context of present bias and procrastination (see Della Vigna and Malmendier 2006).

literacy interventions, can offer a more comprehensive understanding of how planning and financial tools influence behavior.

In full information rational expectations New Keynesian theory, the impact of inflation on welfare is primarily associated with menu costs and relative price dispersion. Our FluctP results reveal an added source of welfare loss: suboptimal decision-making due to cognitive complexity. The inflation and deflation experienced in our experiment were intentionally large to increase the salience of price changes. In a more realistic environment, we anticipate that inattention to price fluctuations would further exacerbate optimization errors and welfare losses.

In conclusion, our study contributes significantly to the field of financial decision-making by highlighting the complexities involved in dynamic optimization and the role of tools like budget calculators in navigating these complexities. It paves the way for future research to build on these findings, ultimately aiming to develop more effective strategies and tools to assist individuals in making better financial decisions amidst an ever-changing economic landscape.

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A Taylor Expansion for Optimal Choice

In this section, we conduct a Taylor expansion on the optimal consumption choice in period 1 (as shown in Equation 6). Our approach is in accordance with the methodology outlined in the work of Gabaix and Graeber (2023) on 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 very small. We can rewrite Equation 6.

$$c_1 = \frac{\sum_{t=1}^{T} \frac{y_1}{(1+r)^{t-1}} + \sum_{t=2}^{T} \frac{\hat{y}_t}{(1+r)^{t-1}}}{\left(p_1 + p_1^{\frac{1}{\sigma}} \left(\sum_{t=2}^{T} \left(\frac{\hat{p}_t + p_1}{(1+r)^{t-1}}\right)^{\frac{\sigma-1}{\sigma}}\right)\right)} \tag{12}$$

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

$$c_1 = \frac{Ty_1}{p_1 + p_1^{\frac{1}{\sigma}} \left((T-1)\, p_1^{\frac{\sigma-1}{\sigma}}\right)} = \frac{y_1}{p_1} \tag{13}$$

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

$$\begin{aligned}
\frac{\partial c_1}{\partial \hat{y}_t} &= \frac{\sum_{t=1}^{T} \left[\frac{1}{(1+r)^{t-1}}\right]}{\left(p_1 + p_1^{\frac{1}{\sigma}} \left(\sum_{t=2}^{T} \left(\frac{\hat{p}_t + p_1}{(1+r)^{t-1}}\right)^{\frac{\sigma-1}{\sigma}}\right)\right)} \\
&= \frac{1}{p_1 + p_1^{\frac{1}{\sigma}} \left(p_1^{\frac{\sigma-1}{\sigma}} (T-1)\right)} \\
&= \frac{1}{Tp_1}
\end{aligned}$$

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

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

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

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

Thus, the Taylor expansion is

$$
c_1 = \frac{y_1}{p_1} + \frac{1}{T p_1} \sum_{t=2}^{T} \hat{y}_t - \frac{y_1 (T-1)}{2\sigma p_1} r + \left(\frac{1-\sigma}{\sigma}\right) \frac{y_1}{T p_1^2} \sum_{t=2}^{T} \hat{p}_t \tag{14}
$$

B Additional Regressions

Table 8: 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***			0.208***			0.115***			0.105***
			(0.02)			(0.02)			(0.02)			(0.02)
Minutes Spent	-0.037***	-0.012***	-0.009*	-0.008	-0.009***	-0.005	-0.011	-0.014***	-0.007	-0.011	-0.000	-0.003
	(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***	0.037***	0.010	-0.018	-0.019	0.042***	0.007	0.023*	0.042***	0.005	-0.001
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Repetition 3	0.047***	0.065***	0.068***	0.038***	0.037**	0.025*	0.059***	0.035***	0.047***	0.059***	0.029	0.018
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Period	-0.010***	0.001	0.001	-0.006***	0.000	-0.000	-0.003*	-0.009***	-0.009***	-0.003*	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	0.005	-0.000	-0.005	0.004	0.005	-0.005	0.041***	0.035**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Backward Induction	-0.001	0.042**	0.036*	-0.015	0.016	0.006	0.024	-0.004	-0.007	0.024	0.027	0.028
	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Financial Literacy	0.092**	-0.018	-0.017	0.022	-0.013	-0.021	0.034	-0.012	-0.013	0.034	-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**	0.019***	0.007	0.012	0.014	0.007	0.002	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Calculator Usage												
Current Period		0.074***	0.075***		-0.028	-0.009		-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***		0.037	0.055**		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		-0.091***	-0.181***		-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		0.086***	-0.073**		-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	0.663*	-0.122	-0.371	-0.202	0.267	0.432	0.266	0.267	0.358	0.526
	(0.48)	(0.44)	(0.40)	(0.73)	(0.40)	(0.27)	(0.51)	(0.53)	(0.52)	(0.51)	(0.68)	(0.67)
Observations	1320	1320	1320	1290	1440	1440	1380	1440	1440	1380	1350	1350
Overall R^2	0.15	0.16	0.21	0.05	0.13	0.25	0.10	0.05	0.14	0.10	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 9: 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			0.099***			0.066***			0.064***			0.102***
			(0.01)			(0.01)			(0.02)			(0.02)
Minutes Spent	0.002	-0.005*	-0.002	0.008	0.000	-0.003	0.001	0.001	0.003	0.001	0.003	-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***	0.038***	-0.000	-0.014	-0.005	0.034***	0.010	0.014	0.034***	0.006	0.031*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Repetition 3	0.057***	0.067***	0.071***	0.031**	0.037***	0.046***	0.055***	0.036***	0.032***	0.055***	0.029*	0.047***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Period	0.011***	0.007***	0.006***	0.018***	0.028***	0.027***	0.011***	0.008***	0.007***	0.011***	0.018***	0.016***
	(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	0.009	0.006	0.005	0.009	-0.004	0.002	0.001	-0.004	0.030**	0.028**
	(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	0.023	-0.009	0.012	0.009	0.019	-0.005	-0.005	0.019	0.025	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	-0.003	0.027	-0.020	-0.020	0.031	-0.005	-0.000	0.031	-0.010	-0.007
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Control Questions	0.000	0.006	0.003	0.011	0.021***	0.019**	0.009	0.012	0.013	0.009	-0.002	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Calculator Usage												
Current Period		0.074***	0.059***		0.004	0.008		-0.053**	-0.055**		-0.001	0.006
		(0.02)	(0.02)		(0.03)	(0.03)		(0.02)	(0.02)		(0.03)	(0.03)
Partial		0.116***	0.095***		0.050**	0.052**		0.020	0.017		-0.023	0.010
		(0.02)	(0.02)		(0.03)	(0.03)		(0.02)	(0.02)		(0.03)	(0.03)
Sequential		0.028	-0.024		-0.050*	-0.066**		0.003	-0.012		0.002	0.024
		(0.02)	(0.02)		(0.03)	(0.03)		(0.02)	(0.02)		(0.03)	(0.03)
Complete		0.069***	0.013		0.089***	0.079***		-0.028	-0.057***		0.064**	0.051**
		(0.02)	(0.02)		(0.02)	(0.02)		(0.02)	(0.02)		(0.03)	(0.03)
Constant	0.285	0.481	0.610	-0.159	-0.567	-0.501	0.152	0.282	0.240	0.152	0.530	0.439
	(0.42)	(0.47)	(0.42)	(0.68)	(0.37)	(0.38)	(0.43)	(0.46)	(0.44)	(0.43)	(0.58)	(0.53)
Observations	1320	1320	1320	1290	1440	1440	1380	1440	1440	1380	1350	1350
Overall R^2	0.19	0.17	0.24	0.08	0.23	0.24	0.11	0.08	0.13	0.11	0.18	0.20

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: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C 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 is represented as ε, a normally distributed random variable with a mean of zero and a standard deviation of σ. Therefore, the actual consumption choice for a given planning horizon, denoted as c_H, is expressed as: $c_H = c_H^* + \varepsilon$, where H ranges from 1 to 10, and c_H^* is the theoretically optimal consumption level in Period 1 for a given H. In addition to this, we account for the possibility that a subset of subjects might make their consumption choices randomly. We model this by assuming that these subjects' decisions follow a uniform distribution ranging from 0 to 10. Consequently, our model treats the population as comprising $H + 1$ distinct planner types, each represented by a proportion p_h for h in the range of [0,10].

To define a log-likelihood function, we combine these proportions with the conditional densities. This integration allows us to compute the sample log-likelihood for the n observations in our sample. The log-likelihood function is formulated 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 $c_{i,R}$ is subject i´s actual consumption in repetition R. Our next step is to determine the proportions $\hat{p}_h$ and the standard deviation $\hat{\sigma}$ that maximize the log-likelihood function.

C.1 Individual-Level Analysis

To evaluate the model's prediction in comparison to the actual horizon on an individual basis, we use $\hat{\sigma}$ to determine a range for c_H for each individual, allowing us to assign a corresponding planning horizon. Figure 11 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

Table 10: 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 11: Estimation Outcome

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: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

during the first period of each repetition. Notably, the patterns observed here inform us further: the actual planning horizon is typically longer than the short-term horizon model's prediction. Furthermore, in over 25 percent of instances, either the model does not categorize an individual or predicts a horizon of 1, yet the subjects opt for the full horizon. Conversely, in only 3 percent of cases where the model predicts full-horizon use, subjects adhere to this prediction. Nevertheless, there are instances—around 3 percent—where the model forecasts full horizon use, but individuals choose a shorter horizon.

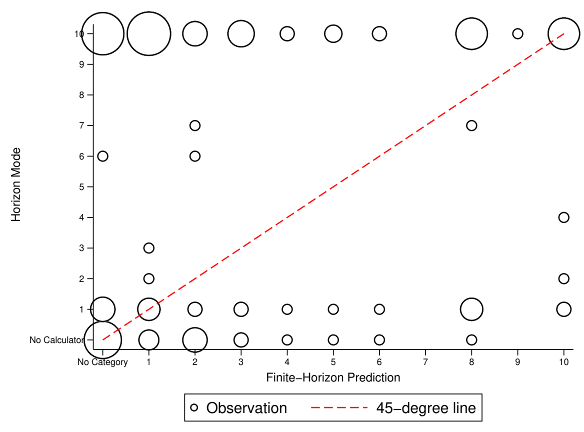


Figure 11: Comparison between the predicted and the observed horizon at the individual level

D 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.[20] For 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: whether this heuristic becomes more prevalent as complexity increases and whether access to the calculator limits its usage.

To address these questions, Figure 12 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 reveals that the adoption of this heuristic varies by treatment.

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.[21]

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.

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

[21] 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 ($p = 0.0699$).

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 highlights the calculator's potential utility in reducing 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 double the number observed when the calculator was available.

Finally, in the FluctP treatment, the H2M heuristic was utilized in 22.46 percent of the periods when the calculator was present, and in 17.05 percent of the periods when the calculator was absent (across all repetitions).[22] Notably, in this treatment, the proportion of subjects employing the heuristic increases during periods with low prices, demonstrating their understanding of the need to purchase more units to take advantage of the lower costs, although they tend to overshoot their consumption. Moreover, if we consider the number of participants that used the heuristic from the beginning to the end of Repetition 3, there are only 3 subjects when the calculator was enabled. This number increases to 7 when the calculator was not available.

[22]We reject the null hypothesis of equality of proportions ($p = 0.0006$). One possible explanation for this behavior is that in these FluctP, employing the H2M heuristic involves relatively more complex arithmetic operations (dividing a number by 50 or by 150) compared to the other treatments where the division is over 100. The budgeting calculator might frame subjects towards the H2M direction by eliminating the arithmetic difficulty.

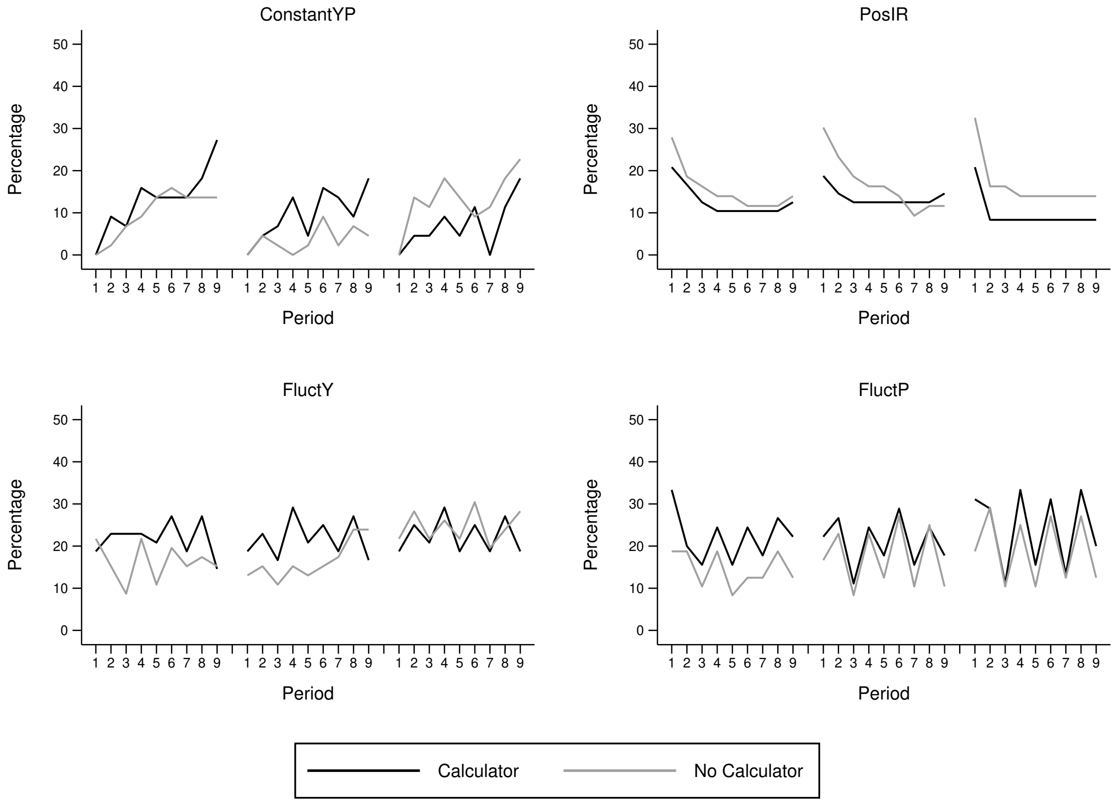


Figure 12: Percentage of Subjects Using the Hand-to-Mouth Heuristic

E Individual Time Series

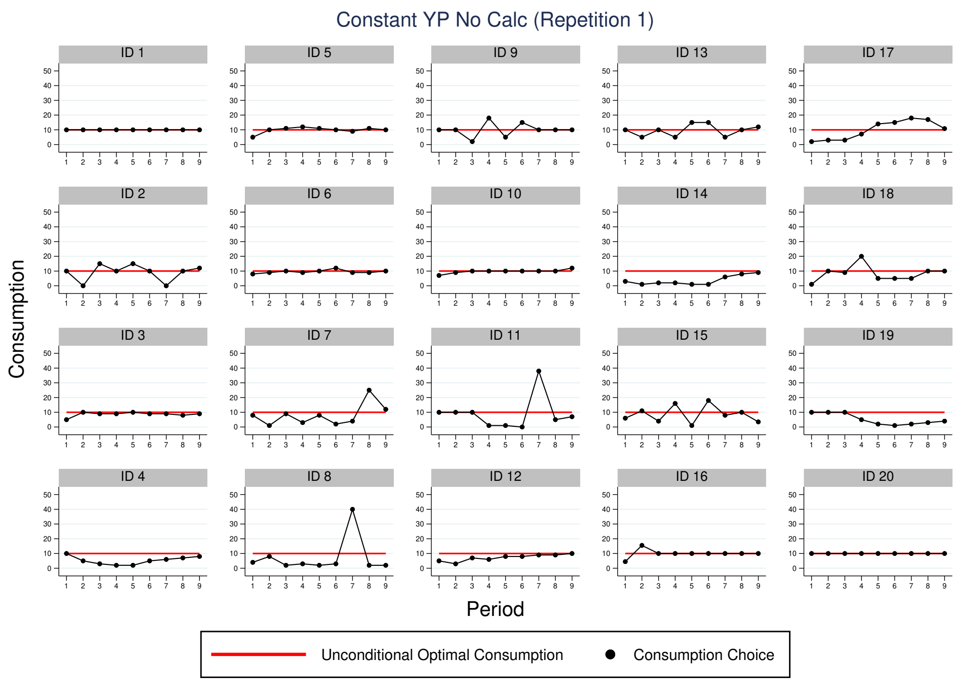


Figure 13: Constant YP No Calc, Repetition 1 (Session 1)

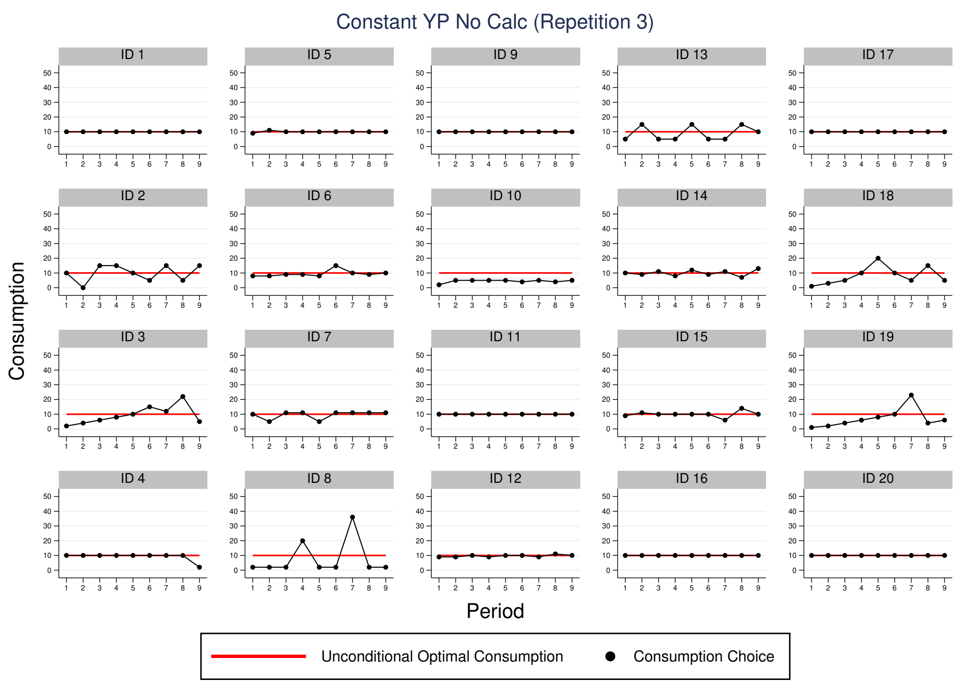


Figure 14: Constant YP No Calc, Repetition 3 (Session 1)

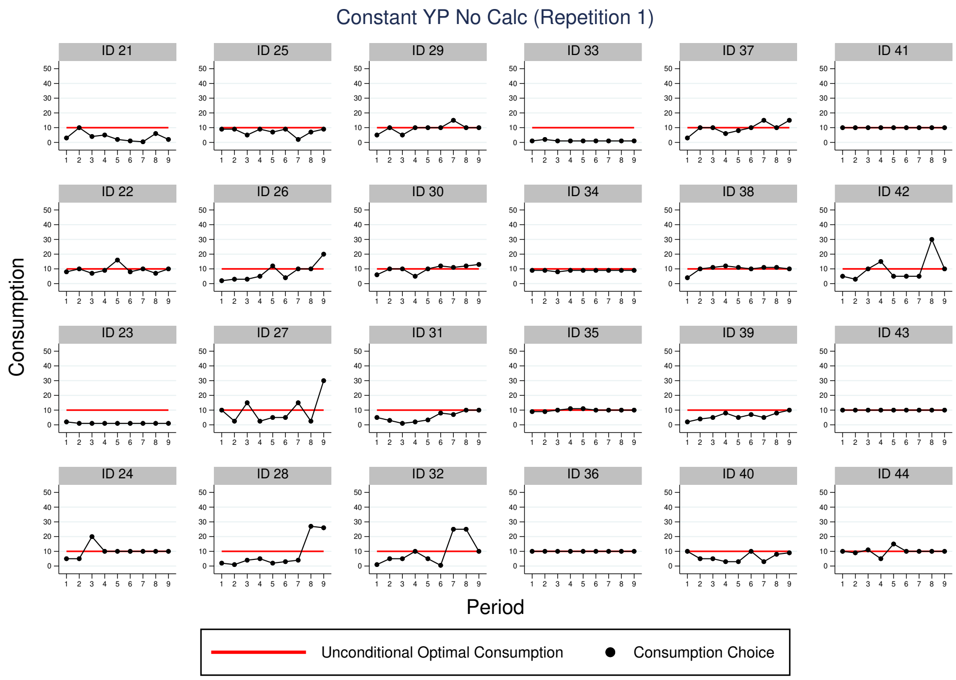


Figure 15: Constant YP No Calc, Repetition 1 (Session 2)

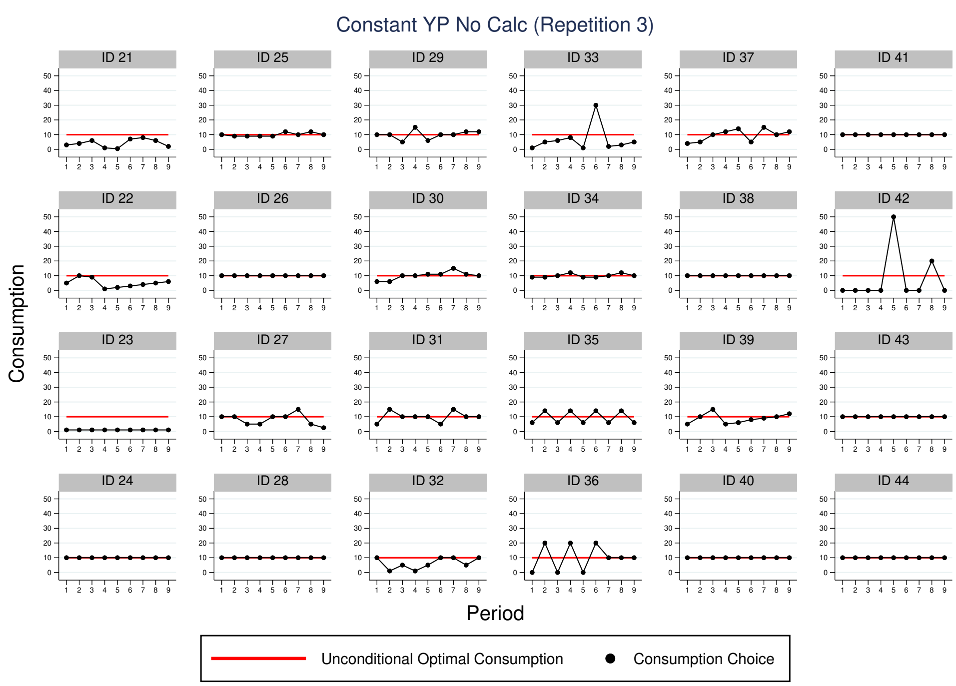


Figure 16: Constant YP No Calc, Repetition 3 (Session 2)

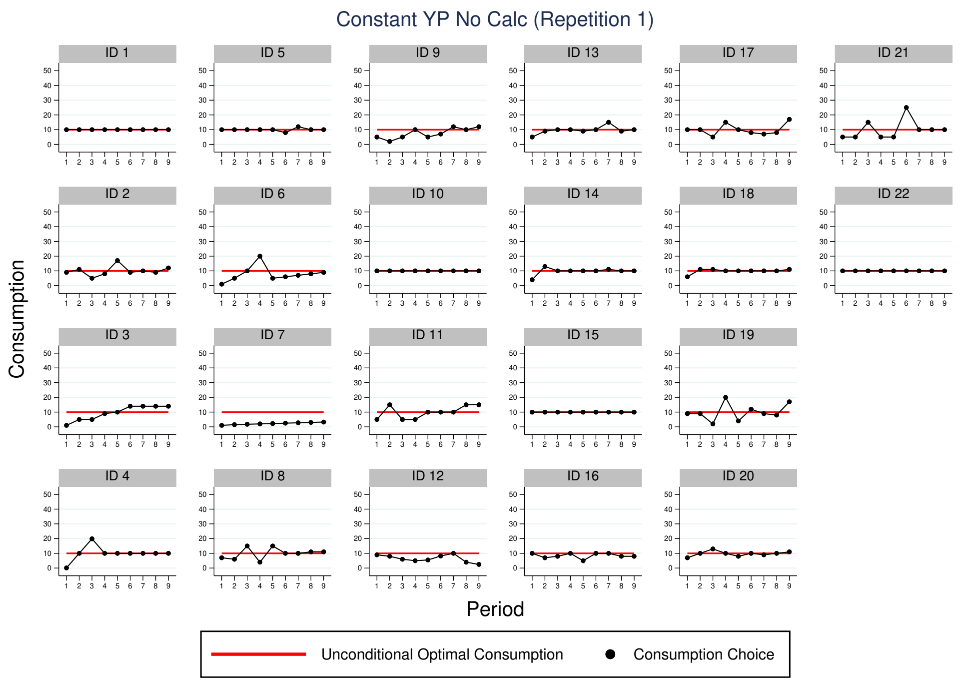


Figure 17: Constant YP Calc, Repetition 1 (Session 1)

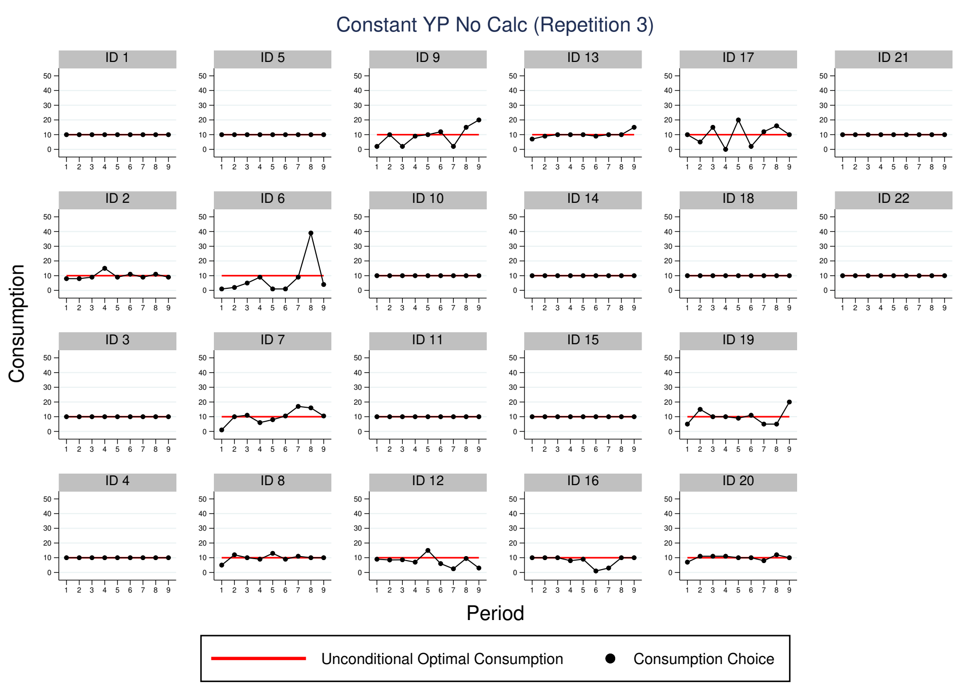


Figure 18: Constant YP Calc, Repetition 3 (Session 1)

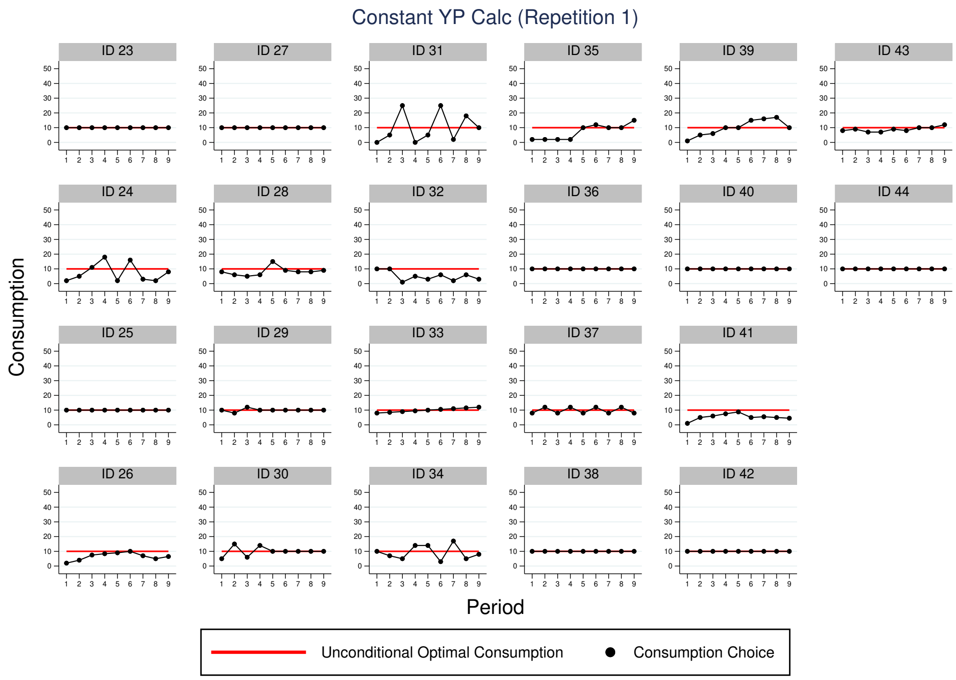


Figure 19: Constant YP No Calc, Repetition 1 (Session 2)

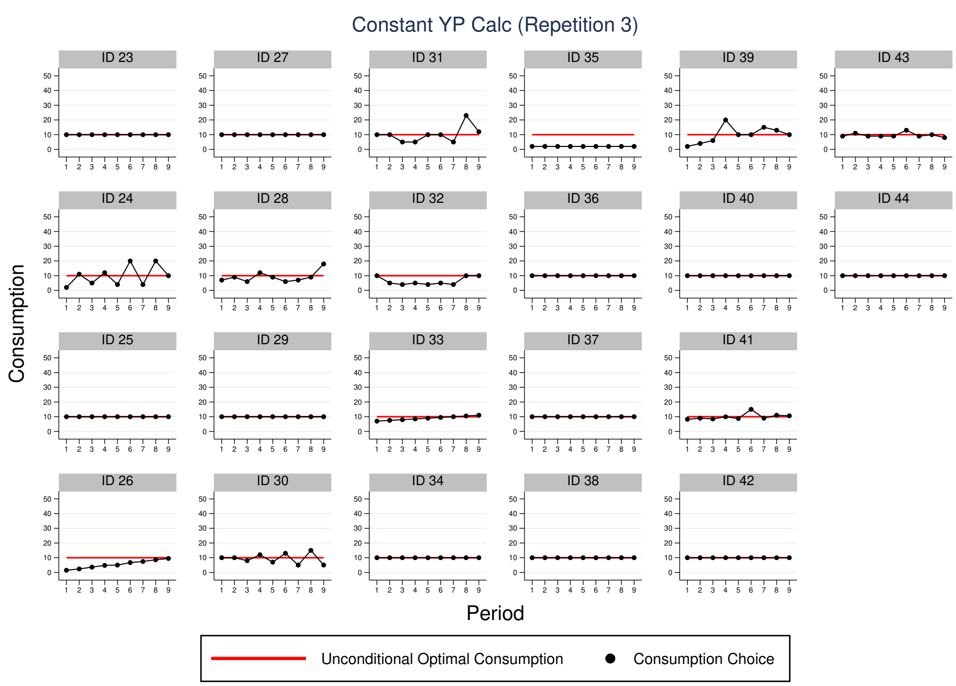


Figure 20: Constant YP Calc, Repetition 3 (Session 2)

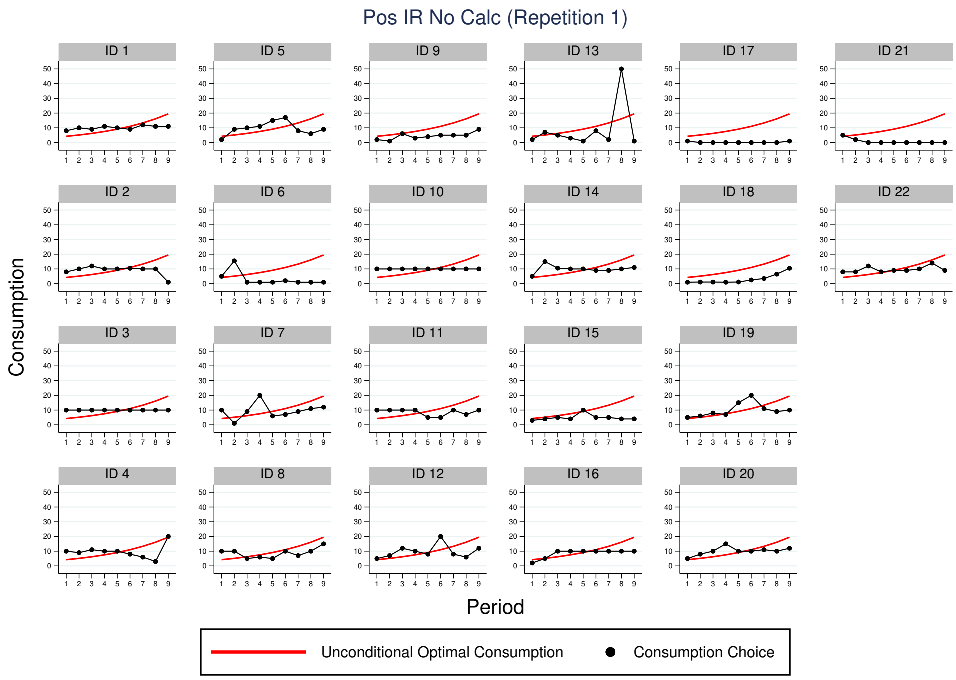


Figure 21: Pos IR No Calc, Repetition 1 (Session 1)

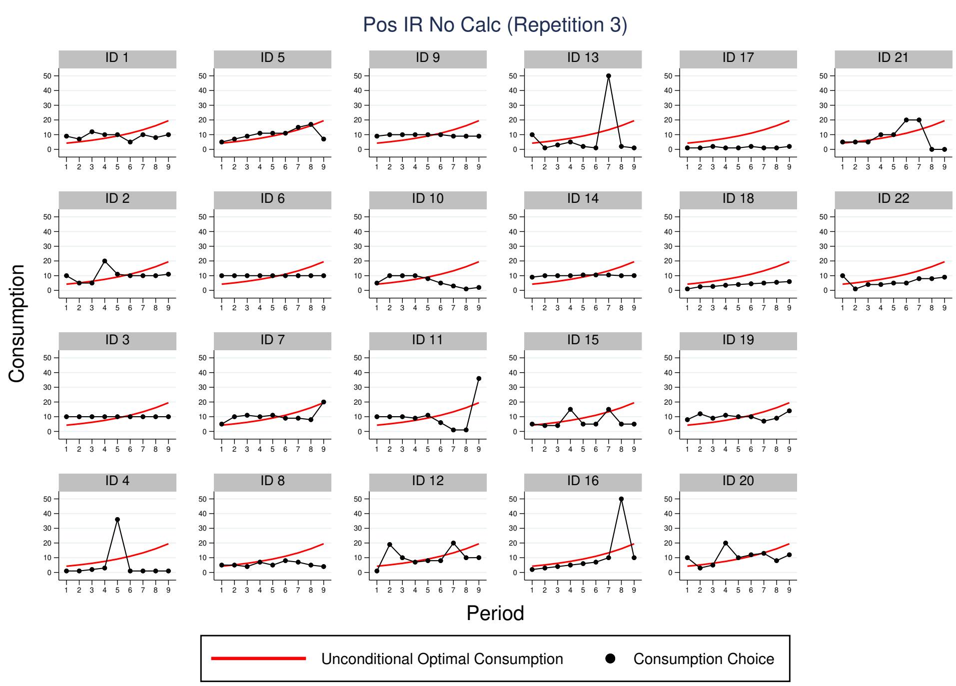


Figure 22: Pos IR No Calc, Repetition 3 (Session 1)

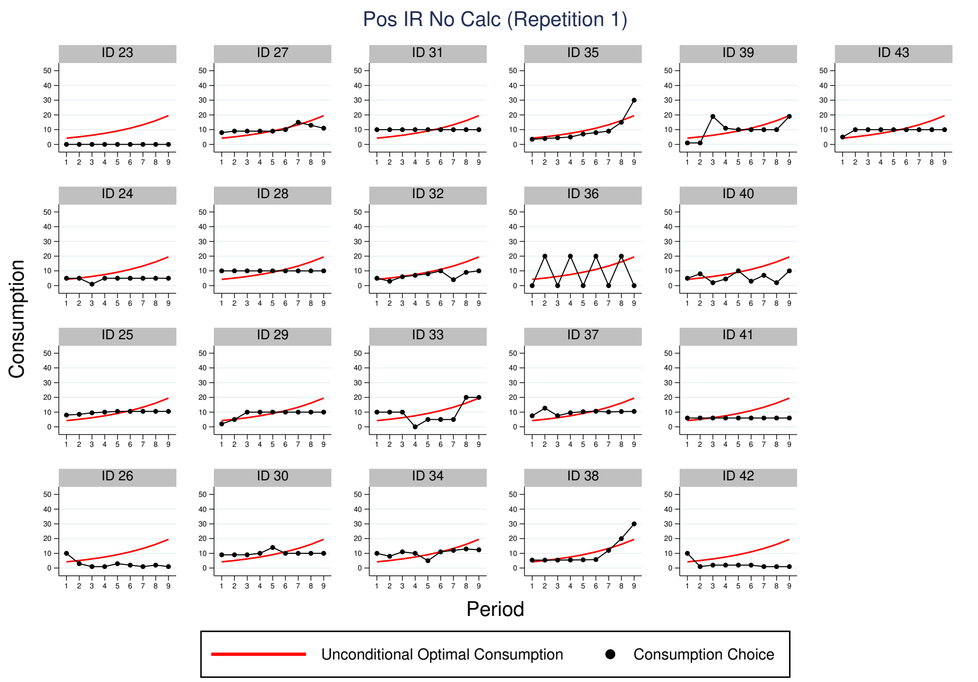


Figure 23: Pos IR No Calc, Repetition 1 (Session 2)

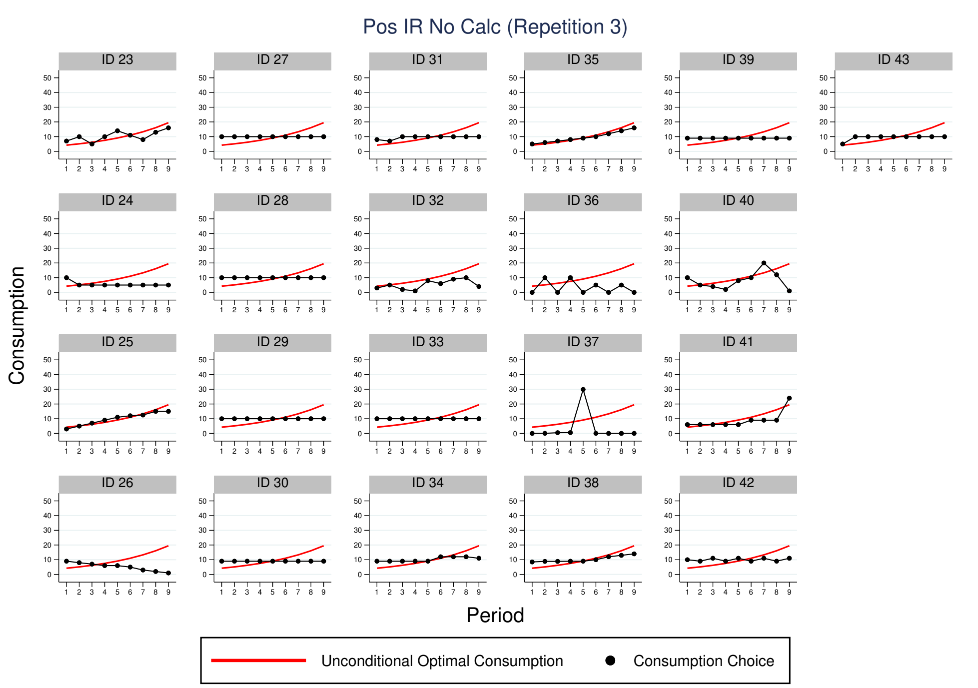


Figure 24: Pos IR No Calc, Repetition 3 (Session 2)

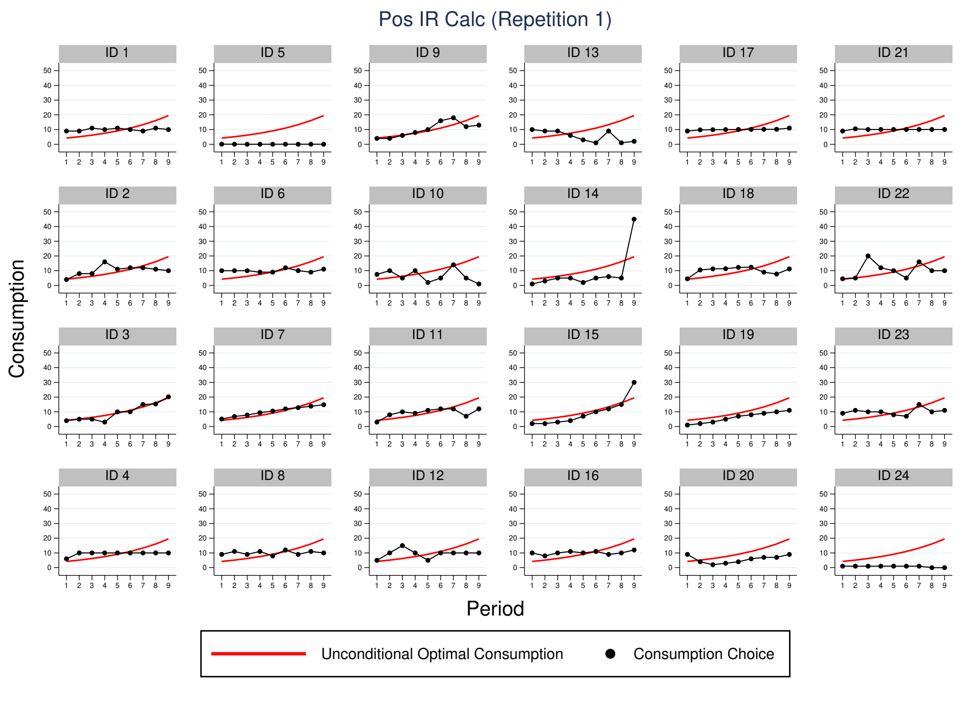


Figure 25: Pos IR Calc, Repetition 1 (Session 1)

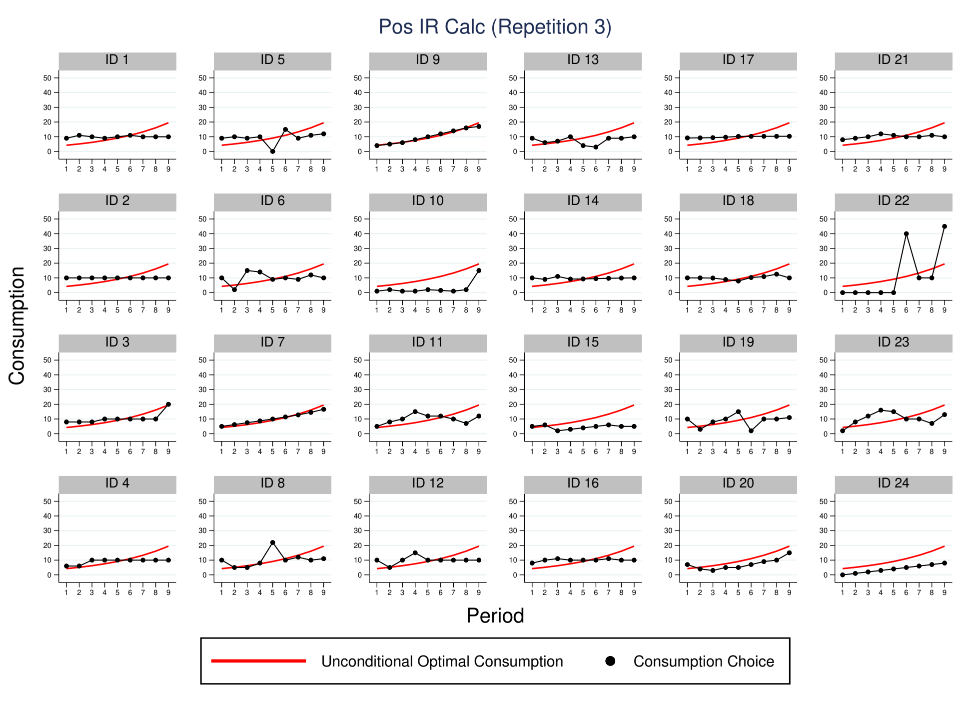


Figure 26: Pos IR Calc, Repetition 3 (Session 1)

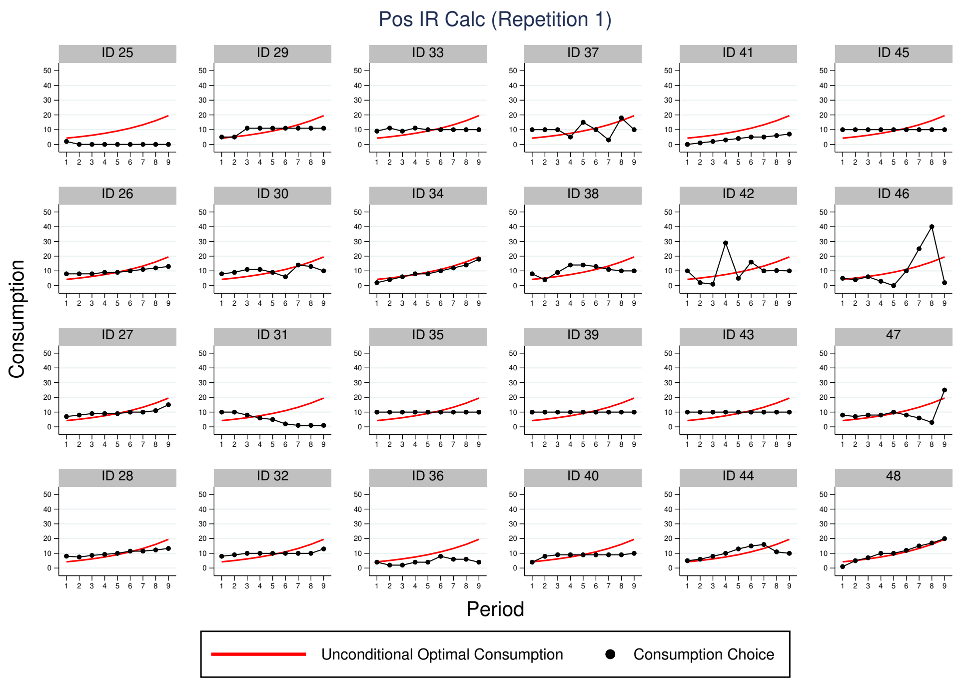


Figure 27: Pos IR No Calc, Repetition 1 (Session 2)

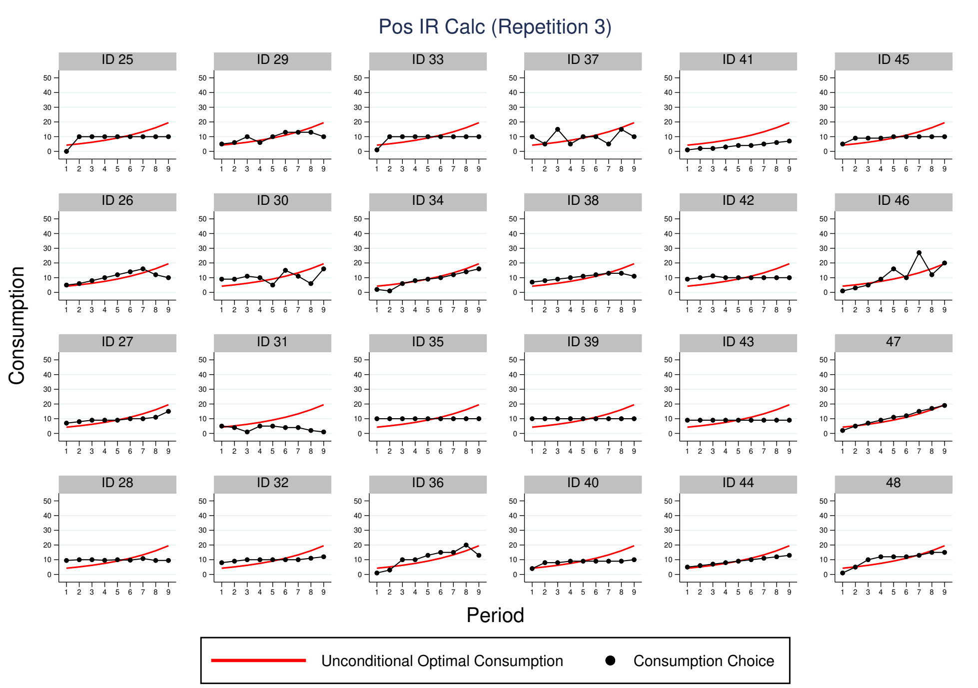


Figure 28: Pos IR Calc, Repetition 3 (Session 2)

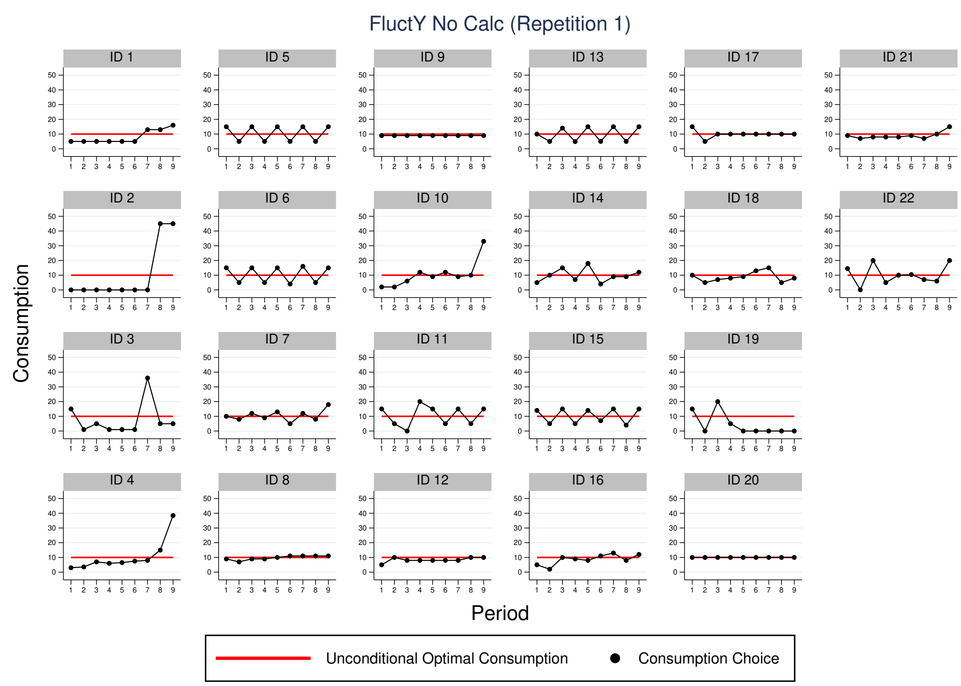


Figure 29: FluctY No Calc, Repetition 1 (Session 1)

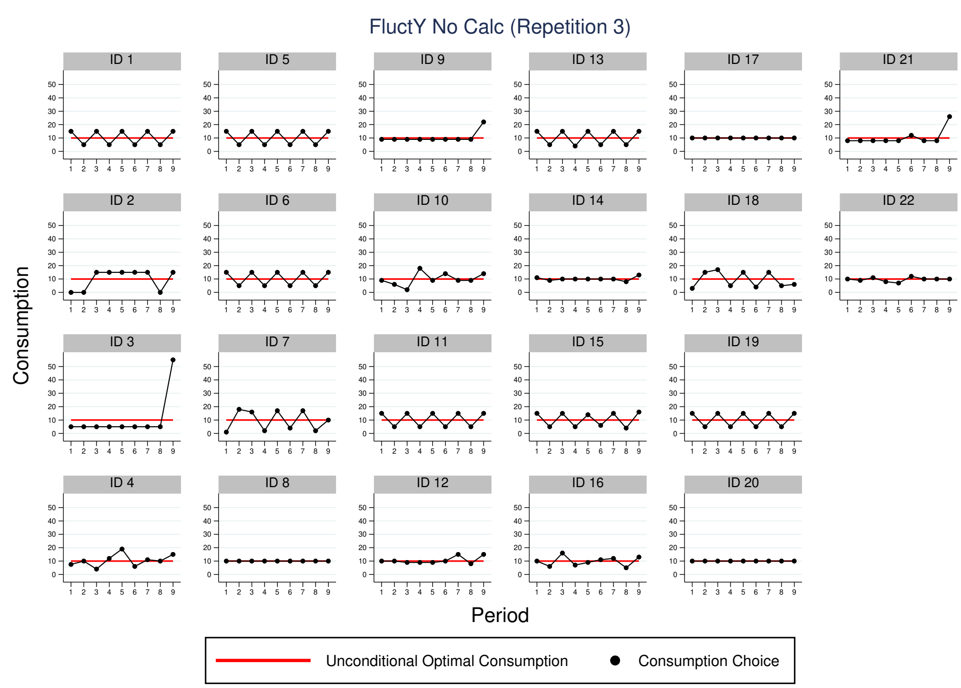


Figure 30: FluctY No Calc, Repetition 3 (Session 1)

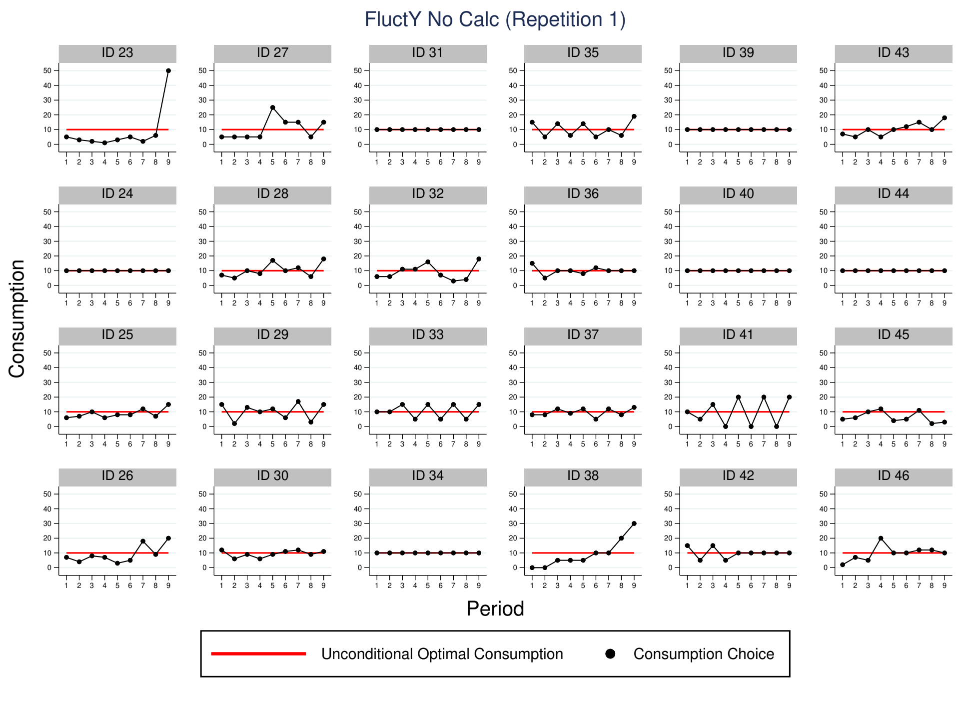


Figure 31: FluctY No Calc, Repetition 1 (Session 2)

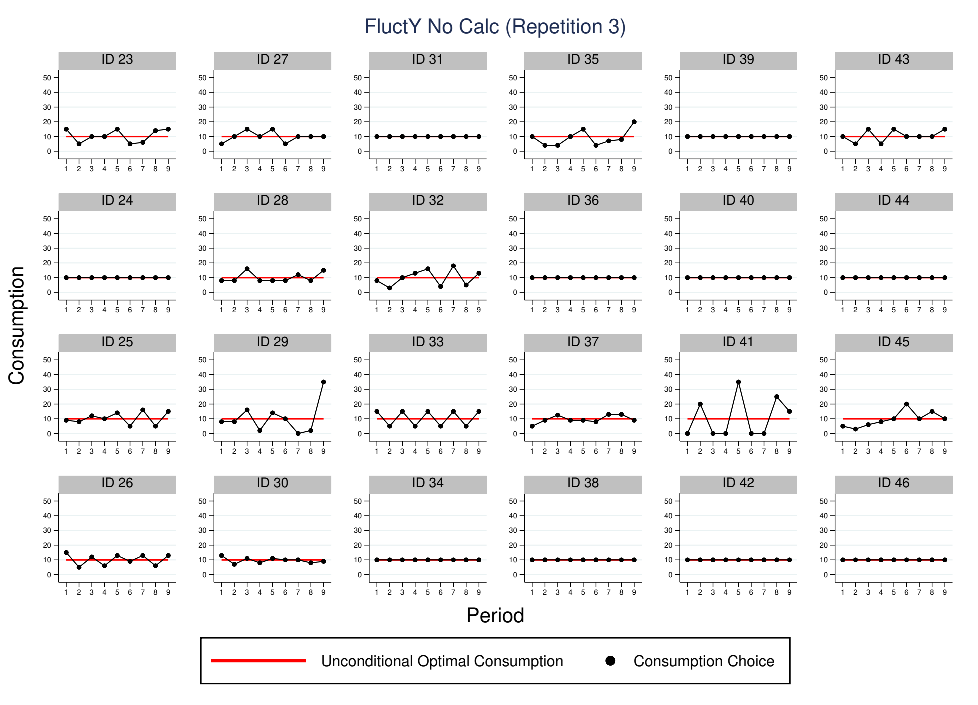


Figure 32: FluctY No Calc, Repetition 3 (Session 2)

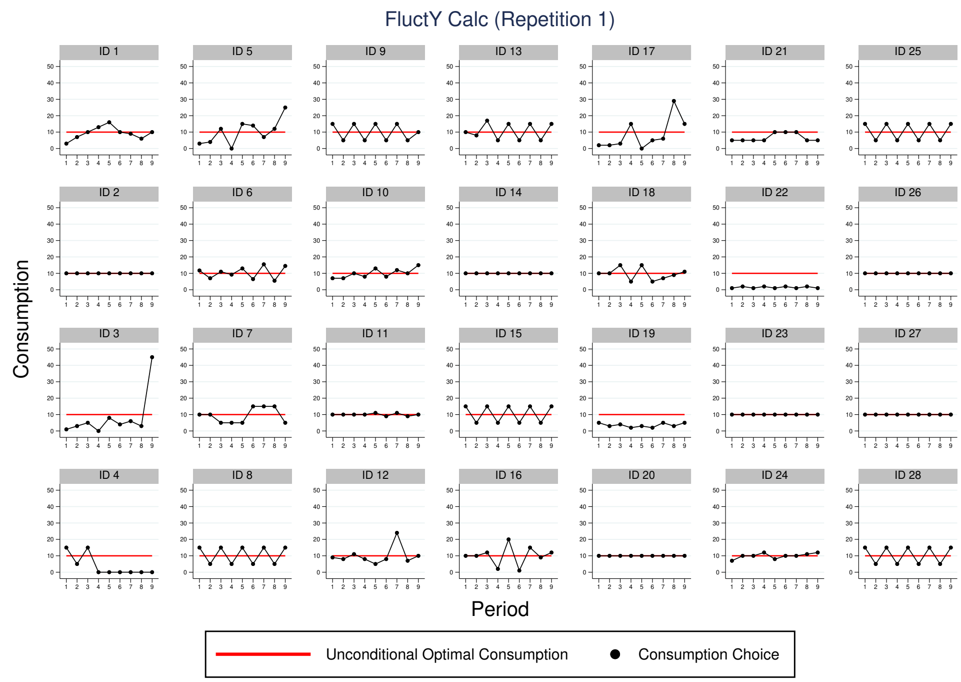


Figure 33: FluctY Calc, Repetition 1 (Session 1)

Figure 34: FluctY Calc, Repetition 3 (Session 1)

Figure 35: FluctY No Calc, Repetition 1 (Session 2)

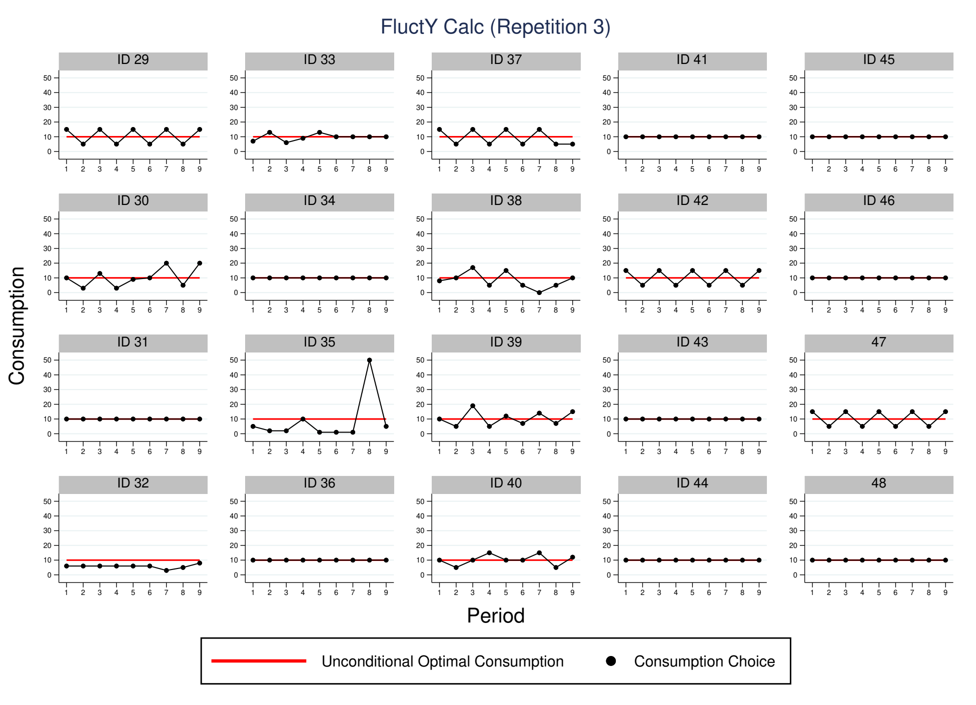


Figure 36: FluctY Calc, Repetition 3 (Session 2)

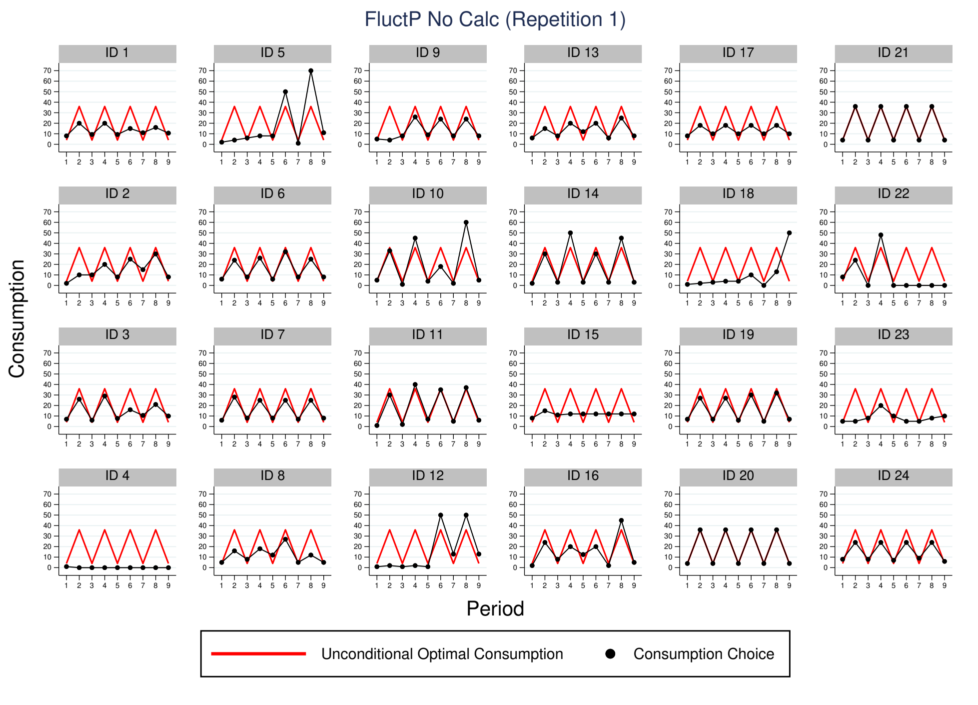


Figure 37: FluctP No Calc, Repetition 1 (Session 1)

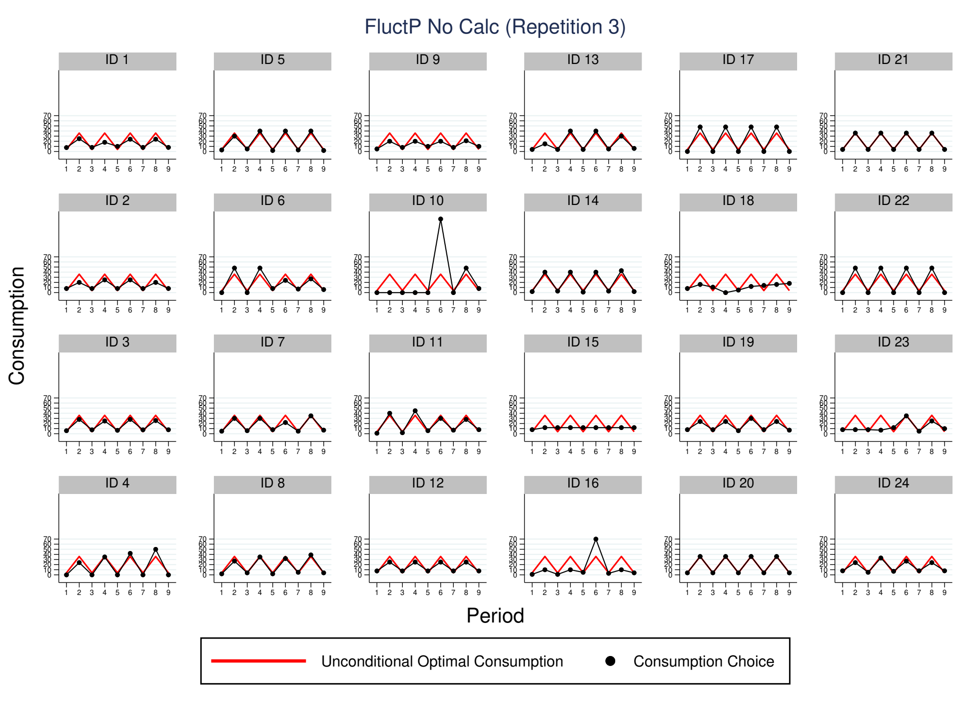


Figure 38: FluctP No Calc, Repetition 3 (Session 1)

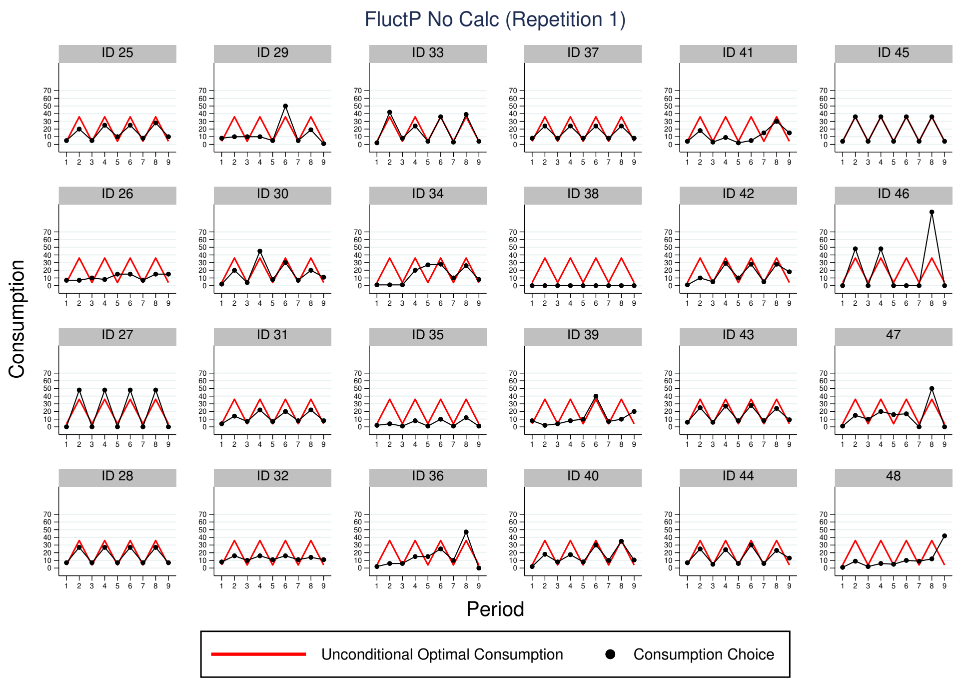


Figure 39: FluctP No Calc, Repetition 1 (Session 2)

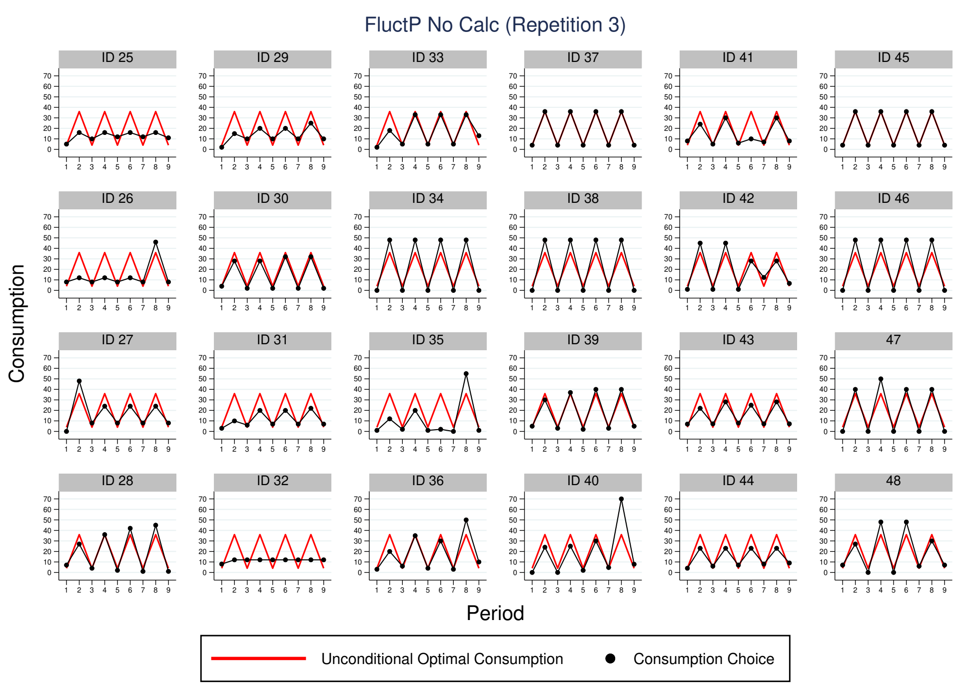


Figure 40: FluctP No Calc, Repetition 3 (Session 2)

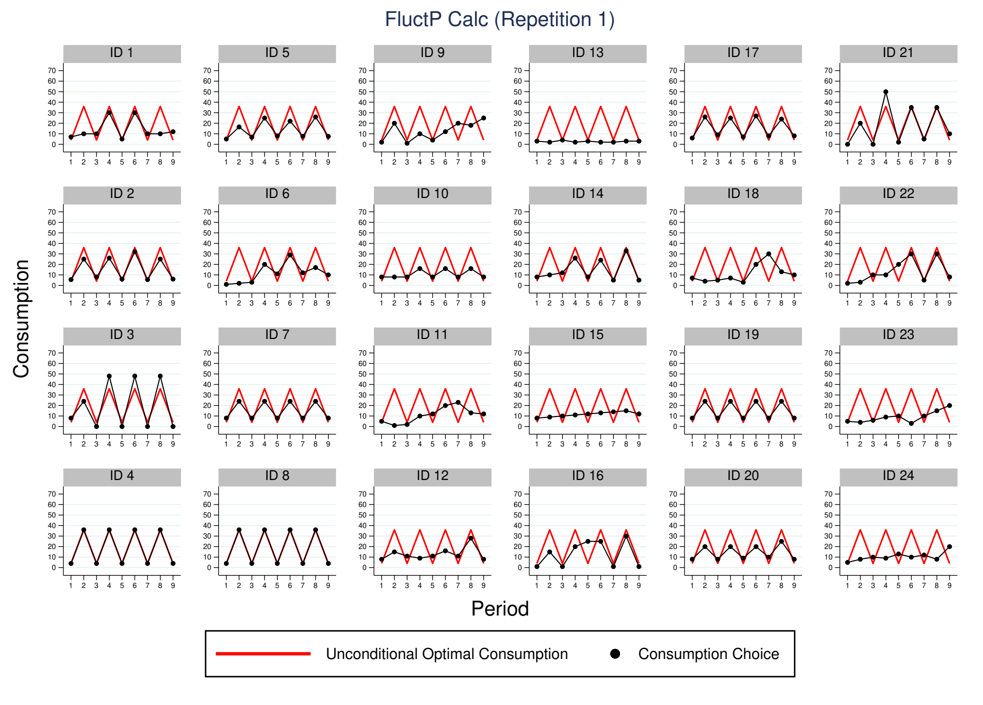


Figure 41: FluctP Calc, Repetition 1 (Session 1)

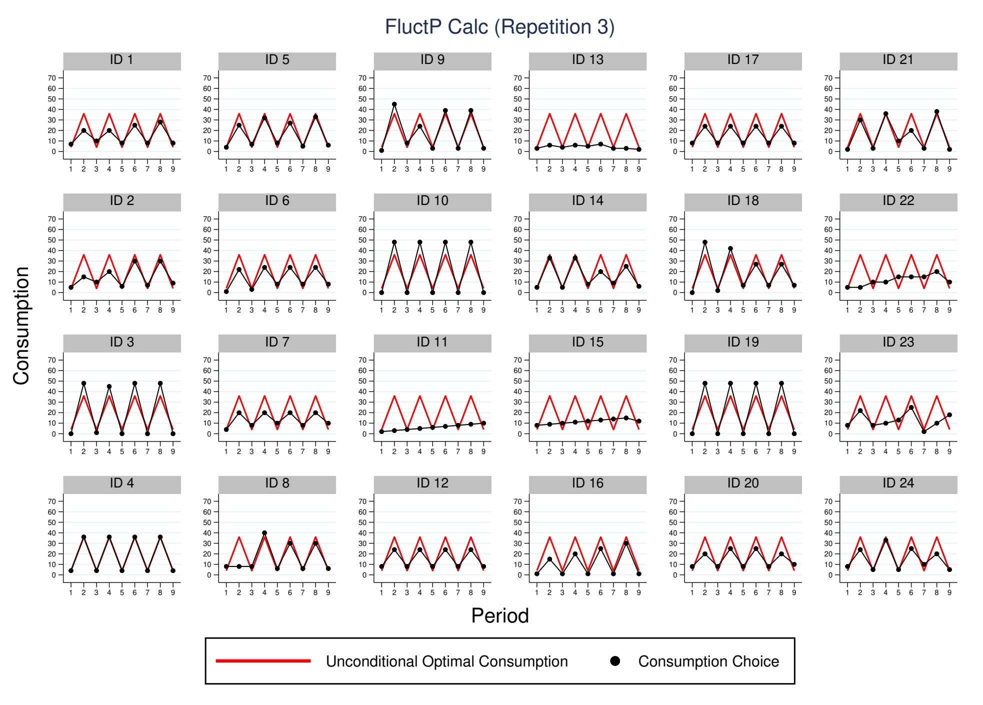


Figure 42: FluctP Calc, Repetition 3 (Session 1)

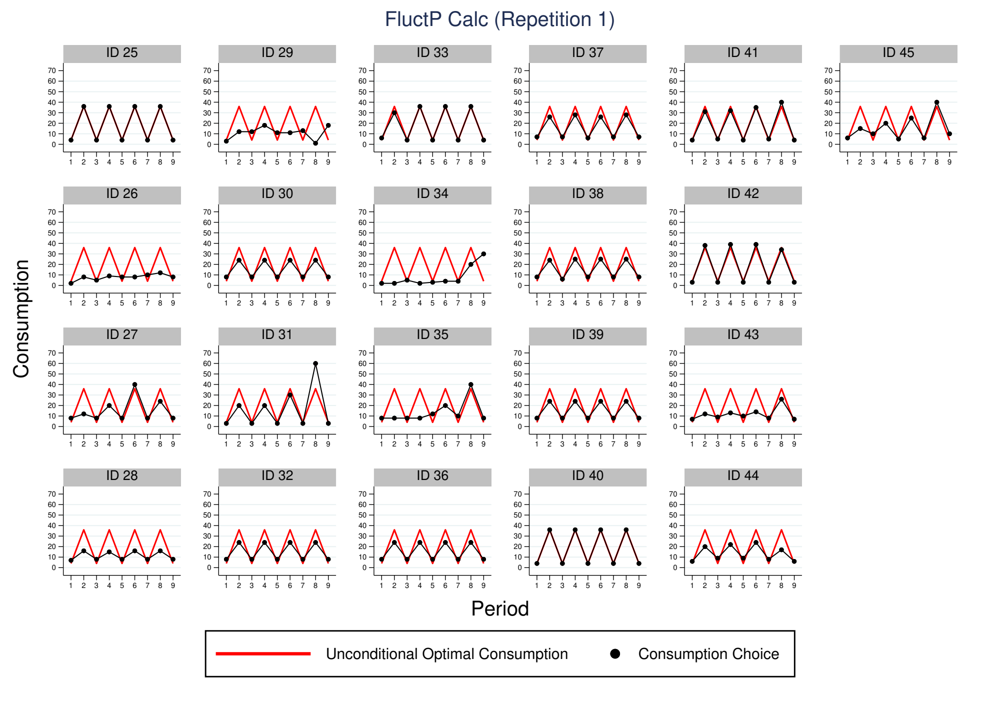


Figure 43: FluctP No Calc, Repetition 1 (Session 2)

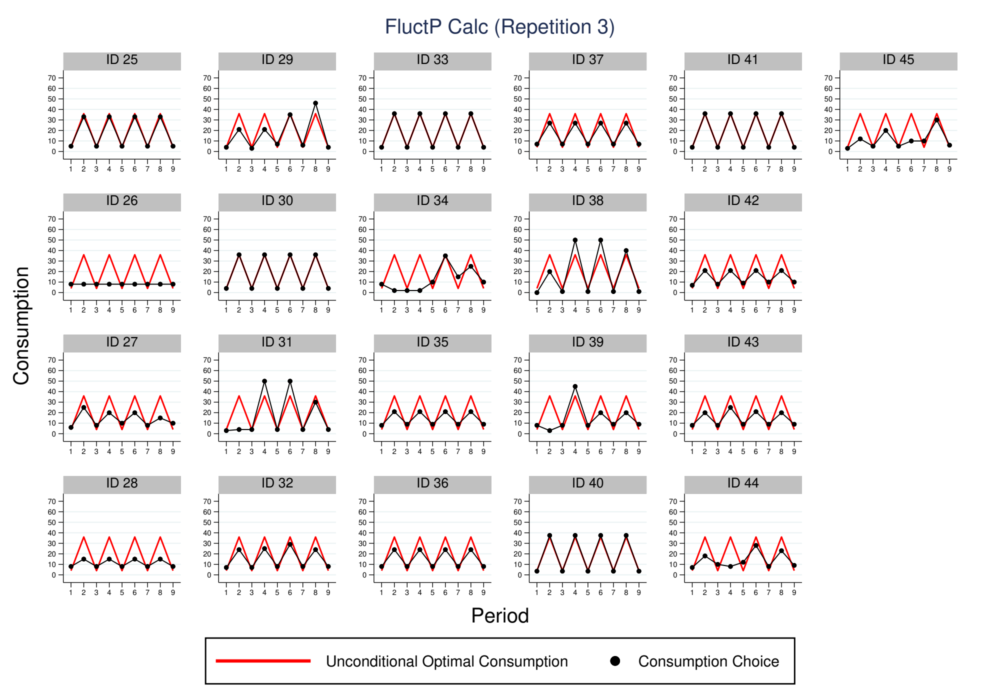


Figure 44: FluctP Calc, Repetition 3 (Session 2)

F Instructions

F.1 Main Instructions

F.1.1 Calc Sessions

The instructions distributed to subjects in treatments in which the calculator was enabled are reproduced on the following pages. All subjects received the same set of instructions except that those in the Pos IR in which we added some small adjusted 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 ($).

   Purchased Output → Points → 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>

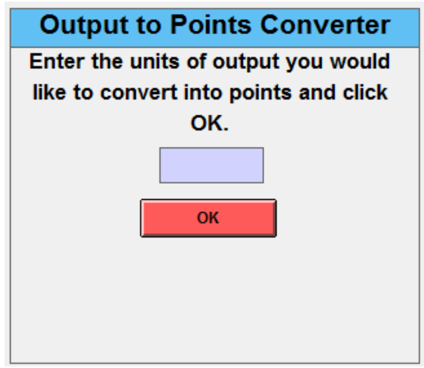
You will be provided precise information about the income and prices you will face in all 10 periods of each repetition. That is, there is no uncertainty about these variables. You will also have information about your previous decisions and economic variables. <u>Please note that prices and income may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

<u>**Repetitions**</u>

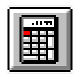
The experiment will consist of 3 repetitions of 10 periods each. After a repetition is completed, you will see a Review Screen that will display your total points from that repetition. There will be no carryover of tokens or points between repetitions. When a new repetition begins, all token balances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

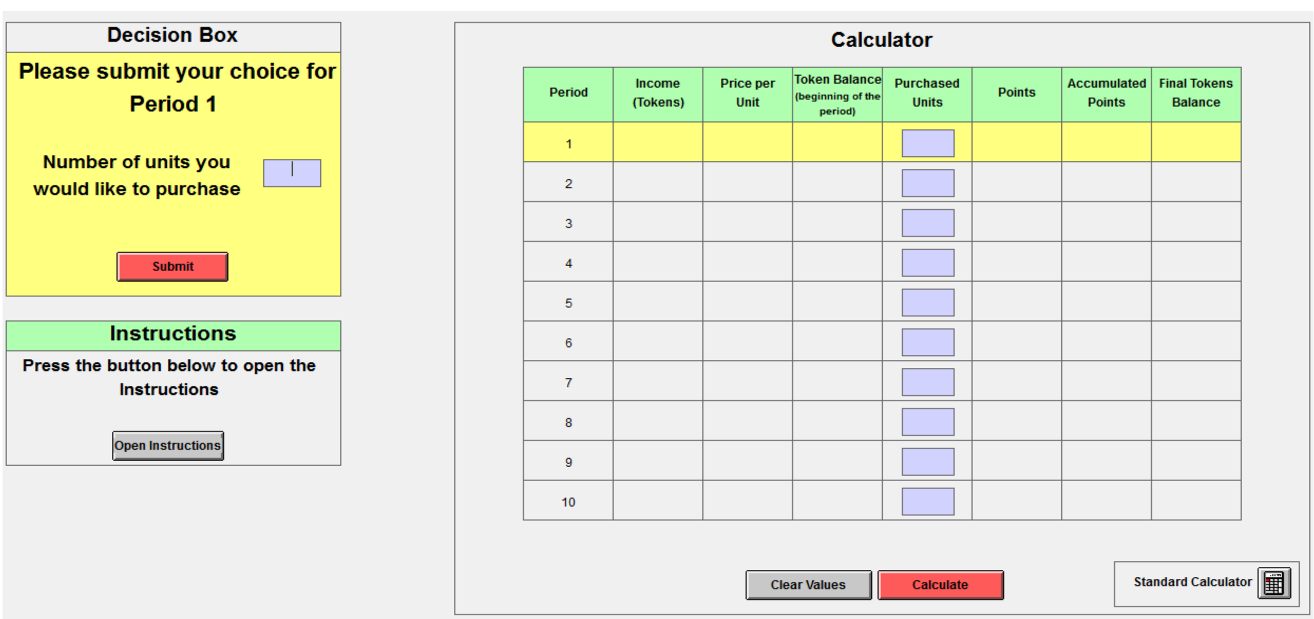


Standard Calculator

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.



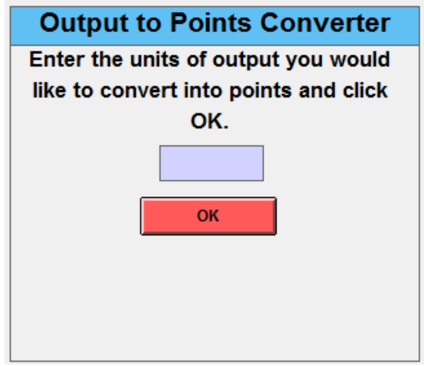
Remember that your actual purchase decision has to be entered on the left hand side of the screen.

F.1.2 No Calc Sessions

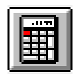
For the sessions in which the budgeting calculator was not enabled the third page of the instructions was adapted as shown below.

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

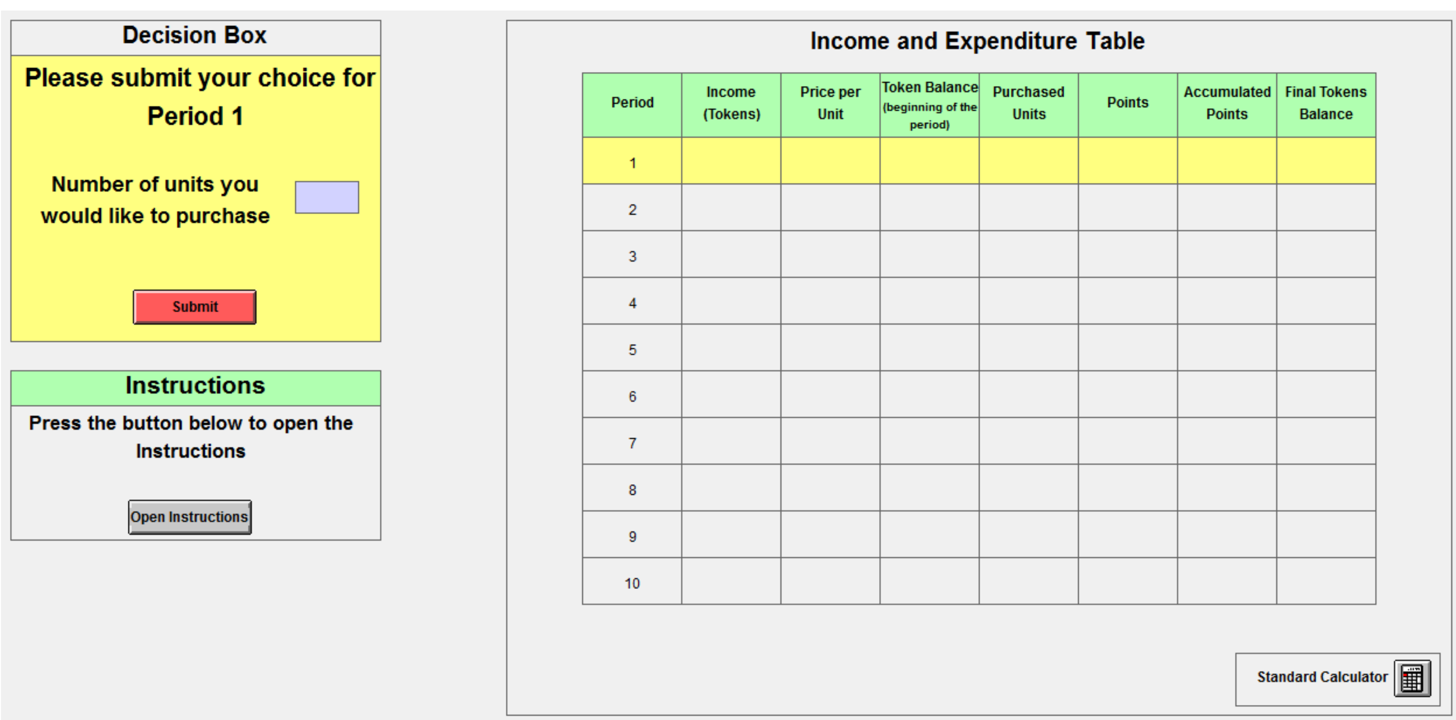
You may use a standard calculator by clicking on 

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.

F.2 Interactive Instructions

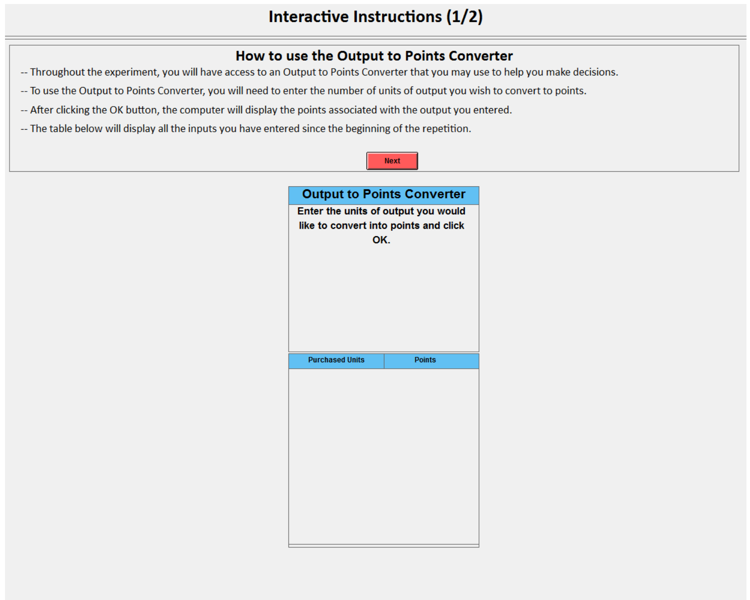


Figure 45: Screenshot for Interactive Instructions 1

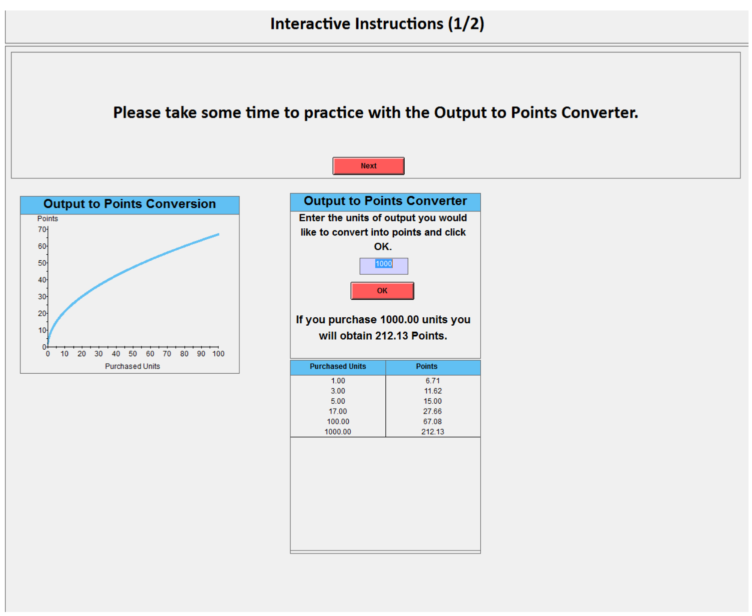


Figure 46: Screenshot for Interactive Instructions 2

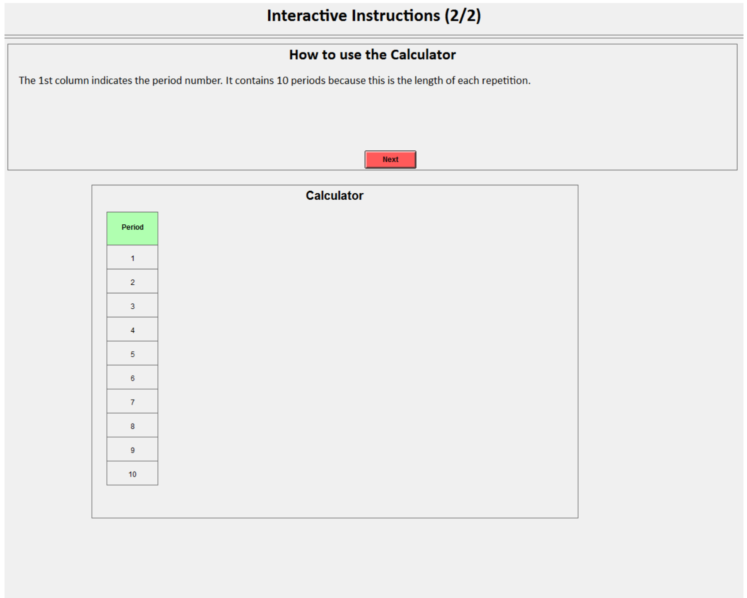


Figure 47: Screenshot for Interactive Instructions 3

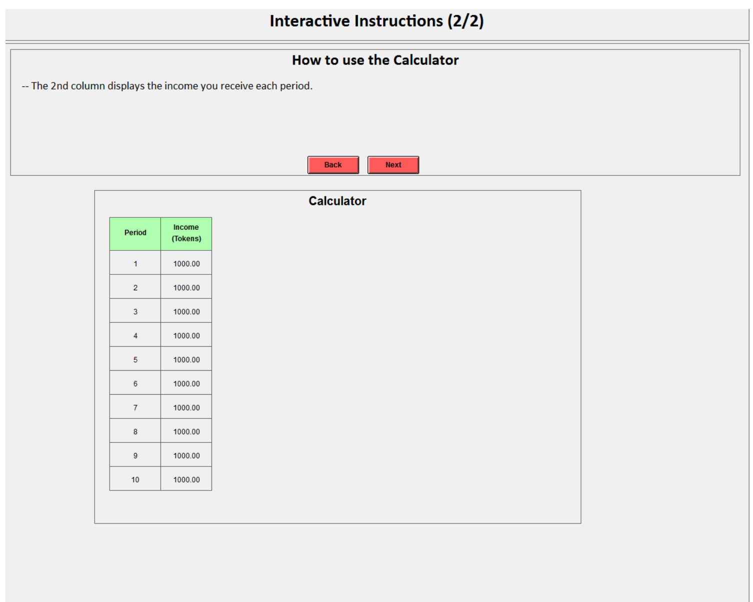


Figure 48: Screenshot for Interactive Instructions 4

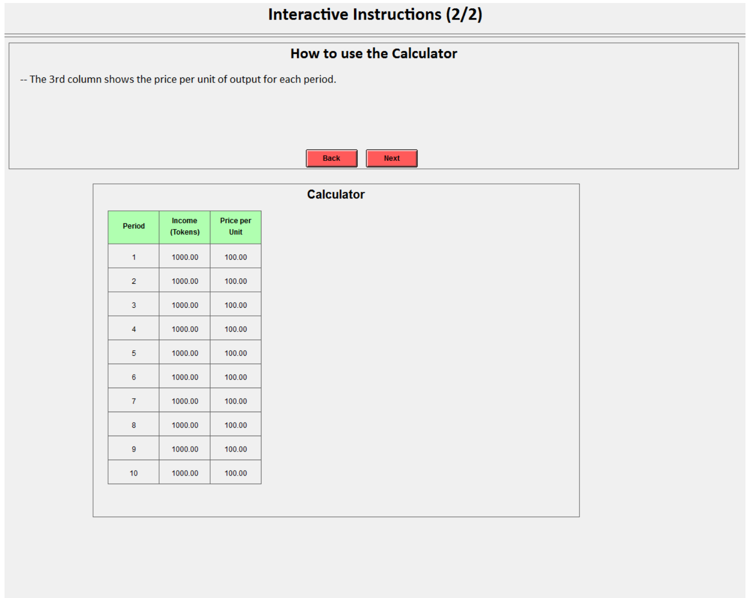


Figure 49: Screenshot for Interactive Instructions 5

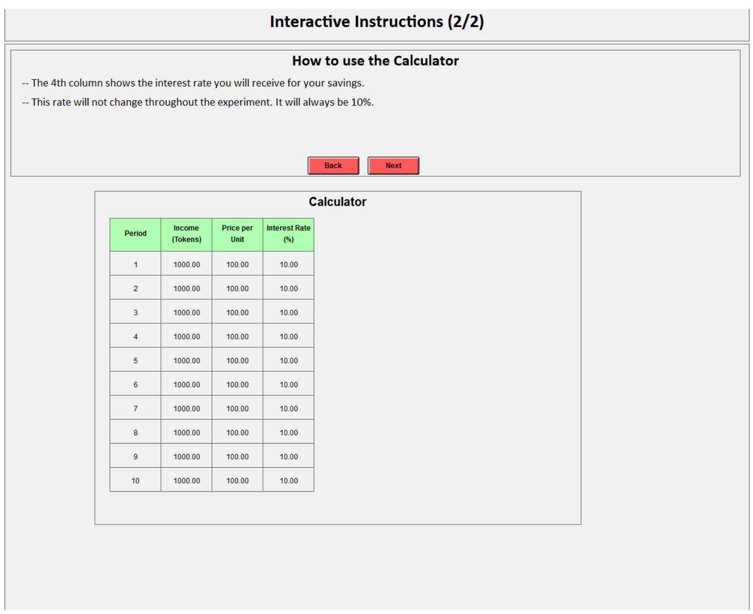
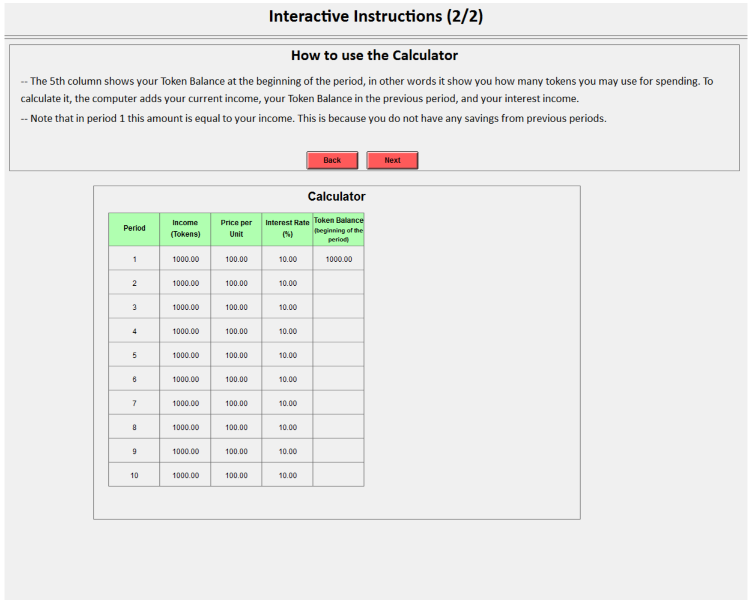


Figure 50: Screenshot for Interactive Instructions 6



Interactive Instructions (2/2)

How to use the Calculator

-- The 5th column shows your Token Balance at the beginning of the period, in other words it show you how many tokens you may use for spending. To calculate it, the computer adds your current income, your Token Balance in the previous period, and your interest income.

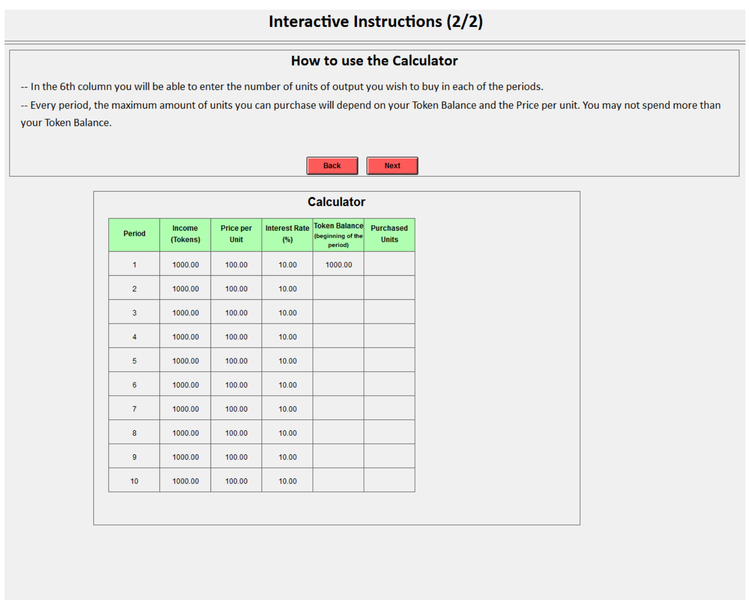
-- Note that in period 1 this amount is equal to your income. This is because you do not have any savings from previous periods.

Back Next

Calculator

Period	Income (Tokens)	Price per Unit	Interest Rate (%)	Token Balance (beginning of the period)
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 51: Screenshot for Interactive Instructions 7



Interactive Instructions (2/2)

How to use the Calculator

-- In the 6th column you will be able to enter the number of units of output you wish to buy in each of the periods.

-- Every period, the maximum amount of units you can purchase will depend on your Token Balance and the Price per unit. You may not spend more than your Token Balance.

Back Next

Calculator

Period	Income (Tokens)	Price per Unit	Interest Rate (%)	Token Balance (beginning of the period)	Purchased Units
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 52: Screenshot for Interactive Instructions 8

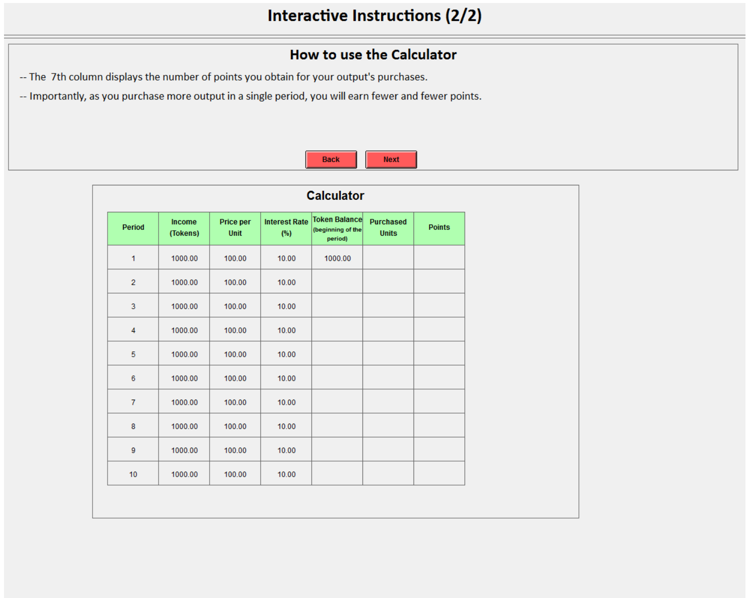


Figure 53: Screenshot for Interactive Instructions 9

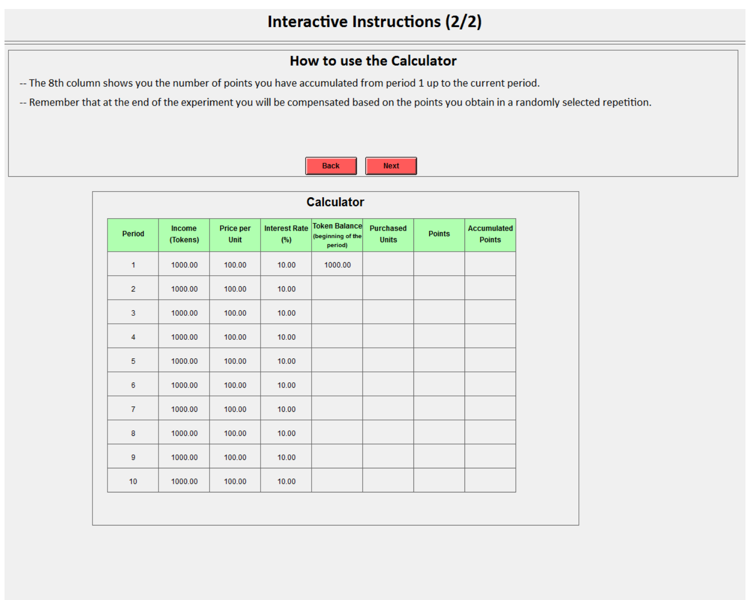


Figure 54: Screenshot for Interactive Instructions 10

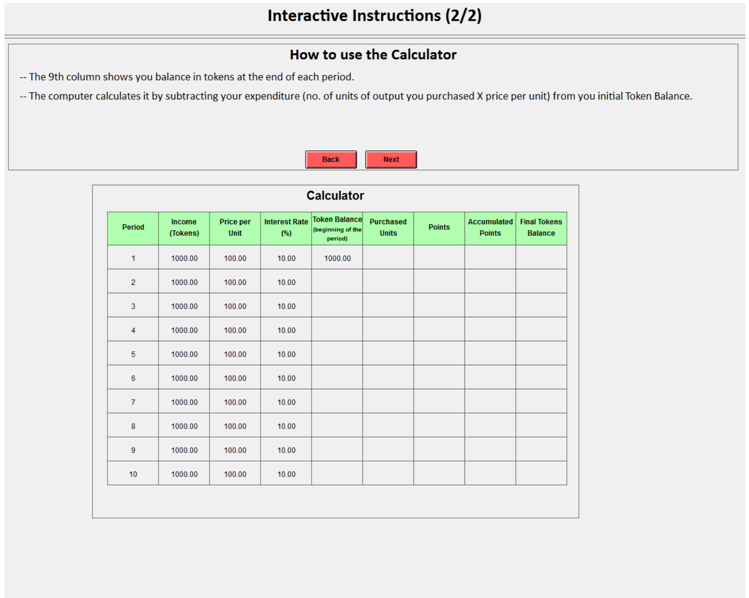


Figure 55: Screenshot for Interactive Instructions 11

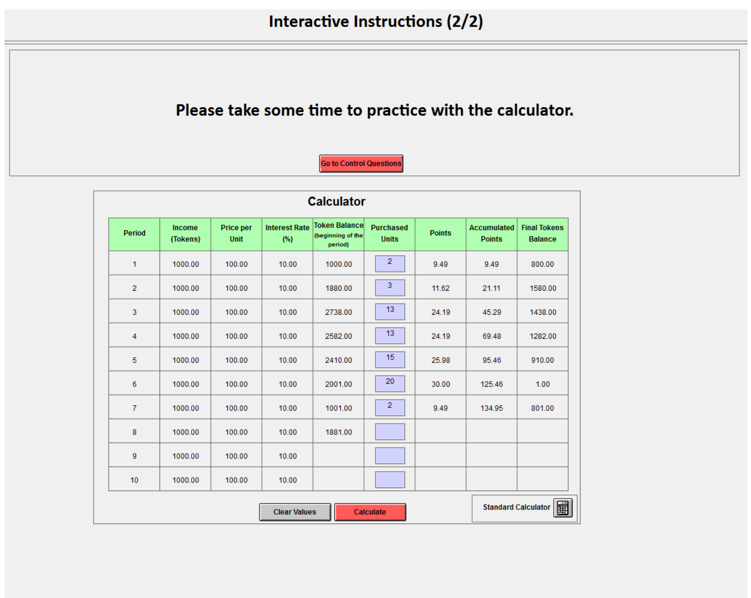


Figure 56: Screenshot for Interactive Instructions 12

G Computer Interface

G.1 Control Questions

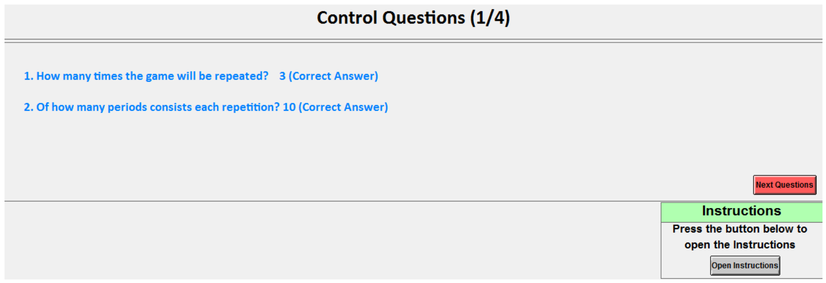


Figure 57: Screenshot for Control Question 13

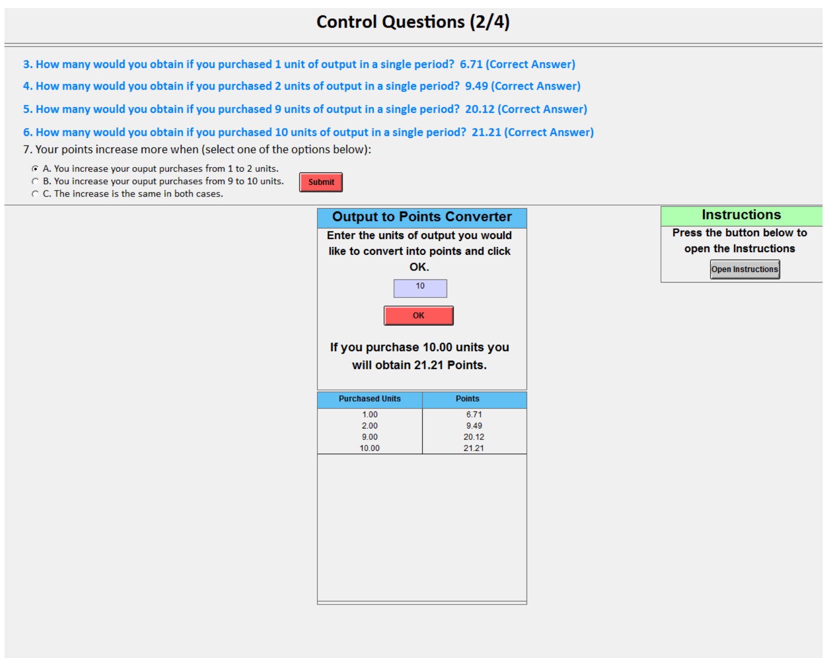


Figure 58: Screenshot for Control Question 2

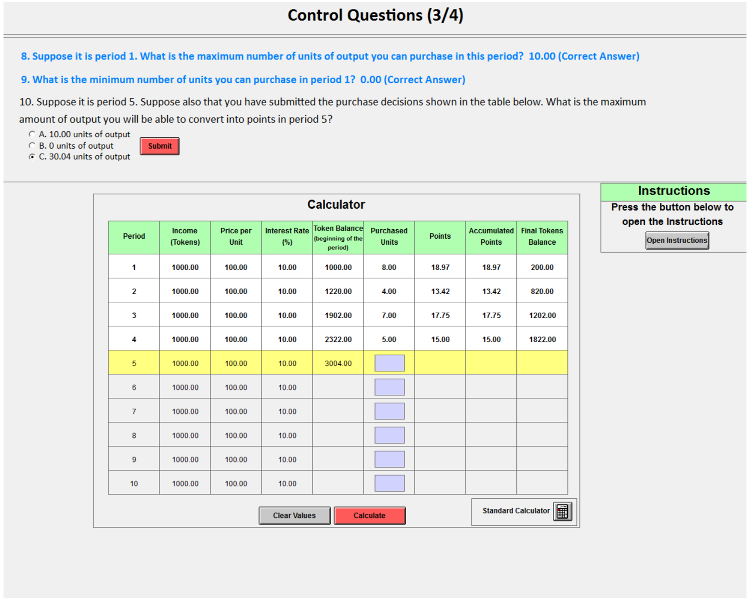


Figure 59: Screenshot for Control Question 3

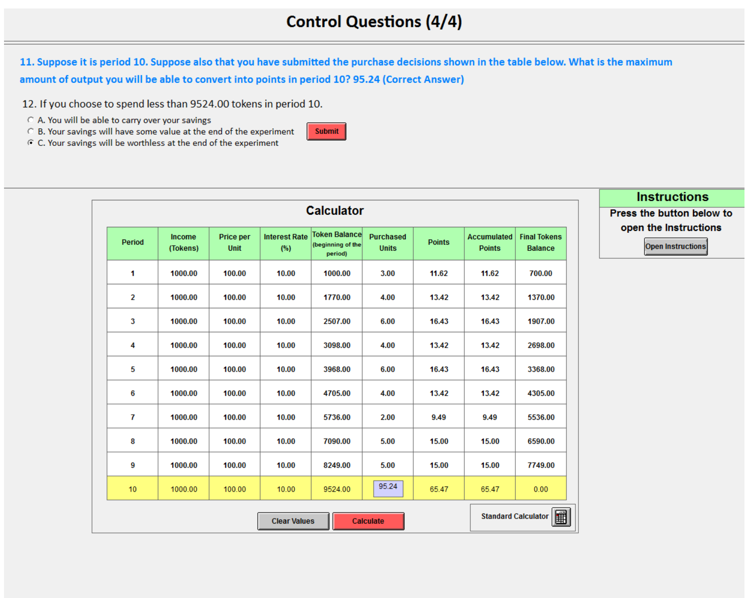
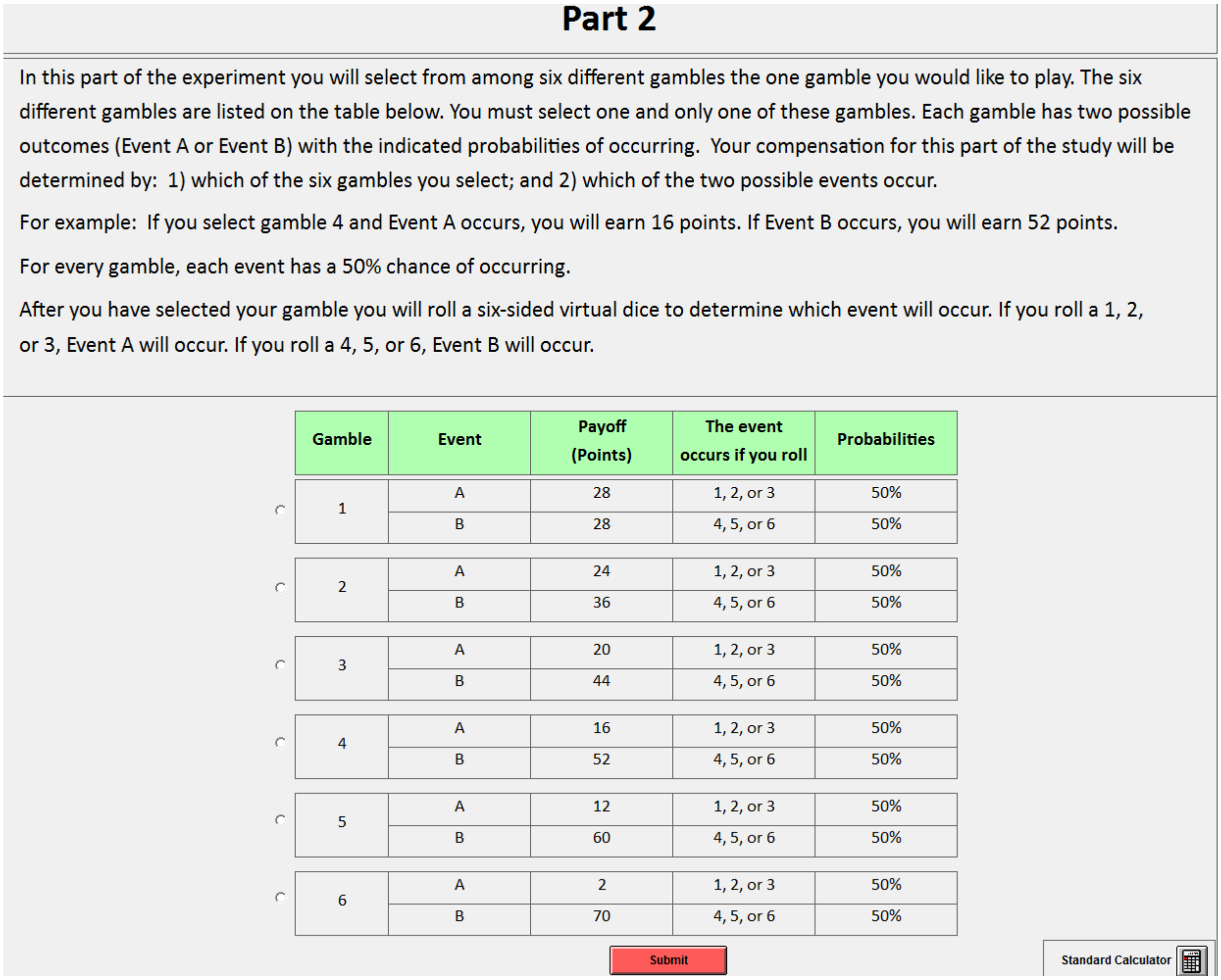


Figure 60: Screenshot for Control Question 4

G.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.

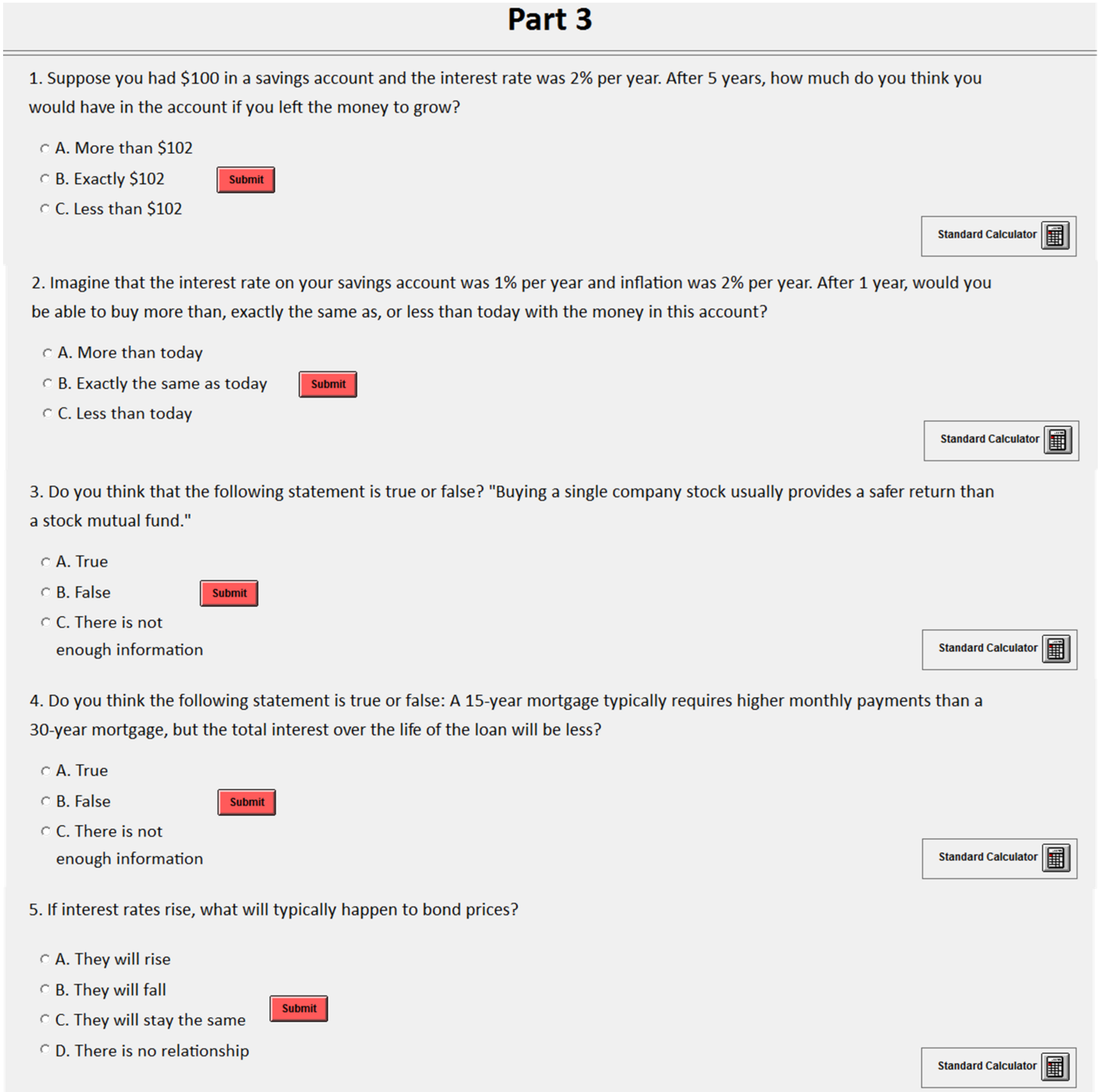
Gamble	Event	Payoff (Points)	The event occurs if you roll	Probabilities
1	A	28	1, 2, or 3	50%
	B	28	4, 5, or 6	50%
2	A	24	1, 2, or 3	50%
	B	36	4, 5, or 6	50%
3	A	20	1, 2, or 3	50%
	B	44	4, 5, or 6	50%
4	A	16	1, 2, or 3	50%
	B	52	4, 5, or 6	50%
5	A	12	1, 2, or 3	50%
	B	60	4, 5, or 6	50%
6	A	2	1, 2, or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

Submit

Standard Calculator

Figure 61: Screenshot for Stage 2

G.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 62: Screenshot for Stage 3

G.4 Race to 60

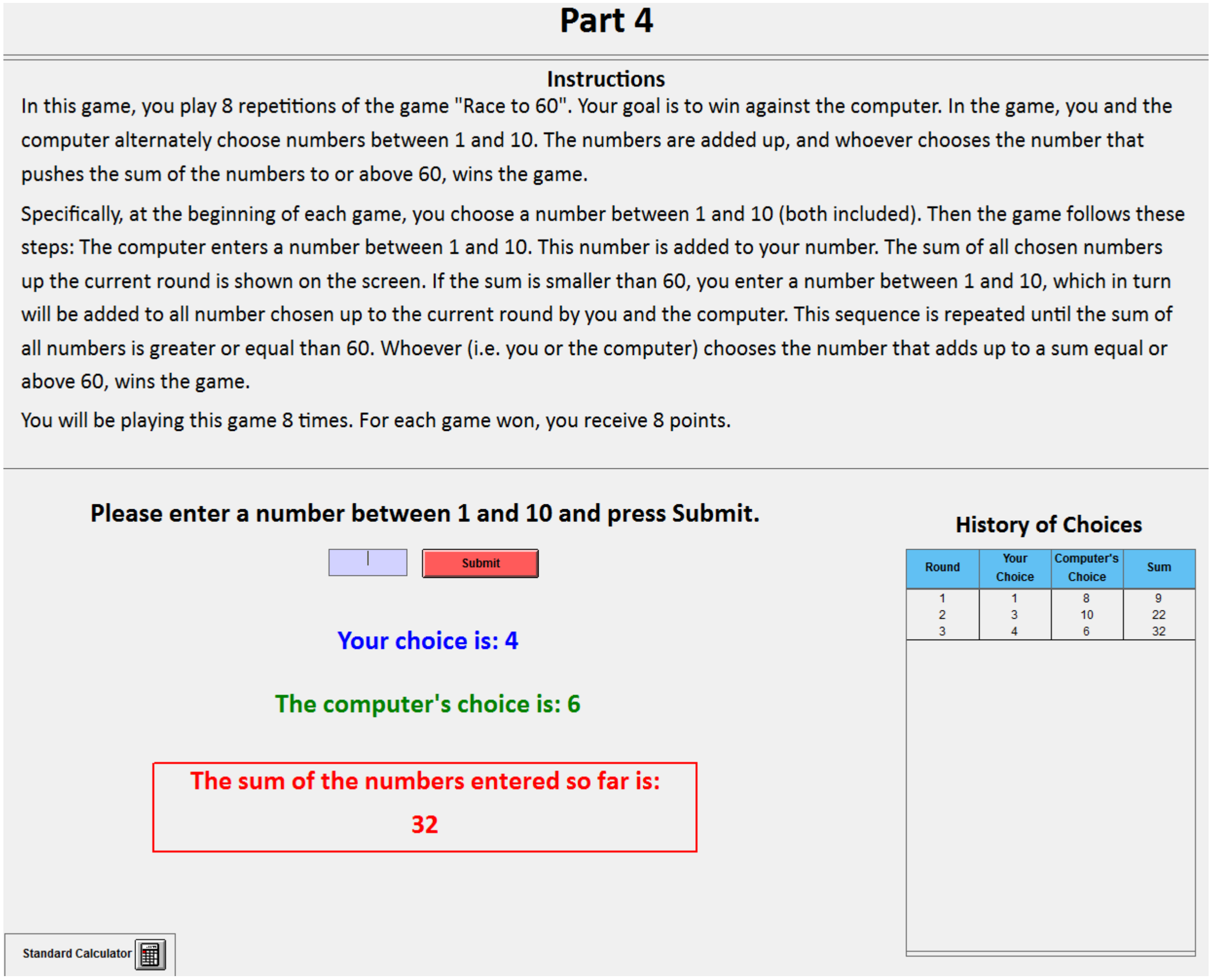


Figure 63: Screenshot for Stage 3