No Pain, No Gain - An Experiment on Skill Accumulation

Bhagya N. Gunawardena[1], Lana Friesen[2], and Kenan Kalaycı[2]

[1]School of Economics, Finance and Marketing, RMIT University, Australia

[2]School of Economics, The University of Queensland, Australia

September 12, 2025

Abstract

Skill accumulation requires a periodic and persistent investment of time and effort. In contrast to financial investments, investing in skills does not allow for saving or borrowing, the maximum periodical investment is capped, and the cost of investment often decreases with the person's cumulative past investment. In this paper, we develop a model that captures the key characteristics of a skill accumulation task where it is optimal to invest relatively high and increasing input levels in earlier periods. Using an online experiment we find that most participants invest too little compared to the rational path, and that a majority of the participants' investments are characterized by myopic optimization. Whereas individual experience over repeated lifecycles improves investments and earnings, social information about a selected peer's investments, earnings, or confidence levels has only a limited effect. Our results demonstrate the difficulty of investing in skill acquisition even in the absence of risk and time factors.

Keywords: skill accumulation, peer information, online experiment, lifecycle optimization, myopic optimization

JEL classifications: J24, J22, D15, D83

1 Introduction

The development of human capital through skill formation is a critical determinant of both individual achievement and overall economic productivity. This can take the form of cognitive skill development, investing in long-term research projects, learning a language, mastering a musical instrument, or engaging

Corresponding author: Bhagya N. Gunawardena. Email: bhagya.gunawardena@rmit.edu.au. We are grateful for helpful comments provided by audiences at the 4th BEST conference at QUT, the 15th and 16th Annual Australia and New Zealand Workshop on Experimental Economics, and 2025 ESA Asia-Pacific Meeting in Osaka, Japan. We thank the University of Queensland for financial support. The study has approval from the University of Queensland, Business, Economics and Law, Low and Negligible Risk Ethics Sub-Committee (2021/HE002132) and is pre-registered on the AEA RCT Registry (AEARCTR-0008602).

in physical or athletic training, among many others. Despite the importance, individuals often underinvest in their own development across both professional and personal domains. For example, individuals may underinvest in effort when the tasks feel hard or when the future benefits of current investments are unclear (de Bruin et al., 2025; Kautz et al., 2014; Stähler et al., 2025; Yu et al., 2025) or prefer short term returns over long term returns (Budish et al., 2015) leading to lower life-cycle earnings and opportunities for individuals and slower growth for economies (Hanushek & Woessmann, 2010; McMahon, 2018).[1] In this paper, we isolate and examine the behavioral determinants of skill investment decisions in a controlled experiment that eliminates complicating factors such as risk, temporal discounting, externalities, and information asymmetries.

First, we develop a model that captures key characteristics of a variety of skill accumulation tasks, such as practicing an instrument, training for a marathon, or learning a language, as described earlier. We consider a dynamic optimization problem in which the individual periodically chooses how much of their endowment (time) to invest in the development of a productive skill. Investment produces an immediate reward but incurs costs. A key feature of the model is that these costs decrease with accumulated prior investment (skill stock), just as it is less painful for a fit person to run a certain distance than it is for a person who is unfit. This also characterizes the short-run costs and long-run returns to education. Individuals maximize lifetime returns by choosing the investment level in each period. A rational investment path requires a relatively high initial investment that follows a gradually increasing investment in early periods. A myopic path, which maximizes payoffs at each period rather than over the life cycle, follows a relatively low initial investment that gradually decreases over the periods. Our definition of rational and myopic behaviors closely align with the concept of broad and narrow bracketing as defined in Read et al. (1999), where rational individuals consider their entire lifecycle (broad bracketing) and myopic individuals only consider the current period (narrow bracketing).[2]

We then test the model's predictions and the effects of individual experience and social information on behavior in an online experiment. The experiment results show that earnings are consistently below rational levels despite some improvements with experience. Participants typically adopt myopic, decreasing investment patterns rather than following the rationally optimal path of initially increasing investments.[3] Providing information about a high-performing peer's investment, earnings, or confidence

[1] In various settings, such underinvestment has further been attributed to institutional barriers (Cisternas, 2018; Rossi & Weber, 2024), information deficiencies (Caliendo et al., 2022; Hastings & Weinstein, 2008; Jensen, 2010; Nguyen, 2008), financial constraints (Carneiro & Heckman, 2002; Castro et al., 2016), and cognitive biases (Cohen & Garcia, 2008; Damgaard & Nielsen, 2020; Lavecchia et al., 2016).

[2] Similar to Gabaix and Laibson (2006) and Iturbe-Ormaetxe et al. (2019), we focus on a specific case of myopia - narrow bracketing - where individuals make decisions in isolation instead of present bias. Early ideas of this concept are introduced in Benartzi and Thaler (1995) and Gneezy and Potters (1997).

[3] This is in line with the broad literature that finds bounded-rational behavior in humans (Chapman, 1996; Furnham & Boo, 2011; Iqbal et al., 2020; Meyer & Hutchinson, 2016; Summerfield & Tsetsos, 2015; Tversky & Kahneman, 1974, 1991). More specifically, this finding aligns with O'donoghue and Rabin (1999) and Oreopoulos and Salvanes (2011) that observe how short-run returns adversely affect potential higher long-run outcomes. However, Cotton et al. (2025) show that individual effort investments in education setting is primarily driven by productivity rather than the motivation.

levels does not significantly impact performance. We also find that most participants who begin with suboptimal strategies continue using them throughout the experiment, suggesting people can become trapped in short-sighted decision patterns that experience or peer information cannot overcome.

In this paper, we make three primary contributions. First, we make a theoretical contribution to the literature on skill formation and behavior change by explicitly modeling the skill production function and contrasting rational and myopic behavior. Characterizing the skill accumulation problem, our model provides salient returns to myopic individuals, where they earn higher current returns than rational individuals, making it more tempting to behave myopically. However, rational investors receive higher overall life cycle returns through built-up stock from higher investments than myopic investors. In this context, our model deviates from regular consumption-saving models with habit stocks, in which future utility decreases with higher habit stocks (Brown et al., 2009; Carroll et al., 2000; Fuhrer, 2000). By focusing on individuals' decisions and behaviors in investing in skill accumulation, our model moves beyond regular skill production functions, which focus on external factors such as parental input, siblings, neighborhood, or factors such as innate ability (Cunha & Heckman, 2007; Cunha et al., 2006; Kaestner & Faundez, 2023). Through this, we examine the individuals' active decision-making, which is within their individual control.

Second, our paper contributes to the experimental literature on dynamic decision-making (Ballinger et al., 2011; Brown et al., 2009; Carbone & Duffy, 2014; Iturbe-Ormaetxe et al., 2019; Loewenstein & Thaler, 1989). Experiments in this literature are concerned with consumption-saving behavior over the lifecycle, whereas our application is short-term skill formation.[4] Nevertheless, the tradeoffs involved and the behavior examined are similar, especially since we use a neutral experimental frame. However, our setting is simpler than the experiments in this literature since it does not involve saving, discounting, or uncertainty. Additionally, we use a dynamic graphical interface, allowing participants to explore various inputs before making a choice. Despite the various simplicities of our setting compared to previous experiments, we also find that participants struggle to solve the dynamic optimization problem even with experience. Similar to Bone et al. (2009), Brown et al. (2009), and Carbone and Duffy (2014), we find that participants have limited learning with experience and struggle with temptation and self-control, resulting in non-rational decisions. However, somewhat contrary to Brown et al. (2009) and Carbone and Duffy (2014), participants in our experiments do not change their behavior with peer information.[5]

Third, we contribute to the experimental literature on social learning. In our experiment, we provide participants with peer information on decisions, decisions along with the final outcome, or decisions along

[4]Bone et al. (2009) is an exception that focuses on whether people plan ahead in a simple dynamic experiment with two decision stages and two chance stages using a decision tree. The findings indicate that people generally do not plan ahead.

[5]Ballinger et al. (2011), Iturbe-Ormaetxe et al. (2019), and Loewenstein and Thaler (1989) focus on other aspects in deviation from the rational decisions, such as cognitive ability, myopic loss aversion, and inconsistency between savings and debt.

with the peer's confidence in the peer information treatments. Several papers find imitative behavior in non-dynamic settings among individuals when information about actions of high-performing peers or firms is provided, though these actions might not be rationally optimal (Bursztyn et al., 2014; Chen & Ma, 2017; Duflo & Saez, 2002; Ouimet & Tate, 2020). Similarly, information about peers' outcomes is also found to result in imitative behavior (Fafchamps et al., 2015; Gortner & van der Weele, 2019; Kaustia & Knüpfer, 2012; Yechiam et al., 2008). Further, in a dynamic consumption-saving setting, Ballinger et al. (2003) and Brown et al. (2009) found faster convergence to the rational optimal investment path, and Carbone and Duffy (2014) found greater deviation from the optimal path when the participants can observe their peers. Although we build on these latter papers, we consider the fact that observing or being observed can affect individual actions due to peer pressure (Austen-Smith & Fryer Jr, 2005; Bursztyn et al., 2017; Bursztyn & Jensen, 2015; Chung, 2000; Georganas et al., 2015; Oxoby, 2008). Therefore, we provide information from a peer who participated in the experiment in a pilot session through which we can control for the observability and the endogeneity of peer effects (known as the reflection problem) (Manski, 1993). Further, we provide the peer's confidence information, moving beyond examining the effects of self-confidence (Bénabou & Tirole, 2002; Kruger & Dunning, 1999). Our experiment shows that neither experiential learning nor social learning is sufficient to help participants learn to follow the optimal path.

Our paper has implications for the behavior change literature, which examines interventions to help people change their behavior for the better. Similar to many studies in this literature (Carbone & Duffy, 2014; Oreopoulos et al., 2018; Oreopoulos & Petronijevic, 2019), our interventions fail to improve behavior. Nevertheless, our paper provides hints at potentially promising directions. Most of the interventions in the behavior change literature highlight the future benefits of behavior change (Malmendier & Della Vigna, 2006; Oreopoulos et al., 2018; Oreopoulos & Petronijevic, 2019). In contrast, highlighting the cost aspect, that the costs can go down over time, might be more promising. In addition, our model, under certain assumptions, provides a relatively simple solution to the complex dynamic optimization problem: bear the pain of learning and do a little more the next time for some time, and you will reap the higher lifelong gains – no pain, no gain.

The remaining sections of the paper proceed as follows. Section 2 presents the theoretical model we developed, followed by the experimental design in Section 3. Section 4 presents the results, and Section 5 provides the discussion and conclusion.

2 Model

In this section, we develop a simple model of skill accumulation without borrowing, saving, time discounting, risk, or uncertainty. The model is as follows.

A lifecycle of an individual consists of a fixed, known number of periods (T) and at the beginning of each period $t(\leq T)$, each individual receives a fixed endowment (E). Each period, the individual must decide how much of this endowment to invest in a costly production activity. Output, $B(e_t)$, increases with the level of current investment (e_t) but at a non-increasing rate; i.e., $\partial B(e_t)/\partial e_t > 0$ and $\partial^2 B(e_t)/\partial e_t \leq 0$. Investment, however, is costly with the cost function given by $C(e_t, S_t)$, where S_t reflects accumulated investment in previous periods up to period t (the opening stock). The marginal cost of investment is positive and convex; i.e., $\partial C(e_t, S_t)/\partial e_t > 0$ and $\partial^2 C(e_t, S_t)/\partial e_t^2 > 0$, but decreases with the stock at a decreasing rate; i.e., $\partial C(e_t, S_t)/\partial S_t < 0$ and $\partial^2 C(e_t, S_t)/\partial S_t^2 > 0$. In any period t, the net current return (utility) is given by the difference between the output and cost of investment; i.e., $B(e_t) - C(e_t, S_t)$. Similar to time, the uninvested portion of the endowment cannot be transferred to other periods, nor does it incur any costs.

A key feature of our model is the stock. In contrast to standard consumption-saving models, where utility decreases with the habit stock, in our model, utility increases with the higher levels of stock via reduced costs of investment. The stock depreciates over time with the stock accumulation factor given by $\gamma \in [0, 1]$.[6] That is, when $\gamma = 1$, the entire investment amount in the previous period is carried forward to the current period without any depreciation and when $\gamma = 0$ there is full depreciation of the investment without any carry forward.

Formally, individuals face the following problem. Given their starting stock, S_1, they need to choose the investment amount for production e_t out of the maximum possible investment E in every period t over T periods to maximize their lifetime returns, which are given by:

$$\begin{aligned} \max_{\{e_t\}_{t=1}^{T}} \sum_{t=1}^{T} [B(e_t) - C(e_t, S_t)] \quad & \text{subject to } 0 \leq e_t \leq E \\ & \text{where } S_{t+1} = e_t + \gamma S_t \\ & S_1 \text{ given} \end{aligned} \tag{1}$$

We focus on the interior solutions for optimal investments where the inequality constraint is non-binding. This focus matches the skill accumulation scenarios we explore in this paper and the parameterization of the experiment.

[6] This is similar to the idea of a decaying memory or the weakening of unused muscles.

Given stock S_t at any period t, equation 1 can be written as the following recursive formula:

$$V_t(S_t) = \max_{e_t}\{B(e_t) - C(e_t, S_t) + V_{t+1}(S_{t+1})\} \tag{2}$$

where $V_t(S_t)$ is the value in period t that gives the maximum possible lifecycle returns from period t forward.[7] Ceteris paribus, $V_t(S_t)$ is increasing in S_t through the reduced cost.[8] We normalize the value after the final period to zero. That is $V_{T+1}(S_{T+1}) = 0$.

In any given period $t \leq T$, a rational individual will fully consider all remaining periods and solve for e_t^{r*} satisfying the first order conditions of Equation 2 as follows:

$$\frac{\partial B(e_t^{r*})}{\partial e_t} - \frac{\partial C(e_t^{r*}, S_t)}{\partial e_t} + \frac{\partial V_{t+1}(S_{t+1})}{\partial S_{t+1}} = 0 \quad (\text{since} \quad \partial S_{t+1}/\partial e_t = 1 \quad \text{from eq1}) \tag{3}$$

As shown in equation 3, a rational individual's optimal investment decision considers their utility in all future periods, therefore necessitating the use of backward induction to solve for their optimal investment path.[9]

While rational individuals consider their entire remaining lifespan and globally optimize their returns, myopic (narrow bracketing) individuals only consider the current period's returns and choose their investment level in each period to maximize current returns, ignoring the value from the future. That is, a myopic individual will ignore $V_{t+1}(S_{t+1})$ from equation 2 and solve the following:

$$U_t(S_t) = \max_{e_t}\{B(e_t) - C(e_t, S_t)\}; \forall t \leq T \tag{4}$$

From equation 4, myopic individuals solve for e_t^{m*} that satisfies the following first order condition:[10]

$$\frac{\partial B(e_t^{m*})}{\partial e_t} - \frac{\partial C(e_t^{m*}, S_t)}{\partial e_t} = 0 \tag{5}$$

Proposition 1:

Given the same stock at the beginning of any period other than the last, rational individuals invest more in that period than myopic individuals.

[7] This is the value function that satisfies the Bellman equation.

[8] Further, $V_t(S_t) = \sum_{\tau=t}^{T}[B(e_\tau) - C(e_\tau, H_\tau)]$. Based on previous assumptions, $B(e_\tau) - C(e_\tau, H_\tau)$ is concave and therefore $V_t(S_t)$ is concave as it is a sum of concave functions.

[9] The second order condition holds as $\frac{\partial^2 B(e_t)}{\partial e_t^2} \leq 0$, $\frac{\partial^2 C(e_t, S_t)}{\partial e_t^2} > 0$, and $\frac{\partial^2 V(S_{t+1})}{\partial S_{t+1}^2} < 0$. $V(s_t)$ is the sum of current utility functions from period t onward. Since the current utility function is concave, $V(s_t)$, the sum of concave functions is concave. The detailed calculation for a rational individual can be found in Appendix A.

[10] The second order condition for myopic optimization holds due to functional specifications mentioned above.

Proof: From equations 3 and 5,

$$\frac{\partial B(e_t^{m*})}{\partial e_t} - \frac{\partial B(e_t^{r*})}{\partial e_t} + \frac{\partial C(e_t^{r*}, S_t)}{\partial e_t} - \frac{\partial C(e_t^{m*}, S_t)}{\partial e_t} = \frac{\partial V(S_{t+1})}{\partial S_{t+1}} > 0$$
$$\implies e_t^{r*} > e_t^{m*} \tag{6}$$
$$\text{since } \frac{\partial^2 B(e_t)}{\partial e_t^2} \leq 0 \text{ and } \frac{\partial^2 C(e_t, S_t)}{\partial e_t^2} > 0$$

■

Proposition 2:

Given the same stock in the last period S_T, both rational and myopic investments are the same.

Proof: Note that, given the stock at period T, S_T, both rational and myopic individuals face the same problem as $V(S_{T+1}) = 0$ in equation 2. Therefore, given the stock at period T, S_T, rational and myopic investments will be the same. From equation 3 and 5,

$$e_T^{r*} = e_T^{m*} = \underset{e_T}{\text{argmax}}[B(e_T) - C(e_T, S_T)] \tag{7}$$

■

Corollary:

Given the same stock S_t at any given period $t < T$, the current utility gained by rational individuals is lower than that of myopic individuals, making it tempting to make myopic decisions.

Proof: Given the stock at any period $t < T$, let the current utility from investment e_t,

$$U(e_t, S_t) = B(e_t) - C(e_t, St_t)$$

By definition, e_t^{m*} maximizes $U(e_t, S_t)$ for any given S_t. From Proposition 1, $e^{r*} > e^{m*}, \forall t < T$. Since $U(e_t, s_t)$ is concave and maximized at e_t^{m*}, the current utility gained by myopic individuals is greater than the current utility gained by rational individuals who invest $e_t^{r*} > e_t^{m*}$ at any period $t < T$.

$$U(e_t^{m*}, s_t) > U(e_t^{r*}, s_t), \forall t < T$$

Therefore, it is tempting to make myopic decisions.

■

3 Experimental Design

3.1 Main Task

We adapt the decision-making problem described in equation 1 and use the following functional specifications to have distinct investment and earning paths for rational and myopic individuals and to simplify the problem as much as possible for our experimental participants.

$$B(e_t) = 5e_t$$
$$C(e_t, S_t) = \frac{8e_t^2}{1 + S_t}$$

Further, we set the endowment $E = 100p$ where $100p$ equals £1, the stock accumulation factor $\gamma = 0.5$, the initial opening stock $S_1 = 100p$, and the number of periods per lifecycle (which we describe as a 'sequence') $T = 10$.

Figure 1 shows the investment paths and associated periodic and accumulated returns for rational and myopic investors based on the chosen model parameters. This shows that there are clear and distinct investment paths for rational and myopic individuals. Rational individuals start their investments at a higher level than myopic individuals, gradually increasing their investments up to period four, and thereafter gradually decreasing their investments. In contrast, myopic individuals continuously decrease their investments over the periods. In terms of periodic returns, rational individuals earn less than myopic individuals in the first three periods, but from period four onward, they earn more than myopic individuals. Consequently, rational individuals have higher lifecycle earnings than myopic individuals, although it is not until period seven that they start to dominate. Overall, accumulated earnings based on our parameters are equal to 614p for rational individuals and 386p for myopic individuals.

3.2 Treatments

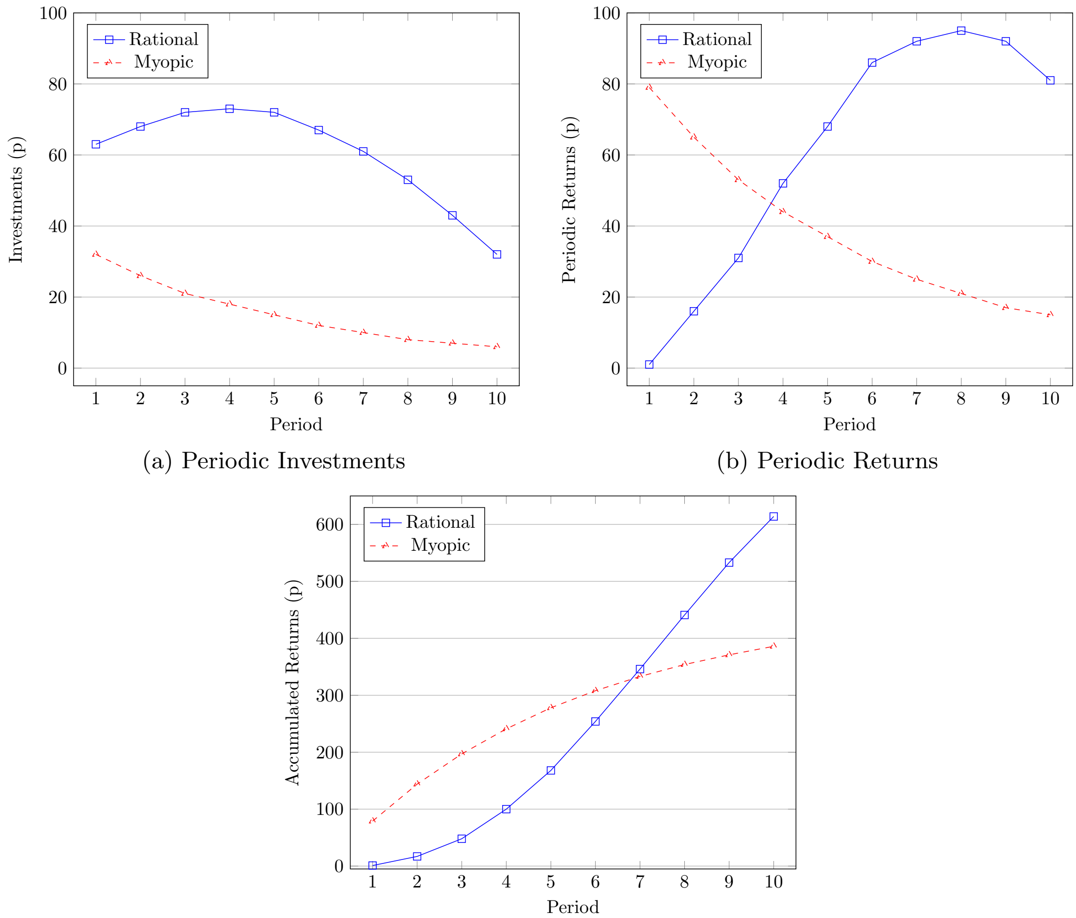
On arrival at the experiment, participants were randomly assigned to one of the following treatments:

- Control ($NoInfo$)
- Investments only ($InvOnly$)
- Investments and Earnings ($InvEarn$)
- Investments and Confidence ($InvConf$)

Peer Information Treatments

Participants in the $NoInfo$ treatment do not receive any peer information. In contrast, in the peer

Figure 1: Investment Paths, Periodic Returns, and Accumulated Returns for Rational and Myopic Investors



(a) Periodic Investments

(b) Periodic Returns

(c) Accumulated Returns

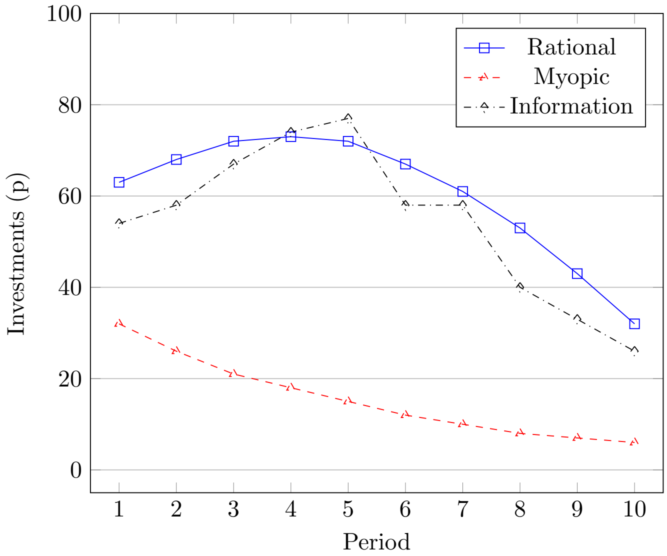
information treatments, all participants receive information about a peer's selected sequence's investments over the periods of the sequence. This is the only peer information provided for the participants in *InvOnly*. In *InvEarn*, participants additionally receive the peer's resulting earnings in that sequence, while participants in the *InvConf* instead receive the stated confidence of the peer rather than the earnings. In summary, participants in all peer information treatments receive information on the selected peer's investments, participants in *InvEarn* receive additional information on earnings, and participants in *InvConf* receive additional information on confidence.

We selected peer information from the last sequence of the best performing participant in a pilot session under *NoInfo*.[11] As shown in Figure 2, this peer's investment path follows the correct direction to the rational investment path while allowing room for learning.[12] Participants are not told how this peer

[11] We ran a pilot session under *NoInfo* to gather this peer information and a small pilot session with all the treatments (including *NoInfo*) to test the experiment. Data from these pilot sessions is not included in the analysis.

[12] Appendix Figure B1 presents the provided peer's investment paths along with optimal, myopic, and information investment paths and resulting periodic returns and accumulated returns.

Figure 2: Investment Path of the Given Information Relative to Rational and Myopic Investment Paths



information is chosen, except that it is selected from a participant in a previous session. Participants in all the peer information treatments receive information from this selected peer's selected sequence. Further, within a treatment, all the participants receive the same peer information (if any) across all the sequences. This selection of information from a participant in a previous session controls for any reflection issues (Manski, 1993). That is, since the information is selected from a participant who performed the task earlier, they are not influenced by the participants who observe that information.

3.3 Implementation

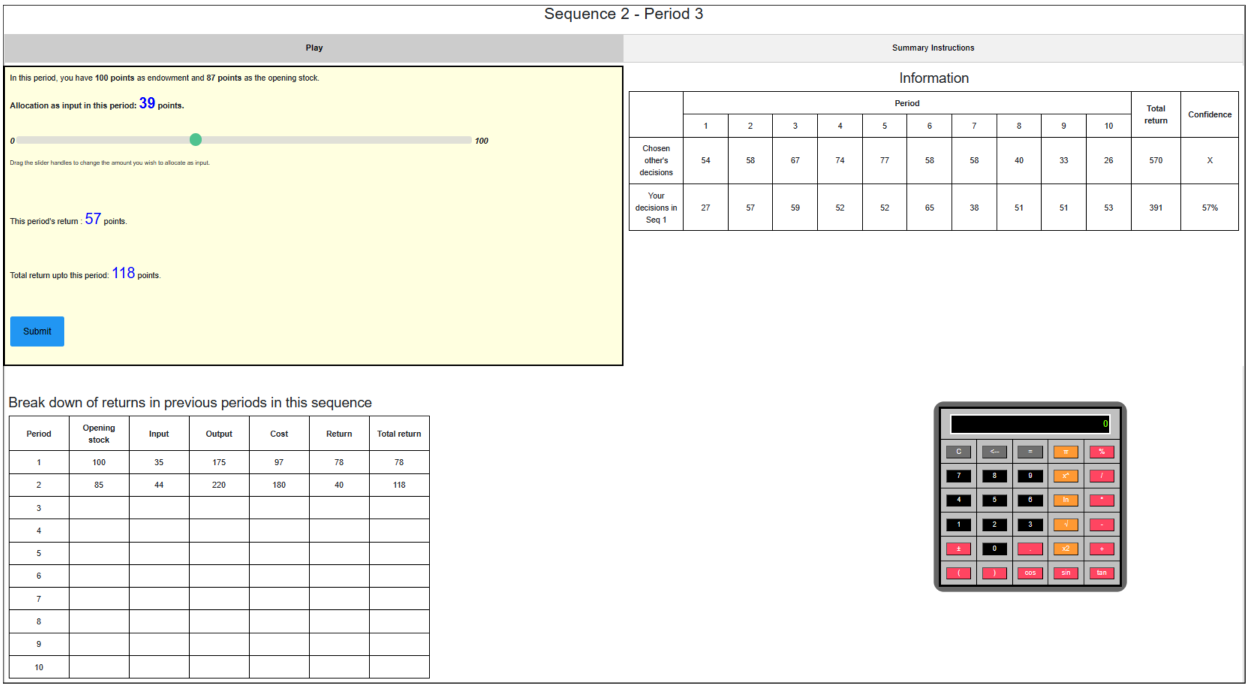
At the beginning of the experiment, participants were instructed about the main task of the decision-making problem, where all information relevant to the optimization problem was provided.[13] In addition to the equations and their interpretations, the instructions also included graphical illustrations where participants could use a slider to see how their investment decisions affected their output, costs, and returns (see Appendix Figure B2). Throughout the instructions, participants were presented with a series of questions designed to check their understanding, and they could not proceed without correctly answering all the questions.[14] In addition, we provided an example interface explaining the task and components of the interface.

After the main instructions, participants were informed that the main task would be repeated five times (in five sequences), and that the computer would randomly choose their total earnings of one of those sequences to add to their final payoff. Therefore, the outcomes of each sequence are equally likely to contribute to the final payoff. At the beginning of each sequence, participants were reminded that the

[13]Full experimental instructions are provided in Appendix C.
[14]We did not restrict the number of attempts to answer the questions correctly.

computer may select that sequence for the payment. Figure 3 shows the main decision-making interface.

Figure 3: Main Decision Making Interface



Note: An example of the main interface a participant would see under *InvEarn* in period 3 of Sequence 2.

Participants make their investment decisions using the slider in the top left yellow area. When participants move their slider, they can see how their current return changes with that investment level in real-time. For example, as shown in the figure, given their investment history, if this participant decides to invest 39 points in this period, they get a return of 57 points added to their returns in the current sequence. This current return changes in real-time as they move the slider. With this feature, we try to mimic a real-life skill accumulation environment where participants can easily see how their current decisions affect their current utility, but not directly the effect on overall lifecycle utility, making it more tempting to focus on current returns.

The information treatment is provided in the table presented in the top right of the decision-making interface, as shown in Figure 3. All participants see their own decisions, total earnings, and their stated confidence in the preceding sequence, as presented in the second row of the information table. If the participant is in *NoInfo*, they only see information about their own preceding sequence, presented in a table of one row, as they do not receive any peer information. Participants in the peer information treatments receive additional information about their peer as presented in the first row of the information table, with them all seeing information regarding the chosen peer's investment choices. The cells in the right two columns in the first row of the information table are populated based on the information treatment, where these are marked as 'x' if the participant is in the *InvOnly*. Figure 3 shows the interface for the *InvEarn* where the earning information is presented in the second last column and 'x' in the last column of the first row. If the participant is in the *InvConf*, they get the information in the last column of the first row and 'x' in the second-last column of the first row. Apart from this peer information, all the participants follow the same instructions and procedures.

At the bottom left of Figure 3, we show the breakdown of the participant's returns in previous periods in the current sequence. Additionally, we provide a simple calculator on the bottom right of the main interface for easier calculations.

At the end of each sequence, participants receive information on their total earnings in that sequence and the converted monetary value that would be added to their payoff if the computer chooses that sequence. Then, we asked the participants to state their confidence in their decisions in that sequence. More explicitly, participants were required to estimate their earnings in that sequence as a percentage of the maximum possible earnings. If the difference between their estimation and the actual percentage earnings is less than five percentage points, then they can earn an additional 10p if that sequence is selected for payment.

We use a between-subjects treatment design with participants randomly assigned to a treatment at the beginning of the experiment. Across all five sequences, participants receive the same peer information according to their assigned treatment. Further, regardless of the treatment, all participants were reminded of their decisions, outcomes, and confidence in the previous sequence to avoid biases due to selective memory recall.

3.4 Additional Tasks

After completing the five sequences of the main task, participants complete two additional incentivized tasks to measure their backward thinking ability (Stoker, 2017) and their risk preference (Gneezy & Potters, 1997).[15] They then completed a short demographic survey before being informed of their earnings.

The experiment was programmed using oTree open source platform (Chen et al., 2016), and the participants were recruited through the online crowd-working platform 'Prolific'.[16] The participants were recruited without any exclusion criteria except that users can only participate once in the experiment. On average, participants completed the experiment within one hour and earned £7.08. The sample consists of 201 participants, of whom 51, 50, 56, and 44 are in the *NoInfo*, *InvOnly*, *InvEarn*, and *InvConf* treatments, respectively. On average, participants are 29 years old, 31% of them are female, 46% use

[15] We adapt the task in Stoker (2017) with target number 12, where participants play against the computer with computer always moving first. We adapt Gneezy and Potters (1997) with an endowment of 20p, multiplier 2.5, and probability of success 0.5.

[16] See Palan and Schitter (2018) and Peer et al. (2017) for detailed explanations and comparisons between Prolific and other crowd-working platforms.

English as their primary language, and 64% have at least a bachelor's degree.[17]

3.5 Experimental Hypotheses

Based on the model and our treatment design, we have the following hypotheses to test in the experiment.

First, based on other findings in the literature (Augenblick et al., 2015; Carbone & Duffy, 2014; Levitt et al., 2016) and given how we have chosen the parameters in our model, we expect that the participants in $NoInfo$ will not reach the rational earnings. This is because the rational path involves sufficiently high investments in earlier periods with increasing investments until period 4, resulting in lower periodic returns than myopic investments until period 4 is reached in line with the Corollary. We expect that these initially lower returns will be very salient. This is summarized in Hypothesis 1 below.

Hypothesis 1: Average earnings in *NoInfo* are significantly lower than the rational earnings level.

Second, given the difficulty of the task, we expect that participants will not learn much from experience. Therefore, we predict that while earnings in the $NoInfo$ will improve with experience, they will not fully reach the rational level. This prediction is consistent with observations in other related experiments (Brown et al., 2009). This is summarized in Hypothesis 2 below.

Hypothesis 2: Average earnings in *NoInfo* increase with experience but remain below the rational level.

Third, we now consider the peer information treatments. Recall that these provide information from a peer whose investments are close to the rational investment path. Importantly, the investments show an upward trajectory over the first five periods. This upward trajectory is shown to participants in all three peer information treatments and suggests a different path they can take. Since participants in *InvEarn* get additional information on peer's earnings, they can compare their earnings to the amount they could get by following the given information. Therefore, participants in *InvEarn* should be able to improve their earnings the most. Although the impact of *InvConf* is less clear compared to *InvEarn*, we expect participants to feel more confident in following the given information.[18] We also conjecture that peer information of all kinds will increase learning from experience. We summarize these conjectures in Hypothesis 3 below.

Hypothesis 3: Peer information (a) increases average earnings relative to *NoInfo* with the greatest improvement in the *InvEarn* followed by *InvConf* and then by *InvOnly* and (b) enhances learning from experience.

[17] Appendix Table B1 reports summary statistics of participant characteristics, while Appendix Table B2 demonstrates balance across the treatments.

[18] The presented confidence of the peer lies within five percentage points of their true percentage earnings.

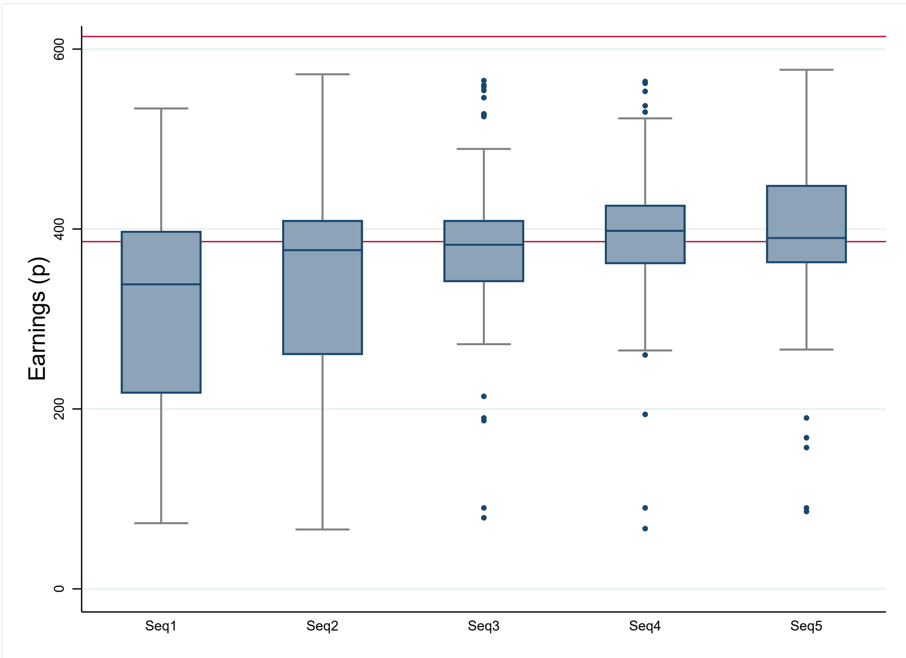
4 Results

4.1 Earnings

Our main analysis focuses on the total (i.e., cumulative) earnings in a sequence, which we refer to as simply 'earnings' hereafter. We begin by investigating the earnings in *NoInfo* (that is, the control group that does not receive any peer information) and then analyze the effects of the peer information treatments. When analyzing the earnings data, we exclude negative earnings sequences from all analyses unless otherwise specified.[19]

Result 1: Earnings in *NoInfo* are significantly lower than the rational earnings level.

Figure 4: Earnings of Participants in *NoInfo*



Note: The figure presents a boxplot of earnings of the participants in *NoInfo*. Only non-negative earnings sequences are considered. The top red vertical line indicates the rational earnings of 614p, and the second red vertical line indicates the myopic earnings of 386p.

Support: Figure 4 and column 1 of Table 1 provide the support for Result 1. As illustrated in Figure 4, no participants in the *NoInfo* achieve the rational earnings. Indeed, until sequence 3, most participants earn less than the myopic level, while in later sequences, the majority earn around the myopic earnings of 386p. Based on column 1 of Table 1, on average, participants in *NoInfo* earn 364p

[19]From the 1,005 participant-sequences we collected, only 24 observations are excluded due to negative earnings. These comprise four observations from *NoInfo* (one in each sequence of Sequence 1 to Sequence 4), nine observations from *InvOnly* (6 in the Sequence 1, 2 in Sequence 2, and 1 in Sequence 3), nine observations from *InvEarn* (4 in Sequence 1, 2 in Sequence 2, and 1 in Sequence 3- Sequence 5) and two from *InvConf* (1 in Sequence 2 and Sequence 3). The boxplot of earnings in Appendix Figure B3 shows that these negative earnings are extreme outliers that might skew our results. Appendix Figure B4 shows the boxplot of earnings for non-negative earnings only.

Table 1: Summary Statistics of Earnings

	NoInfo	InvOnly	InvEarn	InvConf	Treated	Full Sample
Seq1	311.140	332.750	323.904	313.500	323.414	320.184
	[121.237]	[114.512]	[105.351]	[111.653]	[109.746]	[112.685]
	50	44	52	44	140	190
Seq2	346.920	362.229	372.963	375.628	370.200	364.231
	[134.069]	[119.083]	[122.134]	[112.516]	[117.660]	[122.146]
	50	48	54	43	145	195
Seq3	378.840	415.878	410.945	422.581	415.993	406.563
	[108.243]	[99.820]	[103.454]	[121.718]	[107.325]	[108.500]
	50	49	55	43	147	197
Seq4	391.060	428.940	404.564	414.023	415.537	409.387
	[100.608]	[101.406]	[129.353]	[128.394]	[120.022]	[115.697]
	50	50	55	44	149	199
Seq5	396.373	442.080	422.073	435.659	432.799	423.510
	[112.611]	[87.143]	[117.292]	[109.431]	[105.297]	[108.099]
	51	50	55	44	149	200
Average	363.873	395.269	383.617	391.165	389.715	383.158
	[96.122]	[79.399]	[97.286]	[91.991]	[89.632]	[91.773]
	51	50	56	44	150	201

Note: This table presents the mean, standard deviation (in brackets), and the number of observations with non-negative earnings. The first four columns represent these statistics for each treatment. In the fifth column, *Treated* presents these statistics when all peer-information treatments are pooled (excluding the *NoInfo*). The final column presents the statistics for the entire sample. In the last row, the mean earnings of non-negative sequences for each participant are considered.

across the sequences, where this varies from average earnings of 311p in sequence 1 to 396p in sequence 5. We formally test whether these earnings are lower than the rational earnings using two-sided t-tests and find that the average earnings across all sequences, as well as earnings in each individual sequence (including the last), are significantly (at 1% level) lower than the rational earnings of 614p.[20] Supporting the claim in Hypothesis 1, Result 1 confirms that participants face difficulties in identifying the rational investment path and instead tend to locally optimize their earnings.

Result 2: Earnings in *NoInfo* increase with experience but remain below the optimal level.

Support: Columns 1 and 2 of Table 2 and Figure 5 provide support for Result 2. In the first two columns of Table 2, we test Hypothesis 2 using the following random effects panel regression models.

$$Earnings_{is} = \alpha + \gamma' Seq_{is} + U_i + \epsilon_{is} \tag{8}$$

[20]Appendix Figure B5 provides a kernel density plot of earnings in *NoInfo*, further demonstrating that even though the earnings distribution shifts right with experience, earnings remain well below the optimal level.

Table 2: Estimated Treatment Effects on Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Seq2	32.597**	32.690*	44.964***	45.005***	32.797**	33.006**
	(16.607)	(16.966)	(9.085)	(9.121)	(16.467)	(16.521)
Seq3	64.517***	64.610***	86.266***	86.311***	64.717***	64.926***
	(13.557)	(13.870)	(8.640)	(8.670)	(13.418)	(13.448)
Seq4	79.014***	79.142***	92.296***	92.336***	79.061***	79.030***
	(18.246)	(18.517)	(9.771)	(9.805)	(18.140)	(18.195)
Seq5	84.609***	84.816***	105.879***	105.933***	84.643***	84.719***
	(18.274)	(18.563)	(9.522)	(9.563)	(18.166)	(18.235)
InvOnly			29.777*	31.883*	12.128	14.233
			(17.402)	(17.619)	(24.766)	(24.821)
InvEarn			19.426	17.532	6.018	4.291
			(18.592)	(19.570)	(22.681)	(23.590)
InvConf			27.411	23.245	1.770	-2.230
			(19.159)	(19.427)	(23.976)	(24.757)
Constant	311.764***	356.688***	298.061***	300.506***	311.730***	314.524***
	(17.153)	(65.466)	(14.681)	(32.483)	(17.061)	(33.940)
Obs	251	251	981	981	981	981
Mean of Y	364.992	364.992	385.446	385.446	385.446	385.446
R2	0.072	0.137	0.110	0.130	0.113	0.133
Controls	No	Yes	No	Yes	No	Yes
NoInfo only	Yes	Yes	No	No	No	No
Interactions	No	No	No	No	Yes	Yes

Note: Columns (1) and (2) report the estimated effects of learning in *NoInfo* on earnings using random effects regressions specified in Equation 8 and Equation 9, without and with additional controls, respectively. Columns (3) and (4) report the estimated peer information treatment effects on earning using the random effects regression in Equation 10. Columns (5) and (6) report estimates from Equation 11 with additional interaction terms between the treatment groups and the sequence numbers to investigate any differential treatment effects across sequences without and with controls. The controls include the variables specified under Equation 8. Only non-negative earnings are considered. Standard errors in all estimates are clustered at the participant level. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

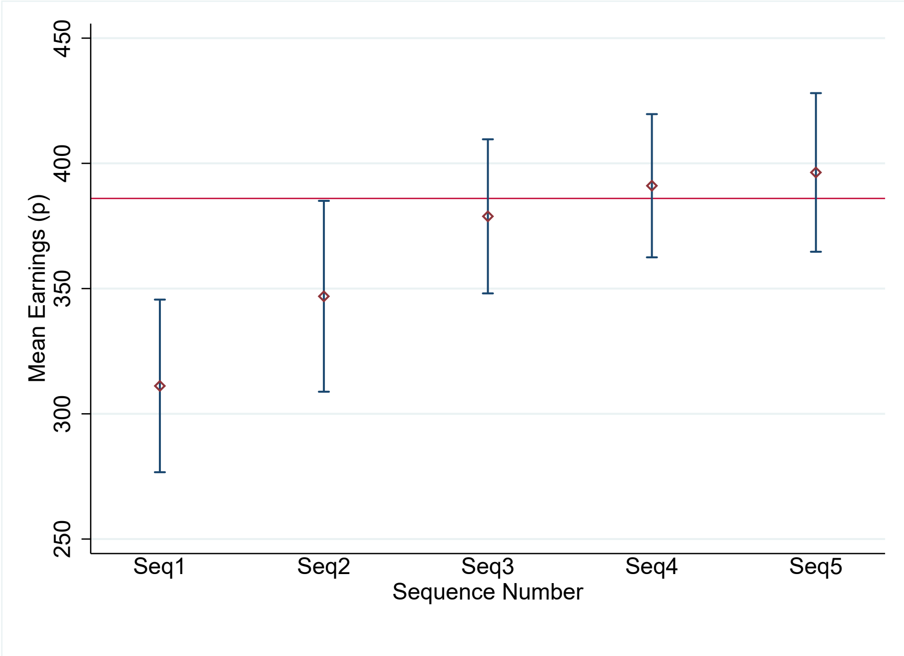
and

$$Earnings_{is} = \alpha + \gamma' Seq_{is} + \delta' X_i + U_i + \epsilon_{is} \tag{9}$$

where i indexes the participant and s indexes the sequence number. The dependent variable $Earnings_{is}$ is the total earnings of participant i in sequence s, Seq_{is} is a vector of dummy variables $Seq_2, Seq_3, Seq_4, Seq_5$ that take the value one for the relevant sequence and zero otherwise, with Seq_1 as the reference group, U_i is the random effect for participant i, and errors (ϵ_{is}) are clustered at the participant level.

After testing the regression specification in Equation 8, we further include additional controls for participant-specific characteristics X_i as in Equation 9. These additional controls include participant-specific characteristics consisting of age in years and a set of binary indicators for females, English as primary language at home, university graduates, and the field of specialization in STEM (Science, Technology, Engineering, or Mathematics) or economics. We also include controls for the amount invested in the risk elicitation task and two binary indicators equal to one if the participant reached the target

Figure 5: Mean Earnings in *NoInfo* with 95% CI over the Sequences



Note: The figure shows average earnings in *NoInfo* with the 95% confidence intervals. The red horizontal line at 386p represents the myopic earnings. For clarity, we do not show the rational earnings level of 614p on the figure.

number (12) in each of their two attempts of the race game.[21]

The first two columns of Table 2 present estimated results for Equation 8 and Equation 9. They show that earnings in Seq_2 - Seq_5 are significantly higher than in Seq_1 where they earn 33p, 65p, 79p, and 85p more than Seq_1 in Seq_2, Seq_3, Seq_4 and Seq_5, respectively. Comparing the estimated coefficients reveals that most learning occurs in the first three sequences and plateaus thereafter with earning improvement from Seq_2 to Seq_3 significant at the 5% level, while improvement from Seq_3 to Seq_4 or from Seq_4 to $Seq_5$is not significant at 10% level. Moreover, the highest average earnings, which occur in Seq_5 are significantly (at 1%) lower than the rational earnings of 614p. These results are robust to including individual-level controls. This supports the claim in Hypothesis 2 that participants in *NoInfo* learn by experience, but only upto a certain level which is still well below the rational level.

Figure 5 provides further support for Result 2, showing that mean earnings in *NoInfo* improve over the sequences. However, from Seq_3 onward, this learning slows and stagnates around the myopic earnings remaining significantly lower than the rational earnings. These results together demonstrate that experience alone is insufficient to surpass myopic earnings, underscoring the importance of external support to facilitate faster convergence to the rational investment path in this dynamic environment.

[21] Appendix Table B3 presents the full set of coefficients and shows that none of these control variables have a significant impact on earnings.

Result 3: Providing peer information has no effect on earnings

Support: Table 2 and Figure 6 provide the primary support for Result 3. In columns (3) and (4) of Table 2, we estimate the average treatment effects on earnings using the following equation:

$$Earnings_{ist} = \alpha + \beta_{ist}T_i + \gamma' Seq_{is} + \delta' X_i + U_i + \epsilon_{is} \tag{10}$$

Here, we extend the regression specification in Equation 9 to consider the treatment effects by including a vector of time-invariant treatment indicators, T_i, for *InvOnly*, *InvEarn*, and *InvConf* with *NoInfo* as the reference category. Column (3) presents the estimation results without the additional controls X_i and column (4) presents the results with additional controls. These results show that only the *InvOnly* treatment has marginally significant positive effects on earnings compared to the *NoInfo*. Therefore, our results reject Hypothesis 3(a), which claims to have improved earnings with peer information, where the greatest improvement is expected from *InvEarn* followed by *InvConf*.[22]

Next, we extend Equation 10 to capture any potential earnings differences between treatments across sequences by including an interaction term as follows:

$$Earnings_{ist} = \alpha + \beta_{ist}T_i + \gamma' Seq_{is} + \eta'_{ist}T_i \times Seq_{is} + \delta' X_i + U_i + \epsilon_{is} \tag{11}$$

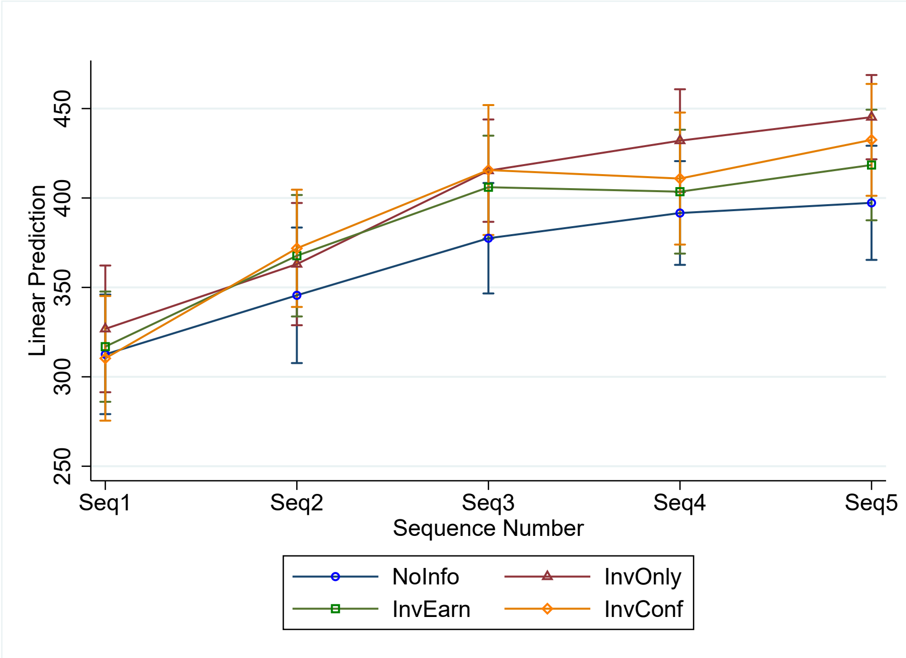
The primary coefficients are presented in columns (5) and (6) of Table 2 without and with additional controls X_i. Appendix Table B3 reports the full set of interaction coefficients of which only one, $InvConf \times Seq3$, is marginally significant ($p < 0.10$).

Appendix Table B5 presents the contrasts for easier interpretation which shows that the effects we observed in *InvOnly* are coming from the latter sequences where they earn 38p, 40p, and 48p significantly more than the *NoInfo* in Seq_3, Seq_4, and Seq_5, respectively. Further, predictive margins presented in Figure 6 illustrate that even though the earnings are increasing over the sequence among all peer-information treatments, they are not significantly different from the *NoInfo*. Moreover, we do not observe differences in earnings between different peer information as presented in Appendix Table B5. This provides further evidence to reject the claim in Hypothesis 3(a) where *InvEarn* or *InvConf* do not significantly improve the earnings compared to *InvOnly* or *NoInfo*.

We also check whether participants who receive peer information learn more or learn more quickly as claimed in Hypothesis 3(b). Beyond not seeing significant effects on interaction terms, we further check performance improvement across sequences in Appendix Table B6. We measure learning (performance

[22]To improve power, Table B4 uses the same regression specification but pools the three peer information treatments into a single treated group. Consistent with the main results, we only see marginal treatment effects from providing peer information.

Figure 6: Predictive Margins of Treatments on Earnings with 95% CI over the Sequences



.

Note: The figure presents the predictive margins and 95% CI for the regression results in column (6) in Table 2

improvement) through improved earnings, where we consider the earnings differences between consequent sequences, between Seq_3 and Seq_1, and between Seq_5 and Seq_1 using a two-sided t-test. However, we do not observe any significant effects of treatments on the learning experience, confirming our findings above and providing further evidence to reject the claim in Hypothesis 3(b).

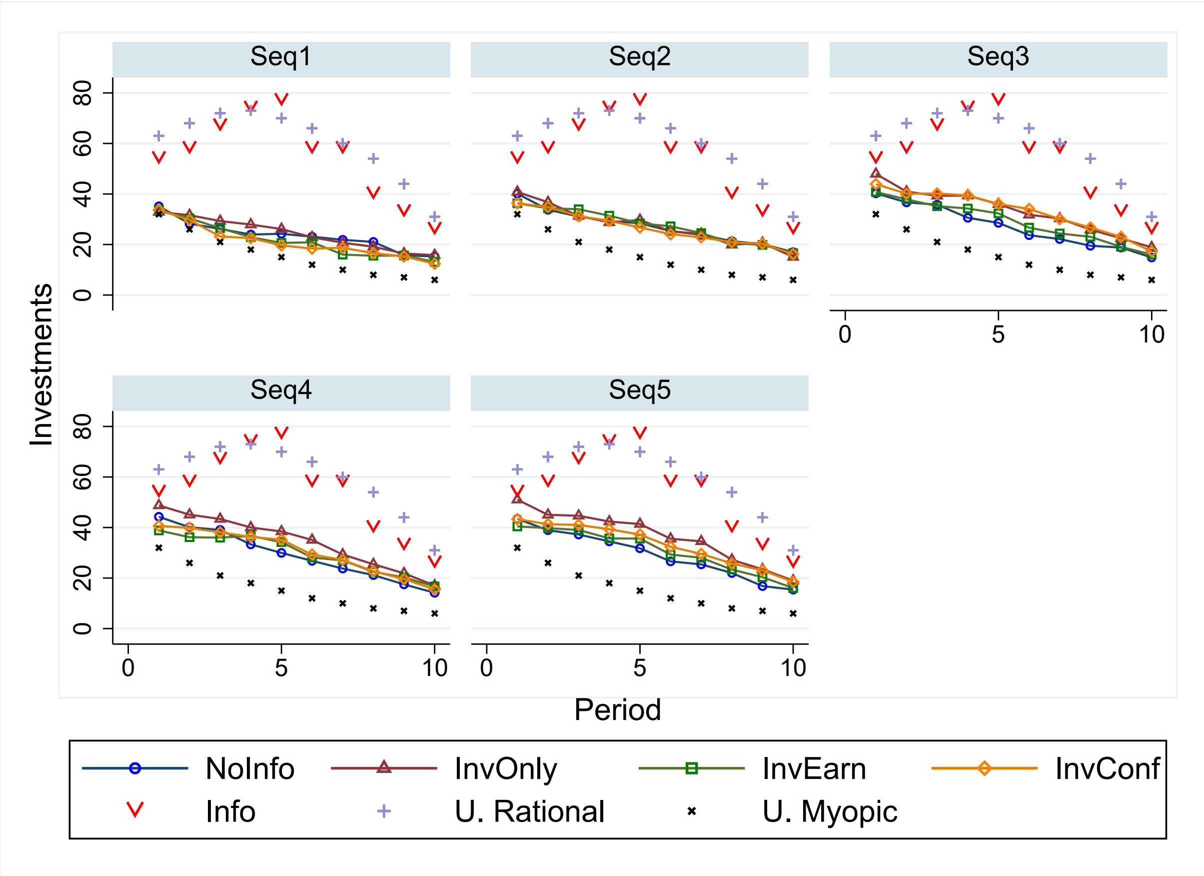
4.2 Potential Mechanism and Additional Results

Having provided support for Hypotheses 1 and 2, but not for Hypothesis 3, we now seek to understand why. To do so, we examine heterogeneity in behavior and how it evolves over the sequences.

To support our additional analysis, we define four additional terms. First, unconditional rational (or just 'rational') investments are the investment amounts that a participant chooses if they follow the rational path in every period from period one. However, if a participant follows a different investment path up to period $t \geq 1$, then the rational investment decision in period $t + 1$ will be different from the unconditional investment amount due to the difference in stock levels at the beginning of period $t + 1$. We define this new rational investment amount, conditional on the actual stock level, as the 'conditional rational' investment. Similarly, unconditional myopic (or just 'myopic') investments are the investment amounts if a participant follows the myopic path from period 1, while 'conditional myopic' investments are the myopic investment amounts conditional on the stock. In period one, the conditional and unconditional rational (and myopic) investment amounts are identical as there is no history.

Result 4: Individual investment paths deviate from both the unconditional rational investment path and the given peer information.

Figure 7: Average Investments



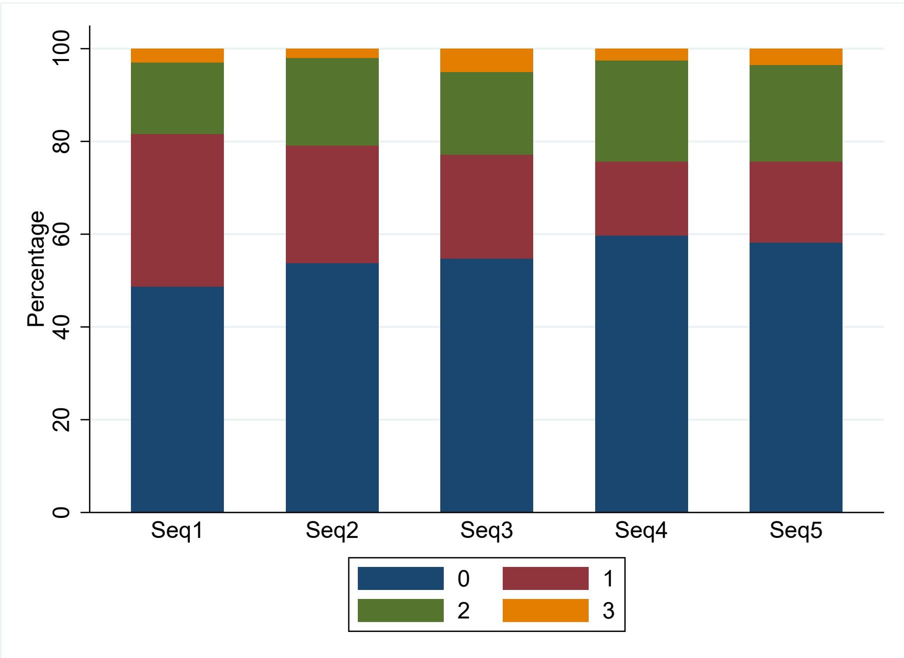
Note: The figure shows the average investments made in each period under different treatments over the sequences. The given investment information (for the peer information treatments), rational investment path, and myopic investment path are also presented for comparison. All sequences of all subjects are considered.

Support: Figure 7 presents the average investments in each period over the sequences by treatment. This clearly shows that in sequence 1, on average, participants in all treatments have investment paths that almost overlap with the myopic investment path. Even though their investment paths move away from the myopic path over the sequences, they still follow a similar declining pattern to the myopic path and stay considerably away from the rational path or the given information path. Further, this figure shows that investments in the first period in the latter sequences move closer to the given information, where the *InvOnly* treatment's average investment in period 1 of sequence 5 almost overlaps with the given information. When focusing on the investment path of *InvOnly* in sequence 5, we observe that their investment path from period 2 onward follows a similar pattern to the myopic path, but it stays above the investment paths of other treatments. This is because *InvOnly* follows the given information and invests a higher amount in the first period. As a result, they build a higher level of stock for the second period, increasing the conditional myopic investment level from period 2 onward.[23]

We then formally test the above claim by estimating the effects of the treatments and experience on the absolute deviation of investment from the conditional rational investment. Appendix Table B7 presents the estimated results using a similar regression specification as in equation 10, considering the first three periods first and all the periods next. Consistent with earnings results, experience reduces the deviation from the conditional optimal investment path. However, similar to earnings, investment behavior is not different across the treatment groups.

Result 5: Most participants follow investment paths in the myopic direction

Figure 8: Percentage of Early Decisions in the Rational Direction



Note: This figure presents the percentage of participants who invested 0, 1, 2, or 3 times in the rational investment direction within the first four periods under each sequence, pooling across the treatments. In the first four periods, if investment in period *t+1* is less than investment in period *t*, then the participant is on the direction of the myopic investment path and otherwise in the direction of the rational investment path. Participants who overly invest in earlier periods, so that their conditional optimal investment in the next period is lower than their investment in the previous period, are excluded.

Support: Based on our model specifications, a participant who follows the rational investment path should invest higher amounts in each period than in the previous period during the first four periods (see Figure 1 (a)). Therefore, we define an investment decision as following the rational direction if the

[23]Appendix Figure B6 presents the investments of each participant in each treatment pooling across sequences. Here, we focus on the distribution of investments in each period, as the average may mask the distribution. The figure clearly shows that most of the participants in each treatment follow an investment path similar to the myopic investment path.

investment in the following period is higher than in the previous period, and as in the myopic direction otherwise. Since we consider only the first four periods, the number of decisions in the rational direction can vary from 0 to 3.[24] Figure 8 presents the number of decisions moving in a rational direction in each sequence as a percentage. In sequence 1, 49% of the participants invest continuously in the myopic direction and only 3% continuously invest in the rational direction, with the remaining having inconsistent patterns where 33% and 15% have only 1 and 2 investments in the rational direction, respectively. This persistent myopic investment pattern continues over the sequences where approximately 60% of the participants make all myopic decisions, where all rational decisions are capped at 5%. This provides further support for the result that participants are more likely to invest in the myopic direction, even though they start to follow the given information in the first period.

Result 6: Once a participant follows a myopic path, they are more likely to continue a similar path in the following sequences.

Support: Following Result 5, we then test whether participants are trapped in myopic investment decisions as a potential mechanism to explain the persistent myopic behavior. We define a participant as investing in the rational pattern if they continuously increase their investments from period 1 to 4 (3 rational direction decisions as in Figure 8), as investing in the myopic pattern if they continuously decrease their investments from period 1 to 4 (3 myopic direction decisions), and as a change pattern, otherwise.[25] Then we use a similar regression specification to equation 10 but with multinomial logistic regression with investment pattern (rational, myopic, or change pattern) in the current sequence as the dependent variable. Additionally, we include the investment pattern in the lagged sequence in the explanatory variables as presented in Equation 12.

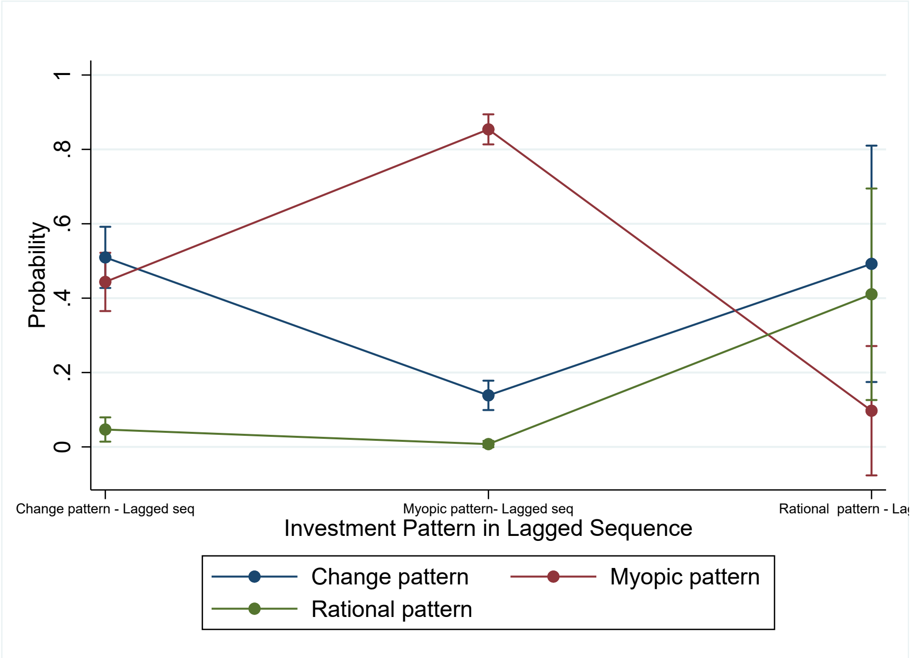
$$InvestmentPattern_{ist} = \alpha + \eta_{is} InvestmentPattern_{i,s-1,t} + \beta_{ist} T_i + \gamma' Seq_{is} + \delta' X_i + \epsilon_{is} \tag{12}$$

Figure 9 provides the predictive margins of the lagged investment pattern, and Appendix Table B8 provides the estimated coefficients of the multinomial logistic model. Given that a participant changed their investment pattern in the previous sequence, they are more likely to change pattern (with 0.51 probability) or follow a myopic path (with 0.44 probability) in the next sequence than follow a rational path (with 0.05 probability). Interestingly, when they are following a myopic pattern in the previous sequence, they follow a myopic pattern in the next sequence with 0.85 probability, whereas they follow a

[24] We consider the change in investment from period 1 to 2, 2 to 3, and 3 to 4. 0 in the rational direction means a persistent myopic direction of investment, and 3 means a persistent rational direction. 1 or 2 rational directions mean that participants change their investment direction from myopic to rational or vice versa.

[25] We consider the strict case where participants follow a persistent pattern.

Figure 9: Margins plot for Multinomial Logistic of Investment Type Evolution



Note: The figure presents the predictive margins of lagged investment pattern on current investment pattern with 95% CI using the multinomial logit model in equation 12.

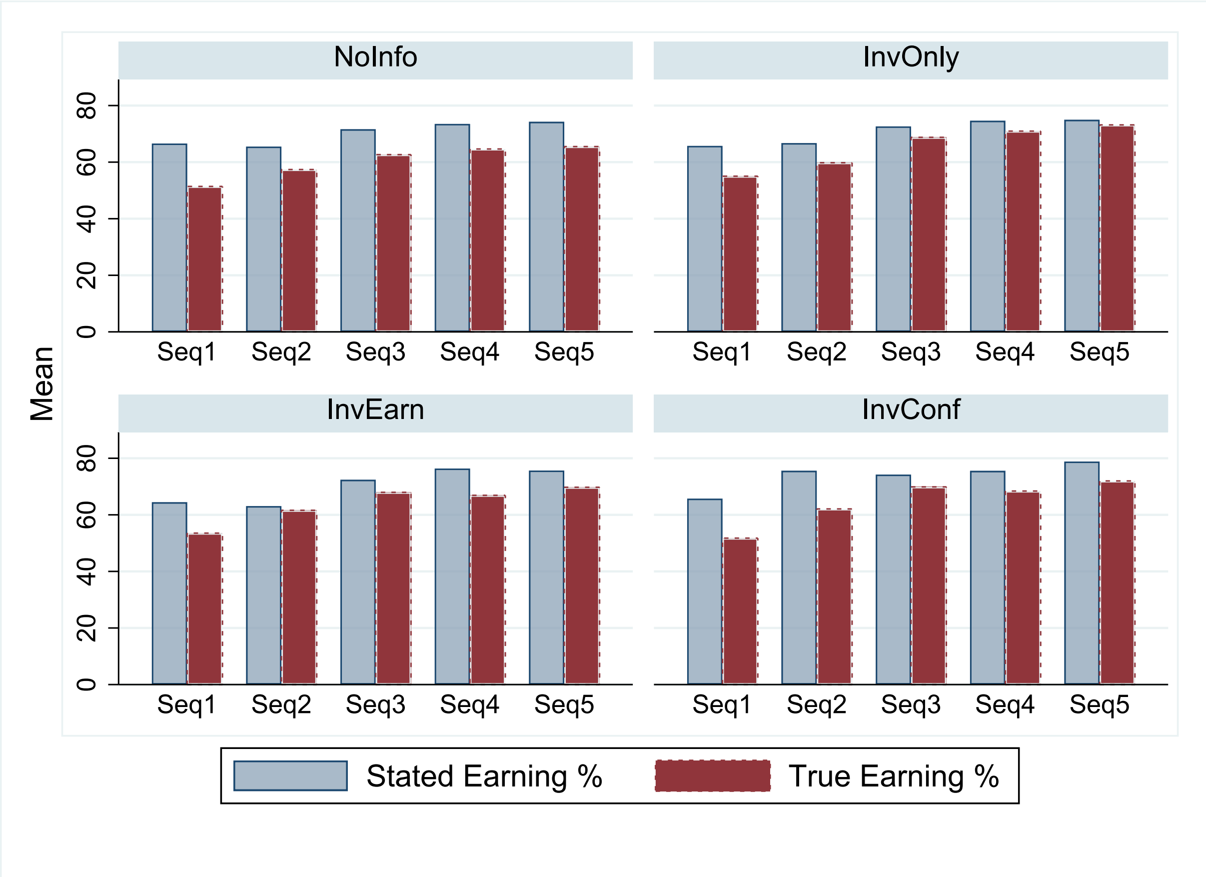
rational pattern with only 0.008 probability and change pattern with 0.14 probability. When they follow a rational pattern in the previous sequence, they follow a rational direction with 0.41 probability and change pattern with 0.49 probability, and a myopic direction with 0.1 probability in the next sequence. Although they are less likely to be myopic following a rational direction in the previous sequence, these probabilities are not significantly different.[26] This clearly shows that when a participant follows a myopic pattern once, they are more likely to get trapped in this behavior and follow a similar pattern, explaining our main results.

Result 7: Overconfident participants are more likely to have lower earnings and a higher deviation from the rational investment path compared to participants who are appropriately confident or underconfident.

Support: Recall that at the end of each sequence, participants are asked to estimate their earnings as a percentage of the maximum possible earnings. Since participants have perfect information about their own earnings, but not about the maximum possible earnings, their estimates will reflect their beliefs about the optimality of their investment decisions. Consistent with the existing literature (Kruger & Dunning, 1999; Moore & Healy, 2008), Figure 10 shows that, on average, the stated percentage

[26]Consistent with this, Appendix Figure B7 illustrates the evolution of earnings where participants are likely to improve their earnings with experience, but when they reach the level of myopic earnings, they are more likely to stay there.

Figure 10: Stated vs True Percentage of the Maximum Earnings



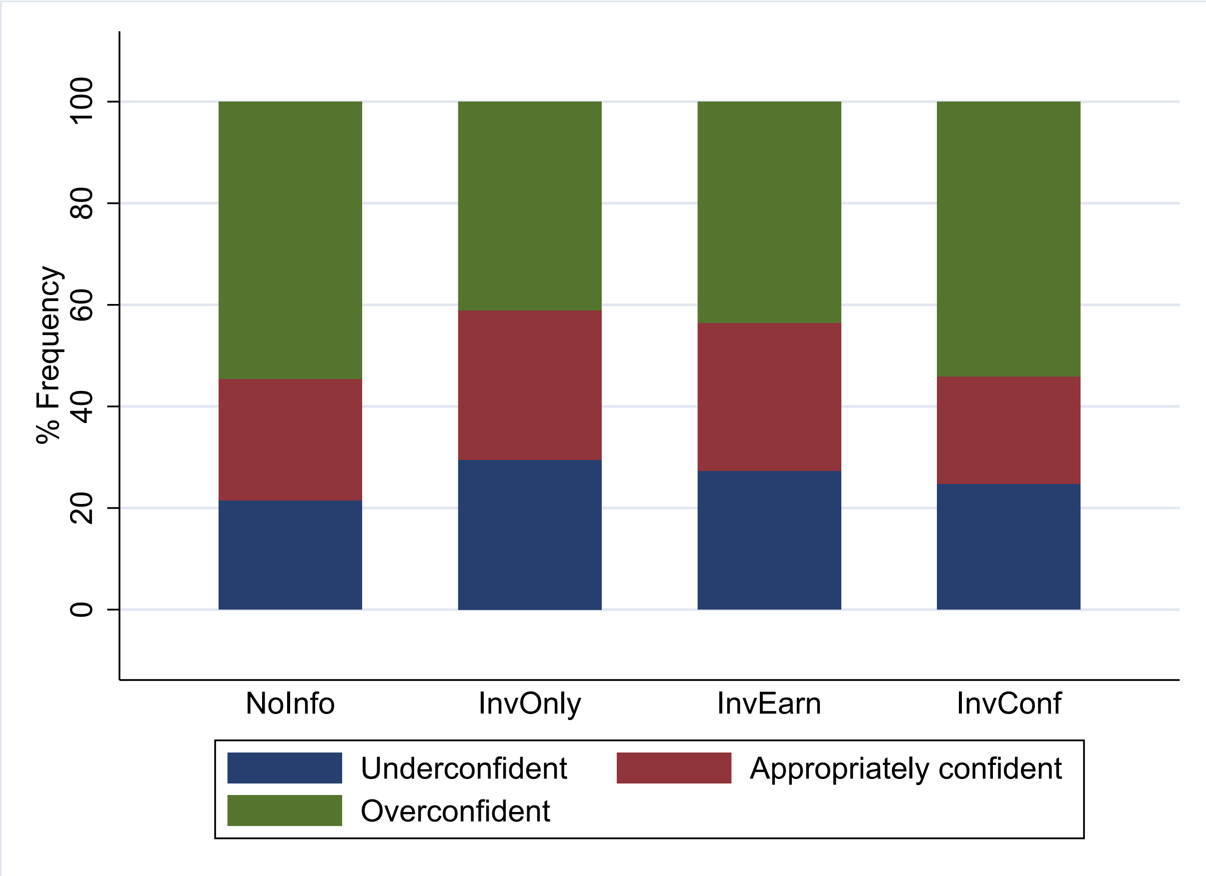
Note: Only the sequences with non-negative earnings are considered.

earnings of the participants are higher than the true percentage earnings regardless of treatment or experience, reflecting overconfidence. We then categorize each participant in each sequence into one of three groups. We consider a participant as 'appropriately confident' if their stated percentage is within 10 percentage points of their true percentage earning. Second, we categorize someone as 'overconfident' if their stated percentage exceeds their true percentage earnings by more than 10 percentage points. Finally, a participant is categorized as 'underconfident' if their stated percentage is more than 10 percentage points below their true percentage earnings.

Figure 11 shows the distribution of confidence types by treatment. The figure shows that overconfidence is the most common type observed with 55%, 41%, 44%, and 54% of the participant-sequences are categorized as overconfident in *NoInfo*, *InvOnly*, *InvEarn*, and *InvConf*, respectively. Further, there are less than 30% of participant-sequences that are categorized as appropriately confident. This provides further support to the fact that regardless of the treatment, the majority of the participants are overconfident.[27]

[27] Despite the fact that most participants are not appropriately confident, there is a moderate positive correlation between the stated and true percentage earnings (Pearson's correlation coefficient of 0.33, significant at 1%).

Figure 11: Distribution of Confidence Types



Note: The figure shows the percentage of participants who are appropriately confident, underconfident, or overconfident, where confidence is calculated as the difference between the stated and true percentage earnings. Participant-sequences are pooled across sequences. Only the non-negative earning sequences are considered.

Next, we test whether experience or the peer information treatments affect the participants' confidence type using the following multinomial logistic regression model.

$$ConfidenceType_{ist} = \alpha + \beta_{ist}T_i + \gamma' Seq_{is} + \delta' X_i + \epsilon_{is} \qquad (13)$$

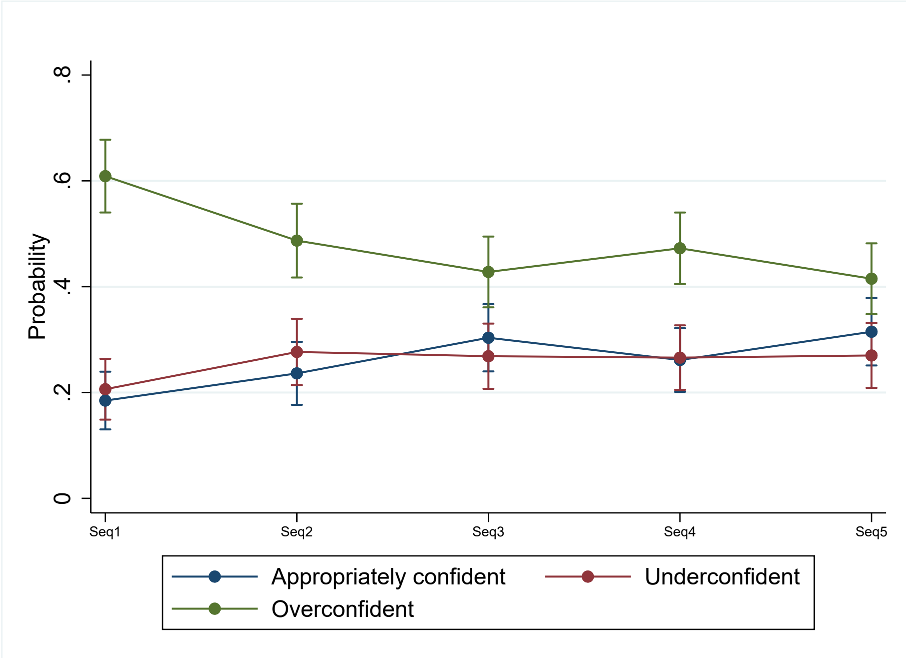
with 'appropriate confidence' as the base in the dependent variable.

Figure 12 shows the results in the form of the predictive margins of the sequence number.[28] The results show that participants are significantly more likely to be overconfident, and this probability gradually decreases up to sequence 3 and then stagnates. The probability of being underconfident is not significantly different from being appropriately confident, and even though not significant, the likelihood of being appropriately confident or underconfident gradually increases over the sequences.

Now we estimate the effects of confidence on outcomes using random effects panel regression models

[28]The estimated coefficients are presented in Appendix Table B9 revealing no differences across treatments. Equivalent margins plots by treatment are presented in Appendix Figure B8, which shows a similar pattern to the main results.

Figure 12: Margins plot for Multinomial Logistic of Confidence Type Evolution



Note: This presents the predictive margins of sequence number on current investment pattern with 95% CI using multinomial logit model in equation 13.

with a similar specification to Equation 10. We additionally include a vector of binary variables to capture the effects of confidence type - underconfidence or overconfidence, keeping appropriate confidence as the reference category.

$$Outcome_{ist} = \alpha + \eta_{is} ConfidenceType_{i,s-1,t} + \beta_{ist} T_i + \gamma' Seq_{is} + \delta' X_i + U_i + \epsilon_{is} \tag{14}$$

We consider two different outcomes, first, earnings, and second, the absolute deviation of the chosen investment from the rational investment level in period one. For the absolute deviation of the investments, we only consider the first period as the conditional and unconditional optimal investments are the same in period one as there is no history at that point. Therefore, the optimality conditions are not affected by the history.

Table 3 provides support for Result 7, which presents the estimated coefficients for Equation 14. For each of these outcomes, we first estimate the effects of confidence type without controlling for the sequence number and then controlling for the sequence number (through a vector of dummy variables for the relevant sequence number). The results show that overconfident participants earn less than those with appropriate confidence or underconfidence, although this effect becomes only marginally significant after adjusting for sequence number, suggesting learning effects with experience.Furthermore, we find that overconfident participants deviate more from the rational investment path (as presented in the second

Table 3: Effects of Confidence on Earnings and Absolute Deviation from Rational Investment

	Earnings		$\|Deviation\|$	
	(1)	(2)	(3)	(4)
InvOnly	37.890**	38.537**	-2.934	-2.963
	(17.009)	(17.539)	(2.136)	(2.156)
InvEarn	20.204	21.442	-0.471	-0.546
	(19.596)	(20.255)	(2.275)	(2.308)
InvConf	31.228	31.597	-2.120	-2.138
	(19.386)	(19.959)	(2.180)	(2.202)
Underconfident	12.972	9.836	-0.407	-0.250
	(9.804)	(8.767)	(1.554)	(1.483)
Overconfident	-26.981***	-15.359*	4.842***	4.079***
	(9.863)	(9.142)	(1.340)	(1.327)
Obs	780	780	780	780
Mean of Y	402.865	402.865	26.054	26.054
R2	0.135	0.132	0.144	0.143
Controls	Yes	Yes	Yes	Yes
Seq. Number	No	Yes	No	Yes

Note: The table presents the coefficients estimated from Equation 14. Only non-negative earnings sequences and period 1 is considered. Standard errors in all estimates are clustered at the participant level. Significance level: $*p < 0.1, **p < 0.05, ***p < 0.01$.

panel), which explains their lower earnings. These findings suggest a psychological mechanism through which myopic participants remain trapped on the myopic path.

5 Conclusion

Investing in human capital accumulation is an important yet challenging task, as individuals must consider lifecycle returns when making decisions in each period, since decisions made in earlier periods can impact later outcomes. Further, making decisions more difficult, individuals may have to forego tempting short-term returns to achieve higher longer-term returns. In this paper, we model this scenario as a dynamic optimization problem with distinct investment paths for rational and myopic behaviors, where myopia is defined by narrow bracketing rather than time discounting. Our model deviates from regular consumption-saving models, where we do not allow savings for or borrowings from the future, and higher habit stocks in earlier periods improve earnings through reduced costs. We then test the model predictions using an online experiment. We focus on participant behavior over repeated lifecycles as well as in the presence of peer information. In terms of peer information, we provide a peer's investment decisions, investment decisions along with overall earnings, or investment decisions along with stated confidence, in contrast to the control group, which does not receive any peer information.

We find that participants are more likely to follow a myopic pattern and earn significantly less than they would if they were rational. In earlier periods, participants invest less than rational investors, followed by a decreasing investment pattern, suggesting the difficulty of overcoming short-term temptations. Although they improve earnings with experience over repeated lifecycles, they are unable to reach their maximum potential. Notably, when participants start to locally maximize and earn myopic earnings, they are more likely to be trapped there and follow a similar pattern in repeated lifecycles. Furthermore, the provided peer information does not significantly affect investment behavior in moving towards rational behavior compared to having no peer information.

Our findings have several policy implications for the design of skill development interventions. First, effective interventions need to move beyond conventional awareness campaigns that focus on long-term returns. Since myopic behavior is reinforced through higher short-term returns resulting from reduced costs of low investments, interventions may need to focus on short-term costs and provide feedback to reduce discouragement. This could be accompanied by information on the intermediate returns they can expect, providing some assurance of the correct investment path. Further, beyond information nudges, policies may need to incorporate commitment strategies to overcome myopia.

While our model captures key characteristics of skill accumulation, we employ several simplifying assumptions. First, we focus on pure rational and myopic behaviors and normalize time discounting to one. Secondly, even with the perfect ability to solve complex problems, the trade-off between short-term and long-term returns on investment in skill accumulation can be much more complex, making it difficult to have a clear, distinct solution path. Further, we assume homogeneous ability where all participants have a similar skill production function.

Future research can relax the above assumptions and extend the model and experimental design to various other settings. For example, this study may be extended to examine the behavior in competitive environments or the willingness to pay for costly information. Furthermore, this analysis could be extended to examine the effects of heterogeneous peer information and investments across varying ability levels.

References

Augenblick, N., Niederle, M., & Sprenger, C. (2015). Working over time: Dynamic inconsistency in real effort tasks. *The Quarterly Journal of Economics*, *130*(3), 1067–1115.

Austen-Smith, D., & Fryer Jr, R. G. (2005). An economic analysis of "acting white". *The Quarterly Journal of Economics*, *120*(2), 551–583.

Ballinger, T. P., Hudson, E., Karkoviata, L., & Wilcox, N. T. (2011). Saving behavior and cognitive abilities. *Experimental Economics*, *14*(3), 349–374.

Ballinger, T. P., Palumbo, M. G., & Wilcox, N. T. (2003). Precautionary saving and social learning across generations: An experiment. *The Economic Journal*, *113*(490), 920–947.

Bénabou, R., & Tirole, J. (2002). Self-confidence and personal motivation. *The Quarterly Journal of Economics*, *117*(3), 871–915.

Benartzi, S., & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, *110*(1), 73–92.

Bone, J., Hey, J. D., & Suckling, J. (2009). Do people plan? *Experimental Economics*, *12*, 12–25.

Brown, A. L., Chua, Z. E., & Camerer, C. F. (2009). Learning and visceral temptation in dynamic saving experiments. *The Quarterly Journal of Economics*, *124*(1), 197–231.

Budish, E., Roin, B. N., & Williams, H. (2015). Do firms underinvest in long-term research? evidence from cancer clinical trials. *American Economic Review*, *105*(7), 2044–2085.

Bursztyn, L., Ederer, F., Ferman, B., & Yuchtman, N. (2014). Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions. *Econometrica*, *82*(4), 1273–1301.

Bursztyn, L., Fujiwara, T., & Pallais, A. (2017). 'acting wife': Marriage market incentives and labor market investments. *American Economic Review*, *107*(11), 3288–3319.

Bursztyn, L., & Jensen, R. (2015). How does peer pressure affect educational investments? *The Quarterly Journal of Economics*, *130*(3), 1329–1367.

Caliendo, M., Cobb-Clark, D. A., Obst, C., Seitz, H., & Uhlendorff, A. (2022). Locus of control and investment in training. *Journal of Human Resources*, *57*(4), 1311–1349.

Carbone, E., & Duffy, J. (2014). Lifecycle consumption plans, social learning and external habits: Experimental evidence. *Journal of Economic Behavior & Organization*, *106*, 413–427.

Carneiro, P., & Heckman, J. J. (2002). The evidence on credit constraints in post-secondary schooling. *The Economic Journal*, *112*(482), 705–734.

Carroll, C. D., Overland, J., & Weil, D. N. (2000). Saving and growth with habit formation. *American Economic Review*, *90*(3), 341–355.

Castro, J. F., Yamada, G., & Arias, O. (2016). Higher education decisions in peru: On the role of financial constraints, skills, and family background [Cited by: 14]. *Higher Education*, *72*(4), 457–486. https://doi.org/10.1007/s10734-016-0040-x

Chapman, G. B. (1996). Temporal discounting and utility for health and money. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*(3), 771.

Chen, D. L., Schonger, M., & Wickens, C. (2016). Otree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97.

Chen, S., & Ma, H. (2017). Peer effects in decision-making: Evidence from corporate investment. *China Journal of Accounting Research*, *10*(2), 167–188.

Chung, K.-S. (2000). Role models and arguments for affirmative action. *American Economic Review*, *90*(3), 640–648.

Cisternas, G. (2018). Career concerns and the nature of skills. *American Economic Journal: Microeconomics*, *10*(2), 152–189.

Cohen, G. L., & Garcia, J. (2008). Identity, belonging, and achievement: A model, interventions, implications. *Current directions in psychological science*, *17*(6), 365–369.

Cotton, C., Hickman, B., List, J. A., Price, J., & Roy, S. (2025). Why don't struggling students do their homework? disentangling motivation and study productivity as drivers of human capital formation. *Journal of Political Economy*.

Cunha, F., & Heckman, J. (2007). The technology of skill formation. *American Economic Review*, *97*(2), 31–47.

Cunha, F., Heckman, J. J., Lochner, L., & Masterov, D. V. (2006). Interpreting the evidence on life cycle skill formation. *Handbook of the Economics of Education*, *1*, 697–812.

Damgaard, M. T., & Nielsen, H. S. (2020). Behavioral economics and nudging in education: Evidence from the field. In *The economics of education* (pp. 21–35). Elsevier.

de Bruin, A. B., Janssen, E. M., Waldeyer, J., & Stebner, F. (2025). Cognitive load and challenges in self-regulation: An introduction and reflection on the topical collection. *Educational Psychology Review*, *37*(3), 1–12.

Duflo, E., & Saez, E. (2002). Participation and investment decisions in a retirement plan: The influence of colleagues' choices. *Journal of Public Economics*, *85*(1), 121–148.

Fafchamps, M., Kebede, B., & Zizzo, D. J. (2015). Keep up with the winners: Experimental evidence on risk taking, asset integration, and peer effects. *European Economic Review*, *79*, 59–79.

Fuhrer, J. C. (2000). Habit formation in consumption and its implications for monetary-policy models. *American Economic Review*, *90*(3), 367–390.

Furnham, A., & Boo, H. C. (2011). A literature review of the anchoring effect. *The Journal of Socio-Economics*, *40*(1), 35–42.

Gabaix, X., & Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics*, *121*(2), 505–540.

Georganas, S., Tonin, M., & Vlassopoulos, M. (2015). Peer pressure and productivity: The role of observing and being observed. *Journal of Economic Behavior & Organization*, *117*, 223–232. https://doi.org/https://doi.org/10.1016/j.jebo.2015.06.014

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, *112*(2), 631–645.

Gortner, P. J., & van der Weele, J. J. (2019). Peer effects and risk sharing in experimental asset markets. *European Economic Review*, *116*, 129–147.

Hanushek, E. A., & Woessmann, L. (2010). Education and economic growth. *Economics of Education*, *60*(67), 1.

Hastings, J. S., & Weinstein, J. M. (2008). Information, school choice, and academic achievement: Evidence from two experiments. *The Quarterly Journal of Economics*, *123*(4), 1373–1414.

Iqbal, K., Islam, A., List, J., & Nguyen, V. (2020). Myopia and investment decisions: From the laboratory to the field. *CDES Working Paper Series*.

Iturbe-Ormaetxe, I., Ponti, G., & Tomás, J. (2019). Is it myopia or loss aversion? a study on investment game experiments. *Economics Letters*, *180*, 36–40.

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics*, *125*(2), 515–548.

Kaestner, R., & Faundez, L. F. (2023). *Estimating a theoretically consistent human capital production function with an application to head start* (tech. rep.). National Bureau of Economic Research.

Kaustia, M., & Knüpfer, S. (2012). Peer performance and stock market entry. *Journal of Financial Economics*, *104*(2), 321–338.

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., & Borghans, L. (2014). Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success. *National Bureau of Economic Research*, (20749). https://doi.org/10.3386/w20749

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*, *77*(6), 1121.

Lavecchia, A. M., Liu, H., & Oreopoulos, P. (2016). Behavioral economics of education: Progress and possibilities. In *Handbook of the economics of education* (pp. 1–74). Elsevier.

Levitt, S. D., List, J. A., Neckermann, S., & Sadoff, S. (2016). The behavioralist goes to school: Leveraging behavioral economics to improve educational performance. *American Economic Journal: Economic Policy*, *8*(4), 183–219.

Loewenstein, G., & Thaler, R. H. (1989). Anomalies: Intertemporal choice. *Journal of Economic Perspectives*, *3*(4), 181–193.

Malmendier, U., & Della Vigna, S. (2006). Paying not to go to the gym. *American Economic Review*, *96*(3), 694–719.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3), 531–542.

McMahon, W. W. (2018). The total return to higher education: Is there underinvestment for economic growth and development? *The Quarterly Review of Economics and Finance*, *70*, 90–111.

Meyer, R. J., & Hutchinson, J. W. (2016). (when) are we dynamically optimal? a psychological field guide for marketing modelers. *Journal of Marketing*, *80*(5), 20–33.

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, *115*(2), 502.

Nguyen, T. (2008). Information, role models and perceived returns to education: Experimental evidence from madagascar. *Unpublished manuscript*, *6*(5).

O'donoghue, T., & Rabin, M. (1999). Doing it now or later. *American Economic Review*, *89*(1), 103–124.

Oreopoulos, P., Patterson, R. W., Petronijevic, U., & Pope, N. G. (2018). *When studying and nudging don't go as planned: Unsuccessful attempts to help traditional and online college students* (tech. rep.). National Bureau of Economic Research.

Oreopoulos, P., & Petronijevic, U. (2019). *The remarkable unresponsiveness of college students to nudging and what we can learn from it* (tech. rep.). National Bureau of Economic Research.

Oreopoulos, P., & Salvanes, K. G. (2011). Priceless: The nonpecuniary benefits of schooling. *Journal of Economic Perspectives*, *25*(1), 159–184.

Ouimet, P., & Tate, G. (2020). Learning from coworkers: Peer effects on individual investment decisions. *The Journal of Finance*, *75*(1), 133–172.

Oxoby, R. J. (2008). Skill uncertainty and social inference. *Labour Economics*, *15*(3), 400–405.

Palan, S., & Schitter, C. (2018). Prolific.ac—a subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22–27. https://doi.org/https://doi.org/10.1016/j.jbef.2017.12.004

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153–163.

Read, D., Loewenstein, G., & Rabin, M. (1999). Choice bracketing. *Journal of Risk and Uncertainty*, *19*(1), 171–197.

Rossi, F., & Weber, M. (2024). *The accumulation and utilization of human capital over the development spectrum*. World Bank.

Stähler, J., Bieleke, M., Wolff, W., & Schüler, J. (2025). Different functions of physical effort in physical activity and sports: A scoping review of the value of physical effort. *Motivation and Emotion*, 1–25.

Stoker, B. (2017). *Counting to 21 strategy*. Retrieved October 12, 2021, from https://boardgamestrategy.blog/2017/02/13/counting-to-21-strategy/

Summerfield, C., & Tsetsos, K. (2015). Do humans make good decisions? *Trends in Cognitive Sciences*, *19*(1), 27–34.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), 1124–1131.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, *106*(4), 1039–1061.

Yechiam, E., Druyan, M., & Ert, E. (2008). Observing others' behavior and risk taking in decisions from experience. *Judgment and Decision Making*, *3*(7), 493.

Yu, T., Xu, Y., Zhang, Z., Sun, Y., Zhong, J., & Ding, C. (2025). The impact of core training on overall athletic performance in different sports: A comprehensive meta-analysis. *BMC Sports Science, Medicine and Rehabilitation*, *17*(1), 112.

Appendices

A Model Solution Steps

$$
\begin{aligned}
\max_{\{e_t\}_{t=1}^{T}} \sum_{t=1}^{T} [B(e_t) - C(e_t, H_t)] \quad \text{subject to } 0 \leq e_t \leq E \\
\text{where } H_{t+1} = e_t + \gamma H_t \\
H_1 \text{ given} \\
\gamma \in [0,1]
\end{aligned}
\tag{A.1}
$$

At any period t, an individual's problem can be extended as follows:

$$
\begin{aligned}
& B(e_t) + B(e_{t+1}) + B(e_{t+2}) + ... + B(e_T) - C(e_t, H_t) - C(e_{t+1}, H_{t+1}) - C(e_{t+2}, H_{t+2}) - ... - C(e_T, H_T) \\
& \Rightarrow B(e_t) + B(e_{t+1}) + B(e_{t+2}) + ... + B(e_T) \\
& \qquad - C(e_t, H_t) - C(e_{t+1}, \gamma H_t + e_t) - C(e_{t+2}, \gamma^2 H_t + \gamma e_t + e_{t+1}) - ... \\
& \qquad - C\left(e_T, \gamma^{T-t} H_t + \gamma^{T-t-1} e_t + \gamma^{T-t-2} e_{t+1} + ... + \gamma e_{T-2} + e_{T-1}\right) \\
& \Rightarrow B(e_t) - C(e_t, H_t) + \sum_{\tau=1}^{T-t} B(e_{t+\tau}) - \sum_{\tau=1}^{T-t} C\left(e_{t+\tau}, \gamma^{\tau} H_t + \sum_{\kappa=1}^{\tau} \gamma^{\kappa-1} e_{t+\tau-\kappa}\right)
\end{aligned}
\tag{A.2}
$$

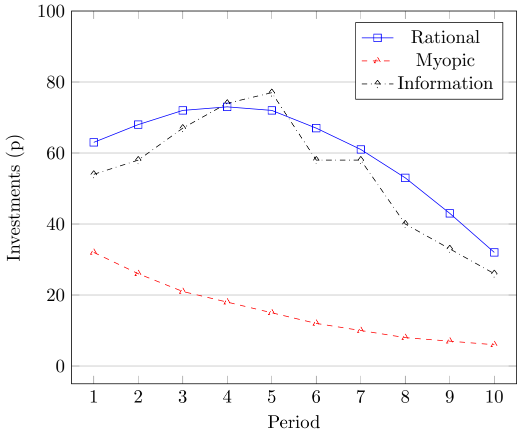
Then the FOC with respect to t is given by

$$
B'(e_t) - C_1'(e_t, H_t) - \sum_{\tau=1}^{T-t} C_2'\left(e_{t+\tau}, \gamma^{\tau} H_t + \sum_{\kappa=1}^{\tau} \gamma^{\kappa-1} e_{t+\tau-\kappa}\right) \gamma^{\tau-1} = 0 \tag{A.3}
$$

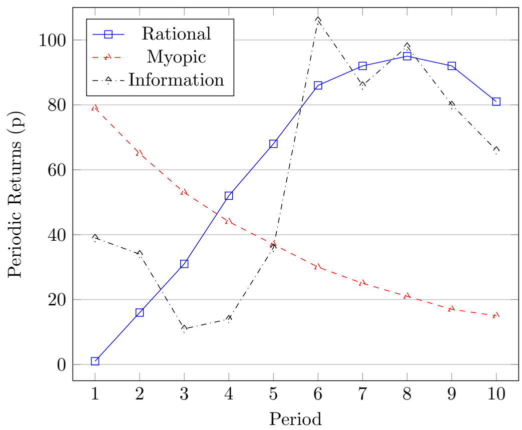
B Additional Figures and Tables

B.1 Additional Figures

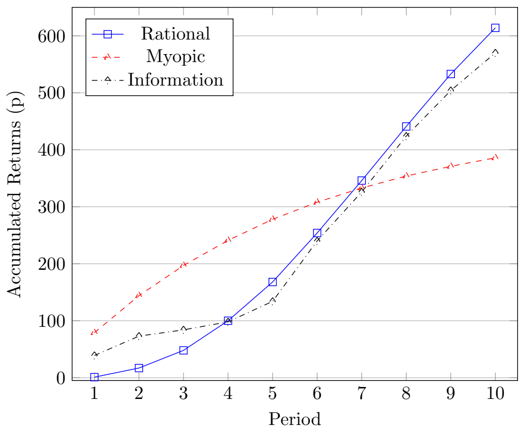
Figure B1: Investment Path, Periodic Returns, and Accumulated Returns for Optimal and Myopic Investors, and Given Information



(a) Periodic Investments

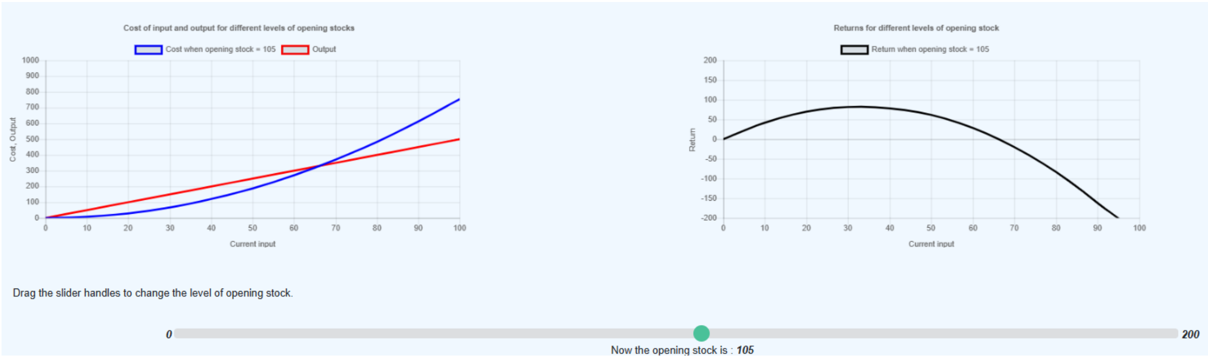


(b) Periodic Returns



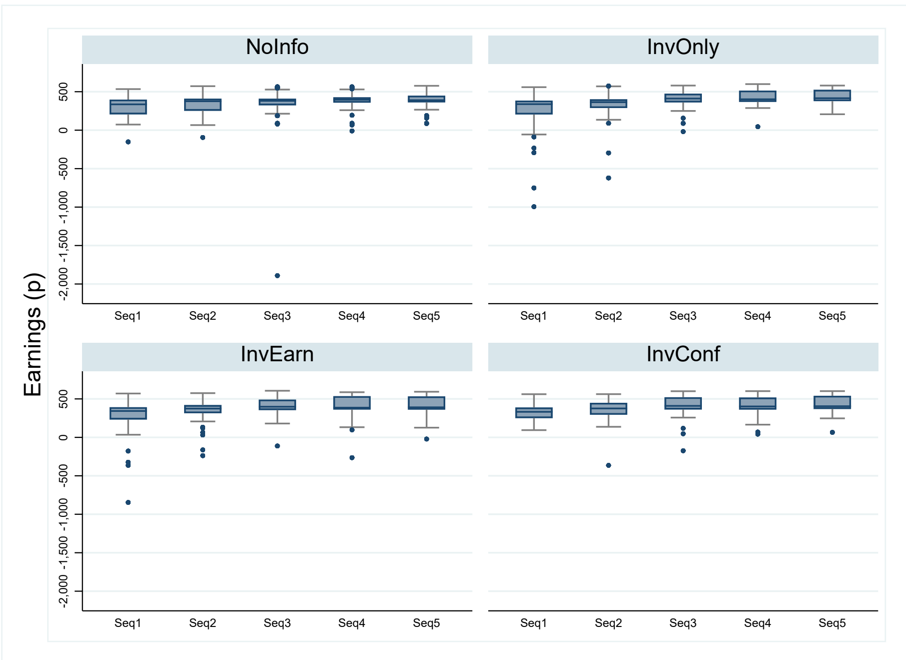
(c) Accumulated Returns

Figure B2: Testing Interface Provided for the Participants



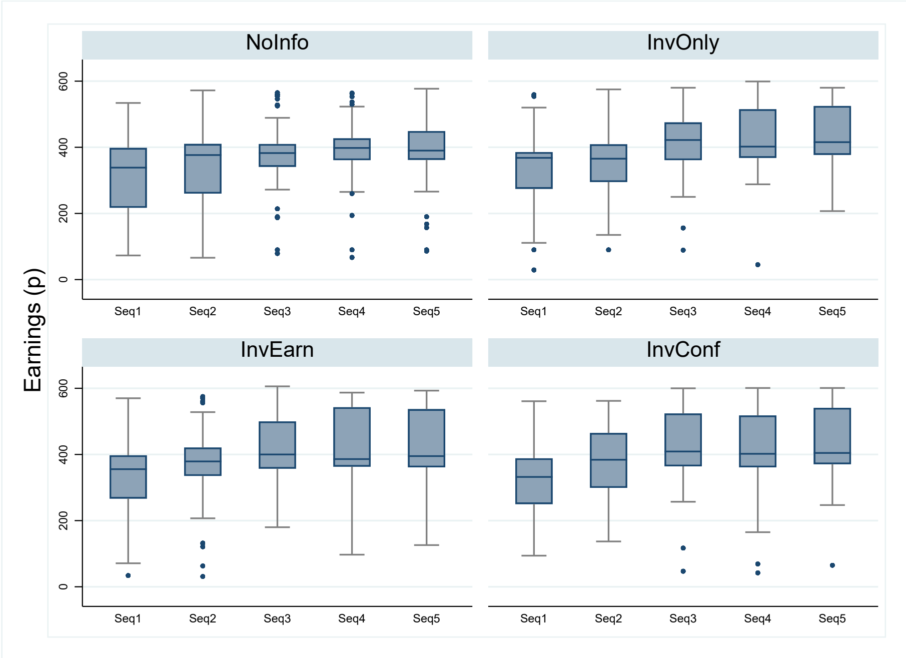
Note: This is the interface provided for the players to further understand how different levels of opening stocks and current level of input affect their output, cost of input, and returns (net of output and cost of input). Participants can move the slider to understand the effects of different levels of stock and the graph changes accordingly in real time as the slider moves.

Figure B3: Distribution of Earnings



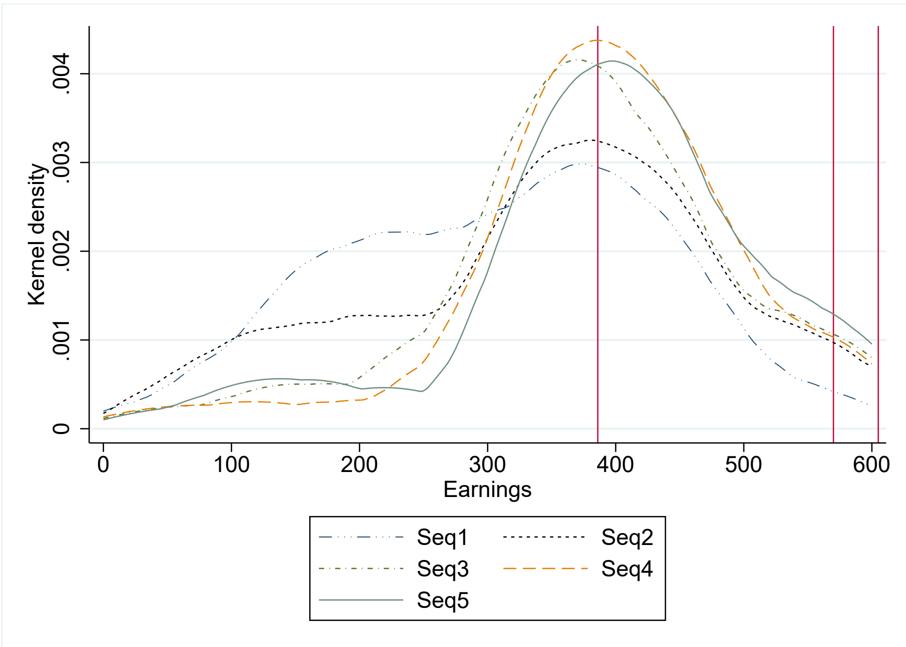
Note: The figure shows a boxplot of earnings in each sequence including the negative earnings

Figure B4: Distribution of Non-Negative Earnings



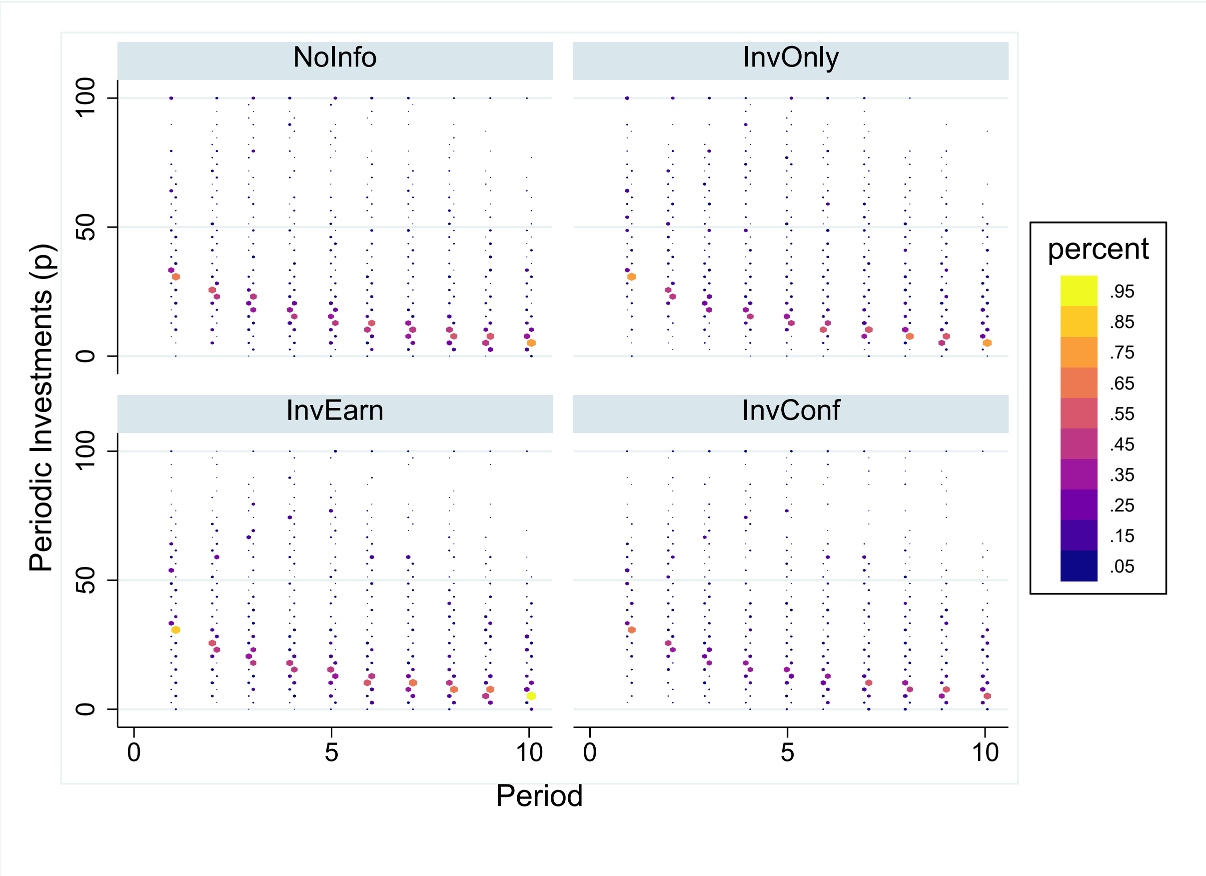
Note: The figure shows a boxplot of earnings in each sequence including only the non-negative earnings

Figure B5: Kernal Density of *NoInfo* Earnings.



Note: The left-most vertical line presents the myopic earning level at 386p, the second line presents the earnings at the given information level at 570p, and the right-most line presents the optimal earnings at 605p.

Figure B6: Investments Under Each Treatment



Note: The figure presents a heat map of investments in each treatment pooling all the sequences of all the participants.

Figure B7: Scatter Plot of Earnings Evolution

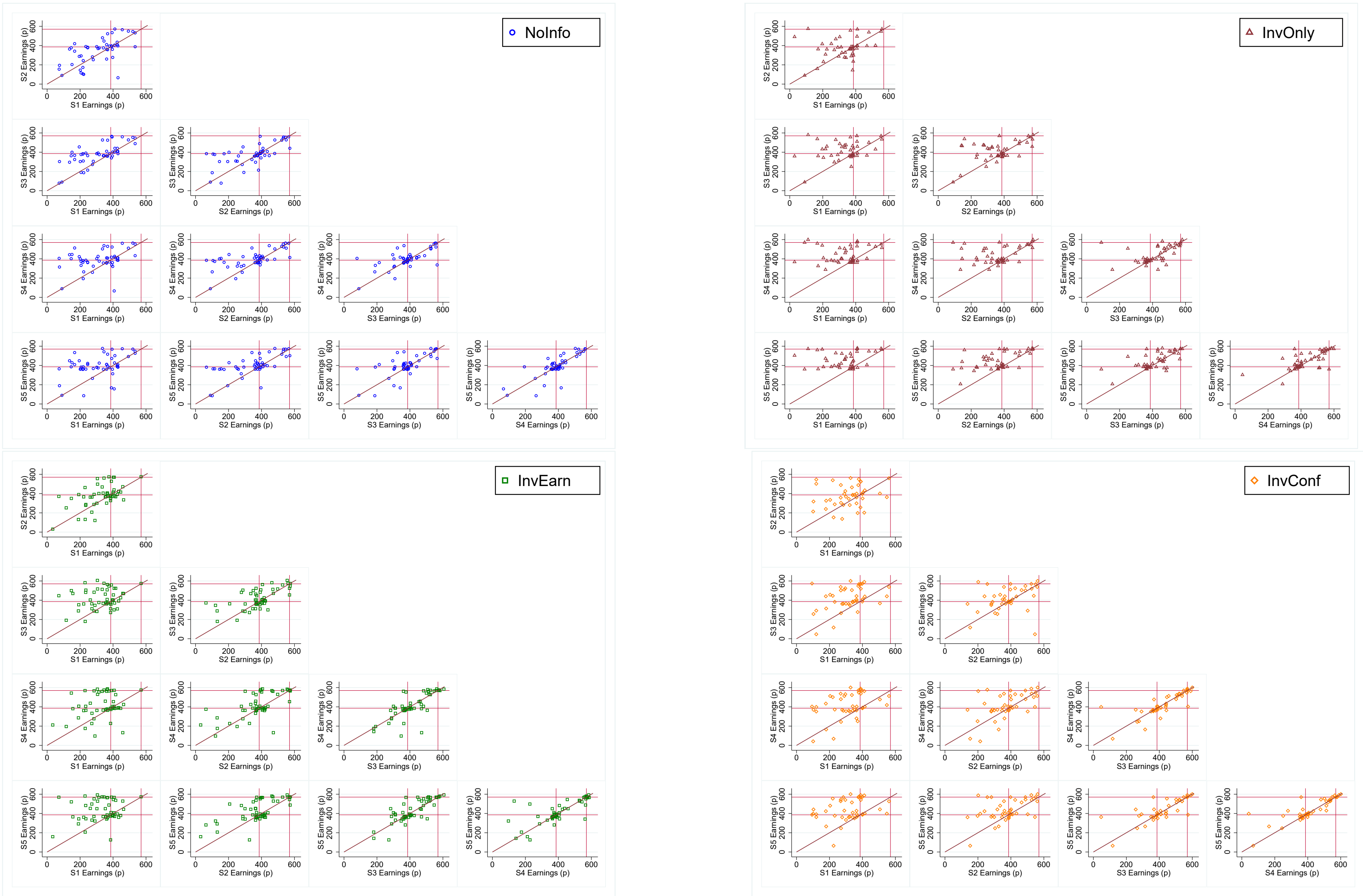
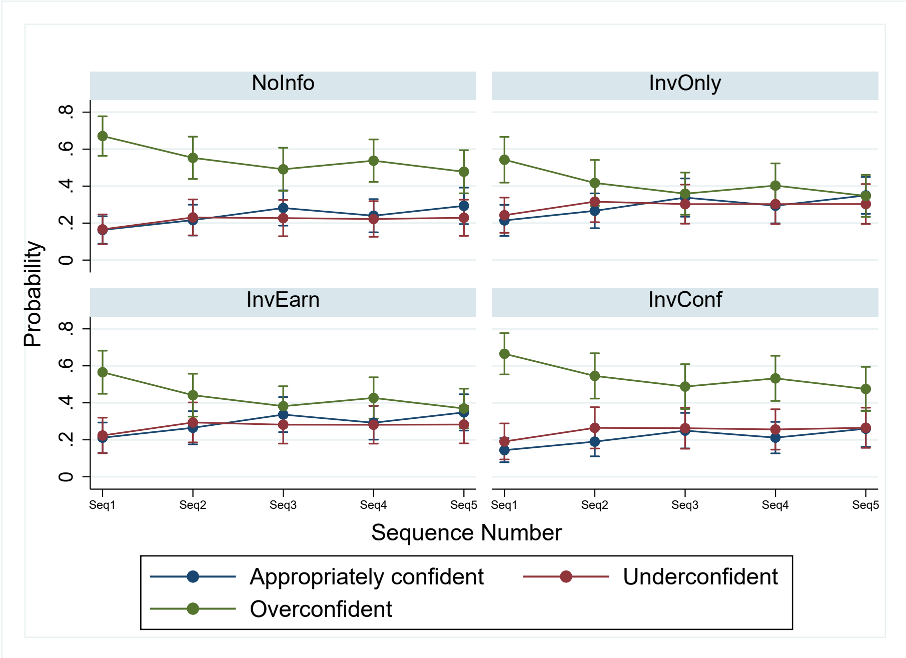


Figure B8: Margins plot for Multinomial Logistic of Confidence Type Evolution



Note: The figure presents the predictive margins of sequence number on current investment pattern with 95% CI using multinomial logit model in equation 13.

B.2 Additional Tables

Table B1: Mean and Standard Deviation (in square brackets) of the Control Variables

	(1) Overall	(2) NoInfo	(3) InvOnly	(4) InvEarn	(5) InvConf
Age	28.861	27.255	28.220	30.000	30.000
	[9.620]	[7.820]	[8.704]	[11.024]	[10.535]
Female	0.308	0.373	0.320	0.321	0.205
	[0.463]	[0.488]	[0.471]	[0.471]	[0.408]
English	0.458	0.451	0.440	0.429	0.523
	[0.499]	[0.503]	[0.501]	[0.499]	[0.505]
Graduate	0.637	0.627	0.560	0.661	0.705
	[0.482]	[0.488]	[0.501]	[0.478]	[0.462]
STEMEcon	0.493	0.451	0.500	0.518	0.500
	[0.501]	[0.503]	[0.505]	[0.504]	[0.506]
InvstmentInRisk	12.438	12.118	11.440	13.161	13.023
	[5.319]	[5.195]	[5.533]	[4.928]	[5.651]
Race1Won	0.159	0.176	0.080	0.161	0.227
	[0.367]	[0.385]	[0.274]	[0.371]	[0.424]
Race2Won	0.567	0.588	0.380	0.607	0.705
	[0.497]	[0.497]	[0.490]	[0.493]	[0.462]
Observations	201	51	50	56	44

Note: Column (1) reports the means of the variables on the left for the entire sample. Columns (2)-(5) report the means of variables in control, investments only treatment, investments and earnings treatment, and investments and confidence, respectively. The standard deviations are reported in brackets. The description of the variables is as follows.Age is the age of the subjects in years (the youngest subject is 18 years old and the oldest subject is 70 years old). Female, Graduate, STEMEcon, and English are dummy variables equal to one if the subject is a female, has a bachelor or above degree, has a field of specialization as economics or in STEM, and uses English as the primary language at home. InvestmentInRisk is the amount invested in a risky asset out of the endowment of 20p. The task in Gneezy and Potters (1997) is used for risk elicitation. Race1Won and Race2Won are dummy variables equal to one if the subject won the tasks that is used to measure the backward thinking ability in attempts one and two, respectively.

Table B2: Balance of the Control Variables

	(1) NoInfo - InvOnly	(2) NoInfo - InvEarn	(3) NoInfo - InvConf	(4) InvOnly - InvEarn	(5) InvOnly - InvConf	(6) InvEarn - InvConf
Age	-0.965	-2.745	-2.745	-1.780	-1.780	0.000
	(1.648)	(1.836)	(1.929)	(1.920)	(2.009)	(2.166)
Female	0.053	0.051	0.168*	-0.001	0.115	0.117
	(0.095)	(0.093)	(0.092)	(0.092)	(0.091)	(0.088)
English	0.011	0.022	-0.072	0.011	-0.083	-0.094
	(0.100)	(0.097)	(0.104)	(0.097)	(0.104)	(0.101)
Graduate	0.067	-0.033	-0.077	-0.101	-0.145	-0.044
	(0.099)	(0.094)	(0.098)	(0.095)	(0.099)	(0.094)
STEMEcon	-0.049	-0.067	-0.049	-0.018	0.000	0.018
	(0.100)	(0.097)	(0.104)	(0.098)	(0.104)	(0.102)
InvstmentInRisk	0.678	-1.043	-0.905	-1.721*	-1.583	0.138
	(1.068)	(0.981)	(1.120)	(1.023)	(1.157)	(1.077)
Race1Won	0.096	0.016	-0.051	-0.081	-0.147*	-0.067
	(0.066)	(0.073)	(0.084)	(0.063)	(0.075)	(0.081)
Race2Won	0.208**	-0.019	-0.116	-0.227**	-0.325***	-0.097
	(0.098)	(0.096)	(0.098)	(0.096)	(0.098)	(0.096)
Observations	101	107	95	106	94	100

Note: This reports the differences of means between treatments using two sided ttest. The description of the variables is as follows. Race1Won and Race2Won are dummy variables equal to one if the subject won the race game in attempts one and two, respectively. InvestmentInRisk is the amount invested in a risky asset out of the endowment of 20p. The task in Gneezy and Potters (1997) is used for risk elicitation. Age is the age of the subjects in years. Female, Graduate, STEMEcon, and English are dummy variables equal to one if the subject is a female, has a bachelor, master or above degree, has a field of specialization as economics or in STEM, and uses English as the primary language at home. The standard errors are reported in parentheses. Significant levels: $*p < .1, \quad **p < .05, \quad ***p < .01$

Table B3: Estimated Treatment Effects on Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Seq2	32.597**	32.690*	44.964***	45.005***	32.797**	33.006**
	(16.607)	(16.966)	(9.085)	(9.121)	(16.467)	(16.521)
Seq3	64.517***	64.610***	86.266***	86.311***	64.717***	64.926***
	(13.557)	(13.870)	(8.640)	(8.670)	(13.418)	(13.448)
Seq4	79.014***	79.142***	92.296***	92.336***	79.061***	79.030***
	(18.246)	(18.517)	(9.771)	(9.805)	(18.140)	(18.195)
Seq5	84.609***	84.816***	105.879***	105.933***	84.643***	84.719***
	(18.274)	(18.563)	(9.522)	(9.563)	(18.166)	(18.235)
Age		0.032		-0.257		-0.271
		(1.905)		(0.728)		(0.736)
Female		-33.637		-19.816		-19.727
		(26.145)		(15.470)		(15.542)
English		-26.059		-14.715		-14.531
		(29.818)		(14.367)		(14.447)
Graduate		14.839		-3.115		-3.190
		(31.674)		(13.517)		(13.613)
STEMEcon		-50.168		7.540		7.474
		(32.442)		(13.139)		(13.226)
InvstmentInRisk		-1.532		0.732		0.725
		(2.752)		(1.269)		(1.278)
Race1Won		29.380		8.596		8.678
		(38.648)		(21.716)		(21.857)
Race2Won		8.454		11.423		11.456
		(26.600)		(14.146)		(14.238)
InvOnly			29.777*	31.883*	12.128	14.233
			(17.402)	(17.619)	(24.766)	(24.821)
InvEarn			19.426	17.532	6.018	4.291
			(18.592)	(19.570)	(22.681)	(23.590)
InvConf			27.411	23.245	1.770	-2.230
			(19.159)	(19.427)	(23.976)	(24.757)
InvOnly $\times$ Seq2					3.331	3.218
					(26.197)	(26.284)
InvOnly $\times$ Seq3					23.635	23.549
					(23.405)	(23.482)
InvOnly $\times$ Seq4					26.021	26.222
					(27.338)	(27.418)
InvOnly $\times$ Seq5					33.579	33.672
					(26.564)	(26.659)
InvEarn $\times$ Seq2					18.132	17.833
					(22.366)	(22.449)
InvEarn $\times$ Seq3					24.504	24.242
					(21.979)	(22.042)
InvEarn $\times$ Seq4					7.552	7.640
					(26.763)	(26.878)
InvEarn $\times$ Seq5					16.936	16.865
					(26.061)	(26.178)
InvConf $\times$ Seq2					28.743	28.507
					(27.083)	(27.178)
InvConf $\times$ Seq3					40.655*	40.353*
					(23.375)	(23.446)
InvConf $\times$ Seq4					21.462	21.493
					(27.045)	(27.147)
InvConf $\times$ Seq5					37.516	37.440
					(27.097)	(27.204)
Constant	311.764***	356.688***	298.061***	300.506***	311.730***	314.524***
	(17.153)	(65.466)	(14.681)	(32.483)	(17.061)	(33.940)
Obs	251	251	981	981	981	981
Mean of Y	364.992	364.992	385.446	385.446	385.446	385.446
R2	0.072	0.137	0.110	0.130	0.113	0.133
Controls	No	Yes	No	Yes	No	Yes
NoInfo only	Yes	Yes	No	No	No	No

Notes: Columns (1) and (2) report the estimated effects of the control group's learning on earnings using random effects regressions specified in Equation 8 without and with additional controls, respectively. Columns (3) and (4) report the estimated peer information treatment effects on earning using the random effects regression in Equation 10. Columns (5) and (6) report the same regression in Equation 10 estimates but additional interaction terms between the treatment groups and the sequence numbers to investigate any differential treatment effects across sequences. In Columns (7) and (8), we use the same regression specification but pool the peer information treatments where *Treated* equals one the participant receives any peer information and 0 if in the control group. The controls include the variables specified under Equation 8. Only the non-negative earnings are considered. Standard errors in all estimates are clustered at participant level. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B4: Estimated Treatment Effects on Earnings

	(1)	(2)	(3)	(4)
PeerInfo	25.220*	24.057	6.616	5.514
	(15.211)	(15.757)	(19.442)	(19.769)
PeerInfo × Seq2			16.556	16.349
			(19.634)	(19.700)
PeerInfo × Seq3			29.163*	28.966*
			(17.073)	(17.122)
PeerInfo × Seq4			18.032	18.148
			(21.432)	(21.509)
PeerInfo × Seq5			28.773	28.771
			(21.226)	(21.311)
Constant	298.058***	305.017***	311.731***	318.614***
	(14.664)	(30.470)	(16.973)	(31.601)
Obs	981	981	981	981
Mean of Y	385.446	385.446	385.446	385.446
R2	0.109	0.128	0.110	0.129
Controls	No	Yes	No	Yes
NoInfo group only	No	No	No	No

Notes: Columns (1) and (2) report the estimated peer information treatment effects on earning using the regression specification Equation 10 but pool the peer information treatments where $Treated$ equals one the participant receives any peer information and 0 if in the control group. The controls include the variables specified under Equation 8. Only the non-negative earnings are considered. Standard errors in all estimates are clustered at participant level. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B5: Estimated Contrasts of Treatment Effects on Earnings

	(1) InvOnly - NoInfo	(2) InvEarn - NoInfo	(3) InvConf - NoInfo	(4) InvEarn - InvOnly	(5) InvConf - InvOnly	(6) InvConf - InvEarn	(7) Treated - NoInfo
Average	31.883*	17.532	23.245	-14.351	-8.638	5.713	24.057
	(0.070)	(0.370)	(0.231)	(0.418)	(0.631)	(0.760)	(0.127)
Seq1	14.233	4.291	-2.230	-9.942	-16.464	-6.522	5.514
	(0.566)	(0.856)	(0.928)	(0.682)	(0.524)	(0.782)	(0.780)
Seq2	17.451	22.125	26.277	4.673	8.826	4.152	21.864
	(0.503)	(0.402)	(0.306)	(0.851)	(0.716)	(0.862)	(0.317)
Seq3	37.782*	28.534	38.123	-9.249	0.340	9.589	34.480*
	(0.079)	(0.193)	(0.118)	(0.659)	(0.989)	(0.682)	(0.059)
Seq4	40.455**	11.931	19.263	-28.524	-21.192	7.331	23.662
	(0.048)	(0.610)	(0.425)	(0.223)	(0.384)	(0.775)	(0.181)
Seq5	47.905**	21.157	35.209	-26.749	-12.696	14.053	34.285*
	(0.018)	(0.356)	(0.125)	(0.180)	(0.531)	(0.528)	(0.063)

Notes: This table presents the contrasts of treatments which are estimated using linear combinations. The first row is estimated using column (4) of Table B3 and the rest of the rows are estimated using column (6) of Table B3. For example, the cell in row S5 and column (6) is calculated from the coefficients as $InvConf + InvConf \times S5 - InvEarn - InvEarn \times S5$. Similarly, column (7) is estimated using the columns (2) and (4) in Table B4 The p-values are presented in parenthesis.

Table B6: Performance Improvement Comparison

	NoInfo - InvOnly	NoInfo - InvEarn	NoInfo - InvConf	InvOnly - InvEarn	InvOnly - InvConf	InvEarn - InvConf	NoInfo - Treated
S[t] - S[t-1] Learning	-10.382	-4.617	-10.001	5.765	0.381	-5.384	-8.131
	(0.310)	(0.623)	(0.370)	(0.566)	(0.974)	(0.624)	(0.314)
S3- S1 Learning	-14.760	-13.750	-25.701	1.010	-10.940	-11.950	-17.768
	(0.523)	(0.527)	(0.241)	(0.969)	(0.674)	(0.630)	(0.284)
S5 - S1 Leaning	-33.189	-4.146	-24.845	29.044	8.344	-20.699	-20.170
	(0.208)	(0.870)	(0.353)	(0.282)	(0.767)	(0.449)	(0.329)

Notes: This table compares the performance improvement (learning) between treatments which is measured through earnings using two-tailed ttest. The first row compares the earnings difference in consecutive sequences (i.e. S2-S1, S3-S2, etc) between treatments. The second row compares the performance improvement from S1 to S3 and the third row compares the performance improvement from S1 to S5 between treatments. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B7: Effects on Absolute Deviation From the Conditional Rational Investment Level

	(1) P1	(2) P2	(3) P3	(4) All Periods	(5) All Periods
InvOnly	-2.132	-1.376	-1.062	-0.495	-2.425
	(1.978)	(1.539)	(1.120)	(0.529)	(1.949)
InvEarn	-0.410	-1.364	-1.297	-0.593	-0.644
	(2.120)	(1.478)	(1.093)	(0.534)	(2.128)
InvConf	-2.003	-1.979	-1.194	-0.732	-1.899
	(2.013)	(1.506)	(1.127)	(0.542)	(2.042)
Seq2	-3.005***	-2.299**	-1.806*	-1.131***	-1.131***
	(1.115)	(0.913)	(0.931)	(0.280)	(0.280)
Seq3	-6.940***	-3.776***	-3.030***	-2.032***	-2.032***
	(1.281)	(0.876)	(0.877)	(0.316)	(0.316)
Seq4	-7.478***	-5.060***	-3.030***	-2.194***	-2.194***
	(1.328)	(0.930)	(0.876)	(0.304)	(0.305)
Seq5	-8.065***	-5.363***	-4.438***	-2.680***	-2.680***
	(1.252)	(0.961)	(0.857)	(0.282)	(0.282)
Constant	32.332***	22.043***	16.254***	29.380***	30.130***
	(3.569)	(2.730)	(1.733)	(1.153)	(1.690)
Obs	1,005	1,005	1,005	10,050	10,050
Mean of Y	27.664	20.347	14.912	11.216	11.216
R2	0.081	0.068	0.057	0.447	0.449
Controls	Yes	Yes	Yes	Yes	Yes
Period × Treatment	No	No	No	No	Yes
All Periods				Yes	Yes

Notes: In columns (1) to (3), we test the effects of the treatments and experience on absolute deviation from the conditional rational investment amounts in period 1, period 2, and period 3, respectively. Then we check the same effects considering all the periods (periods 1- 10) at once in column (4) and then include interaction terms of treatments with period number in column (5) to check whether there are any differential treatment effects across different periods. In columns (4) and (5), periods are included as categorical variables to capture any potential non-linearities. We use random effect models where player id and round number ($SeqNumber \times Period$) as panel variables. For this analysis, all sequences are considered. Standard errors in all estimates are clustered at the participant level. Significance level:$*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B8: Multinomial Logistic Regression for Investment Type Evolution

	(1) Myopic Direction	Rational Direction
Myopic Direction- Lagged seq	2.033***	-0.644
	(0.247)	(0.755)
Rational Direction - Lagged seq	-1.564	2.798**
	(1.117)	(1.183)
InvOnly	-0.040	1.362
	(0.357)	(1.329)
InvEarn	0.022	1.103
	(0.307)	(1.277)
InvConf	-0.460	1.551
	(0.328)	(1.305)
Seq3	-0.029	1.528*
	(0.315)	(0.928)
Seq4	0.609**	0.652
	(0.302)	(0.967)
Seq5	0.182	1.297*
	(0.294)	(0.742)
Controls	Yes	
N	552	

Notes: This presents the estimation results of the equation 12 using multinomial logistic model. The dependent variable the the investment direction in sequence 2 to 5 and the referent group is the Change Pattern. Significance level: $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table B9: Multinomial Logistic Regression for Confidence Type Evolution

	(1)	
	Underconfident	Overconfident
InvOnly	0.081	-0.502
	(0.395)	(0.353)
InvEarn	-0.028	-0.511
	(0.384)	(0.343)
InvConf	0.215	0.081
	(0.419)	(0.364)
Seq2	0.044	-0.492**
	(0.268)	(0.240)
Seq3	-0.240	-0.887***
	(0.257)	(0.238)
Seq4	-0.098	-0.628**
	(0.283)	(0.254)
Seq5	-0.272	-0.958***
	(0.258)	(0.244)
Controls	Yes	
N	981	

Notes: This presents the estimation results of the equation 13 using multinomial logistic model. The dependent variable is the confidence type (appropriately confident, underconfident, or overconfident) and where referent group is the appropriate confidence. Significance level: $*p < 0.1, **p < 0.05, ***p < 0.01$.

C Experiment - Instructions

The content in square brackets are not shown to the participants.

Welcome

Welcome to our experiment. Please read the instructions carefully.

The experiment will consist of several stages with different tasks. You will get instructions for each task as you go along. Please note that once you have finished a task on a page and moved on to the next, you will not be able to go back to the previous page to review or modify your answers.

You will earn points during the experiment. At the end of the experiment, the points you earned will be converted to money and paid to you in British pounds. **1 point = 0.01 GBP.**

Please click 'Next' to proceed.

Instructions - Overview

This is the main stage of decision-making tasks.

This stage consists of 5 ‘sequences’, and each sequence consists of 10 periods. In this task, you will be deciding how many points to allocate for production in each period. At the beginning of each **period** of every **sequence**, you will be given **100 points**. You can choose any number between **0** and **100 points** to allocate as input for production where input is costly.

In this experiment, **‘input’** refers to the number of points you allocate for production and **‘output’** refers to the outcome of production. Moreover, **‘return’** refers to the difference between the ‘output’ and ‘cost of input’. Finally, **‘total return’** in a sequence refers to the sum of ‘returns’ in each period in that sequence.

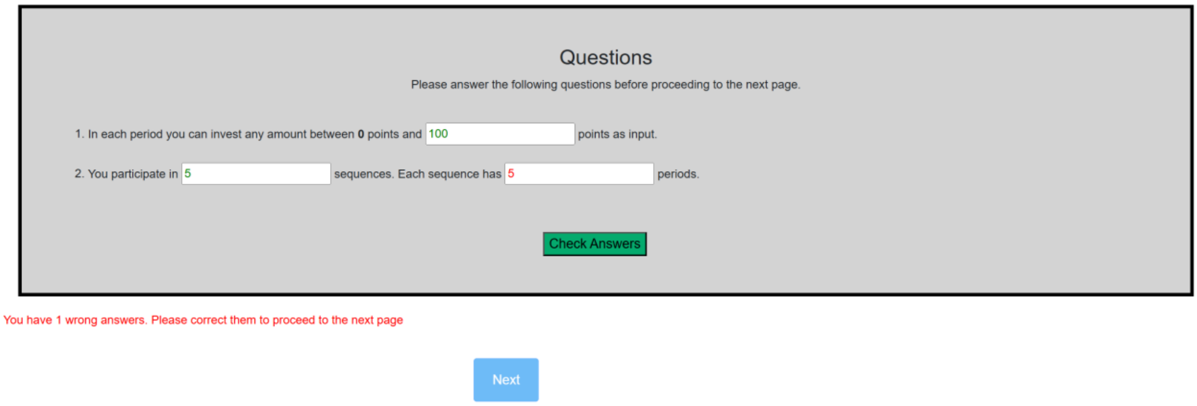
At the end of the experiment, one of the 5 sequences will be randomly chosen by the computer, and the converted monetary value of your’ **total return’** in that sequence will be added to your payoff.

Questions

Please answer the following questions before proceeding to the next page.

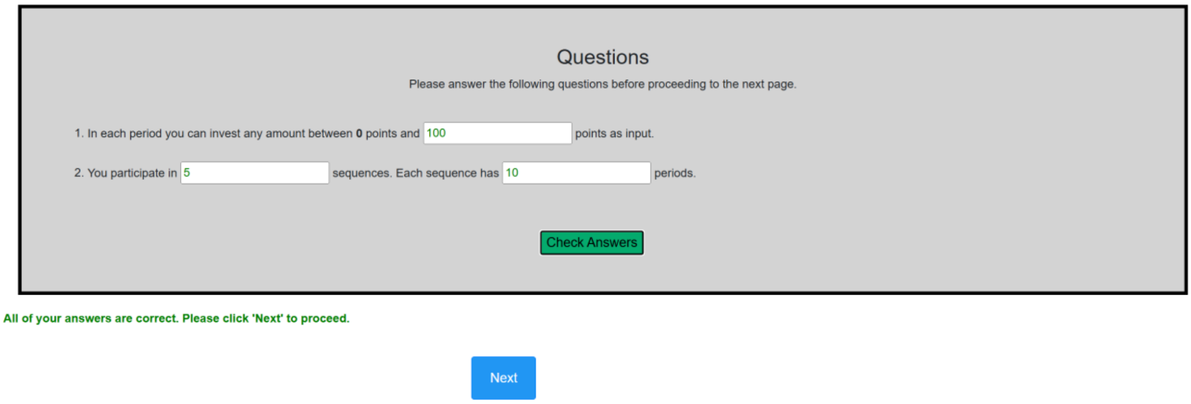
1. In each period you can invest any amount between **0** points and _____ points as input
2. You participate in ____ sequences and each sequence has ___ periods

[The image below shows how a participant sees the question section when they provide (an) incorrect answer(s). The next button is disabled until the participant provides the correct answers. All the question sections have this feature.]



[Figure 1: Question section when provided a wrong answer.]

[The image below shows how a participant sees the question section when they provide all correct answers. The next button is now enabled until the participant provides the correct answers. All the question sections have this feature.]



[Figure 2: Question section when all correct answers are provided]

Instructions – Specifications

General Specifications

The opening stock of a period (later than the first period) is the input in the previous period and the depreciated opening stock at the beginning of the previous period. That is, the opening stock at the beginning of a period depends on the input allocations of all previous periods and stock increases with the input allocations in previous periods. Opening stock at the beginning of the first period is 100 points.

Opening stock of the current period is calculated as

$$Opening\ stock\ at\ the\ beginning\ of\ a\ period\ =\ Input\ in\ the\ previous\ period \\ +\ 0.5 \times Opening\ stock\ at\ the\ beginning\ of\ the\ previous\ period$$

The inputs are costly, and the cost of the input depends on both the amount of input in the current period and the stock of input at the beginning of that period (opening stock). The cost increases with the input in the current period and decreases with the stock at the beginning of that period.

The cost of input is calculated as

$$Cost\ of\ input = 8 \times Current\ Input \times Current\ Input(1 \\ + 1 \times Opening\ stock\ at\ the\ beginning\ of\ the\ current\ period)$$

The output in any period depends only on the input allocation in that period and output increases with the input.

Output is calculated as

$$Output = 5 \times Current\ input$$

Return at any period is the difference between the output and the cost of input.

$$Return = Output - Cost\ of\ input$$

At the end of the periods of a sequence, the total return is calculated as the sum of returns at each period.

(*All the values will be rounded to the nearest whole number.*)

Please click on the “Detailed Specification” tab above for detailed graphical representation of the above equations. By answering the questions in “Detailed Specification”, you can proceed to the next page. On this page, you can freely swap between “General Specification” tab and “Detailed Specification” tab.

Instructions - Specifications

Detailed Specifications

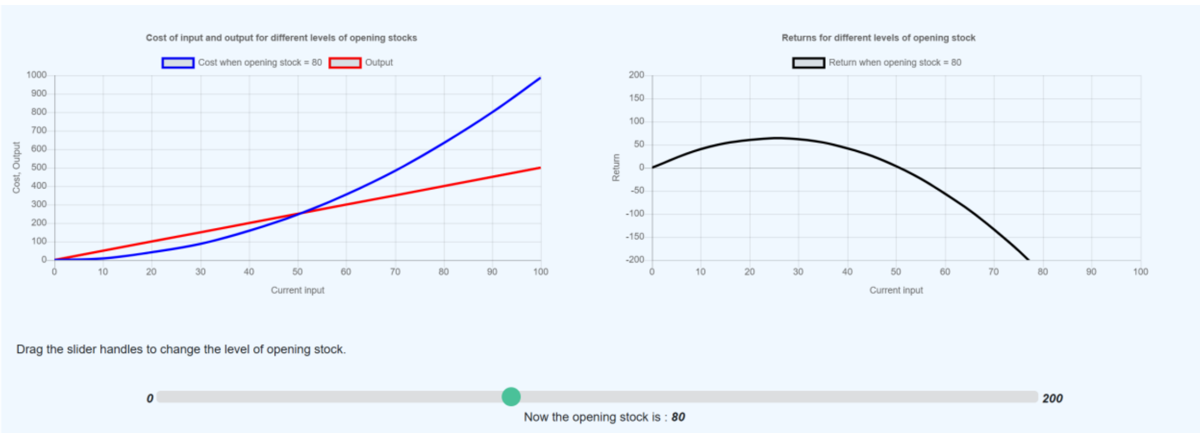
The graph on the left provides a visual representation of cost of input and output for different levels of stocks at the beginning of the period (opening stocks). The graph on the right provides a visual representation of the returns in a period for different levels of opening stocks.

In the left graph, the blue line represents the cost of input when the opening stock is 80 points.

In the left graph, the red line represents the output for different levels of inputs (as you can see, the output does not change with the stock).

In the right graph, the black line represents the returns when the opening stock is 80 points.

You can drag the slider handles below to see how the output, cost of input, and return in a period vary with stock from the previous period.



[Figure 3: Graphs presented to the participant visualizing how different opening stocks affect output, cost of input and current returns. The highlighted numbers and the graphs change as the slider moves.]

Questions

Please answer the following questions to the nearest whole number before proceeding to the next page.

1. At the beginning of period 1, you have _______ points as opening stock. Therefore, if you allocate **25** points as input in period 1, your opening stock at the beginning of period 2 is ________ points.
2. Select the correct answer.
    1. For a given level of opening stock at the beginning of any period, if you increase input allocation in that period,
        - Your output in that period will be unaffected, but the cost of input will increase
        - Your output in that period will increase, and the cost of input will increase
        - Your output in that period will increase, but the cist of input will not be affected
    2. For a fixed level of input allocation,
        - Your cost and return in that period will be lower if you have a higher opening stock in that period
        - Your output will be higher, and cost will be lower if you have a higher opening stock in that period
        - Your cost will be lower if you have a higher opening stock, but the output will not be affected by the opening stick, and as a result, return in that period will be higher.

3. If your current period's output is **195** points and cost of input is **70** points, your return in the current period is _________ points.

4. If your current period's output is **10** points and cost of input is **50** points, your return in the current period is _________ points.

Instructions – Earnings

Any remaining points from your endowment (points you have not allocated as input for production) in any period cannot be carried to future periods, or you cannot borrow points from future periods. Moreover, these remaining points from the endowment will not cost you anything, and they will not provide you with any return.

Your final payoff depends on the 'total return' (sum of the returns in all periods) in a sequence. That is, at the end of the experiment, the computer will randomly select a sequence, and then the converted dollar amount of your' total return' in that will be added to your payoff.

Questions

Please select the correct answer for the following questions before proceeding to the next page

1. The remaining points (which you do not invest) from the endowment in any period will
   - Cost you 0 points but contribute to the return in that period
   - Contribute 0 points to the return but affect the cost in that period
   - Cost you 0 points and contribute 0 points to the return

2. Your final payoff is affected by the selected sequence's
   - Total cost in that sequence
   - Total net return in that sequence
   - Return of a randomly selected period in that sequence

Instructions - Example

This is an example of a period where you have to decide how much of your endowment is to allocate as input for production.

Assume this is "Period 6" (any period >1) in sequence 3.

Top left section - Decision area

- You will see your endowment for that period and the opening stock at the beginning of that period.
- You need to decide the amount you wish to allocate as input for production using the slider.
- You can drag the slider handle left or right and change the amount you wish to allocate as input in the current period.
- When you drag the slider handle, you will see how your returns in the current period vary with your decision.
- Moreover, you will see your total returns from all previous periods (sum of returns in each period upto current period excluding the current period) based on your decisions
- Click the "Submit" button when you are ready to submit your decision for the current period and proceed to the next period.
- You will be asked to confirm your decision when you click the "Submit" button. You can change your decision before confirming. You cannot change your decision for the period after you confirm your submission.
- You can click on the "Summary Instructions" tab and find summary instructions. You can freely swap between "Play" tab where you make the decision and submit the decision and "Summary Instructions" tab.

[The instructions under "Top right section – Information" vary depending on the treatment]

[Top-right section for participants in "NoInfo"]

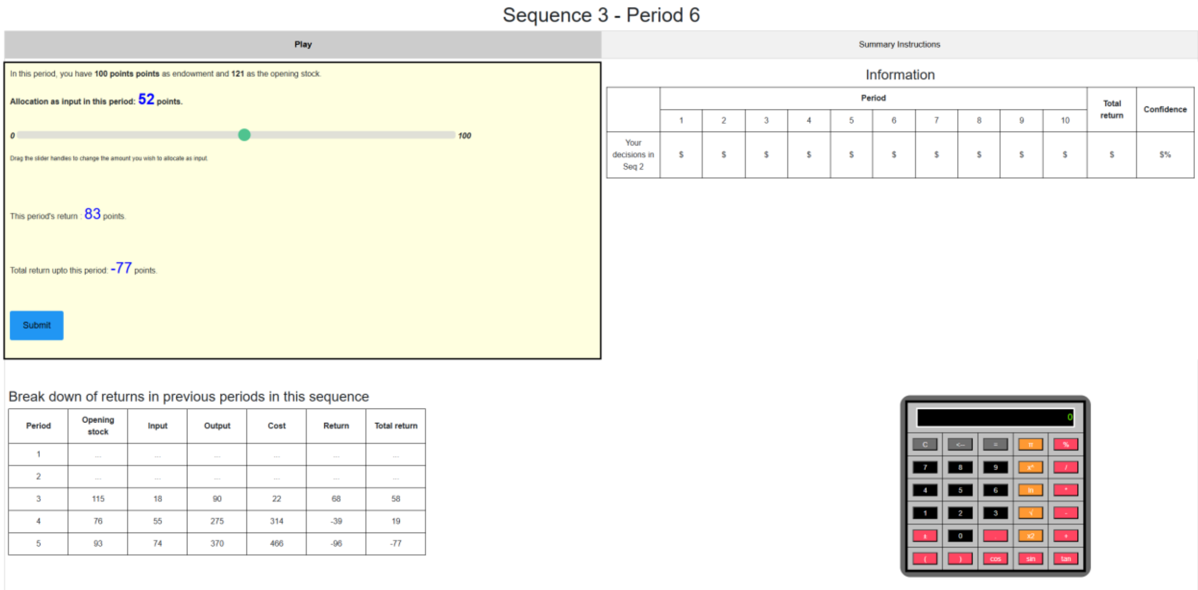
Top right section - Information

- Your decisions in each period at the previous sequence and total net return at the end of the previous sequence. This row will be empty in sequence 1 as there is no 'previous sequence'.

Bottom section - Break down of returns

- The table in the bottom presents the history of your decisions and outcomes up to the last period.
- For your convenience, a calculator is provided in the bottom right.

- **You can try the below example by dragging the slider handle below.** (Note that unlike in real rounds, the "Submit" button will not take you to the next period/page.)
- Please click the "Next" button in the bottom to proceed to a trail sequence.

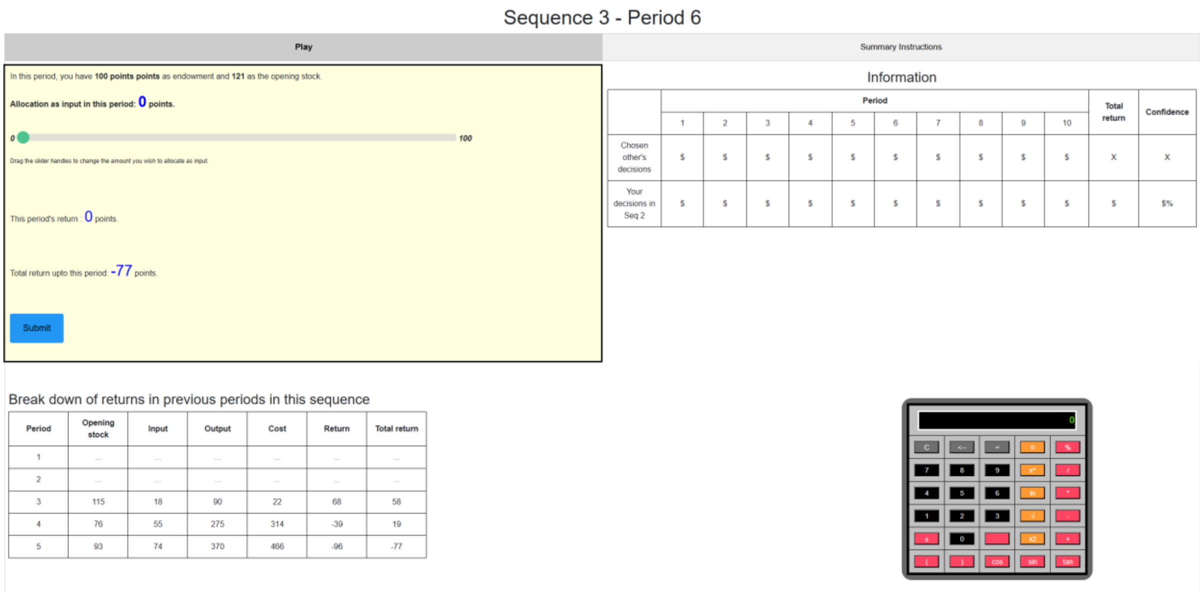


[Figure 4: Trial period shown to participants in "NoInfo"]

[Top-right section for participants in "InvOnly"]

Top right section - Information

- Your decisions in each period at the previous sequence and total net return at the end of the previous sequence. *This row will be empty in sequence 1 as there is no 'previous sequence'.*
- Decisions made during a selected sequence by a participant in a previous session. (*In this experiment, this chosen participant from a previous session is referred by "other" and faced the same tasks as you.*)

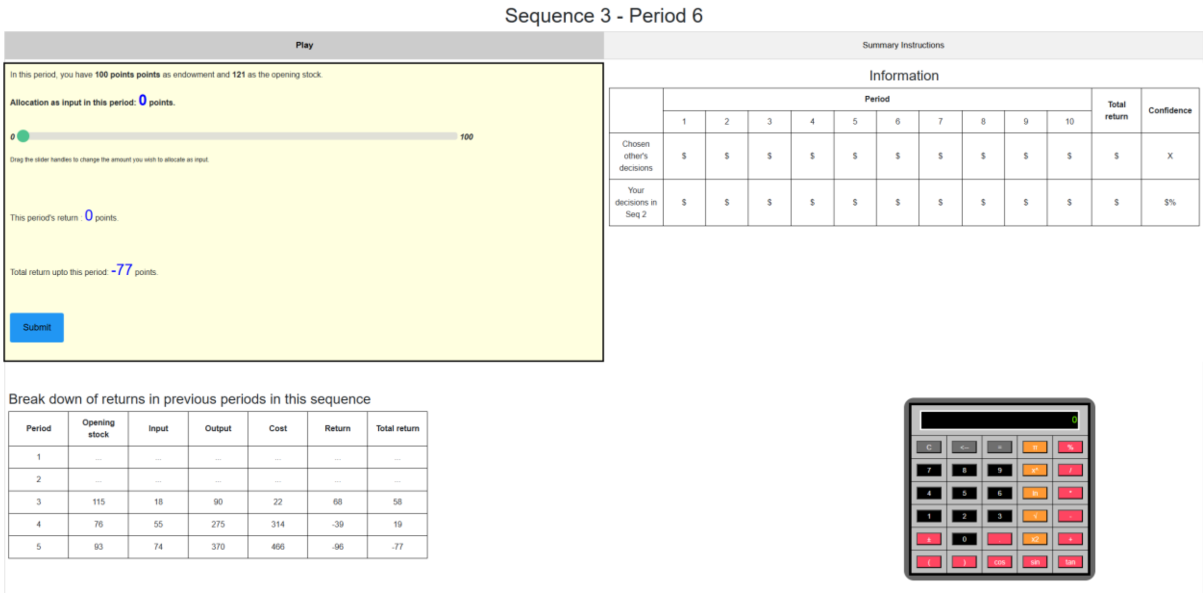


[Figure 5: Trial period shown to participants in "InvOnly"]

[Top-right section for participants in "InvEarn"]

Top right section - Information

- Your decisions in each period at the previous sequence and total net return at the end of the previous sequence. *This row will be empty in sequence 1 as there is no 'previous sequence'.*
- Decisions made during a selected sequence by a participant in a previous session and his/her net return at the end of that Sequence. (*In this experiment, this chosen participant from a previous session is referred by "other" and faced the same tasks as you.*)

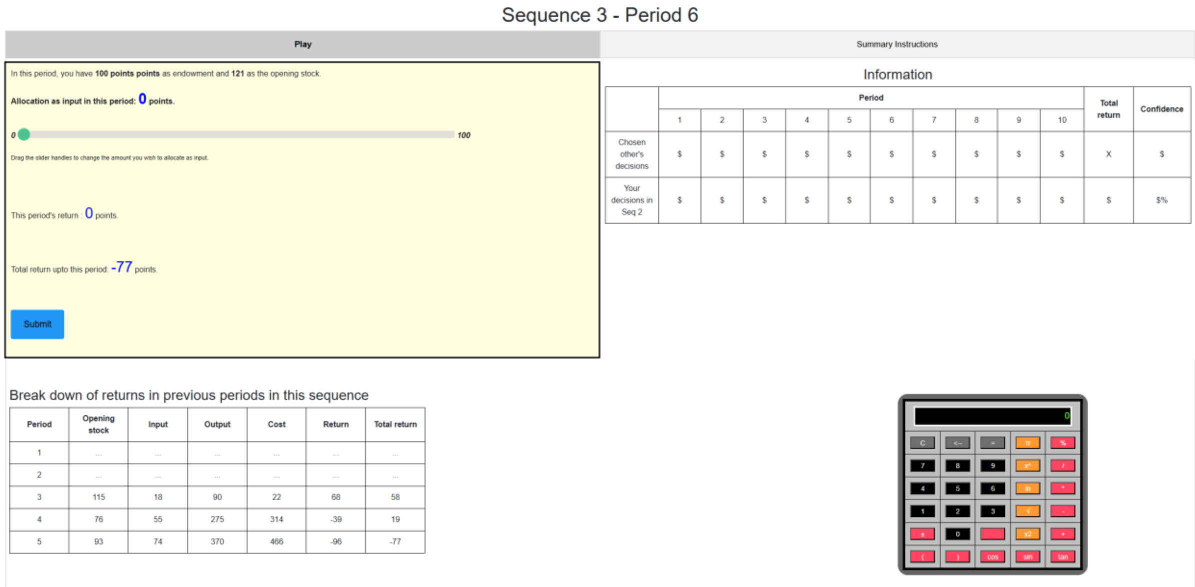


[Figure 6: Trial period shown to participants in "InvEarn"]

[Top-right section for participants in "InvConf"]

Top right section - Information

- Your decisions in each period at the previous sequence and total net return at the end of the previous sequence. *This row will be empty in sequence 1 as there is no 'previous sequence'.*
- Decisions made during a selected sequence by a participant in a previous session and his/her confidence about the decisions. (*In this experiment, this chosen participant from a previous session is referred by "other" and faced the same tasks as you.*)



[Figure 7: Trial period shown to participants in "InvConf"]

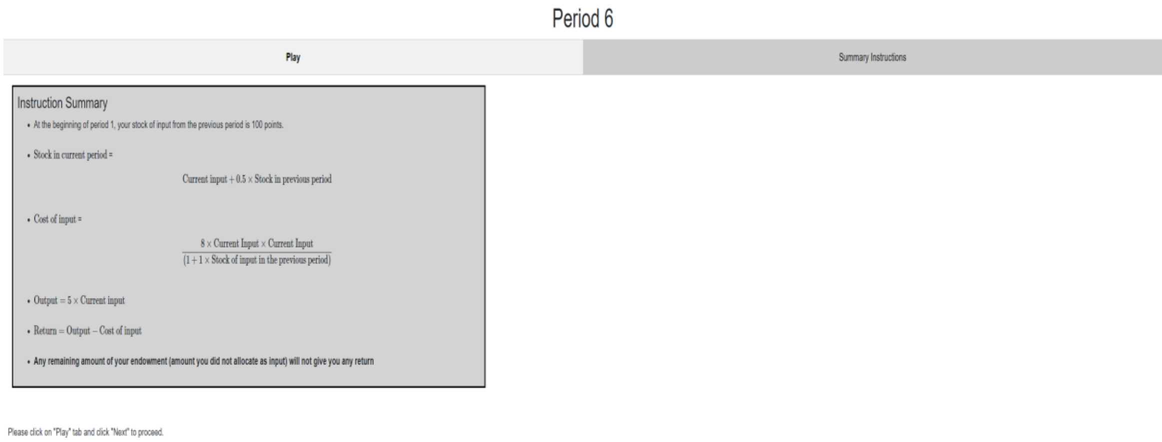


Figure 8: Instructions Summary tabs

Sequence 1

Now you are ready to start **"Sequence 1"** of decision making. You have 10 periods in this sequence.

[The following information varies based on the treatment]

You will get the following information.

- Since this is the Sequence 1, you will not have information on your previous decisions.[1]
- Decisions made during a selected sequence by a participant in a previous session. (In this experiment, this chosen participant from a previous session is referred by "other" and faced the same tasks as you.)[2]
- Decisions made during a selected sequence by a participant in a previous session and his/her net return at the end of that Sequence. (In this experiment, this chosen participant from a previous session is referred by "other" and faced the same tasks as you.)[3]
- Decisions made during a selected sequence by a participant in a previous session and his/her confidence about the decisions. (In this experiment, this chosen participant from a previous session is referred by "other" and faced the same tasks as you.)[4]

Remember, your payoff may depend on the total return you earn during this sequence. That is, one of the randomly chosen sequence will contribute to your final payoff. Therefore, if this sequence is selected for the payment, then the converted monetary value of the total return in this sequence will be added to your payoff.

Please click "Next" to proceed.

[1] Information provided in sequence 1 for all the participants. This point will change to "Your decisions in each period at the previous sequence and your total net return at the end of the previous sequence, along with your confidence." in all the other sequences (> 1)

[2] This bullet point is shown only to the participants in *InvOnly*

[3] This bullet point is shown only to the participants in *InvEarn*

[4] This bullet point is shown only to the participants in *InvConf*

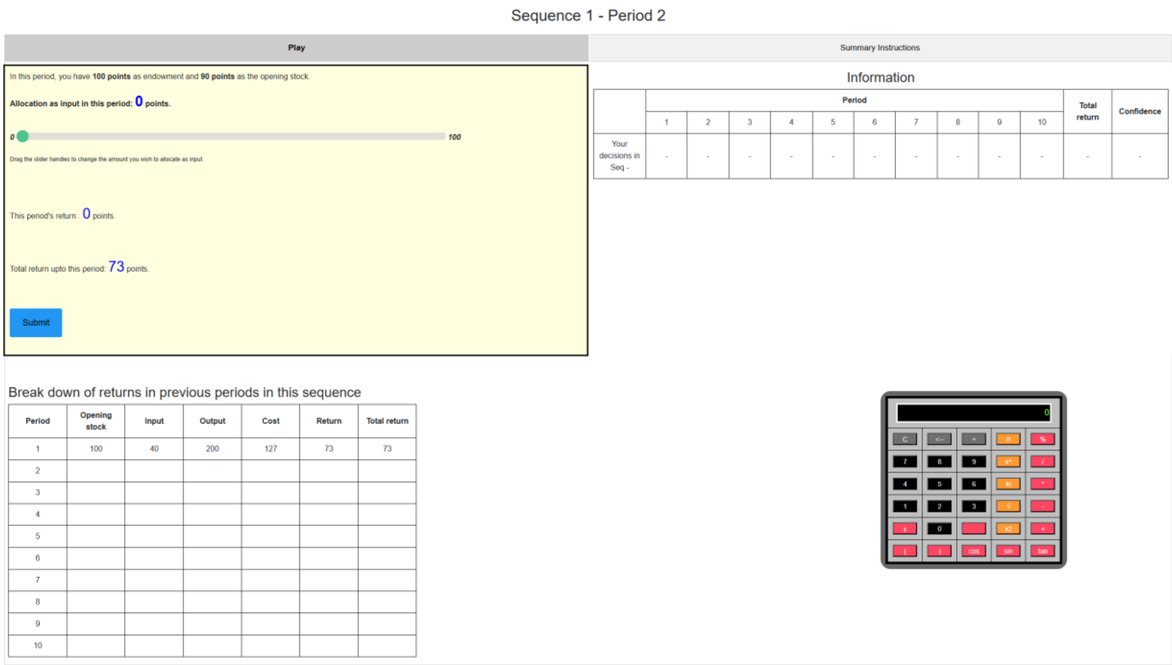


Figure 9: Seq1 interface for NoInfo

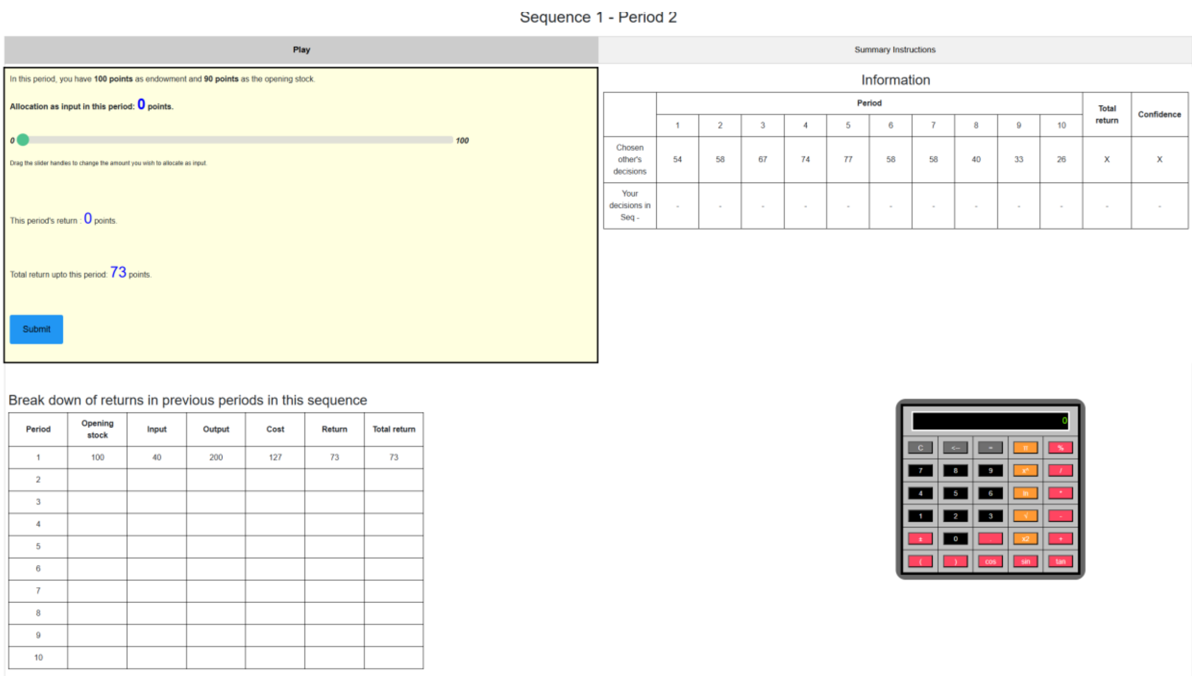


Figure 10: Seq1 interface for InvOnly

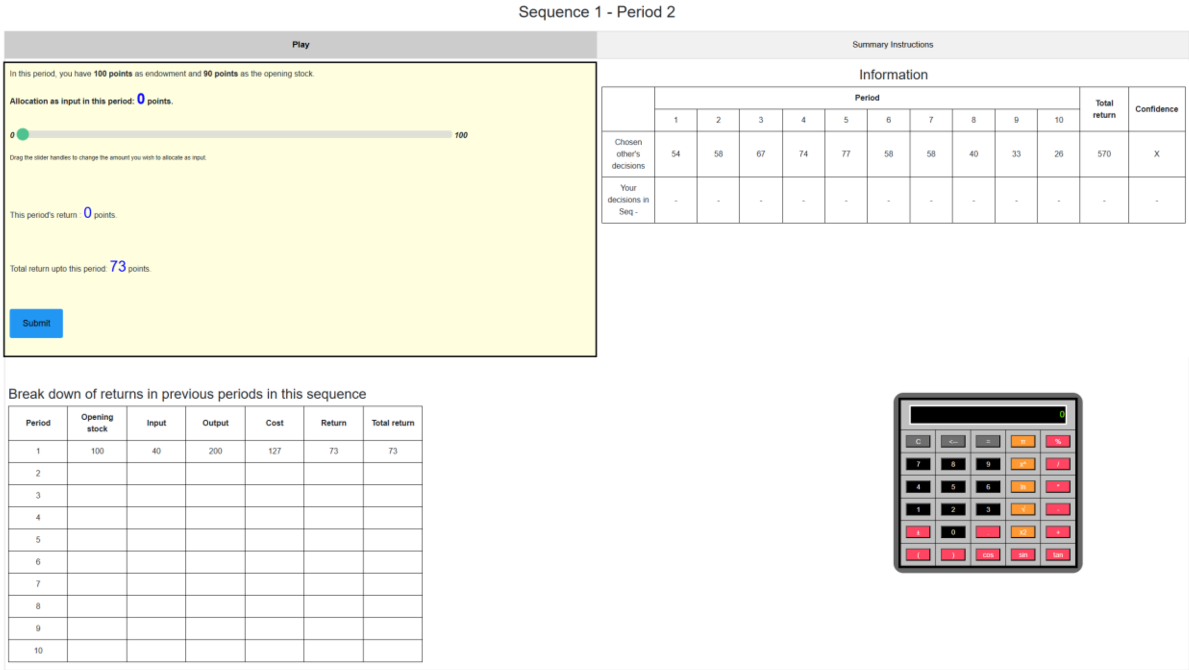


Figure 11:Seq1 interface for InvEarn

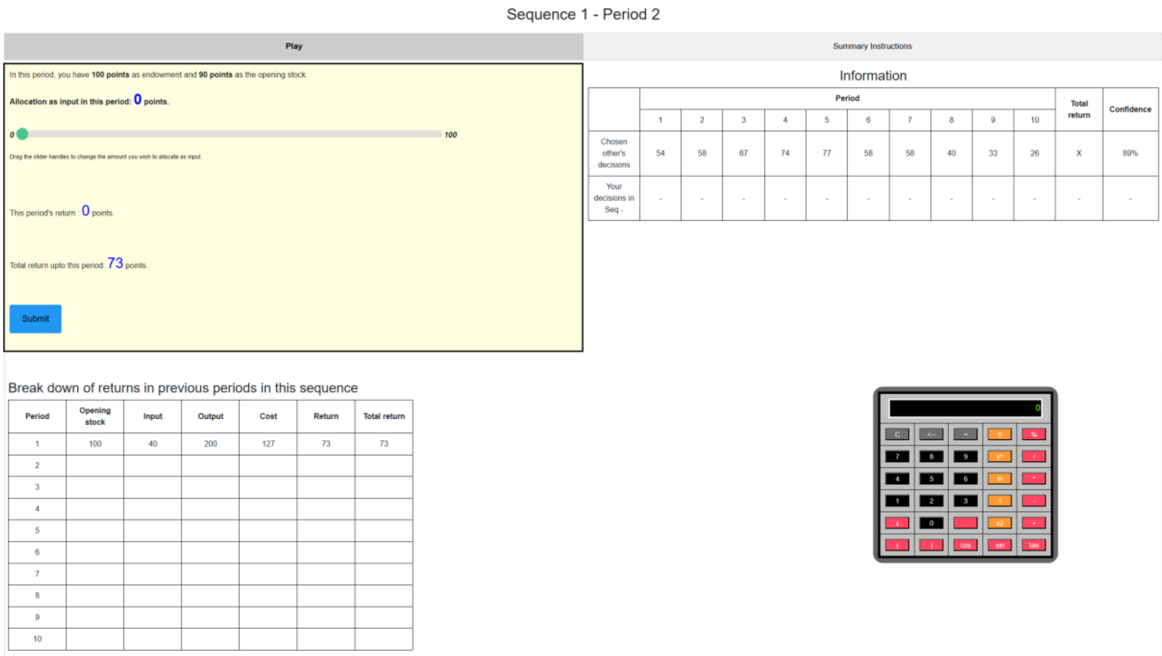


Figure 12: Seq1 interface for InvConf

Results - Sequence 1

Period	Opening stock	Input	Output	Cost	Return	Total return
1	100	40	200	127	73	73
2	90	58	290	296	-6	67
3	103	35	175	94	81	148
4	87	50	250	227	23	171
5	94	47	235	186	49	220
6	94	41	205	142	63	283
7	88	38	190	130	60	343
8	82	32	160	99	61	404
9	73	27	135	79	56	460
10	64	20	100	49	51	511

Therefore, your total net return in **Sequence 1** is: ***511***

The converted monetary value is: ***5.11 GBP***

Please click 'Next' to proceed.

Next

Figure 13: Result page at the end of 10th period of each sequence. This result page is similar across all the treatments.

Confidence - Sequence 1

In this step, you are required to elicit your confidence in the decisions you made during sequence 1.

You need to express your total return as a percentage of the maximum possible total returns. You need to guess the maximum possible total returns. Your correct guess will be rewarded at the end of the experiment. That is if this sequence is selected for the payment and if your total return as a percentage of maximum possible total return is between “your guess - 5%” and “your guess + 5%”, you will earn 10 points.

Your total return in sequence 1 is 511 points. As a percentage of “maximum possible earnings”, how much do you think you have earned during sequence 1?

I’m confident that I earned between **45%** and **55%** from the maximum possible earnings.

[This confidence question is asked of all the participants at the end of each sequence. The sequence number and the total returns are updated accordingly.

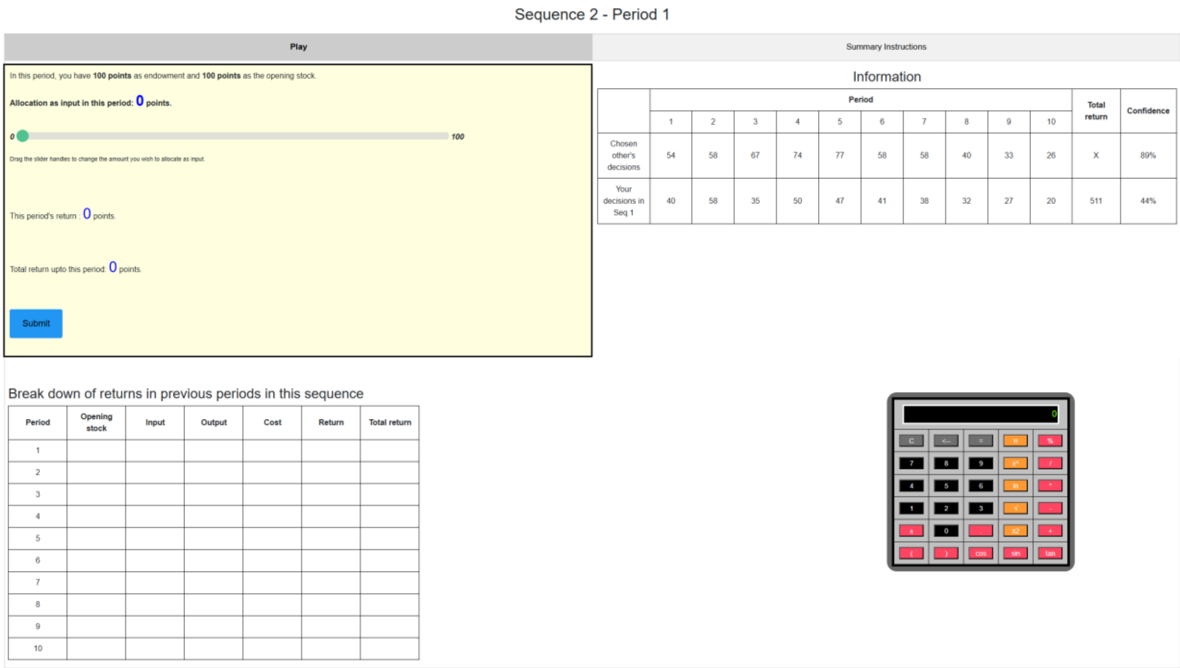


Figure 14: Sequence 2 interface.

[Only the numbers in "Your decisions in Seq x" are changed from sequence to sequence, where x is the immediate last sequence number. If any peer information is provided, that will remain the same across all the sequences under each treatment.]

Task 2 - Attempt 1 - Instructions

Now you are proceeding to the next task of the experiment.

In this task, you are playing against the computer.
The goal of this task is to be the first one to choose the number **12**. You and the computer (the other player) are to take alternate turns in choosing a number. The rules are that a player can only add one (1) or two (2) to the number the other player said in the immediate last period.

Example: Assume the computer makes the first move. Then the computer can choose either "1" or "2". If the computer chose "1" (from 1 and 2), then you can choose "2" or "3". Instead, if the computer chooses "2" in the first move, then you can choose "3" or "4". After your decision, then the computer will select a number and so on. This process will continue until either you or the computer reaches 12, and the one who chooses the number 12 will be the winner.

If you win, you will get **25 points** added to your payoff.

You have two attempts for this task.

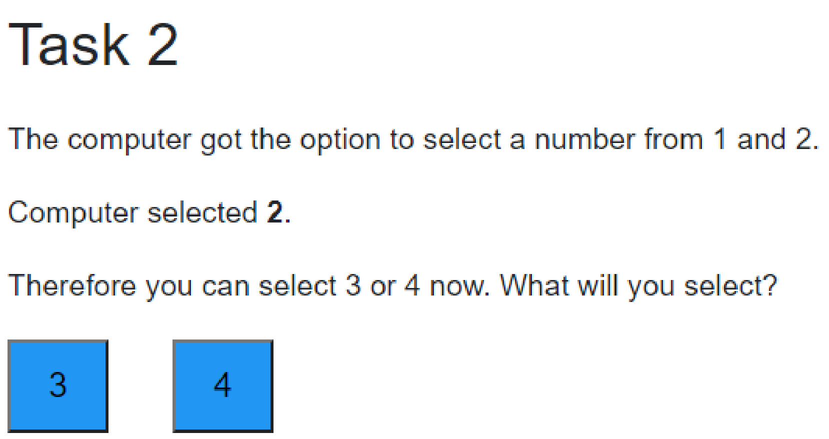


Figure 15: Example period of task 2

[Attempt 2 of Task 2 is identical to attempt 1, and all the participants face the same task]

Task 3

Instructions

Now you are proceeding to task 3 of the experiment

In this task, you are endowed with 20 points. You need to decide on how much of your endowment to be invested in a risky asset which gives you either 2.5 times the investment with a 50% chance or zero (0) return with a 50% chance. That is, assume you flip a fair coin and if you get head, your investment is successful, and you receive 2.5 times the investment. If you get tails, your investment is failed, and you lose the amount you invested. You can keep the remaining of the endowment, which you do not invest. Based on the success or failure of your investment, the converted monetary value of your earnings in this task will be added to your payoff.

Example: Assume you decided to invest 10 points. Then you will earn 25 points if your investment is successful (with 50% chance) or 0 points, if your investment is not successful. You have remaining 10 points from the endowment. Therefore you will earn 35 points if the investment is successful, otherwise, you will receive only 10 points.

Please enter the amount you wish to invest.

Demographic Questionnaire

Please answer All of the questions in this brief survey as accurately as you can.

1. What is your age in years?

2. What is your gender?
    - Male
    - Female
    - Other

3. What is the highest level of education you have completed?
    - Grade 12 or less
    - Vocational training
    - Bachelor's degree
    - Master's or above

4. What is your field of specialisation?
    - Management/ Business/ Law
    - Economics
    - Science/ Technology/ Engineering/Medicine
    - Other

5. What is the primary language you use at home?
    - English
    - French
    - Spanish
    - Chinese
    - Other

6. You chose x1, x2, x3, x4, and x5 as the period 1 investments in sequence 1, sequence 2, and so on.

What is the reason for you to choose these allocations in period 1?

Payoff

Your total return and guess on earnings as a percentage of maximum possible earnings (confidence) in sequences of the main task is summarized below.

Sequence	Total return	Guess on earnings as a %
1	512	50%
2	518	75%
3	116	71%
4	289	50%
5	224	68%

The computer has randomly chosen Sequence 1 for the payment.

The maximum possible earnings from any of the sequence is 603 points. Therefore, your earnings from sequence 1 as a percentage of maximum possible earnings is 85 %.
Since your guess is not between 80% and 90% you will earn 0 points from your guess

---

Payoff from task 1: 512 points

Payoff from guess in task 1: 0 points

Payoff from task 2 attempt 1: 25 points

Payoff from task 2 attempt 2: 0 points

Payoff from task 3: 38 points

Your total payoff from the tasks : 575 points

Therefore, your earnings in real world currency (including participation fee of £5.00) is **£10.75.**

Thank you for completing the experiment. Please use "30F7B0D8" as your completion code.