The Debt Payment Puzzle: An Experimental Investigation[†]

Hakan Özyılmaz
(UCSB)

Guangli Zhang
(UCSB)

Abstract

This paper studies the sources of suboptimal allocations observed in credit card repayments using a diagnostic laboratory experiment. We find that optimization ability and limited attention are jointly insufficient to explain the puzzle. Moving beyond existing results, we find that the inherent negative frame of the debt payment problem interferes with subjects' ability to optimize and hinders learning. We show that subjects predominantly rely on the irrelevant balance information while forming their decisions, regardless of how vividly the balance information is displayed. Using additional treatments, we find that the debt frame increases subjects' focus on the irrelevant balance information.

JEL Codes: C91, D14, D18, D91

Keywords: consumer protection, household finance, bounded rationality, experiment, salience, financial frames

[†]We thank Emanuel Vespa, Juan Carillo, Gary Charness, Ignacio Esponda, Erik Eyster, Chad Kendall, Elif Kubilay, Annamaria Lusardi, Ryan Oprea, Charles Sprenger, Sevgi Yuksel, seminar participants at SWEBE 2019, ESA 2019 North America and WashU EGSC 2019 for helpful comments. Research support from UCSB Department of Economics is gratefully acknowledged. Özyılmaz: Department of Economics, UCSB, 3045 North Hall, University of California Santa Barbara, CA 93106, hozyilmaz@ucsb.edu. Zhang: Department of Economics, UCSB, 3045 North Hall, University of California Santa Barbara, CA 93106, guanglizhang@ucsb.edu.

December 28, 2020

1. Introduction

Borrowing households frequently make decisions that appear inconsistent with models of rational choice. Recent examples include insufficient search effort while choosing a mortgage contract, failure to refinance a mortgage contract when market conditions improve, and borrowing on a higher interest rate credit card while there is available credit limit on a lower interest rate credit card (Bhutta, Fuster and Hizmo (2020), Andersen et al. (Forthcoming), Ponce, Seira and Zamarripa (2017)). Understanding the sources of suboptimal borrowing behavior is fundamental to developing informed consumer financial protection policies and improving the descriptive success of boundedly rational models of decision making.

In this paper, we use a diagnostic laboratory experiment to study how people make financial decisions when the decision involves a debt frame. Specifically, we investigate *the debt payment puzzle* where people pay down debt on a lower interest rate credit card while forgoing the opportunity to pay down debt on a higher interest rate credit card.[1] A distinct advantage of *the debt payment problem* over other "problematic" debt settings is that the optimal payment rule is unambiguously determined without any assumption on time and risk preferences.

Two recent studies, Ponce, Seira and Zamarripa (2017) and Gathergood et al. (2019), show that the average credit card holder misallocates 50% of her payment to the card with lower interest rate and leaves a significant amount of money on the table annually.[2] Moreover, both studies show that suboptimal repayments cannot be rationalized with various plausible explanations that can be tested with observational data.[3] Despite the strength

[1]Consider a cardholder with revolving debt on two credit cards who cannot afford to pay off both cards at the end of the month. The uniquely optimal rule would prescribe one pays the card with the higher interest rate while making the minimum required payment on each card.

[2]This type of allocation decision is common and costly. 1) The revolving credit card debt reached $1.3-trillion in the US in the last quarter of 2019, constituting almost 6% of the US GDP (NY Fed, Consumer Credit Panel). 2) 61% of the Americans have at least one credit card and the average card holder has four credit cards (according to the credit reporting agency Experian's nationally representative data, 2019). 3) Gathergood et al. (2019) calculate that 71.5% of credit card holders in the U.S. market have two or more cards, and this group accounts for 91.8% of balances. Moreover, Gathergood et al. (2019) find the average annual cost of misallocation to be $85 for individuals who hold two cards and $325 for individuals who hold five cards. The authors further document that the degree of misallocation does not decline in stakes: the cost of misallocation at the 90th percentile rises from $218 in the two-card sample to $1,213 in the five-card sample.

[3]Ponce, Seira and Zamarripa (2017) document that the following explanations are at best able to account for small variations: 1) Differences in due dates 2) Differences in the ease of payment 3) Differences in unobserved characteristics 4) Strategic manipulation of interest rates and credit limits. Gathergood et al. (2019) show that the following explanations do not account for the observed behavior: 1) Consumers face a fixed cost of optimization due to time, psychological or cognitive costs. 2) Consumers learn over time to make correct payments but the cross-sectional data masks this learning behavior.

and persistence of the evidence on suboptimal repayments, it is still an open question why consumers behave inconsistently with the presumption of welfare maximization.

This paper studies the potential sources of suboptimal credit card repayments. Specifically, we design a diagnostic laboratory experiment that aims to answer what features of the debt payment problem make it hard for consumers to solve correctly. There are a number of potential explanations for this puzzling behavior. Two immediate explanations are financial literacy and limited attention. Researchers in household finance have long emphasized the role of financial literacy (Lusardi and Mitchell (2014), Lusardi and Tufano (2015)). It is plausible that consumers who self-select into having revolving credit card debt are not sufficiently financially literate to optimally manage their repayments given the plethora of evidence linking financial literacy and suboptimal household behavior (Campbell (2016), Beshears et al. (2018)). The behavioral economics literature has emphasized the role of limited attention in consumer choice (Chetty, Looney and Kroft (2009), Stango and Zinman (2014), Karlan et al. (2016), Bordalo, Gennaioli and Shleifer (2017)). In the context of credit card repayments, consumers might not know their interest rates or even if they do, they might not remember what the rates are at the time of decision making. A common feature of these explanations is that their identification often requires more detailed information of consumers and their choice processes than what is available in a typical administrative data set. However, developing informed consumer financial protection policies and improving the descriptive success of boundedly rational models of decision making crucially depend on identifying mechanisms that underlie such puzzling repayment behavior.[4][5] A controlled laboratory environment allows us to circumvent the identification challenges faced by observational studies, and to study how consumers make their allocations and how the quality of their decisions are affected by their choice environment.

We begin our investigation by establishing suboptimal allocation behavior in an extremely simple decision environment where potential confounds that exist in the field are minimized. Moreover, we show that suboptimization is not specific to people who lack the skills to solve an optimization problem or the knowledge of their interest rates at the time

[4] Handel and Schwartzstein (2018) is an excellent reference on why people might not use readily available information to make better decisions and the importance of mechanisms for developing descriptive theories of decision making.

[5] In particular, if consumers struggle with their repayments due to their inability to solve simple optimization problems, this would necessitate promoting financial literacy education. On the other hand, if consumers' struggles are related to a lack of attention to their interest rates, this would make the case for information disclosure policies. Indeed, the current policy debates regarding consumer protection revolve around financial literacy education and information disclosures.

of decision making. We show that the share of optimal allocations in our baseline treatment - where the decision environment captures the essential features of a typical online payment screen - is only 18.8% despite the fact that 82% of our subjects can solve simple optimization problems and 93% of our subjects actively seek interest rate information before making their decisions.[6] Our findings clearly indicate that even the combination of optimization ability and the knowledge of interest rates is insufficient to explain this puzzle. We further show that subjects do not learn to make better decisions nor do they respond to higher incentives, corroborating the findings of Ponce, Seira and Zamarripa (2017) and Gathergood et al. (2019). Finally, we show that allocation behavior causally moves with balance information. Specifically, subjects allocate higher amounts to an account with higher balances without regard to interest rate information - a finding that is consistent with the balance matching heuristic documented in Gathergood et al. (2019).

The fact that we are able to replicate the field findings in a tightly controlled environment with an algebraically sophisticated subject pool deepens this puzzle and urges us to investigate mechanisms that underlie this suboptimal behavior. Although our baseline findings suggest that people pay attention to interest rate information, psychology experiments suggest that this might not be sufficient to make optimal allocations as choices are influenced by *salience* of information; that is if one part of the environment attracts more attention, then the information contained in that part is reflected more in the choices.

We move beyond existing findings by examining the role of information salience. Specifically, we examine two potential channels that could affect the salience of interest rate information: *information vividness* and *framing*. The reason that we focus on channels that revolve around salience is that it is an established cognitive mechanism that guides choice behavior in various contexts (Nisbett and Ross (1980), Taylor and Thompson (1982)). Its applications in behavioral economics have been particularly fruitful in capturing deviations from rational choice in simple environments (Bordalo, Gennaioli and Shleifer (2013), Kőszegi and Szeidl (2012)).

A critical aspect of the credit card repayment environment is the predominant display of balance information. A typical credit card statement or an online account displays balance information more vividly than any other information. The vivid display of balance information might increase the salience of balance information, leading consumers to form their allocation decisions by relying on irrelevant balance information. This would indeed justify

[6] Ponce, Seira and Zamarripa (2017) find the share of optimal allocations to be approximately 15% among people who hold two comparable credit cards using observational data. Gathergood et al. (2019) find this rate to be 11.8% .

the suboptimality of allocations as irrelevant balance information is incorporated into the decision process.[7] Interestingly, our result suggests that subjects' allocation decisions are not affected by the vividness of balance information. Compared to our baseline treatment with vividly displayed balance information, maximizing the vividness of interest rate information surprisingly has a null effect on the share of optimal allocations.

Another way the salience mechanism might operate in the credit card repayment environment is through the framing of the allocation problem. The credit card payment environment is inherently a negative situation. Specifically, the balance information indicates how much a person owes on an account – an amount that affects the welfare of the decision maker negatively. Psychologists document that such inherent negativity of a piece of information changes the amount of attention that information attracts (Soroka, Fournier and Nir (2019), Baumeister et al. (2001), Kahneman (1979)). If balance information attracts more differential attention due to its inherent negativity, this creates another channel for the salience mechanism to interfere with the decision process and lead to suboptimal allocations. We confirm this hypothesis and find that the inherent debt frame of the problem interferes with subjects' decisions. Compared to a subject who faces this allocation problem under an otherwise identical debt frame, a subject who faces the investment frame has a 24.2 percentage point higher probability of making an optimal allocation -this is equivalent to a 128% increase in the share of optimal allocations.

To further investigate why we observe such an asymmetry in the share of optimal allocations across frames, we conduct two additional treatments. Our results hint at two explanations that are not necessarily mutually exclusive: asymmetric attention and asymmetric heuristic use. First, we document an asymmetry in measured attention across two frames. We show that an average subject spends significantly more time on balance information compared to interest rate information under the debt frame; under the investment frame, there is no difference in time spent on the interest rate and balance information. Second, we document an asymmetry in heuristic use across frames. Under the debt frame, we find subjects' allocations are mostly consistent with a balance matching heuristic i.e. they seem to make their allocations roughly proportional to their balances. Under the investment frame, a majority of the subjects' allocations are consistent with an *interest matching heuristic* i.e. they seem to make their allocations roughly proportional to interest rates.

We contribute to the growing body of evidence showing that people seem to struggle with correctly resolving simple trade-offs with financial frames (Ponce, Seira and Zamarripa

[7] *Irrelevant* in the sense that objectively optimal allocation does not depend on balances.

(2017), Gathergood et al. (2019)). It is hard to establish that deviations from the rational benchmark are *mistakes* using observational data since we do not know the exact trade-off people face in the field. They must solve a dynamic allocation problem with varying income streams, due dates, card limits, cash rewards, and alike where their attention to this allocation problem is limited. A critical point here is that consumers with multiple accounts might not even be aware of the fact that they face a simple trade-off regarding their repayments. Using the power of a controlled environment where such concerns are brought to a minimum, we show that people indeed struggle with simple trade-offs with financial frames as severely and persistently in the field. This finding has a broader implication on the case for consumer protection as people seem to suffer pecuniary losses by deviating from normative prescriptions given their preferences.

We also contribute to the policy discussion regarding how to improve consumer financial decisions using empirically informed interventions (Sunstein (2011)). Our results have implications on the performance of two popular policy alternatives: mandating disclosure policies and promoting financial education.[8] A common finding in previous studies that investigate financial behavior in the debt domain is that conventional disclosure policies are ineffective in improving financial outcomes (Bertrand and Morse (2011), Seira, Elizondo and Laguna-Müggenburg (2017)). We find evidence aligning with previous findings. We show that vividly disclosing interest rate information has no significant effect on the share of optimal allocations compared to our baseline treatment where interest rate information is disclosed *non-vividly*. This does not mean to say that every potential disclosure policy will fall short of restoring rational choice. We think that non-conventional disclosures of interest rate information might prove useful in improving the quality of decisions in this repayment context.

A popular policy alternative to information disclosure policies is financial education. Financial literacy surveys indicate that many households struggle with algebraic calculations related to interest rates (Hastings, Madrian and Skimmyhorn (2013), Lusardi and Mitchell (2014)). While confirming that optimization ability is associated with improved decision making, we find a significant majority of subjects capable of solving simple optimization problems fail to make their allocations optimally during the experiment. Our finding suggests that an effective financial education program should acknowledge the mental gaps between real-life financial decision problems and algebraic counterparts, and focus on training people

[8]Figuring whether to implement information disclosure policies or to bolster financial education programs is particularly important as neither of them comes without a trade-off. See Campbell (2016) for a discussion of these trade-offs.

how to translate these problems into simple optimization problems.

Our final contribution is to the vast framing literature in behavioral economics. We show that many subjects have a harder time making optimal allocations under a debt frame despite exhibiting similar optimization abilities on the algebraic version of the problem. Our further investigation into the asymmetry in the share of optimal allocations across frames hints at systematic differences in how attention is allocated under different frames. The asymmetric attention allocation pattern that we observe is inconsistent with optimal allocation of attention (Gabaix (2014)), models of salience (Bordalo, Gennaioli and Shleifer (2013)), focusing (Kőszegi and Szeidl (2012)) and selective attention (Karlsson, Loewenstein and Seppi (2009)). This suggests that exploring how frames affect attention allocation might be worthwhile. We also document how different frames may trigger different heuristics. Although the use of heuristics in financial decision making has long been documented (Benartzi and Thaler (2007), Gathergood et al. (2019)), we present systematic evidence on how an algebraically identical allocation problem under different frames induces different distributions of heuristic use over subjects.

2. Evidence for Suboptimal Repayments

The purpose of the baseline experiment is two-fold. First, it helps us documenting the severity and persistence of suboptimal repayments even in extremely simple environments, corroborating the field findings. Second, it documents that the combination of limited attention and optimization ability is not sufficient to explain this puzzling behavior.

2.1. Baseline Design

2.1.1. Decision Environment

Our experiment interface captures the essential features of the decision environment faced by credit card consumers who make their repayments in the field (See Figure 1). Each subject is endowed with two hypothetical credit card accounts and a hypothetical checking account. The experiment consists of multiple periods. At the beginning of each period, we deposit a fixed amount of 500 *Experimental Currency Unit*s (ECU) into their checking account. Subjects' task in each period is to make repayments toward their credit cards using their deposit. During a period, subjects face a screen that is split into two halves. Each half represents a credit card account. At the top part of each half of the screen, subjects see the current balance information. At the center of the screen, subjects see a list of other account attributes that are typically displayed on a credit card statement. These attributes are interest rate, interest charged, previous balance and previous repayment. The information on each of these attributes is presented simultaneously and singularly to a subject once she clicks on the *information button* that carries the name of that attribute.[9] Clicking on information buttons is costless and subjects are allowed to click freely. Each period ends once a subject submits an allocation decision.

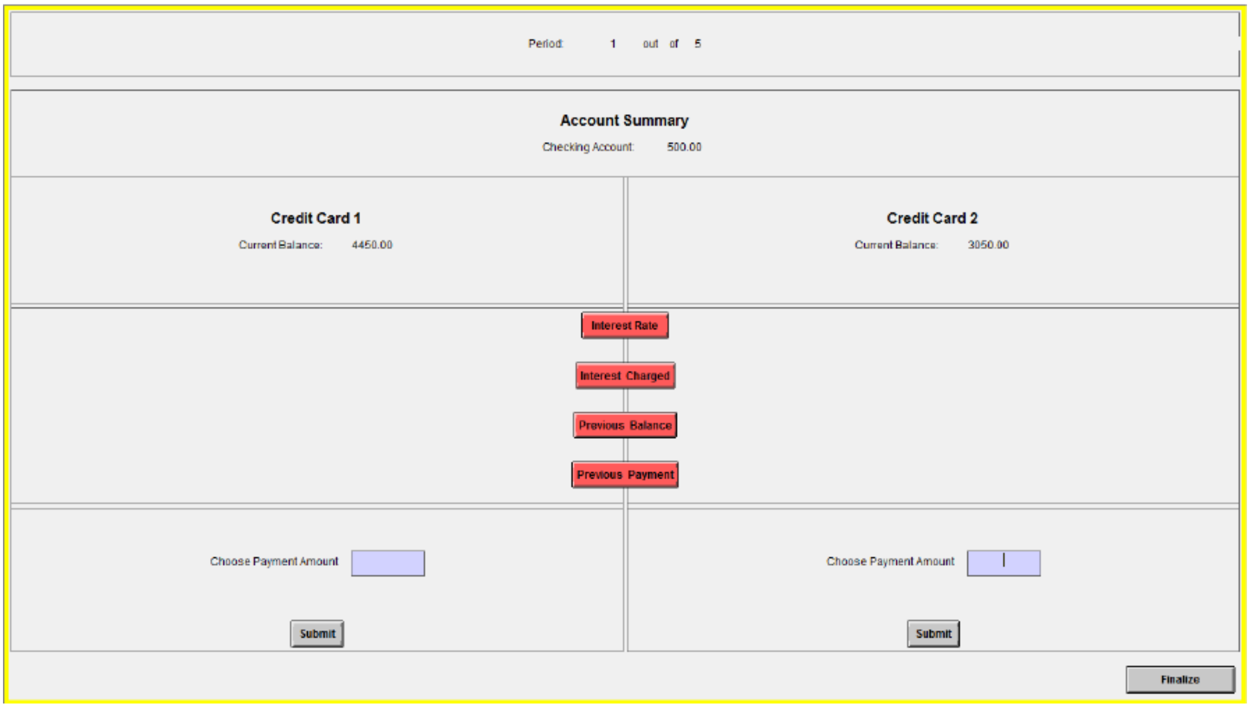


Figure 1: Experiment Interface

It is important to emphasize that subjects **always** see how much they owe on an account at the top part of the screen and they *need not* click any button to acquire balance information while they *need* to click the information buttons to see other attributes. We describe the information that is always displayed at the top part of the screen and that does not require the click of subjects as *vividly displayed* - an important point that we will revisit in Section 3. Hence in the baseline design current balance information is vividly displayed.

Our interface allows us to sidestep many confounding features of the actual decision environment and focus on the allocation problem that lies at the core of this repayment situation. An essential feature of our design is that interest rate information is readily available at the time of decision making at a cost as low as clicking a button. Indeed in

[9]For instance, a subject who wants to find out the interest rate information on both accounts needs to click the *Interest Rate* button. Once she clicks the interest rate button, she sees the interest rate information on both cards at the same time and does not see any other information until she clicks on some other information button.

all of our sessions, an overwhelming majority of subjects clicks the interest rate button and acquires their interest rate information.[10] Other important simplifications we make include no minimum required repayment, simultaneity of repayments and no previous purchase decision.[11][12]

A crucial aspect of this repayment problem in the field is that consumers do not get feedback on the quality of their decisions. The only feedback consumers get is the amount of interest charged on each account which is then incorporated in the total debt they owe to each card in the subsequent period. We recreate this implicit feedback mechanism in the laboratory by employing a block design where we combine decision periods into stages. Each stage consists of five decision periods.[13] In the first period of each stage, we determine the amount of debt on each card. In the subsequent periods, each subject's debt on each card is endogenously determined by their previous allocation decisions in that stage. Since subjects are assigned some debt at the beginning of each stage, we endow subjects with a fixed positive amount in order for each subject to make some money in the experiment. We determine a subject's payoff for a stage by their end of stage balance on each card subtracted by the fixed endowment. We then convert their stage payoffs into US dollars and randomly choose one of their stage payoffs for their actual payment.

We employ six stages with different balance and interest rate configurations. The first four stages of the experiment have the same structure, and together they constitute the first part of the experiment. The parameter choices for the first period of these stages are presented in Table 1. We choose the interest rate difference to be 1.5% as a plausible upper bound of the the observed monthly interest rate differences in the field.[14] We keep the interest rate difference across stages fixed to keep the incentives the same across these stages. We choose the initial balances to be consistent with the average credit card debt observed in the field and keep the balance difference around 1,500 ECU in order to separate potential

[10]Knowledge of interest rate information at the time of repayment is a significant source of variation in the actual decision environment as the interest rate information is complexly disclosed.

[11]See the online appendix of Ponce, Seira and Zamarripa (2017) for a larger set of potential confounds that exist in the actual credit card repayment environment.

[12]Empirical studies (Keys and Wang (2018), Stewart (2009)) have documented robust findings on how minimum required payments could create anchoring on the required amount. Our experiment eliminates the use of minimum payment in order to remove any potential anchoring that is induced from making the minimum payment.

[13]We choose five periods per stage to have a sense of subjects' within stage learning and to keep the duration of the experiment reasonable.

[14]Gathergood et al. (2019) document that the observed annual interest rate difference is 15% at the 90th percentile corresponding to a monthly interest rate difference of 1.25%. Ponce, Seira and Zamarripa (2017) find the average monthly interest rate gap to be 1.1% in their data.

balance-matching behavior from naively allocating equal amounts to each account ($1/N$ heuristic).[15] To provide causal evidence for the impact of higher interest rate and higher balances on allocation decisions, we design our stages so that each credit card account carries observations under each potential balance/interest rate configuration. The shaded stages in Table 1 represent *aligned stages*: a higher interest rate account is also assigned a higher initial balance. In contrast, non-shaded stages represent *misaligned stages*: a higher interest rate account is assigned a lower initial balance.

Table 1: Parameter Choices and Balance Reallocation

Stage	Account	Interest Rate (per period)	Initial Balance	Balance Reallocation
1	1 2	4.9% 3.4%	4,450 3,050	No
2	3 4	5.7% 4.2%	2,950 4,350	No
3	5 6	3.7% 5.2%	4,550 2,950	No
4	7 8	3.9% 5.4%	2,850 4,450	No
5	9 10	5.3% 3.8%	4,650 3,150	Yes
6	11 12	5.9% 4.4%	3,050 4,550	Yes

In the second part of the experiment, subjects face the remaining stages, namely 5 and 6. These stages differ from the first four stages in one important way - there is an additional period at the end of each stage.[16] In the last period of stage 5 and 6, subjects are asked to reallocate their balances between the two accounts. This intervention tightens the screws on the potential suboptimal repayment behavior as it simplifies the allocation problem even further and increases the incentives to optimize.[17]

[15] According to Experian's 2019 data, the average American owes $6,200 on their credit cards and 80% of credit card holders owe less than $10,000.

[16] See Figure D1 for a screenshot of these periods.

[17] Given these parameter choices, the payoff difference for a subject who allocates all her deposit into the high interest rate account throughout a stage makes $5 more than a subject who allocates all her deposit into the lower interest rate account throughout a stage. In the last two stages, we increase this payoff difference to $12 by introducing the balance reallocation period.

2.1.2. Timeline

Upon arrival, each subject is provided with instructions where the rules of the experiment and how their payment is determined are clearly explained.[18] After the experimenter goes through the instructions, the experiment starts with an explanation phase where subjects are familiarized with the interface. When the explanation phase ends, subjects move on the first part of the experiment. The first part of the experiment contains four stages. Subjects are provided ten minutes for the first two stages and seven minutes for the subsequent stages. Subjects are advanced to the next stage if they complete a stage or if they exceed the maximum allotted time.[19]

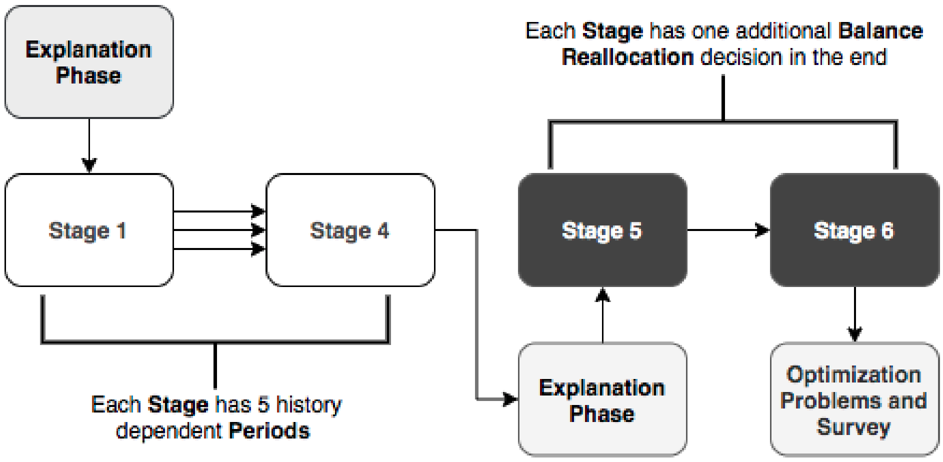


Figure 2: Experiment Timeline

Upon completing the first part of the experiment, subjects are provided with instructions on balance reallocation. After the experimenter goes through the balance reallocation instructions, subjects face an explanation phase where they learn how to reallocate their balances using the interface. Once the explanation phase is over, subjects go through Stages 5 and 6. Subjects are provided ten minutes for each stage in this part of the experiment.

Once the main parts of the experiment ends, subjects are asked four incentivized optimization problems represented in algebraic expressions. These problems correspond to algebraic versions of the allocation problems subjects go through in the main part of the experiment.[20] We use subjects' scores on these problems as a proxy for their optimization

[18]Experiment Instructions are located in Appendix G.

[19]Only 2 out of 44 subjects used up the maximum time in a given stage. We discard these auto-advanced periods in our analysis.

[20]The four optimization problems that we ask the participants are: i) $\min_{x,y} 3(1000 - x) + 2(2000 - y)$ ii)

ability. An important design choice here is that we do not ask optimization problems at the beginning of the experiment as it might affect subjects' ability to optimize in the experiment. The experiment ends with subjects answering exiting survey questions that record basic demographic information and subjects' justification for their allocation behavior.

2.1.3. Procedural Information

We conducted our experiment at the UCSB Experimental and Behavioral Economics Laboratory. The experiment was coded using z-Tree software (Fischbacher (2007)). A total of 44 subjects, recruited through ORSEE (Online Recruitment System For Economic Experiments), participated in the baseline experiment . The average payment per subject was \$13.2 including a \$5 show-up fee. The average duration of a session was 75 minutes.

2.2. Baseline Results

2.2.1. Do subjects know their interest rates?

An important question that arises from previous studies is "Do people actually know their interest rates? And if they do, do they recall the interest rate information at the time of decision making?" Since we track the information buttons that a subject clicks, we can answer this question with our baseline treatment. Figure 3 shows the proportion of subjects acquiring the interest rate information by the first period of each stage.[21] In the first period of the first stage, 100% of the subjects click the interest rate button to acquire the interest rate information. Although this proportion decreases in later stages, on average 93.2% of the first period decisions are made after acquiring the interest rate information. Moreover, we find that the average response time for the first period decisions is 38.7 seconds and 11.3 of these seconds are spent on the interest rate information. In light of these findings, we conclude that an overwhelming majority of our subjects know their interest rates at the time of decision making.

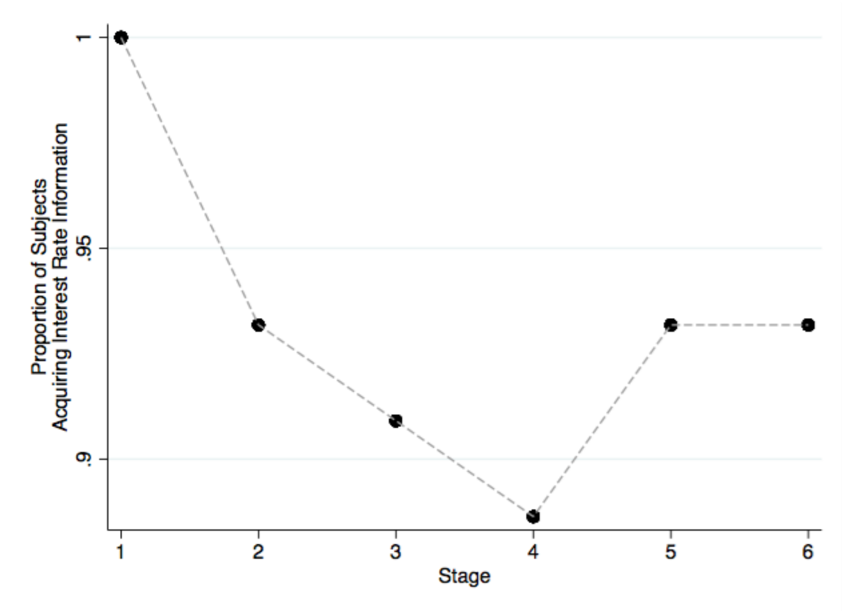
2.2.2. Can subjects solve optimization problems?

Another potential explanation for suboptimal repayments is that people are not good at solving optimization problems. In order to see if inability to solve optimization problems drives this mistake, we ask subjects four incentivized optimization problems after the main experiment. We find that 82% of our subjects are able to solve at least one of the four simple optimization problems. Hence we conclude that a significant majority of our subjects can solve simple optimization problems.

$\max_{x,y} 3(1000+x)+2(2000+y)$ iii) $\min_{x,y} -3x-2y$ iv) $\max_{x,y} 3x+2y$ all subject to $x+y=300,\ \ x,y\geq 0$

[21] Recall that the interest rate on each card is fixed within a stage.

Figure 3: Proportion of Subjects Acquiring Interest Rate Information



Note: Figure shows the proportion of subjects acquiring interest rate information by the *first period* of each stage.

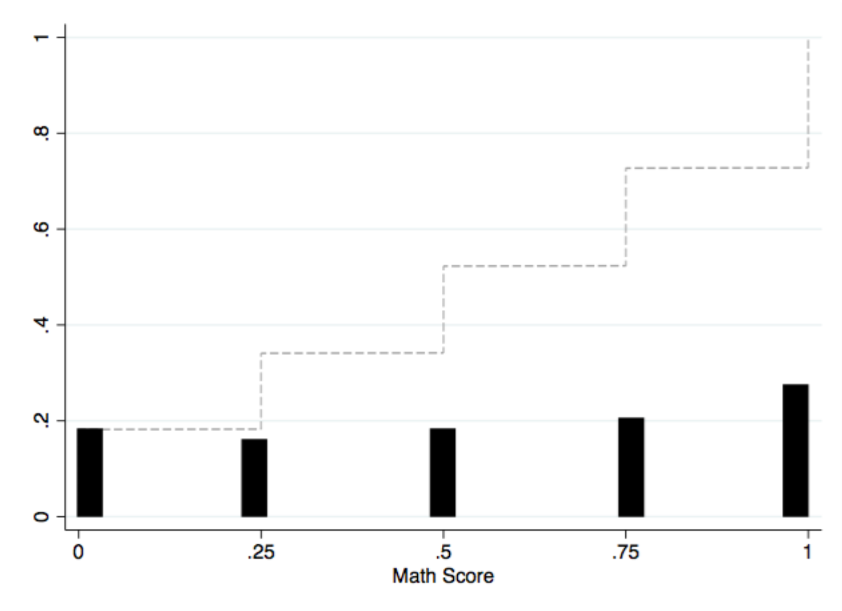
2.2.3. How do subjects make their payments?

Now that we know most of our subjects do look at the interest rate at the time of decision making, and they can deal with simple optimization problems, we turn to the main analysis of our baseline treatment. For the remainder of this chapter, we restrict the sample to the first period decisions while excluding observations from subjects who do not acquire interest rate information or fail to answer any optimization question correctly. Most of our results are qualitatively similar when we extend our analyses to include all observations. We indicate and discuss when our results depend on the sample restrictions.

Result 0. *Suboptimal allocations persist when the potential confounds that exist in the field are removed, knowledge of interest rates and optimization ability are ensured.*

Theoretically, subjects should allocate 100% of their assigned deposit to the card with the higher interest rate. However, as illustrated by Figure 5, only 22.4% of the repayments are allocated toward the card with the higher interest rate. The distribution of optimal repayments is significantly different than the observed repayments (clustered Wilcoxon signed-rank test, $p < 0.001$). The optimality rate decreases to 18.8% when we do not impose any sample restriction. Our results corroborate the field findings: despite the simplifications we make in the decision making environment, subjects seem to make similar levels of optimal

Figure 4: Distribution of Subjects' Optimization Abilities



Note: Figure shows the distribution of subjects' optimization abilities. *Math Score* represents the fraction of correctly answered optimization problems. Each bar represents the fraction of subjects achieving a certain score. The dotted line represents the empirical cumulative distribution function of math scores.

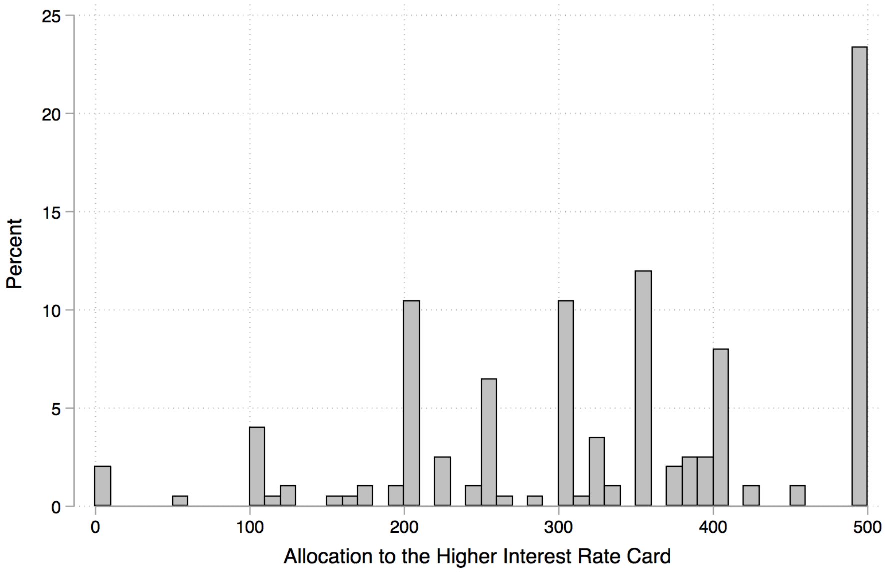
allocations compare to the field findings. Ponce, Seira and Zamarripa (2017) find the share of optimal allocations to be approximately 15% among people who hold two comparable credit cards. Gathergood et al. (2019) find this rate to be 11.8%.

Since optimality seems to be a stringent test on how well subjects make their payments, we also report the fraction of misallocated repayments - the fraction of repayment that is incorrectly allocated to the lower interest card. We find that 33.5% of the repayments is misallocated.[22] Ponce, Seira and Zamarripa (2017) report that consumers misallocate 50% of their repayments to the low interest rate card and Gathergood et al. (2019) report a misallocation level of 48.5%.[23] The difference in the misallocation rate between our experiment and the field studies, combined with the similarity in the share of optimal allocations, suggest that our participants deviate less from the rational benchmark given that there is a deviation. Nevertheless, our participants' allocation behavior is still far from the rational benchmark despite the fact that they actively seek interest rate information and they can solve simple optimization problems.

[22] The misallocation rate is 36.3% when we do not impose any sample restriction.

[23] These numbers are the amount of misallocation in excess of the minimum required payments for consumers who hold two credit cards.

Figure 5: Distribution of Allocations - Period 1 Decisions

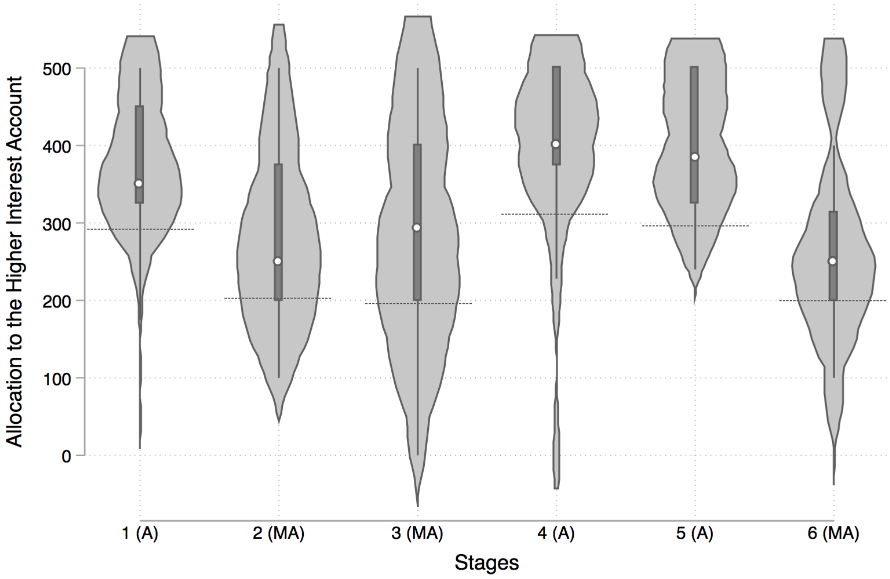


Note: Figure shows the distribution of payments subjects make toward the high interest rate card in the first period of each stage. The sample excludes (1) those who fail to correctly answer at least one out of four math questions and (2) those who do not acquire interest rate information. This eliminates 63 out of 264 observations at the *subject* $\times$ *stage* level. The histogram contains 50 equally sized bins. The rational choice theory predicts a distribution with full mass located at 500.

To get a sense of how subjects make their repayments, we first show the distribution of allocations made to the high interest rate card by stage. Figure 6 provides some suggestive evidence on subjects' tendency to allocate more towards the card with higher balances. In *aligned stages* where the high interest rate card comes with higher initial balances (Stages 1, 4 and 5), the median allocation is well above 250 ECU (more than half of their assigned deposit). We find that 94% of the subjects allocate more than 250 ECU to the high interest rate card indicating that an overwhelming majority of the subjects are at least partially responsive to interest rates.[24] However, this interpretation overstates the extent that subjects' decisions are influenced by the high interest rate as the effect of high interest rate on the allocations made is confounded with the effect of high balances. In order to discuss the impact of high interest rate separate from the impact of high balances, we present our findings from the *misaligned stages* where the high interest rate card comes with lower initial balances (Stages 2, 3 and 6). We find in each of the *misaligned stages*, the median allocation is

[24]The proportion of subjects who allocate at least 250 ECU to the high interest rate account in each aligned stage is exactly 94%.

Figure 6: Allocation Patterns Across Stages - Period 1 Decisions



Note: The violin plot shows the distribution of repayments subjects make toward high interest rate card in the first period of each stage. The center white dot represents the median allocation towards the higher interest rate card in a given stage. The thick bars around the median represents allocations within the interquartile range. The end of the whisker represents the maximum and the minimum allocation. The violin shape visualizes the kernel density distribution of the allocation patterns - the wider sections of the violin represents a higher likelihood of allocating in the corresponding value. The letters A and MA next to stage numbers represent if that stage is aligned or misaligned. The dotted horizontal reference lines represent the hypothetical allocation under an exact balance matching heuristic towards the higher interest card in the first period of each stage. The rational choice theory predicts a distribution with full mass located at 500 for all stages.

250 ECU which is virtually indistinguishable from a baseline where subjects are completely unresponsive to interest rates.[25] Taken together, we interpret our findings from aligned and misaligned stages as subjects being responsive to the irrelevant balance information as well as the relevant interest rate information. In particular, subjects' allocations seem to move away from the high interest rate card when it comes with lower initial balances.[26]

We solidify this interpretation by quantifying the effect of having a higher interest rate on a card (and a higher balance) on the allocation made towards that card. We are able to provide causal evidence on these effects using a simple linear regression on our subjects' first

[25]The proportion of subjects who allocate at least 250 ECU to the high interest rate account in Stages 2,3 and 6 is respectively 50%, 52% and 50%.

[26]The results are nearly identical when we do not impose any sample restriction. The proportion of subjects who allocate at least 250 ECU to the high interest rate account in each stage is respectively 93%, 50%, 50%, 88%, 88% and 50%.

Table 2: OLS Estimation of Repayments

	(1) Left Card Allocation	(2) Left Card Allocation
Higher Interest Rate	164.0	184.5
	(25.80)	(31.79)
Higher Balance	109.7	80.83
	(16.69)	(16.89)
Constant	117.2	111.4
	(14.03)	(16.45)
Observations	201	645
R^2	0.423	0.406
Period	First	All

Note: Column 1 represents a model of repayments made in the first period of each stage. The dependent variable is the amount of allocation made on the left card which takes a value in between 0 and 500. The regressor *Higher Interest Rate* is a dummy variable that takes the value 1 when interest rate on the left card is higher compared to the right card. The regressor *Higher Balance* is another dummy variable that takes the value 1 when balance on the left card is higher compared to the right card. The rational choice theory requires that *Higher Interest Rate* to perfectly predict all allocation behavior and give no predictive power to *Higher Balance*. Column 2 extends the analysis by including repayments for all periods. Standard errors in parentheses. Errors are clustered at the subject level.

period decisions in each stage since we exogenously and independently assign the interest rates and debt levels to be high or low on a single card. We choose, without loss of generality, the left card on our subjects' screens for our analysis. We call the left card "treated" with a higher interest rate if the assigned interest rate on the left card is greater than the assigned interest rate on the right card, and we denote this "treatment" with the dummy variable *Higher Interest Rate*. Similarly, we call the left card treated with a higher balance if the assigned current balance on the left card is greater than the assigned current balance on the right card and we denote this treatment with the dummy variable *Higher Balance*.[27]

A rational decision maker's allocation behavior should solely be guided by the interest rate information, giving no predictive power to the normatively irrelevant balance informa-

[27]One caveat here is that whenever the left card has a higher balance, it also has a higher interest charge and a higher previous balance by design. In other words, higher current balance perfectly correlates with higher interest charges and higher previous balances. Hence the "treatment" *Higher Balance* captures an aggregate effect of all normatively irrelevant information presented to the subjects.

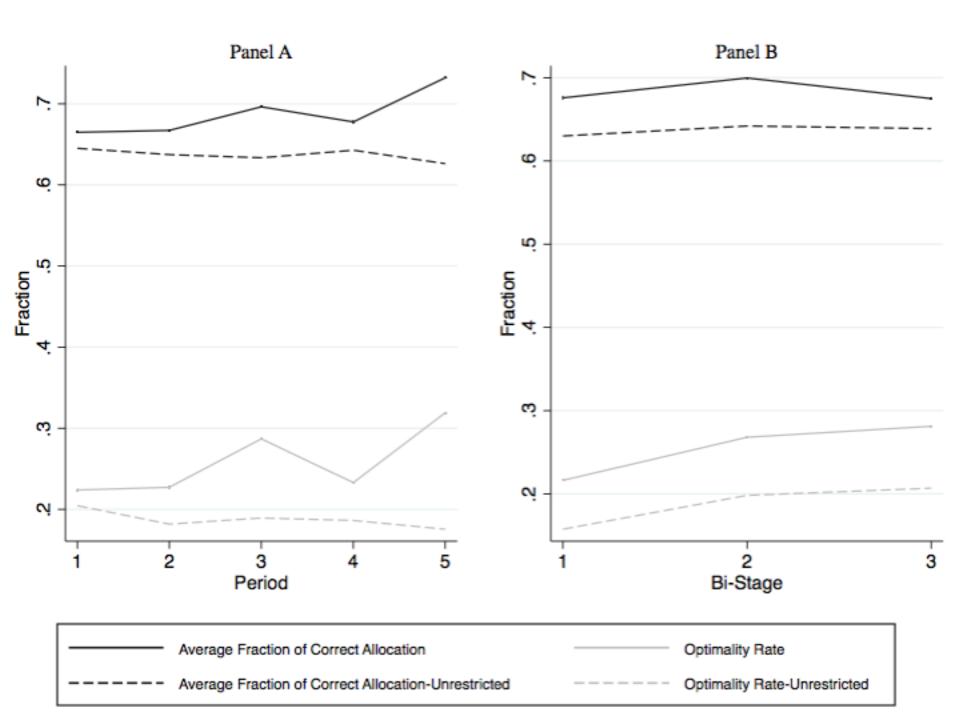
tion. Table 2 provides the regression results. In Column 1, we see that subjects take both the relevant interest rate information and the irrelevant balance information into account while determining their allocations. On average, subjects allocate 164 ECU more to the card with a higher interest rate and 109.7 ECU more to the card with a higher balance. These effects are significant ($p = 0.0000$ for both) and statistically equal in magnitude ($p = 0.13$). These results suggest that subjects are indeed responsive to a higher interest rate although the effect's magnitude is less than the prescription of rational choice. However, we see that subjects are similarly responsive to the irrelevant balance information, which indicates that the deviations from the rational choice are not random errors but systematic mistakes that are governed by the irrelevant balance information. In Column 2, we extend the analysis to all periods. Although this analysis loses the causal interpretation, we see that both higher interest rates and higher balance information predict allocation behavior in all periods significantly ($p = 0.0000$ for both) yet the effect of higher interest rate is greater in magnitude ($p = 0.03$).

These results corroborate the field findings that people take irrelevant balance information into account while making their payments. Gathergood et al. (2019) find, using various machine learning algorithms, that balance information has the highest variable importance, which is 3 to 40 times larger than the variable importance of interest rates in predicting allocation behavior. Ponce, Seira and Zamarripa (2017), using regression analysis, find that fraction of outstanding balances on a card explains almost 10 times greater variation in the allocation behavior than the variation explained by the interest rate difference. Although our findings are consistent with the field results, we find no difference in the predictive power of higher balances and higher interest rates on allocation behavior. We see this improvement in the predictive power of interest rates relative to the field findings as a manifestation of subjects' increased appreciation toward the importance of interest rates due to the simplifications we make in the decision environment and our subject pool's relatively higher algebraic sophistication.

2.2.4. Do subjects learn to make better decisions?

Subjects are not provided any feedback between periods or stages. In addition, there is no explicit intervention in the first part of the experiment that would potentially induce them to change their allocation decisions. The only source of learning in the first part of the experiment is repetition which is similar to how such decisions are made in the field. However, once subjects complete the first part of the experiment, we inform them that the remaining stages have a balance reallocation period, which might induce subjects to re-evaluate their decision making strategies.

Figure 7: Measures of Optimality Within and Between Stages



Note: Panel A shows both the average fraction of correctly made allocations and the share of optimal allocations by periods within a stage. Panel B shows the same optimality measures by bi-stages. A bi-stage consists of two consecutive stages with one aligned and one misaligned stage. The solid lines indicate the optimality measures 1) for allocations made after acquiring interest rate information, 2) for the subjects who solve at least one optimization question correctly. The dashed lines indicate the optimality measures without imposing any sample restriction.

We find that subjects do not learn to make better decisions within a stage or between stages. Figure 7 shows the average fraction of correctly made allocations and the share of optimal allocations within and between stages.[28] Although subjects' average fraction of correctly made allocation increases from 66% to 73% within a stage corresponding to a 1.4% per period increase, this effect is insignificant ($p = 0.068$). Similarly, the share of optimal allocations increase from 22.4% to 31.9% within a stage corresponding to a 1.9% per period increase yet the effect is insignificant ($p = 0.18$). Moreover, we do not find any significant evidence that subjects' allocations improve between bi-stages ($p = 0.12$ for the share of

[28]The fraction of correctly made allocation refers to the fraction of the deposit that is assigned to the high interest rate card. For instance, the fraction of correct allocation for an allocation that assigns 400 ECU to the high interest rate card is 0.8.

optimal allocations, $p = 0.96$ for the average fraction of correctly made allocations).[29]

The results are consistent with previous findings and serve as direct evidence regarding the difficulty of learning to avoid interest charges in the context of debt payment even for people who pay attention to interest rates and who are equipped with sufficient optimization ability.[30]

2.2.5. Do subjects respond to higher incentives?

An important class of economic models explain the deviations from rational choice by arguing cost-benefit considerations of making an optimal decision (Sims (2003), Gabaix (2014)). In particular, if our subjects face a fixed cost of optimization due to time, psychological or cognitive costs of making an optimal payment, the reduction in interest charges due to optimization may not be high enough to justify to incur this fixed cost. Therefore, one might expect an increase in the incentive to optimize would improve subjects' allocation decisions. The balance reallocation periods in our design allows us to test this explanation as we effectively increase the incentives to optimize from \$1 per period to \$7 while simplifying the problem even further by directly asking subjects how much debt they would like to have on each card. As illustrated in Figure 8, the drastic increase in incentives to optimize do not lead to any improvement in the share of optimal allocations. In fact, the share of optimal balance reallocations is 16.7% - which is lower than the share of optimal allocations observed in the main part of the experiment. Our findings from balance reallocation is consistent with previous findings (Gathergood et al. (2019), Ponce, Seira and Zamarripa (2017)), which have documented the degree of misallocation is virtually invariant to the economic stakes.

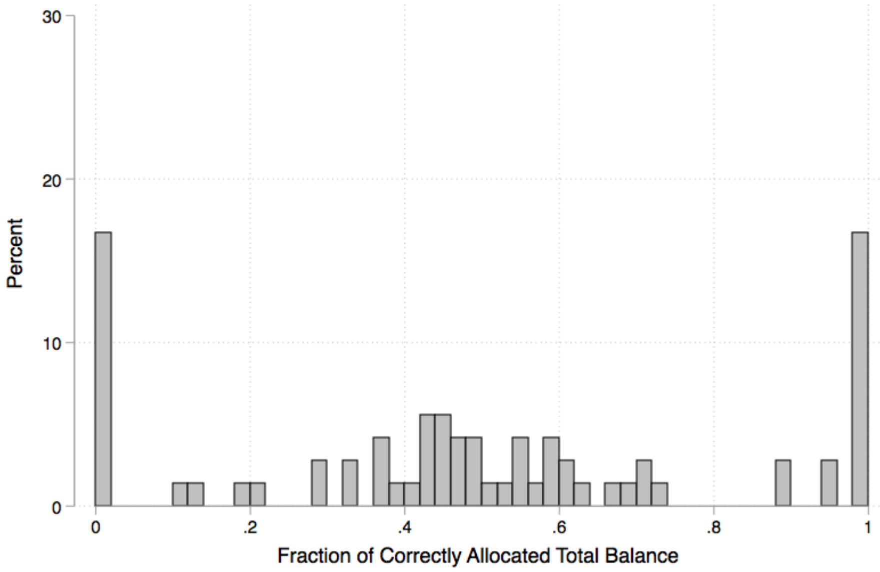
3. Mechanisms: The Role of Information Salience

After establishing the suboptimality of allocation behavior and characterizing the suboptimal repayments as balance-dependent, we extend our baseline design to include further treatments with the goal of understanding what features of the decision environment leads to suboptimal repayments. Although the suboptimality of choices has no justification from the perspective of rational choice and hence standard economic theory, substantial research in psychology documents departures from normative models of decision making and inves-

[29]The results are qualitatively similar when we do not impose any sample restriction, the regressions can be found in Appendix C.

[30]Both Gathergood et al. (2019) and Ponce, Seira and Zamarripa (2017) find that the fraction of correctly made allocations do not increase with the length of account tenure.

Figure 8: Distribution of Balance Reallocation Decisions



Note: Figure shows the distribution of fraction of total balances subjects reallocate toward the high interest rate card in balance reallocation periods. The distribution is represented with 50 equally sized bins. The sample is restricted to subjects who can solve at least one of the optimization problems. This restriction removes 8 out of 44 subjects, and leaves us 72 subject $\times$ period observations. The rational choice theory predicts a distribution with full mass located at 1.

tigate various mechanisms that could explain such departures.[31] Moreover, there has been significant advances in behavioral economics literature that incorporates these insights from psychology to develop descriptive theories of financial decision making (Bordalo, Gennaioli and Shleifer (2013), Kőszegi and Szeidl (2012), Gabaix (2014), Schwartzstein (2014), Handel and Schwartzstein (2018)).

In the context of credit card repayments, one way such suboptimization can arise is through the *vivid* display of balance information. A typical credit card statement or an online account displays balance information more vividly than any other information. Psychologists argue that vividly displayed information has more impact on judgments compared to other information (Nisbett and Ross (1980)) and they think such vividness effects to be generated through differential attention to one portion of the environment (Taylor and Thompson (1982)).[32] Comparing to interest rate information, the vividly displayed balance information

[31]These mechanisms include selective attention (Nisbett and Ross (1980), Fiske and Taylor (2013)), mental models (Thompson (2009), Johnson-Laird (2010)), dual process theories (Kahneman (2003), Evans (2006)) and heuristics (Tversky and Kahneman (1974), Gigerenzer and Gaissmaier (2011)).

[32]We use the word attention to indicate *observable attention* which is simply the amount of time spent.

might therefore attract greater attention and influence the subsequent decisions more heavily.

Another way such suboptimality can arise is through the debt frame of the decision problem. The credit card repayment problem has an intrinsic negative frame: it is an optimization problem over *balances that affect utility negatively.* A parsimonious explanation for why the debt frame might yield balance-dependence is the *valence* of information. Psychologists define valence as the intrinsic attractiveness and aversiveness possessed by events, objects and situations (Frijda (1986)).[33] Although the negative valence of balance information should play no role in the decisions made by consumers from the perspective of rational choice, there is substantial research in psychology that documents that negative information attracts greater attention and contributes more strongly to the observed choices (Soroka, Fournier and Nir (2019), Baumeister et al. (2001), Kahneman (1979)).

In order to motivate our experimental design and show how our manipulations in the decision environment might lead to different payment behavior, we outline a simple framework in Appendix F where we conceptualize a behavioral decision maker whose decisions are influenced by the salience of information that is presented to her. It is important to emphasize that we think of salience mechanism as a psychologically founded way of generating context-dependent choice behavior within optimizing agent paradigm that could unify our hypotheses, while acknowledging that there might be other mechanisms that could lead to differences in payment behavior across the decision environments we create in the laboratory.

In the next subsection, we describe our treatments that aim to change the salience of interest rate information.

3.1. Mechanism Treatments

We extend our baseline design to test if certain features of the decision environment plays a role in driving suboptimal allocations. In the extended design, we vary two main factors: the information that is vividly displayed and the frame of the decision problem. Table 3 presents an overview of our treatments.[34] It is important to note that the *Debt Balance* treatment is exactly our baseline treatment. In treatment *Debt Interest Rate*, we decrease the vividness of balance information while increasing the vividness of interest rate information.

Although how observable attention relates to attention is an open question, measuring observable attention is an established way of measuring attention. See Gabaix (2017) for a detailed discussion.

[33]Levin, Schneider and Gaeth (1998) discusses how differences in valence of information can trigger different cognitive processes that lead to different decisions. The idea of valence-dependent encoding is far from being strange to the field of economics. Kahneman (1979) was a critique of expected utility theory that is based on framing of outcomes as gains and losses which lead to subsequent development of an immense literature on reference-dependent preferences and its applications.

[34]See Appendix G for the screenshots of the interface of these new treatments.

We implement this manipulation by displaying the information that we call *vivid* at the top part of the experiment interface while keeping every other feature of the design unchanged. In treatment *Investment Balance*, we manipulate the frame of the allocation problem by reframing the credit card repayment problem as a mutual fund investment problem. The allocation problems that subjects face under each frame are algebraically identical and offer the same incentives to optimize. Similarly, the interface under both frames is identical in all respects except for the language that we use: treatments under the debt frame feature a *checking account* and two *credit cards*; treatments under the investment frame feature an *investment account* and two *mutual funds*.[35] In treatment *Investment Interest Rate*, we manipulate both the vividness of interest rate information and the frame of the allocation problem to capture any interaction between these two factors.

Table 3: Overview of Mechanism Treatments

Treatments	**Design Features**	**Sample Size**
Debt Balance [**DB**]	Debt Frame, Vivid Balance	44
Debt Interest Rate [**DR**]	Debt Frame, Vivid Interest Rate	43
Investment Balance [**IB**]	Investment Frame, Vivid Balance	38
Investment Interest Rate [**IR**]	Investment Frame, Vivid Interest Rate	40

Role of Information Vividness. If the vividness of information plays a role in driving the suboptimal repayments, a decrease in the vividness of balance information and an increase in vividness of interest rate information should increase the salience of interest rate information. The increase in salience of interest rate information increases the probability that a behavioral decision maker accounts for interest rate information and makes the objectively optimal allocation.

Prediction 1. *An increase in vividness of interest rate information increases the share of optimal allocations and the average allocation to the high interest rate account.*

Role of Framing. If the framing of the decision problem plays a role in driving the suboptimal repayments, a positive frame of the decision problem (and hence an increase in valence of balance information) should lead to less attention being allocated to balance information and increase the salience of interest rate information. The increase in salience of interest rate information increases the probability that a behavioral decision maker accounts for interest rate information and makes the objectively optimal allocation.

[35] Another semantic difference across frames is the substitution of the words *charged* and *earned*; and *payment* and *investment*.

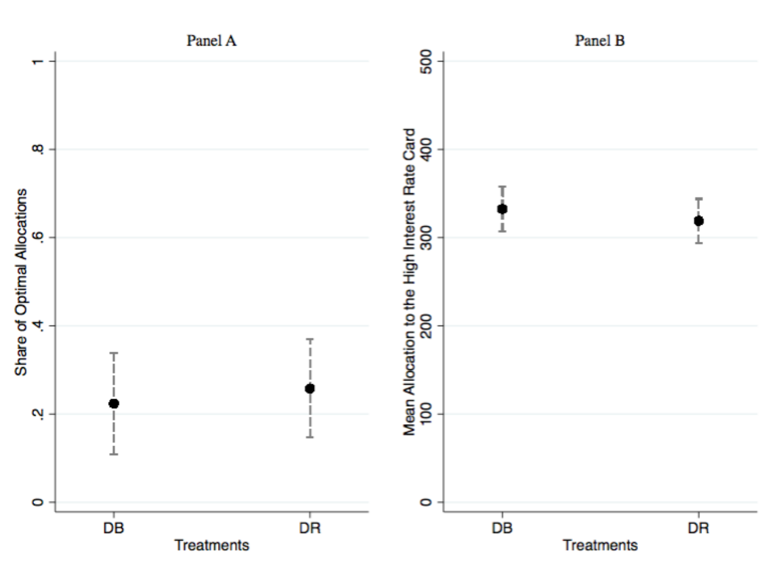
Prediction 2. *A positive framing of the decision problem increases the share of optimal allocations and the average allocation to the high interest rate account.*

3.2. Results from Mechanism Treatments

3.2.1. Role of Information Vividness

In Figure 9, Panel A shows the share of optimal repayments made across treatments and Panel B shows the average allocation made to the high interest rate card for subjects who can solve optimization problems and who acquire interest rate information before making their decision in the first period of each stage. We see that there is no significant increase, on average, in any of the optimality measures. The share of optimal allocations increases by 3.4 percentage points -from 22.4% in **DB** to 25.8% in **DR** ($p = 0.68$). The average allocation to the high interest rate account goes in the opposite direction of our prediction, and decreases by 13 ECU - from 332 ECU to 319 ECU ($p = 0.46$). The results are qualitatively similar when we relax our sample restrictions and control for demographic information (See Tables A1 and A2 in Appendix).

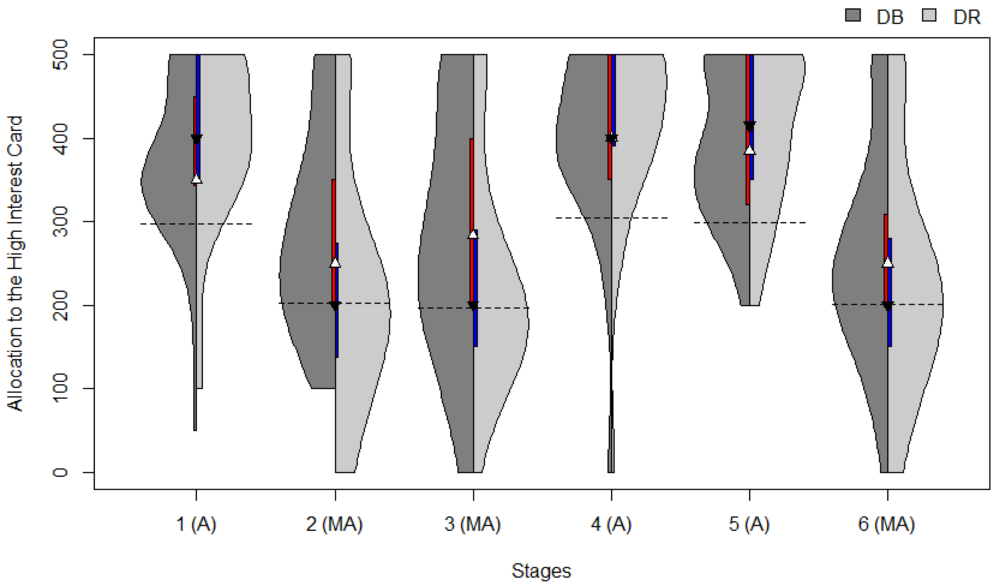
Figure 9: Optimality Measures Across Debt Treatments - Period 1 Decisions



Note: Panel A shows the share of optimal allocations made under **DB** and **DR**. The whiskers indicate 95% confidence interval calculated using subject-level clusters. Panel B shows the average allocation made to the high interest rate card under **DB** and **DR**.

Figure 10 documents further evidence that allows us to compare the allocation patterns across treatments. The patterns seem mostly similar. We find that in all aligned stages 94% of the subjects allocate more than half of their deposit into the high interest rate card

Figure 10: Allocation Patterns Across Debt Treatments - Period 1 Decisions



Note: The violin plots show the distribution of repayments subjects make toward the high interest rate card in the first period of each stage. The upward white triangle and the downward black triangle represent the median allocation towards the higher interest rate card in a given stage for **DB** and **DR**, respectively. The thick red and blue bars around the median represents allocations within the interquartile range for **DB** and **DR**, respectively. The violin shape visualizes the kernel density distribution of the allocation patterns - the wider sections of the violin represents a higher likelihood of allocating in the corresponding value. The letters A and MA next to stage numbers represent if that stage is aligned or misaligned. The dotted horizontal reference lines represent the hypothetical allocation under an exact balance matching heuristic towards the higher interest card in the first period of each stage. The rational choice theory predicts a distribution with full mass located at 500 for all stages.

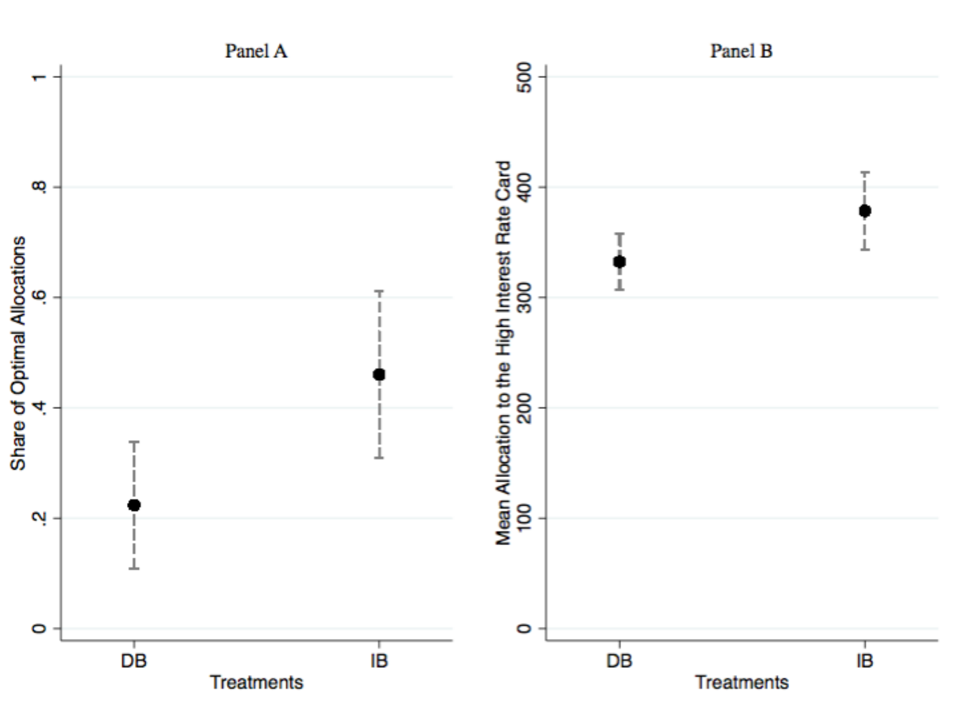
which is identical to the same measure calculated in our baseline treatment. However, the percentage of subjects' that allocate more than half of their deposit into the high interest rate card in misaligned stages is respectively 26%, 29% and 36% which is lower than the same measure calculated in the baseline treatment. This finding is particularly striking given that subjects can achieve a higher payoff by simply uniformly randomizing their payments in misaligned stages. Taken together, these patterns suggest that subjects in **DR** are responsive to both interest rate and balance information, yet their decisions seem to be more responsive to balance information compared to the decisions of the subjects in our baseline treatment. Indeed, we surprisingly find that subjects are significantly more responsive to balance information in **DR** compared to **DB** ($p = 0.02$) whereas there is no difference in responsiveness to interest rate information across treatments ($p = 0.47$). Although subjects in **DR** are more responsive to balance information compared to the subjects in **DB**, they are not significantly more responsive to balance information compared to interest rate information ($p = 0.13$). These findings are robust to relaxing our sample restrictions and including demographic controls (See Tables A3 and A4 in Appendix).

Result 1. *Neither the share of optimal allocations nor the average allocation to the high interest rate account improves with an increase in the vividness of interest rate information.*

As a final note, we show that subjects in **DR** do not seem to learn to make better decisions within or between stages, similar to the subjects in **DB**. These results suggest that subjects in **DR** also struggle with learning how to make their allocations correctly.

3.2.2. Role of Framing

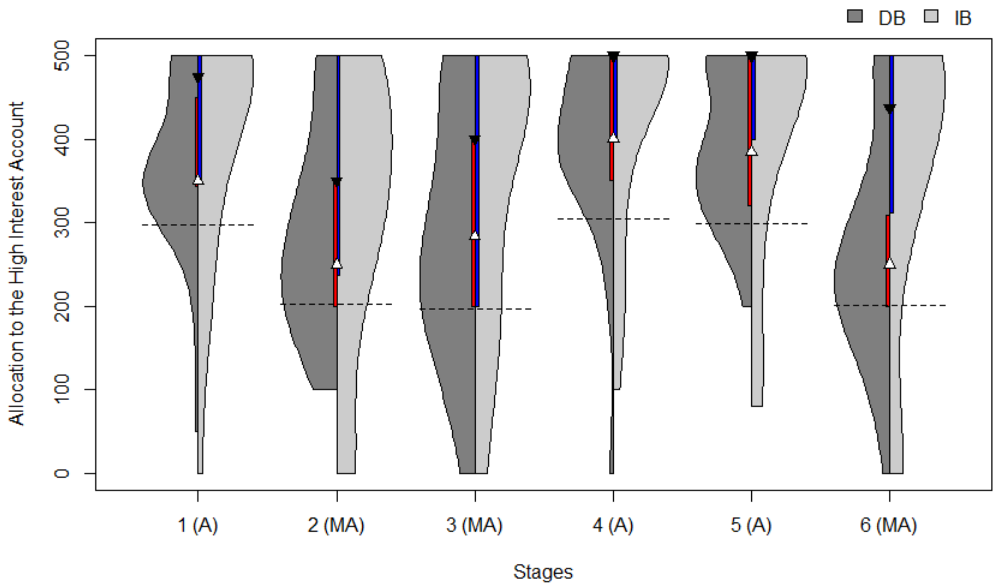
Figure 11: Comparison of Balance Treatments



Note: Panel A shows the share of optimal allocations made in **DB** and **IB**. The whiskers indicate 95% confidence interval calculated using subject-level clusters. Panel B shows the average allocation made to the high interest rate card.

In Figure 11, Panel A shows the share of optimal repayments made across treatments and Panel B shows the average allocation made to the high interest rate card for subjects who can solve optimization problems and who acquire interest rate information before making their decision in the first period of each stage. We see that there is a significant increase, on average, in each optimality measure. The share of optimal allocations more than doubles - increases from 22.4% in **DB** to 46.1% in **IB** ($p = 0.0166$). The average allocation to the high interest rate account increases by 46.14 ECU - from 332.4 ECU to 378.54 ECU ($p = 0.038$). The results are qualitatively similar when we relax our sample restrictions and control for demographic information (See Tables A5 and A6 in Appendix).

Figure 12: Allocation Patterns Across Vivid Balance Treatments - Period 1 Decisions



Note: The violin plots show the distribution of repayments subjects make toward the high interest rate card in the first period of each stage. The upward white triangle and the downward black triangle represent the median allocation towards the higher interest rate card in a given stage for **DB** and **IB**, respectively. The thick red and blue bars around the median represents allocations within the interquartile range for **DB** and **IB**, respectively. The violin shape visualizes the kernel density distribution of the allocation patterns - the wider sections of the violin represents a higher likelihood of allocating in the corresponding value. The letters A and MA next to stage numbers represent if that stage is aligned or misaligned. The dotted horizontal reference lines represent the hypothetical allocation under an exact balance matching heuristic towards the higher interest card in the first period of each stage. The rational choice theory predicts a distribution with full mass located at 500 for all stages.

Figure 12 documents further evidence that allows us to compare the allocation patterns across treatments. There are stark differences in the distribution of allocations made across treatments. We find that in all aligned stages 85% of the subjects allocate more than half of their deposit into the high interest rate account which is lower than the same measure calculated in our baseline treatment. However, the percentage of subjects that allocate more than half of their deposit into the high interest rate card in misaligned stages is respectively 71%, 68% and 81% which is significantly higher than the same measure calculated in the baseline treatment. The fact that the mass of allocations that are made in the correct direction is high and do not move much across aligned and misaligned stages suggest that subjects in **IB** are more responsive to interest information than balance information. We confirm this intuition statistically: we find that subjects in **IB** are more responsive to interest rate information compared to the balance information ($p = 0.01$). Moreover, we find that subjects in **IB** take interest rate information more into account while making their decisions compared to the subjects in **DB** ($p = 0.04$) and there is no difference in the extent that balance information is taken into account across **IB** and **DB** ($p = 0.21$). These findings are robust to relaxing our sample restrictions and including demographic controls (See Tables A7 and A8 in Appendix).

Result 2. *Subjects make significantly better allocations under the investment frame. There is a 23.7 percentage point increase - more than doubling - in the share of optimal allocations from **DB** to **IB**.*

Furthermore, we find that subjects in **IB** exhibit small yet significant learning which stands in contrast to the subjects' behavior in **DB**. This suggests that the debt frame of the problem do not only interfere with subjects' ability to optimize but also hinders learning.

3.3. Role of Vividness under the Investment Frame

We find that, similar to our finding under the debt frame, neither the share of optimal allocations nor the average allocation to the high interest rate account improves with an increase in the vividness of interest rate information across investment frames. The comparison between the treatments Investment Debt and Investment Interest Rate can be found in Appendix B.

3.4. Information Acquisition Patterns and Use of Allocation Heuristics

The results presented in this subsection have implication for models of bounded rationality. In particular, we present evidence towards two channels that pertain to models of attention and salience, and the literature on the use of heuristics. First, we find a sharp asymmetry in the way subjects acquire information across frames and we show how this asymmetric pattern correlates with allocation behavior. Second, we document an asymmetry in the response times and link this with the use of allocation heuristics across frames.

3.4.1. Information Acquisition Patterns

To understand the cognitive channels that lead to an asymmetric optimality rate across decision frames, we introduce two new treatments (*Debt No-Vivid* and *Investment No-Vivid*) where we do not display any information vividly, and thus require subjects to actively click on information buttons to reveal the corresponding piece of information before making their decisions. This representation-neutral information environment allows us to capture how subjects allocate their attention in a clear way. Specifically, we keep track of how many times a subject clicks on an information button, how much time they spend on each information button and in which order they decide to acquire information.[36]

Table 4: Overview of Information Acquisition Treatments

Treatments	**Design Features**	**Sample Size**
Debt No-Vivid [**DN**]	Debt Frame, No Vivid Attribute	15
Investment No-Vivid [**IN**]	Debt Frame, No Vivid Attribute	22

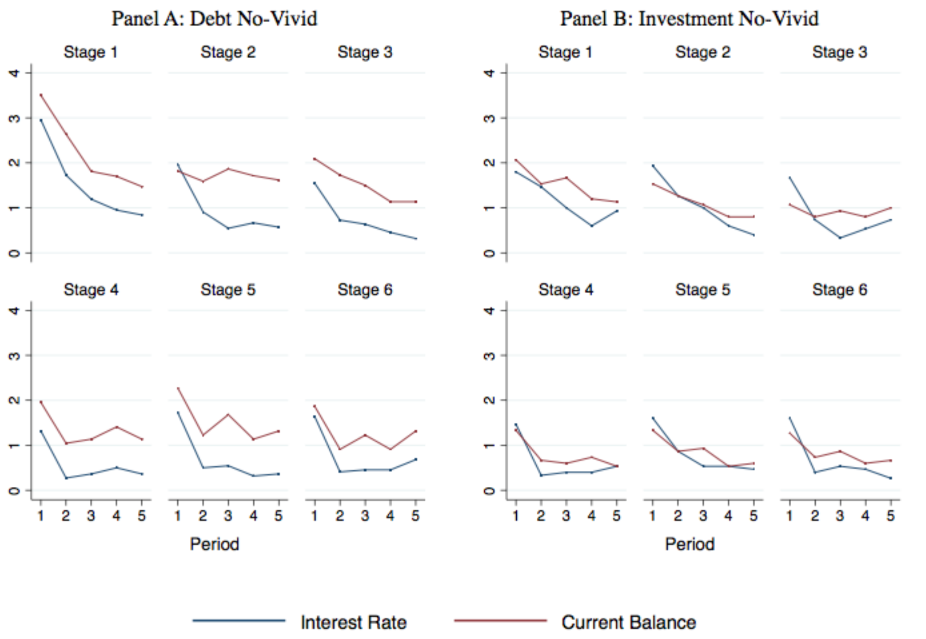
In Figure 13, Panel A shows the average click rates on current balance and interest rate buttons in each period by stage for the subjects in **DN**. We see that subjects consistently click more on the current balance button than interest rate button ($p = 0.0000$). Panel B documents the same measures for **IN**. In sharp contrast with the click patterns in **DN**, we find that subjects in **IN** click on the current balance and interest rate buttons at similar rates ($p = 0.44$). Using additional analysis, we find that a subject who is assigned to **IN** clicks, on average, 0.6 times less on the current balance compared to a subject who is assigned to **DN** ($p = 0.005$) while the click rates on interest rate information is similar across treatments ($p = 0.87$). See Table D1. When we analyze the time spent on each information button and the order in which subjects click on the information buttons, we find a similar *balance-focusedness* under the debt frame that does not exist under the investment frame.[37]

[36]See Figures D5 and D6 for the screenshots of the interface.

[37]When we compare the time spent on information buttons across treatments, we find that subjects in **DN** spend significantly more time on the current balance information compared to the interest rate information ($p = 0.0000$) while there is no such difference in the behavior of subjects in **IN** ($p = 0.07$). Moreover, we find that subjects in **IN** treatment spend significantly less time on the current balance information compared to the subjects in **DN** ($p = 0.001$) although there is no difference in the time spent on interest rate information across these two treatments ($p = 0.62$). See Table D2.

When we look at the click order, we see that the mode of first information button a subject clicks within a period is the current balance button if the subject is assigned to **DN** and interest rate button if the subject is assigned to **IN**. Figure D1 presents the click order data.

Figure 13: Average Click Rates Across No-Vivid Treatments



Note: Panel A documents the difference in average click rates on interest rate and current balance button for each period in each stage under DN treatment. Panel B presents the same measures for IN treatment.

Result 3. *Subjects pay significantly less attention to the irrelevant balance information under the investment frame. Compared to the debt frame, subjects click significantly less to the current balance button and spend significantly less time on the current balance button under the investment frame.*

We further show that clicking and spending more time on current balance information are tightly correlated with making lower quality decisions. See Appendix D.

3.4.2. Use of Allocation Heuristics

An alternative way balance-dependent allocations could occur is through the use of heuristics. In order to uncover potential regularities in allocation decisions, we investigate the following set of heuristics that we see as the most relevant:

1. **Optimal (OPT)**: Allocate optimally.[38]

[38] We allow for a 5% margin for error. Hence a subject is considered to be an *Optimal* type in a given period if she allocates at least 475 ECU to the high interest rate account in that period.

2. **Balance Matching (BM)**: Allocate more into the account with higher balances.[39]
3. **Interest Matching (IM)**: Allocate more into the account with higher interest rates.[40]

Table 5: Distribution of Heuristic Types Across Frames at Bi-Stage Level

Panel A: Strict Classification - 80% of Periods

	OPT	BM	IM	Other	Total
Debt (Bi-Stage 1)	6	**46**	13	44	109
Debt (Bi-Stage 2)	5	**49**	19	36	109
Debt (Bi-Stage 3)	9	**39**	18	43	109
Investment (Bi-Stage 1)	**19**	15	**25**	34	93
Investment (Bi-Stage 2)	**27**	11	**22**	33	93
Investment (Bi-Stage 3)	**24**	16	**28**	25	93

Panel B: Weak Classification - 60% of Periods

	OPT	BM	IM	Other	Total
Debt (Bi-Stage 1)	7	**61**	32	9	109
Debt (Bi-Stage 2)	5	**60**	33	11	109
Debt (Bi-Stage 3)	10	**55**	31	13	109
Investment (Bi-Stage 1)	**21**	20	**34**	18	93
Investment (Bi-Stage 2)	**27**	14	**33**	19	93
Investment (Bi-Stage 3)	**24**	17	**37**	15	93

Note: The table documents the number of subjects that are classified as a certain heuristic type under each frame at the bi-stage level. Panel A documents the distribution of heuristic types when the classification requires a subject to be consistent with a heuristic type for at least 8 out of 10 periods in a bi-stage. Panel B executes the same analysis by requiring a subject to be consistent with a heuristic type for at least 6 out of 10 periods in a bi-stage. Since there is no significant difference in the way that subjects make their allocations within the debt treatments and within the investment treatments, we conduct the heuristic analysis at the frame level by grouping subjects across the debt treatments **DB, DR, DN** and across the investment treatments **IB, IR, IN**.

Panel A of Table 5 shows the heuristic distribution across frames under a fairly strict classification requirement. According to this classification, a subject is classified as a certain heuristic type *i)* if her allocation is consistent with the same heuristic for at least 8 out of 10 periods in a given bi-stage, and *ii)* the assigned heuristic is a strictly better fit than

[39] Our definition of the balance matching heuristic is less strict than Gathergood et al. (2019) although it still captures the same intuition that greater balances on an account lead to greater allocations on that account.

[40] Specifically, a subject who allocates between 250 ECU and 475 ECU into the higher interest account in a given period is considered to be an *Interest Matching* type for that period. Recall that we classify those who allocate at least 475 ECU to the high interest rate account as an *Optimal* type.

any other heuristic. Using this approach we are able to classify around 60% of the subjects in each frame. The distribution of heuristic types is drastically different across the two frames. Under the debt frame, the number of subjects classified as the balance matching type is strictly greater than the number of subjects classified as the other two heuristic types. However, this is reversed under the investment frame: there is always a greater number of subjects who are classified as the interest matching or the optimal type compared to the number of subjects who are classified as the balance matching type. In Panel B of Table 5 we show the heuristic distribution under each frame when we weaken the classification requirement.[41] This approach allows us to classify a significantly higher portion of the subjects and the results remain qualitatively similar.

Result 4. *A significant majority of the subjects are classified as the balance matching type under the debt frame. In contrast, the majority of the subjects are classified as either optimal or the interest matching type under the investment frame.*

In addition to the asymmetry in the distribution of heuristic types across two frames, we find that subjects' assigned heuristic types to be persistent over time. In both debt and investment treatments, subjects whose allocations are consistent with the dominating heuristic in a given bi-stage (**BM** under the debt frame, and **IM** or **OPT** under the investment frame) are highly likely to be classified as the same heuristic type in the following bi-stage. We report the heuristic transition matrices in Appendix E.

3.4.3. Summary

To sum up this subsection, the asymmetry we document in information acquisition patterns is directly associated with the asymmetry in the share of optimal allocations and consistent with the distribution of heuristic types across frames. In particular, the tight connection between higher click rates/longer time spent on balance information and the share of optimal allocations is consistent with the salience mechanism. This suggests that frames can systematically affect decision makers' attention allocation and information processing while improving or worsening outcomes depending on the normative relevance of the information that the decision maker is drawn to.

[41]Now a subject is classified as a heuristic type *i)*when her allocation is consistent with that rule for at least 6 out of 10 periods in a given bi-stage *ii)* and the assigned rule is a strictly better fit than any other rule.

4. Discussion

4.1. Policy Implications

Many researchers studying household finance have gathered an abundance of evidence toward departures from rational choice in the last three decades. These departures are not specific to one branch of financial decision making but cover every aspect of household finance. Credit card markets, being one of these domains, have offered various suboptimal consumer behavior and inefficient market outcomes (Campbell (2016), Beshears et al. (2018)). The welfare consequences of such departures for the households have alerted policy makers to consider the tools available to them in order to restore the choices that consumers would make if they were rational and well informed.[42] Two widely discussed policies that aim to improve consumer financial decision making are mandating disclosure policies and promoting financial education.

A common finding in previous studies that investigate financial behavior in the debt domain is that conventional disclosure policies are ineffective in improving financial outcomes (Bertrand and Morse (2011), Seira, Elizondo and Laguna-Müggenburg (2017)). We find evidence aligning with previous findings. We show that *vividly* disclosing interest rate information has no significant effect on the misallocation rate compared to our baseline treatment where we *non-vividly* disclosure the interest rate information. We consider the quality of decisions in the vivid interest rate treatment (**DR**) to be an upper bound of the quality of decisions that can be obtained through conventional disclosure policies in the field. This is due to our removal of potential confounds that exist in the field and relatively high optimization ability of our subjects. This does not mean to say that any potential disclosure policy will fall short of restoring rational choice. We think that non-conventional disclosures of interest rate information might prove useful in improving the quality of decisions in this repayment context.[43]

A widely discussed alternative to information disclosure policies is financial education. According to recent financial literacy surveys, an important aspect of financial decision making that many households seem to struggle is the capacity to undertake algebraic calculations related to interest rates (Hastings, Madrian and Skimmyhorn (2013), Lusardi and Mitchell

[42]In the United States, the Truth in Lending Act of 1968 standardized the format of interest rate and other financial charge disclosures. The CARD Act of 2009 increased the amount of notice consumers receive in their credit terms. The Dodd-Frank Act of 2010 established the Consumer Financial Protection Bureau (CFPB) with the goal of protecting consumers from unfair, deceptive, or abusive practices of lenders.

[43]Both Bertrand and Morse (2011), Seira, Elizondo and Laguna-Müggenburg (2017) explore psychology-guided disclosures in similar borrowing situations and find them to have modest effects.

(2014)). While confirming that optimization ability is associated with improved decision making, we find that a significant majority of subjects who are capable of solving simple optimization problems fail to make their allocations optimally during the experiment. We think the reason for this discrepancy is subjects' inability to translate the credit card repayment problem into a simple algebraic problem that they are clearly better at thinking through.[44] Our finding suggests that an effective financial education program should acknowledge the mental gaps between real-life financial decision problems and algebraic counterparts, and focus on training people how to translate these problems into simple optimization problems as well as solving algebraic problems.

A critical insight that arises from our findings is that people with similar levels of optimization ability struggle managing their allocations more as borrowers than investors. The welfare consequences of such mismanagement are particularly strong if we think of the allocation problems that we investigate as a simplified version of a larger allocation problem across various types of debt and investment accounts with differing interest rates. This insight has a direct implication on the evolution of wealth inequality. Households that have similar levels of optimization ability yet extensively borrow rather than invest will end up with lower overall wealth over their lifetime simply due to the greater mismanagement of their allocations that follows from the psychology of being in debt.[45] This is especially concerning for young adults as their mismanagements are amplified through compounding over their lifetime and they tend to be more on the borrowing than investment side. We believe that the incorporation of this mechanism into life-cycle models where people endogenously determine their level of financial education (an excellent example is Lusardi, Michaud and Mitchell (2017)) should enhance the descriptive power of these models and the accuracy of policy evaluations obtained under these models.

4.2. Implications for Models of Attention

In the last decade, one of the exciting developments in the behavioral economics literature is the increasing number of theoretical accounts of attention. We present evidence on how attention to various attributes systematically changes across frames and we further relate those findings to allocation behavior.

[44] There is a substantial educational psychology literature that discusses mechanisms that underlie errors in algebraic thinking and methods to overcome these errors (Herscovics and Linchevski (1994), Stacey and MacGregor (1999)).

[45] A related psychology and economics literature investigates how scarcity might affect various cognitive functions and lead to suboptimal behavior in many domains (e.g. Mullainathan and Shafir (2013)).

According to the salience theory proposed by Bordalo, Gennaioli and Shleifer (2013), a salient thinker allocates strictly greater attention to balance information compared to interest rate information since the balance information shows greater variability.[46] Similar to salience theory, both Kőszegi and Szeidl (2012)'s model of focusing and Gabaix (2014)'s model of sparsity predict greater attention to balance information as the range of outcome utilities differ more in that attribute compared to interest rate information. Our results on time spent on each attribute justify this prediction under the debt frame. However, we observe our subjects allocating similar levels of attention toward balance and interest rate information under the investment frame which stands in contrast to the predictions of these models. This suggests that accounting for the valence of information might improve the descriptive success of these theories.

These models' consequent predictions on the choices that agents make do not help us explain subjects' choices in our experiment. Bordalo, Gennaioli and Shleifer (2013) is constructed to accommodate additively separable utility functions in attributes, and do not capture the richer interaction in attributes in the allocation problems that we investigate. Although Kőszegi and Szeidl (2012) and Gabaix (2014)'s models allow for a more general class of utility functions, their predictions align with rational choice, which is clearly inconsistent with our results.

Our results on asymmetric attention allocation are also inconsistent with models of selective attention where people derive direct utility from attending to information (e.g. Karlsson, Loewenstein and Seppi (2009)). In this class of models people optimally choose to avoid information that negatively affects their welfare. Although such models predict an asymmetry in attention allocation to balance information across debt and investment frames, the direction of the asymmetry is in contrast to our findings.

5. Conclusion

This paper provides clear evidence regarding people's struggle with correctly solving simple trade-offs with financial frames. We move beyond existing findings in the literature by examining the sources of such suboptimal behavior using a diagnostic laboratory experiment. We show that standard explanations for consumer mistakes such as optimization ability and limited attention fall short of explaining the observed misallocations. We document the role

[46] In order to obtain predictions from these models, we think of our subjects' choice as a discrete choice problem with 501 choice objects. Each choice object c is a four-tuple that lays out the balance on the left account after allocating $x \in \{0, 1, ..., 500\}$ to the left account, balance on the right account after allocating x to the left account, interest rate on the left account, and interest rate on the right account.

of information salience by examining two channels that could affect allocation behavior. We find that vividness of balance information plays no role in driving the suboptimal allocations. Instead, we show that people's ability to solve such simple trade-offs is substantially hindered by the instrinsic negative frame of the debt payment situation.

Our findings have both applied and theoretical implications. On the policy side, we show limited effectiveness of traditional disclosure policies. We think that further research in psychology-guided disclosure policies is needed to establish their overall effectiveness as a way to restore rational choice. We also show that optimization ability does not pin down our subjects' ability to correctly resolve such simple trade-offs. We think that the mixed results that are obtained on the effectiveness of financial education programs might be partially due to the differences in the content of such programs. Specifically, we think that financial education programs that acknowledge the mental gaps between algebraic problems and real-world counterparts might be more effective in improving financial outcomes of the decision makers.

On the theory side, we show that existing models of attention are not able to fully capture the way that attention affects choice behavior across frames. We think that a valence-based approach to attention might be fruitful in generating insights regarding the richness of consumer behavior.

References

Andersen, Steffen, John Y. Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai. Forthcoming. "Sources of Inaction in Household Finance: Evidence from the Danish Mortgage Market." *American Economic Review.*

Baumeister, Roy F, Ellen Bratslavsky, Catrin Finkenauer, and Kathleen D Vohs. 2001. "Bad is stronger than good." *Review of general psychology*, 5(4): 323–370.

Benartzi, Shlomo, and Richard Thaler. 2007. "Heuristics and Biases in Retirement Savings Behavior." *Journal of Economic Perspectives*, 21(3): 81–104.

Bertrand, Marianne, and Adair Morse. 2011. "Information disclosure, cognitive biases, and payday borrowing." *The Journal of Finance*, 66(6): 1865–1893.

Beshears, John, James J Choi, David Laibson, and Brigitte C Madrian. 2018. "Behavioral Household Finance." National Bureau of Economic Research Working Paper 24854.

Bhutta, Neil, Andreas Fuster, and Aurel Hizmo. 2020. "Paying too much? Price dispersion in the US mortgage market."

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2013. "Salience and Consumer Choice." *Journal of Political Economy*, 121(5): 803–843.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2017. "Memory, attention, and choice." National Bureau of Economic Research.

Campbell, John Y. 2016. "Restoring rational choice: The challenge of consumer financial regulation." *American Economic Review*, 106(5): 1–30.

Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and taxation: Theory and evidence." *American economic review*, 99(4): 1145–77.

Evans, Jonathan St BT. 2006. "The heuristic-analytic theory of reasoning: Extension and evaluation." *Psychonomic Bulletin & Review*, 13(3): 378–395.

Fischbacher, Urs. 2007. "z-Tree: Zurich toolbox for ready-made economic experiments." *Experimental economics*, 10(2): 171–178.

Fiske, Susan T, and Shelley E Taylor. 2013. *Social cognition: From brains to culture.* Sage.

Frijda, Nico H. 1986. *The emotions.* Cambridge University Press.

Gabaix, X. 2014. "A Sparsity-Based Model of Bounded Rationality." *Quarterly Journal of Economics*, 129(4): 1661–1710.

Gabaix, Xavier. 2017. "Behavioral inattention." National Bureau of Economic Research.

Gathergood, John, Neale Mahoney, Neil Stewart, and Jörg Weber. 2019. "How Do Individuals Repay Their Debt? The Balance-Matching Heuristic." *American Economic Review*, 109(3): 844–75.

Gigerenzer, Gerd, and Wolfgang Gaissmaier. 2011. "Heuristic decision making." *Annual review of psychology*, 62: 451–482.

Handel, Benjamin, and Joshua Schwartzstein. 2018. "Frictions or Mental Gaps: What's Behind the Information We (Don't) Use and When Do We Care?" *Journal of Economic Perspectives*, 32(1): 155–78.

Hastings, Justine S, Brigitte C Madrian, and William L Skimmyhorn. 2013. "Financial literacy, financial education, and economic outcomes." *Annu. Rev. Econ.*, 5(1): 347–373.

Herscovics, Nicolas, and Liora Linchevski. 1994. "A cognitive gap between arithmetic and algebra." *Educational studies in mathematics*, 27(1): 59–78.

Johnson-Laird, Philip N. 2010. "Mental models and human reasoning." *Proceedings of the National Academy of Sciences*, 107(43): 18243–18250.

Kahneman, Daniel. 1979. "Prospect theory: An analysis of decisions under risk." *Econometrica*, 47: 278.

Kahneman, Daniel. 2003. "Maps of bounded rationality: Psychology for behavioral economics." *American economic review*, 93(5): 1449–1475.

Karlan, Dean, Margaret McConnell, Sendhil Mullainathan, and Jonathan Zinman. 2016. "Getting to the top of mind: How reminders increase saving." *Management Science*, 62(12): 3393–3411.

Karlsson, Niklas, George Loewenstein, and Duane Seppi. 2009. "The ostrich effect: Selective attention to information." *Journal of Risk and uncertainty*, 38(2): 95–115.

Keys, Benjamin J, and Jialan Wang. 2018. "Minimum payments and debt paydown in consumer credit cards." *Journal of Financial Economics*.

Kőszegi, Botond, and Adam Szeidl. 2012. "A model of focusing in economic choice." *The Quarterly journal of economics*, 128(1): 53–104.

Levin, Irwin P, Sandra L Schneider, and Gary J Gaeth. 1998. "All frames are not created equal: A typology and critical analysis of framing effects." *Organizational behavior and human decision processes*, 76(2): 149–188.

Lusardi, Annamaria, and Olivia S Mitchell. 2014. "The economic importance of financial literacy: Theory and evidence." *Journal of economic literature*, 52(1): 5–44.

Lusardi, Annamaria, and Peter Tufano. 2015. "Debt literacy, financial experiences, and overindebtedness." *Journal of Pension Economics & Finance*, 14(4): 332–368.

Lusardi, Annamaria, Pierre-Carl Michaud, and Olivia S Mitchell. 2017. "Optimal financial knowledge and wealth inequality." *Journal of Political Economy*, 125(2): 431–477.

Mullainathan, Sendhil, and Eldar Shafir. 2013. *Scarcity: Why having too little means so much.* Macmillan.

Nisbett, Richard E, and Lee Ross. 1980. "Human inference: Strategies and shortcomings of social judgment."

Ponce, Alejandro, Enrique Seira, and Guillermo Zamarripa. 2017. "Borrowing on the Wrong Credit Card? Evidence from Mexico." *American Economic Review*, 107(4): 1335–61.

Schwartzstein, Joshua. 2014. "Selective attention and learning." *Journal of the European Economic Association*, 12(6): 1423–1452.

Seira, Enrique, Alan Elizondo, and Eduardo Laguna-Müggenburg. 2017. "Are information disclosures effective? evidence from the credit card market." *American Economic Journal: Economic Policy*, 9(1): 277–307.

Sims, Christopher A. 2003. "Implications of rational inattention." *Journal of monetary Economics*, 50(3): 665–690.

Soroka, Stuart, Patrick Fournier, and Lilach Nir. 2019. "Cross-national evidence of a negativity bias in psychophysiological reactions to news." *Proceedings of the National Academy of Sciences*, 116(38): 18888–18892.

Stacey, Kaye, and Mollie MacGregor. 1999. "Learning the algebraic method of solving problems." *The Journal of Mathematical Behavior*, 18(2): 149–167.

Stango, Victor, and Jonathan Zinman. 2014. "Limited and varying consumer attention: Evidence from shocks to the salience of bank overdraft fees." *The Review of Financial Studies*, 27(4): 990–1030.

Stewart, Neil. 2009. "The cost of anchoring on credit-card minimum repayments." *Psychological Science*, 20(1): 39–41.

Sunstein, Cass R. 2011. "Empirically informed regulation." *The University of Chicago Law Review*, 78(4): 1349–1429.

Taylor, Shelley E, and Suzanne C Thompson. 1982. "Stalking the elusive" vividness" effect." *Psychological review*, 89(2): 155.

Thompson, Valerie A. 2009. "Dual-process theories: A metacognitive perspective."

Tversky, Amos, and Daniel Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." *Science*, 185(4157): 1124–1131.

For Online Publication

Appendix A Additional Results

Table A1: Differences in Optimality Measures Across Debt Treatments

	Optimality Rate			Correct Allocation Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Debt Interest Rate	0.0342	-0.0303	-0.0121	-13.41	-20.90	-4.441
	(0.0810)	(0.0848)	(0.0579)	(17.98)	(18.23)	(12.89)
Constant	0.224	0.251	0.188	332.4	341.4	318.5
	(0.0583)	(0.0688)	(0.0435)	(12.76)	(15.20)	(10.29)
Observations	387	1573	2605	387	1573	2605
R^2	0.002	0.001	0.000	0.002	0.006	0.000
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No

Note: Each column reports the effect of being assigned to *Debt Interest Rate* treatment on some optimality measure using an OLS regression. In Columns 1,2 and 3, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3,4 and 5, the dependent variable is the amount of allocation made to the high interest rate card which takes a value between 0 and 500. Columns 1 and 4 restrict the sample to observations from the first period in each stage where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 5 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 3 and 6 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table A2: Differences in Optimality Measures Across Debt Treatments with Demographic Controls

	Optimality Rate			Correct Allocation Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
DR	-0.0121	-0.00259	-0.0742	-4.441	-2.351	-13.76
	(0.0579)	(0.0531)	(0.0512)	(12.89)	(11.87)	(12.50)
Math Score		0.265	0.126		58.36	36.65
		(0.0760)	(0.0597)		(16.84)	(13.98)
Gender			-0.180			-30.81
			(0.0649)			(15.42)
STEM/Economics			0.163			22.55
			(0.0532)			(12.86)
Constant	0.188	0.0563	0.213	318.5	289.6	317.3
	(0.0435)	(0.0392)	(0.0709)	(10.29)	(9.457)	(17.29)
Observations	2605	2605	2605	2605	2605	2605

Note: Column 1 to 3 represent the differences in the share of optimal allocations between *Debt Balance* and *Debt Interest Rate* treatments. The dependent variable *Optimal* is a dummy variable that takes the value 1 if the allocation is made optimally. Column 4 to 6 represent the differences in the amount of correctly made allocations between **DB** and **DR**. The dependent variable is the amount of allocation made on the high interest rate card which takes a value in between 0 and 500. The unit of observation is *subject x period*. The term **DR** is a dummy variable that takes the value 1 for observations made under Debt Interest Rate treatment. *Math Score* is a discrete variable that takes values [0,0.25,0.5,0.75,1] representing the percentage of correct answers to four optimization problems. *Gender* is a dummy variable that takes the value 1 for female subjects. *STEM/Economics* is a dummy variable that takes the value 1 for subjects whose majors are either STEM or Economics. Standard errors in parentheses. Errors are clustered at the subject level.

Table A3: Estimation of Repayments Across Debt Treatments

	(1)	(2)	(3)	(4)	(5)	(6)
Higher Interest Rate	137.8	151.0	135.2	164.0	184.5	140.7
	(25.40)	(21.79)	(16.80)	(25.67)	(31.58)	(21.27)
Higher Balance	182.8	147.6	136.7	109.7	80.83	91.95
	(25.65)	(15.32)	(12.24)	(16.61)	(16.78)	(14.97)
DR x Higher Interest Rate				-26.21	-33.47	-5.442
				(35.98)	(38.26)	(27.05)
DR x Higher Balance				73.09	66.80	44.75
				(30.39)	(22.64)	(19.29)
DR				-24.23	-4.473	-13.70
				(21.19)	(20.45)	(16.85)
Constant	93.01	106.9	118.5	117.2	111.4	132.2
	(16.06)	(12.40)	(10.10)	(13.96)	(16.34)	(13.53)
Observations	186	928	1288	387	1573	2605
R^2	0.477	0.445	0.433	0.452	0.430	0.370
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No
$\beta_{HigherInterestRate} = \beta_{HigherBalance}$	$p = 0.27$	$p = 0.90$	$p = 0.94$			
$\beta_{\mathbf{DR}xHigherInterestRate} = 0$				$p = 0.47$	$p = 0.39$	$p = 0.84$
$\beta_{\mathbf{DR}xHigherBalance} = 0$				$p = 0.02$	$p = 0.0044$	$p = 0.02$

Note: Columns 1 to 3 estimate, using OLS, how having a higher interest rate and a higher balance on a card affects the allocations made towards that card in *Debt Interest Rate* treatment. The dependent variable is the amount of allocation made on the left card (without loss of generality) which takes a value in between 0 and 500. The regressors *Higher Interest Rate* and *Higher Balance* are two dummy variables that takes the value 1 whenever the interest rate and the balance on the left card, respectively, is higher compared to the right card. Columns 4 to 6 estimate, using OLS, how having a higher interest rate and a higher balance on a card affect the allocations made towards that card using observations from both *Debt Interest Rate* and *Debt Balance* treatments. The term **DR** is a dummy variable that takes the value 1 if the allocation is made under *Debt Interest Rate* treatment. The terms **DR** x Higher Interest Rate and **DR** x Higher Balance are interaction variables. *Period* indicates if the analysis is limited to the first period decisions or not. *Restrict to Optimizers* indicate if the analysis is limited to subjects who can solve optimization problems. *Restrict to Interest Rate Acquirers* indicate if the analysis is limited to observations where the subjects acquired interest rate information before making their decisions. The last part of the table reports the parametric test results on estimated coefficients through associated p-values. Standard errors in parentheses. Errors are clustered at the subject level.

Table A4: Estimation of Repayments Across Debt Treatments with Demographic Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Higher Interest Rate	137.4	150.5	135.1	164.5	184.7	140.9
	(25.36)	(21.41)	(16.57)	(25.70)	(31.64)	(21.27)
Higher Balance	182.8	147.7	136.8	109.8	80.92	91.95
	(25.79)	(15.29)	(12.23)	(16.65)	(16.78)	(14.97)
Gender	-12.68	-19.39	-8.734	13.26	0.723	-1.794
	(13.20)	(7.063)	(7.937)	(12.27)	(9.171)	(7.340)
STEM/Economics	-8.656	-3.355	8.926	11.66	4.803	7.012
	(13.32)	(7.674)	(7.837)	(10.64)	(8.624)	(5.495)
DR x Higher Interest Rate				-26.38	-33.72	-5.477
				(36.10)	(38.29)	(26.95)
DR x Higher Balance				73.00	66.70	44.78
				(30.46)	(22.63)	(19.29)
DR				-22.06	-4.875	-15.15
				(21.54)	(21.04)	(17.45)
Constant	104.8	119.1	119.1	101.3	108.6	131.0
	(21.16)	(13.01)	(13.10)	(21.32)	(19.00)	(15.61)
Observations	186	928	1288	387	1573	2605
R^2	0.479	0.449	0.435	0.453	0.430	0.370
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No
$\beta_{HigherInterestRate} = \beta_{HigherBalance}$	$p = 0.27$	$p = 0.92$	$p = 0.93$			
$\beta_{\mathbf{DR}xHigherInterestRate} = 0$				$p = 0.47$	$p = 0.38$	$p = 0.84$
$\beta_{\mathbf{DR}xHigherBalance} = 0$				$p = 0.02$	$p = 0.0044$	$p = 0.02$

Note: The table executes the analysis in Table A3 with demographic controls. *Gender* is a dummy variable that takes the value 1 for female subjects. *STEM/Economics* is a dummy variable that takes the value 1 for subjects whose majors are either STEM or Economics. Standard errors in parentheses. Errors are clustered at the subject level.

Table A5: Differences in Optimality Measures Across Balance Treatments

	Optimality Rate			Correct Allocation Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Investment Balance	0.237	0.247	0.242	46.14	50.13	48.19
	(0.0960)	(0.110)	(0.0759)	(21.78)	(23.91)	(18.53)
Constant	0.224	0.251	0.188	332.4	341.4	318.5
	(0.0583)	(0.0689)	(0.0435)	(12.77)	(15.21)	(10.29)
Observations	353	1095	2452	353	1095	2452
R^2	0.063	0.065	0.069	0.026	0.031	0.028
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No

Note: Each column reports the effect of being assigned to *Investment Balance* treatment on some optimality measure using an OLS regression. In Columns 1,2 and 3, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3,4 and 5, the dependent variable is the amount of allocation made to the high interest rate account which takes a value between 0 and 500. Columns 1 and 4 restrict the sample to observations from the first period in each stage where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 5 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 3 and 6 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table A6: Differences in Optimality Measures Across Balance Treatments with Demographic Controls

	Optimality Rate			Correct Allocation Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
IB	0.242	0.268	0.162	48.19	55.54	40.24
	(0.0759)	(0.0725)	(0.0868)	(18.53)	(17.47)	(20.13)
Math Score		0.221	0.191		61.97	59.84
		(0.0964)	(0.0854)		(24.05)	(23.05)
Gender			-0.287			-49.35
			(0.0874)			(21.66)
STEM/Economics			0.0432			-3.269
			(0.0771)			(18.99)
Constant	0.188	0.0643	0.300	318.5	283.9	326.7
	(0.0435)	(0.0520)	(0.0969)	(10.29)	(13.89)	(23.08)
Observations	2452	2452	2452	2452	2452	2452
R^2	0.069	0.102	0.182	0.028	0.053	0.076

Note: Column 1 to 3 represent the differences in the share of optimal allocations between *Debt Balance* and *Investment Balance* treatments. The dependent variable *Optimal* is a dummy variable that takes the value 1 if the allocation is made optimally. Column 4 to 6 represent the differences in the amount of correctly made allocations between **DB** and **IB**. The dependent variable is the amount of allocation made on the high interest rate card which takes a value in between 0 and 500. The unit of observation is *subject x period.* The term **IB** is a dummy variable that takes the value 1 for observations made under Debt Interest treatment. *Math Score* is a discrete variable that takes values [0,0.25,0.5,0.75,1] representing the percentage of correct answers to four optimization problems. *Gender* is a dummy variable that takes the value 1 for female subjects. *STEM/Economics* is a dummy variable that takes the value 1 for subjects whose majors are either STEM or Economics. Standard errors in parentheses. Errors are clustered at the subject level.

Table A7: Estimation of Repayments Across Balance Treatments

	(1)	(2)	(3)	(4)	(5)	(6)
Higher Interest Rate	255.1	271.1	221.3	164.0	184.5	140.7
	(35.20)	(34.66)	(29.02)	(25.70)	(31.62)	(21.28)
Higher Balance	62.05	71.58	90.21	109.7	80.83	91.95
	(33.79)	(27.56)	(23.99)	(16.63)	(16.81)	(14.97)
IB x Higher Interest Rate				91.08	86.64	80.63
				(43.27)	(46.62)	(35.82)
IB x Higher Balance				-47.62	-9.246	-1.741
				(37.33)	(32.02)	(28.14)
IB				-10.44	-16.79	-25.69
				(29.68)	(33.27)	(23.84)
Constant	106.8	94.58	106.5	117.2	111.4	132.2
	(26.47)	(29.30)	(19.76)	(13.98)	(16.36)	(13.54)
Observations	152	450	1135	353	1095	2452
R^2	0.430	0.502	0.414	0.428	0.461	0.374
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No
$\beta_{HigherInterestRate} = \beta_{HigherBalance}$	$p = 0.01$	$p = 0.0001$	$p = 0.0027$			
$\beta_{\mathbf{IB}xHigherInterestRate} = 0$				$p = 0.04$	$p = 0.07$	$p = 0.03$
$\beta_{\mathbf{IB}xHigherBalance} = 0$				$p = 0.21$	$p = 0.77$	$p = 0.95$

Note: Columns 1 to 3 estimate, using OLS, how having a higher interest rate and a higher balance on a fund affects the allocations made towards that fund in *Investment Balance* treatment. The dependent variable is the amount of allocation made on the left fund (without loss of generality) which takes a value in between 0 and 500. The regressors *Higher Interest Rate* and *Higher Balance* are two dummy variables that takes the value 1 whenever the interest rate and the balance on the left fund, respectively, is higher compared to the right account. Columns 4 to 6 estimate, using OLS, how having a higher interest rate and a higher balance on an account affect the allocations made towards that account using observations from both *Investment Balance* and *Debt Balance* treatments. The term **IB** is a dummy variable that takes the value 1 if the allocation is made under *Investment Balance* treatment. The terms **IB** x Higher Interest Rate and **IB** x Higher Balance are interaction variables. *Period* indicates if the analysis is limited to the first period decisions or not. *Restrict to Optimizers* indicate if the analysis is limited to subjects who can solve optimization problems. *Restrict to Interest Rate Acquirers* indicate if the analysis is limited to observations where the subjects acquired interest rate information before making their decisions. The last part of the table reports the parametric test results on estimated coefficients through associated p-values. Standard errors in parentheses. Errors are clustered at the subject level.

Table A8: Estimation of Repayments Across Balance Treatments with Demographic Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Higher Interest Rate	253.6	271.4	220.5	164.9	184.7	140.9
	(35.18)	(33.80)	(28.93)	(25.69)	(31.44)	(21.23)
Higher Balance	61.83	70.80	90.01	109.8	81.04	91.95
	(33.91)	(27.14)	(23.96)	(16.69)	(16.75)	(14.97)
Gender	-5.178	-16.12	0.0103	16.47	10.04	4.796
	(18.33)	(17.28)	(11.35)	(13.38)	(12.74)	(8.899)
STEM/Economics	18.50	-2.535	16.45	21.19	4.828	9.604
	(17.72)	(16.25)	(11.58)	(10.55)	(10.96)	(6.967)
IB x Higher Interest Rate				88.85	85.81	79.83
				(43.24)	(46.29)	(35.74)
IB x Higher Balance				-48.03	-9.068	-1.849
				(37.37)	(31.88)	(28.12)
IB				-7.739	-15.08	-26.00
				(30.67)	(33.48)	(24.64)
Constant	99.55	105.3	97.09	94.27	101.5	124.7
	(32.96)	(34.75)	(21.96)	(20.80)	(20.09)	(15.86)
Observations	152	450	1135	353	1095	2452
R^2	0.433	0.503	0.416	0.432	0.462	0.375
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No
$\beta_{HigherInterestRate} = \beta_{HigherBalance}$	$p = 0.001$	$p = 0.0001$	$p = 0.003$			
$\beta_{\mathbf{IB}xHigherInterestRate} = 0$				$p = 0.04$	$p = 0.07$	$p = 0.03$
$\beta_{\mathbf{IB}xHigherBalance} = 0$				$p = 0.20$	$p = 0.78$	$p = 0.95$

Note: The table executes the analysis in Table A3 with demographic controls. *Gender* is a dummy variable that takes the value 1 for female subjects. *STEM/Economics* is a dummy variable that takes the value 1 for subjects whose majors are either STEM or Economics. Standard errors in parentheses. Errors are clustered at the subject level.

Table A9: Differences in Optimality Measures Across Investment Treatments

	Optimality Rate			Correct Allocation Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Investment Interest Rate	0.0673	0.0994	-0.0224	8.864	10.09	-10.85
	(0.108)	(0.114)	(0.0889)	(27.19)	(26.26)	(22.71)
Constant	0.461	0.498	0.429	378.5	391.5	366.7
	(0.0765)	(0.0863)	(0.0623)	(17.69)	(18.48)	(15.42)
Observations	296	1170	2335	296	1170	2335
R^2	0.005	0.009	0.001	0.001	0.001	0.001
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No

Note: Each column reports the effect of being assigned to *Investment Interest Rate* treatment on some optimality measure using an OLS regression. In Columns 1,2 and 3, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3,4 and 5, the dependent variable is the amount of allocation made to the high interest rate fund which takes a value between 0 and 500. Columns 1 and 4 restrict the sample to observations from the first period in each stage where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 5 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 3 and 6 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table A10: Differences in Optimality Measures Across Investment Treatments with Demographic Controls

	Optimality Rate			Correct Allocation Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
IR	-0.0224	-0.0264	0.00209	-10.85	-11.86	-7.052
	(0.0889)	(0.0823)	(0.0765)	(22.71)	(21.05)	(20.34)
Math Score		0.373	0.377		94.74	97.58
		(0.0952)	(0.0935)		(26.10)	(26.95)
Gender			-0.300			-52.58
			(0.0773)			(20.74)
STEM/Economics			-0.0776			-18.91
			(0.0846)			(22.36)
Constant	0.429	0.265	0.460	366.7	325.0	361.4
	(0.0623)	(0.0729)	(0.0949)	(15.42)	(19.44)	(25.82)
Observations	2335	2335	2335	2335	2335	2335
R^2	0.001	0.094	0.188	0.001	0.060	0.089

Note: Column 1 to 3 represent the differences in the share of optimal allocations between *Investment Balance* and *Investment Interest Rate* treatments. The dependent variable *Optimal* is a dummy variable that takes the value 1 if the allocation is made optimally. Column 4 to 6 represent the differences in the amount of correctly made allocations between **IB** and **IR**. The dependent variable is the amount of allocation made on the high interest rate fund which takes a value in between 0 and 500. The unit of observation is *subject x period*. The term **IR** is a dummy variable that takes the value 1 for observations made under Investment Interest Rate treatment. *Math Score* is a discrete variable that takes values [0,0.25,0.5,0.75,1] representing the percentage of correct answers to four optimization problems. *Gender* is a dummy variable that takes the value 1 for female subjects. *STEM/Economics* is a dummy variable that takes the value 1 for subjects whose majors are either STEM or Economics. Standard errors in parentheses. Errors are clustered at the subject level.

Table A11: Estimation of Repayments Across Investment Treatments

	(1)	(2)	(3)	(4)	(5)	(6)
Higher Interest Rate	275.0	286.5	204.4	255.1	271.1	221.3
	(42.15)	(36.58)	(31.82)	(34.93)	(34.32)	(28.83)
Higher Balance	89.21	93.43	56.45	62.05	71.58	90.21
	(27.65)	(22.13)	(18.16)	(33.53)	(27.30)	(23.83)
IR x Higher Interest Rate				19.93	15.35	-16.89
				(54.43)	(49.88)	(42.80)
IR x Higher Balance				27.16	21.85	-33.76
				(43.29)	(35.00)	(29.90)
IR				-40.46	-42.92	7.296
				(35.05)	(34.45)	(27.94)
Constant	66.35	51.66	113.8	106.8	94.58	106.5
	(23.43)	(18.76)	(20.00)	(26.27)	(29.02)	(19.63)
Observations	144	720	1200	296	1170	2335
R^2	0.483	0.533	0.327	0.458	0.524	0.371
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No
$\beta_{HigherInterestRate} = \beta_{HigherBalance}$	$p = 0.005$	$p = 0.0006$	$p = 0.0001$			
$\beta_{\mathbf{IR}xHigherInterestRate} = 0$				$p = 0.72$	$p = 0.76$	$p = 0.7$
$\beta_{\mathbf{IR}xHigherBalance} = 0$				$p = 0.53$	$p = 0.54$	$p = 0.26$

Note: Columns 1 to 3 estimate, using OLS, how having a higher interest rate and a higher balance on a fund affects the allocations made towards that card in *Investment Interest Rate* treatment. The dependent variable is the amount of allocation made on the left card (without loss of generality) which takes a value in between 0 and 500. The regressors *Higher Interest Rate* and *Higher Balance* are two dummy variables that takes the value 1 whenever the interest rate and the balance on the left fund, respectively, is higher compared to the right fund. Columns 4 to 6 estimate, using OLS, how having a higher interest rate and a higher balance on a fund affect the allocations made towards that card using observations from both *Investment Interest Rate* and *Investment Balance* treatments. The term **DR** is a dummy variable that takes the value 1 if the allocation is made under *Investment Interest Rate* treatment. The terms **IR** x Higher Interest Rate and **IR** x Higher Balance are interaction variables. *Period* indicates if the analysis is limited to the first period decisions or not. *Restrict to Optimizers* indicate if the analysis is limited to subjects who can solve optimization problems. *Restrict to Interest Rate Acquirers* indicate if the analysis is limited to observations where the subjects acquired interest rate information before making their decisions. The last part of the table reports the parametric test results on estimated coefficients through associated p-values. Standard errors in parentheses. Errors are clustered at the subject level.

Table A12: Estimation of Repayments Across Investment Treatments with Demographic Controls

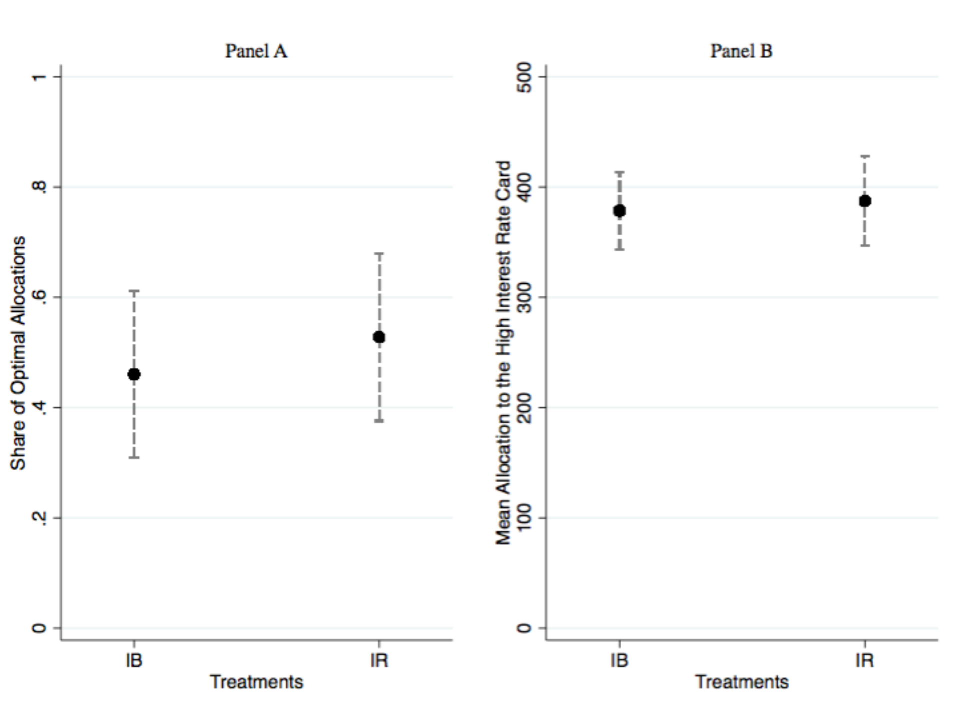
	(1)	(2)	(3)	(4)	(5)	(6)
Higher Interest Rate	274.5	286.6	205.1	253.9	272.7	221.3
	(42.34)	(36.46)	(31.77)	(34.87)	(33.87)	(28.80)
Higher Balance	89.21	93.08	56.14	61.87	71.11	90.20
	(27.85)	(22.35)	(18.25)	(33.58)	(27.06)	(23.83)
Gender	-5.804	-14.20	-7.793	-5.467	-14.96	-1.986
	(22.91)	(14.65)	(12.28)	(14.35)	(10.98)	(8.325)
STEM/Economics	9.392	-18.30	-16.19	14.64	-11.25	0.105
	(30.58)	(22.15)	(11.81)	(16.39)	(14.14)	(8.333)
IR x Higher Interest Rate				20.48	13.72	-16.93
				(54.34)	(49.85)	(42.79)
IR x Higher Balance				27.33	21.92	-33.80
				(43.43)	(34.81)	(29.92)
IR				-43.15	-40.17	7.539
				(35.37)	(34.79)	(28.04)
Constant	62.69	73.19	127.6	101.8	108.6	107.4
	(40.73)	(31.60)	(21.61)	(31.74)	(32.07)	(21.20)
Observations	144	720	1200	296	1170	2335
R^2	0.484	0.535	0.329	0.459	0.525	0.371
Period	First	All	All	First	All	All
Restrict to Optimizers	Yes	Yes	No	Yes	Yes	No
Restrict to Interest Rate Acquirers	Yes	Yes	No	Yes	Yes	No
$\beta_{HigherInterestRate} = \beta_{HigherBalance}$	$p = 0.005$	$p = 0.0006$	$p = 0.0001$			
$\beta_{\mathbf{IR}xHigherInterestRate} = 0$				$p = 0.71$	$p = 0.78$	$p = 0.69$
$\beta_{\mathbf{IR}xHigherBalance} = 0$				$p = 0.53$	$p = 0.53$	$p = 0.26$

Note: The table executes the analysis in Table A11 with demographic controls. *Gender* is a dummy variable that takes the value 1 for female subjects. *STEM/Economics* is a dummy variable that takes the value 1 for subjects whose majors are either STEM or Economics. Standard errors in parentheses. Errors are clustered at the subject level.

Appendix B Role of Vividness under the Investment Frame

In Figure B1, Panel A shows the share of optimal repayments made across treatments and Panel B shows the average allocation made to the high interest rate fund for subjects who can solve optimization problems and who acquire interest rate information before making their decision in the first period of each stage. We see that there is no significant increase, on average, in any of the optimality measures. The share of optimal allocations increases by 6.7 percentage points -from 46.1% in **IB** to 52.8% in **IR** ($p = 0.54$). The average allocation to the high interest rate account increases by 8.9 ECU - from 378.5 ECU to 387.4 ECU ($p = 0.75$). The results are qualitatively similar when we relax our sample restrictions and control for demographic information (See Tables A9 and A10 in Appendix).

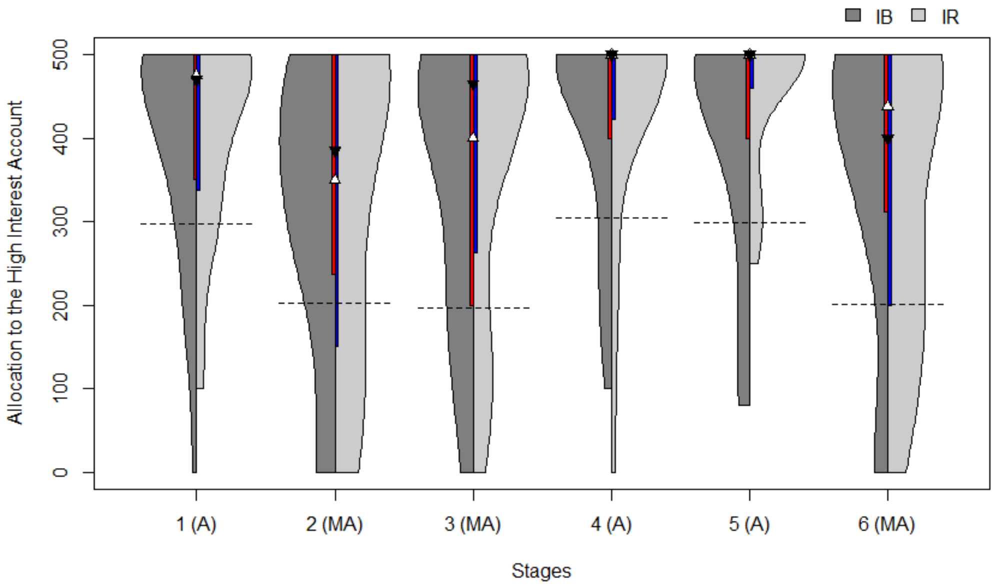
Figure B1: Comparison of Investment Treatments



Note: Panel A shows the share of optimal allocations made in **IB** and **IR**. The whiskers indicate 95% confidence interval calculated using subject-level clusters. Panel B shows the average allocation made to the high interest rate card.

Figure B2 documents further evidence that allows us to compare the allocation patterns across treatments. The patterns seem mostly similar. We find that in aligned stages 92%, 84% and 96% (respectively) of the subjects allocate more than half of their deposit into

Figure B2: Allocation Patterns Across Investment Treatments - Period 1 Decisions



Note: The violin plots show the distribution of repayments subjects make toward the high interest rate fund in the first period of each stage. The upward white triangle and the downward black triangle represent the median allocation towards the higher interest rate card in a given stage for **IB** and **IR**, respectively. The thick red and blue bars around the median represents allocations within the interquartile range for **IB** and **IR**, respectively. The violin shape visualizes the kernel density distribution of the allocation patterns - the wider sections of the violin represents a higher likelihood of allocating in the corresponding value. The dotted horizontal reference lines represent the hypothetical allocation under an exact balance matching heuristic towards the higher interest card in the first period of each stage. The rational choice theory predicts a distribution with full mass located at 500 for all stages.

the high interest rate fund which are similar to the rates calculated in Interest Balance treatment. Moreover, the percentage of subjects that allocate more than half of their deposit into the high interest rate fund in misaligned stages is respectively 63%, 75% and 55% which are, again, similar to the rates calculated in **IB**. Overall, we find no statistical difference in responsiveness to interest rate and balance information across subjects in **IR** and **IB** ($p = 0.71$ and $p = 0.53$, respectively). These findings are robust to relaxing our sample restrictions and including demographic controls (See Tables A11 and A12 in Appendix).

Result B1. *Similar to the debt frame, neither the share of optimal allocations nor the average allocation to the high interest rate account improves with an increase in the vividness of interest rate information across investment frames.*

Appendix C Learning

Table C1: Within Stage Learning in **DB**

	Optimal		Correct Fraction	
	(1)	(2)	(3)	(4)
Period	0.0189	-0.00534	0.0136	-0.00324
	(0.0138)	(0.00553)	(0.00723)	(0.00346)
Constant	0.202	0.204	0.647	0.647
	(0.0599)	(0.0488)	(0.0266)	(0.0221)
Observations	645	1317	645	1317
R^2	0.004	0.000	0.006	0.000

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the decision period within a stage denoted with the variable *Period*. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C2: Between Stage Learning in **DB**

	Optimality Rate		Mean Correct Fraction	
	(1)	(2)	(3)	(4)
Bi-Stage	0.0334	0.0246	0.000657	0.00441
	(0.0212)	(0.0136)	(0.0125)	(0.00848)
Constant	0.188	0.138	0.682	0.628
	(0.0680)	(0.0426)	(0.0339)	(0.0235)
Observations	645	1317	645	1317
R^2	0.004	0.003	0.000	0.000

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the bi-stages. A bi-stage consists of two consecutive stages with one aligned and one misaligned stage, and takes an integer value in between 1 and 3. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C3: Within Stage Learning in **DR**

	Optimal		Correct Fraction	
	(1)	(2)	(3)	(4)
Period	-0.0153	-0.00717	0.00345	0.00634
	(0.00570)	(0.00519)	(0.00466)	(0.00397)
Constant	0.267	0.197	0.631	0.609
	(0.0589)	(0.0461)	(0.0266)	(0.0214)
Observations	928	1288	928	1288
R^2	0.003	0.001	0.000	0.001

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the decision period within a stage denoted with the variable *Period*. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C4: Between Stage Learning in **DR**

	Optimality Rate		Mean Correct Fraction	
	(1)	(2)	(3)	(4)
Bi-Stage	0.0155	0.0147	0.0139	0.00929
	(0.0130)	(0.00966)	(0.00689)	(0.00610)
Constant	0.190	0.146	0.613	0.609
	(0.0494)	(0.0376)	(0.0209)	(0.0167)
Observations	928	1288	928	1288
R^2	0.001	0.001	0.002	0.001

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the bi-stages. A bi-stage consists of two consecutive stages with one aligned and one misaligned stage, and takes an integer value in between 1 and 3. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C5: Within Stage Learning in **IB**

	Optimal		Correct Fraction	
	(1)	(2)	(3)	(4)
Period	0.0192	0.0207	0.0183	0.0107
	(0.0176)	(0.00832)	(0.00794)	(0.00381)
Constant	0.449	0.367	0.737	0.701
	(0.0741)	(0.0620)	(0.0390)	(0.0317)
Observations	450	1135	450	1135
R^2	0.003	0.003	0.008	0.002

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the decision period within a stage denoted with the variable *Period*. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C6: Between Stage Learning in **IB**

	Optimality Rate		Mean Correct Fraction	
	(1)	(2)	(3)	(4)
Bi-Stage	0.00438	0.0369	0.0311	0.0270
	(0.0246)	(0.0148)	(0.0181)	(0.0125)
Constant	0.489	0.355	0.724	0.679
	(0.0844)	(0.0601)	(0.0527)	(0.0366)
Observations	450	1135	450	1135
R^2	0.000	0.004	0.008	0.005

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the bi-stages. A bi-stage consists of two consecutive stages with one aligned and one misaligned stage, and takes an integer value in between 1 and 3. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C7: Within Stage Learning in **IR**

	Optimal		Correct Fraction	
	(1)	(2)	(3)	(4)
Period	0.0215	0.0163	0.00247	0.00333
	(0.00934)	(0.00666)	(0.00597)	(0.00459)
Constant	0.533	0.358	0.796	0.702
	(0.0785)	(0.0644)	(0.0401)	(0.0357)
Observations	720	1200	720	1200
R^2	0.004	0.002	0.000	0.000

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the decision period within a stage denoted with the variable *Period*. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Table C8: Between Stage Learning in **IR**

	Optimality Rate		Mean Correct Fraction	
	(1)	(2)	(3)	(4)
Bi-Stage	0.0167	0.0150	0.0102	0.00929
	(0.0277)	(0.0171)	(0.0243)	(0.0155)
Constant	0.564	0.377	0.783	0.693
	(0.0989)	(0.0741)	(0.0696)	(0.0495)
Observations	720	1200	720	1200
R^2	0.001	0.001	0.001	0.001

Note: Each column reports the coefficients from an OLS regression of some optimality measure on the bi-stages. A bi-stage consists of two consecutive stages with one aligned and one misaligned stage, and takes an integer value in between 1 and 3. In Columns 1 and 2, the dependent variable is a dummy that takes the value 1 if the allocation made is optimal. In Columns 3 and 4, the dependent variable is the fraction of correctly made allocation that takes a value between 0 and 1. Columns 1 and 3 restrict the sample to observations where the subject acquires interest rate information and solves at least one optimization question correctly. Columns 2 and 4 execute the same analysis without imposing any sample restrictions. Standard errors in parentheses. Errors are clustered at the subject level.

Appendix D Information Acquisition and the Measures of Optimality

Table D1: Click Rates on Information Buttons across No-Vivid Treatments

	(1) Interest Rate	(2) Current Balance	(3) Other	(4) Total
IN	-0.0168	-0.597	-0.333	-0.947
	(0.102)	(0.200)	(0.277)	(0.458)
Constant	0.863	1.595	1.526	3.985
	(0.0776)	(0.133)	(0.216)	(0.358)
Observations	1102	1102	1102	1102

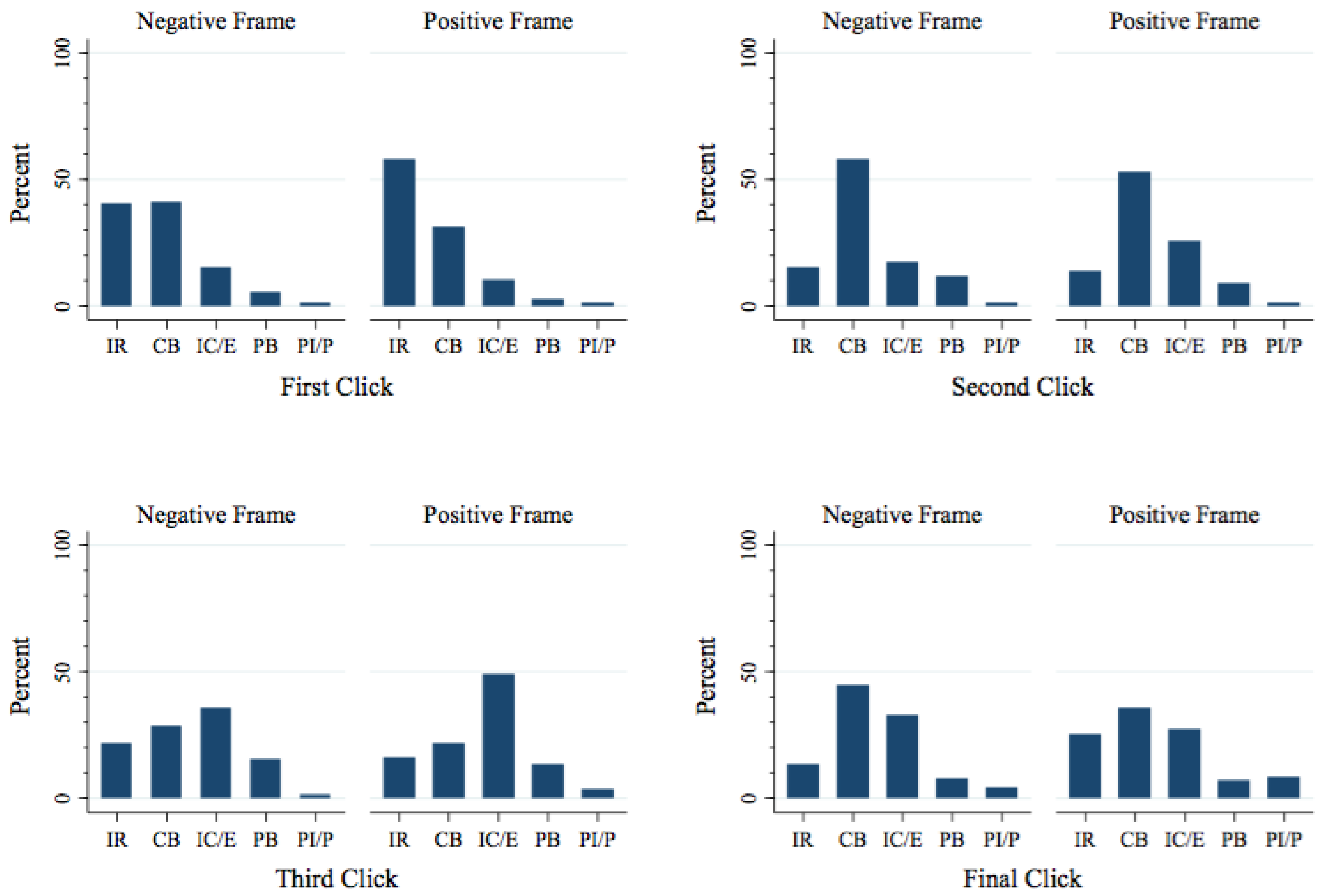
Note: The table documents the differences in average click rates on various information buttons between *Debt No-Vivid* and *Investment No-Vivid* treatments. The unit of observation is *subject* × *period* × *click rate*. The regressor **IN** is a dummy variable that takes the value 1 for observations under *Investment No-Vivid* treatment. The dependent variables *Interest Rate*, *Current Balance*, and *Total* take non-negative integer values that respectively indicate the number a subject click on interest rate button, current balance button, and any information button. Similarly, the dependent variable *Other* in Column 3 takes non-negative integer values that indicates the total number a subject clicks on either interest charged/earned button, previous payment/investment button and previous balance button. Standard errors in parentheses. Errors are clustered at the subject level.

Table D2: Time Spent on Information Buttons across No-Vivid Treatments

	(1) Interest Rate	(2) Current Balance	(3) Other	(4) Total
IN	-0.262	-4.498	-1.961	-6.721
	(0.529)	(1.225)	(1.406)	(2.227)
Constant	3.404	9.562	7.832	20.80
	(0.373)	(0.947)	(1.006)	(1.716)
Observations	1110	1110	1110	1110

Note: The table documents the differences in time spent on various information buttons between Debt No-Vivid and Investment No-Vivid treatments. The unit of observation is *subject x period*. The regressor **IN** is a dummy variable that takes the value 1 for observations under *Investment No-Vivid* treatment. The dependent variable *Interest Rate* in Column 1 takes a positive real value that indicates the time (in seconds) a subject spends on interest rate button within a period. The dependent variable *Current Balance* in Column 2 takes a positive real value that indicates the time (in seconds) a subject spends on current balance button within a period. The dependent variable *Other* in Column 3 takes a positive real value that indicates the total time (in seconds) a subject spends on interest charged/earned button, previous payment/investment button and previous balance button within a period. The dependent variable *Total* in Column 4 takes a positive real value that indicates the total time (in seconds) a subject spends on all information buttons. Standard errors in parentheses. Errors are clustered at the subject level.

Figure D1: Click Order for All Periods



In Section 3, we present evidence that there is a wedge in the share of optimal allocations across frames as well as in the click rates and time spent on current balance information button. Here, we tie these pieces of evidence together by presenting how clicking and spending time on certain information buttons are correlated with consequent choices of the subjects.

Table D3: Click Rates, Time Spent and Measures of Optimality

	Click Rate		Time Spent	
	(1)	(2)	(3)	(4)
	Optimal	Allocation	Optimal	Allocation
Interest Rate	0.0563	25.23	0.000939	1.086
	(0.0288)	(9.985)	(0.00236)	(0.919)
Current Balance	-0.0683	-20.39	-0.00593	-2.069
	(0.0323)	(9.864)	(0.00197)	(0.696)
Other	-0.0219	-8.497	-0.00484	-1.483
	(0.0148)	(4.336)	(0.00185)	(0.695)
IN	0.101	37.18	0.111	39.54
	(0.0910)	(25.37)	(0.0986)	(26.14)
Math Score	0.347	59.99	0.343	59.24
	(0.117)	(33.34)	(0.125)	(35.78)
Constant	0.159	295.8	0.159	300.3
	(0.0591)	(17.43)	(0.0604)	(17.66)
Observations	1102	1102	1102	1102
R^2	0.171	0.092	0.161	0.083

Note: The table documents how click rates and time spent on information buttons are correlated with making an optimal allocation. The regressors *Interest Rate, Current Balance* and *Other* represent click rates (in Columns 1 and 2) and time spent (in Columns 3 and 4) on the respective buttons. The regressor **IN** is a dummy variable that takes the value 1 for observations under *Investment No-Vivid* treatment. *Math Score* is a discrete variable that takes values [0,0.25,0.5,0.75,1] representing the percentage of correct answers to four optimization problems. The dependent variable *Optimal* is a dummy that takes the value 1 for optimal payments. The variable *Allocation* indicates the amount of correctly made allocation by a subject in a period. Standard errors in parentheses. Errors are clustered at the subject level.

Table D3 shows how our measures of optimality are correlated with click rates and time spent on information buttons. Column 1 indicates that each click to interest rate button is correlated with 5.6% increase in optimal allocations ($p = 0.058$) whereas each click to current balance button is correlated with a 6.8% decrease ($p = 0.04$). The difference in magnitude of these changes is significant ($p = 0.03$). Column 2 indicates that each click to interest rate button is correlated with an increase of 25.2 ECU in correctly made allocations ($p = 0.02$) whereas each click to current balance button is correlated with a decrease of 20.4 ECU ($p = 0.05$). The difference in magnitude of these changes is significant ($p = 0.02$).

Columns 3 and 4 show how time spent correlates with our measures of optimality. Here we find that each additional second spent on interest rate button has no impact on either the share of optimal allocations or on the amount of allocation correctly made ($p = 0.7$). However, we find that each additional second that is spent on current balance button correlates with a 0.59 percentage point decrease in the level of optimality ($p = 0.005$). Similarly, each additional second spent on other information buttons correlates with a 0.48 percentage point decrease ($p = 0.01$) in the share of optimal allocations. The amount of correctly made allocation decreases by 2 ECU for each second spent on current balance button ($p = 0.005$) and decreases by 1.48 ECU for each second spent on other information ($p = 0.04$).

Result D1. *Each click to interest rate button is correlated with an increase in the correctly allocated amount whereas each click to current balance button correlates with a decrease. Moreover, time spent on the interest rate button does not correlate with the correctly allocated amount whereas each second spent on current balance information correlates with a decrease.*

Appendix E Use of Heuristics - Heuristic Transition Matrices

Table E1: Debt Frame: Bi-Stage 1 to Bi-Stage 2

	Other_2	IM_2	Opt_2	BM_2
Other_1	4	2	0	3
IM_1	3	18	1	10
Opt_1	0	3	4	0
BM_1	4	10	0	47

Table E2: Debt Frame: Bi-Stage 2 to Bi-Stage 3

	Other_3	IM_3	Opt_3	BM_3
Other_2	4	2	0	5
IM_2	4	13	5	11
Opt_2	0	0	5	0
BM_2	5	16	0	39

Table E3: Investment Frame: Bi-Stage 1 to Bi-Stage 2

	Other_2	IM_2	Opt_2	BM_2
Other_1	10	5	1	2
IM_1	3	23	5	3
Opt_1	0	3	17	1
BM_1	6	2	4	8

Table E4: Investment Frame: Bi-Stage 2 to Bi-Stage 3

	Other_3	IM_3	Opt_3	BM_3
Other_2	10	8	0	1
IM_2	4	21	2	6
Opt_2	0	6	19	2
BM_2	1	2	3	8

Note: The tables describe the share of subjects who are assigned to a heuristic type in a certain bi-stage by the heuristic type they are assigned in the consecutive bi-stage. In order to construct these matrices, we employ the weak classification requirement. Under the weak classification, a subject is considered as a balance matching (BM) type if she allocates at least 50% of her deposit to the account with the higher balances for at least 6 out of 10 periods within a bi-stage. Similarly, a subject is considered as an interest matching (IM) type if she allocates between 50% to 95% of her deposit to the account with the higher interest rate for at least 6 out of 10 periods. A subject is considered as an optimal type if she allocates at least 95% of her deposit to the account with the higher interest rate for at least 6 out of 10 periods. When the criteria for both BM and IM are satisfied, we give the tie breaker to BM.

Appendix F Conceptual Framework

There is a unit mass of identical decision makers who allocate a fixed amount of income M to two accounts with differing interest rates $r = (r_1, r_2) \in [0,1]^2$ and balances $b = (b_1, b_2) \in \mathbb{R}^2$. We assume for simplicity $r_1 > r_2$. The decision maker i chooses $c^i \in [0, M]^2$ where each dimension represents an allocation made to an account and each choice satisfies $c_1^i + c_2^i = M$. A decision maker's outcome-based utility if she chooses the allocation (c_1^i, c_2^i) is given by $U(c^i; r, b) = \sum_{j=1}^{2}(1 + r_j)(c_j^i + b_j)$ which simply states that the utility from a choice is the sum of total balances after both accounts accrue interest. Hence the outcome-based utility strictly increases in c_1^i and decreases in c_2^i. However, instead of maximizing outcome-based utility, the decision maker maximizes the salience-adjusted utility function

$$\tilde{U}(c^i; r, b) = \sum_{j=1}^{2}(1 + w_r r_j)(c_j^i + b_j)$$

where $w_r \in \{0, 1\}$ is the salience adjustment on interest rate information.

Our model's central assumption concerns how salience adjustment w_r is determined. We model the decision maker's salience to interest rate information as a function of attention to interest rate and balance information. The decision maker i's attention to interest rate and balance information are respectively given by the parameters $a_r^i \in \mathbb{R}_+$ and $a_b^i \in \mathbb{R}_+$. Following Taylor and Thompson (1982), we define the salience of interest rate information $\sigma_r^i \in \mathbb{R}$ as the attention differential between interest rate information and balance information

$$\sigma_r^i = a_r^i - a_b^i$$

We assume that σ_r^i follows a normal distribution with mean μ and variance σ_ε^2, and is independent and identical across decision makers. The decision maker obtains a realization of σ_r^i and uses the salience adjustment rule $w_r = \mathbb{1}(\sigma_r^i \geq 0)$. This stylized salience adjustment rule that we assume is consistent with the view of many psychologists and economists that information that attracts greater attention contributes more strongly to the observed choices (Bordalo, Gennaioli and Shleifer (2013), Kőszegi and Szeidl (2012), Gabaix (2014)). The model captures how salience of interest rate information affects the decision maker's choices in a simple fashion: If the decision maker obtains a non-negative realization of salience of interest rate information, then her optimal decision overlaps with the optimal decision of a rational decision maker. Otherwise she does not take the interest rate information into account and her optimal decision involves uniformly randomizing over choices that are available to her.

Given this salience adjustment rule, we expect the allocation to the high interest rate account to be

$$\mathbb{E}[\bar{c}_1] = \left(1 + \Phi\left(\frac{\mu}{\sigma_\varepsilon}\right)\right) M/2$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution function. A critical observation here is that the expected allocation to high interest rate account is strictly increasing in the mean attention differential to interest rate μ. Hence any change in the decision environment that increases the salience of interest rate information should lead to an increase in the average allocation made to the high interest rate account.

Appendix G Experiment Interface and Instructions

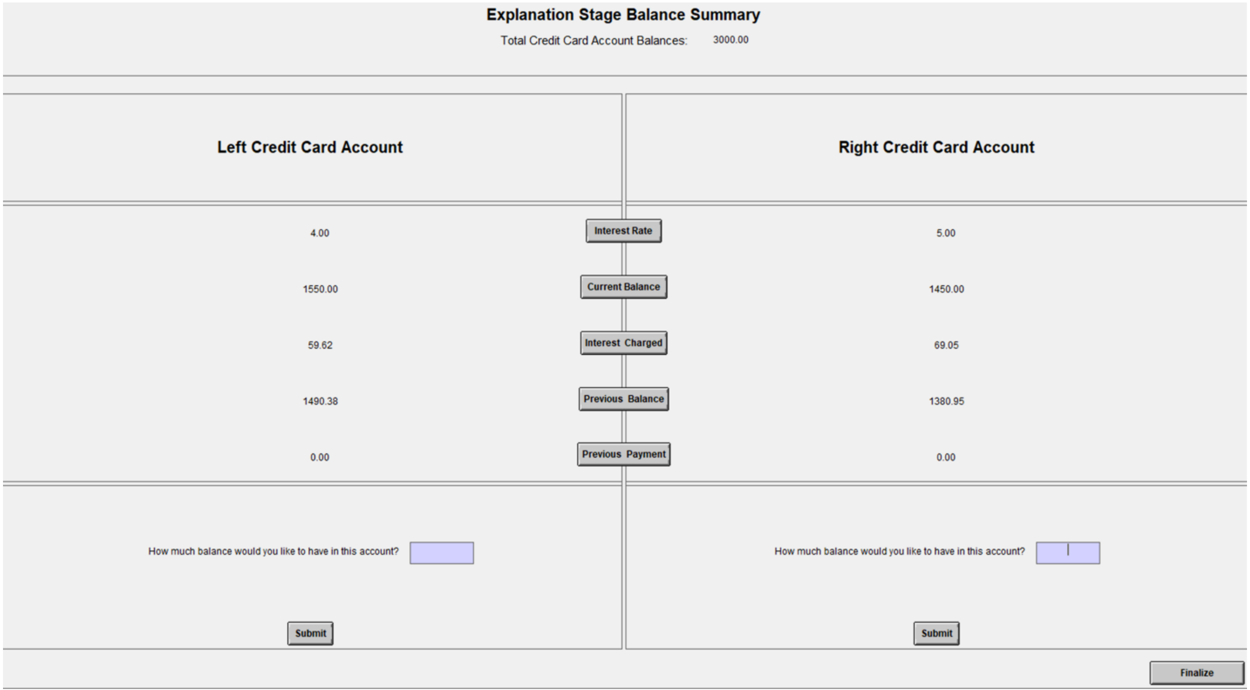


Figure D1: Experiment Interface for the treatment **DB** in Balance Reallocation Periods

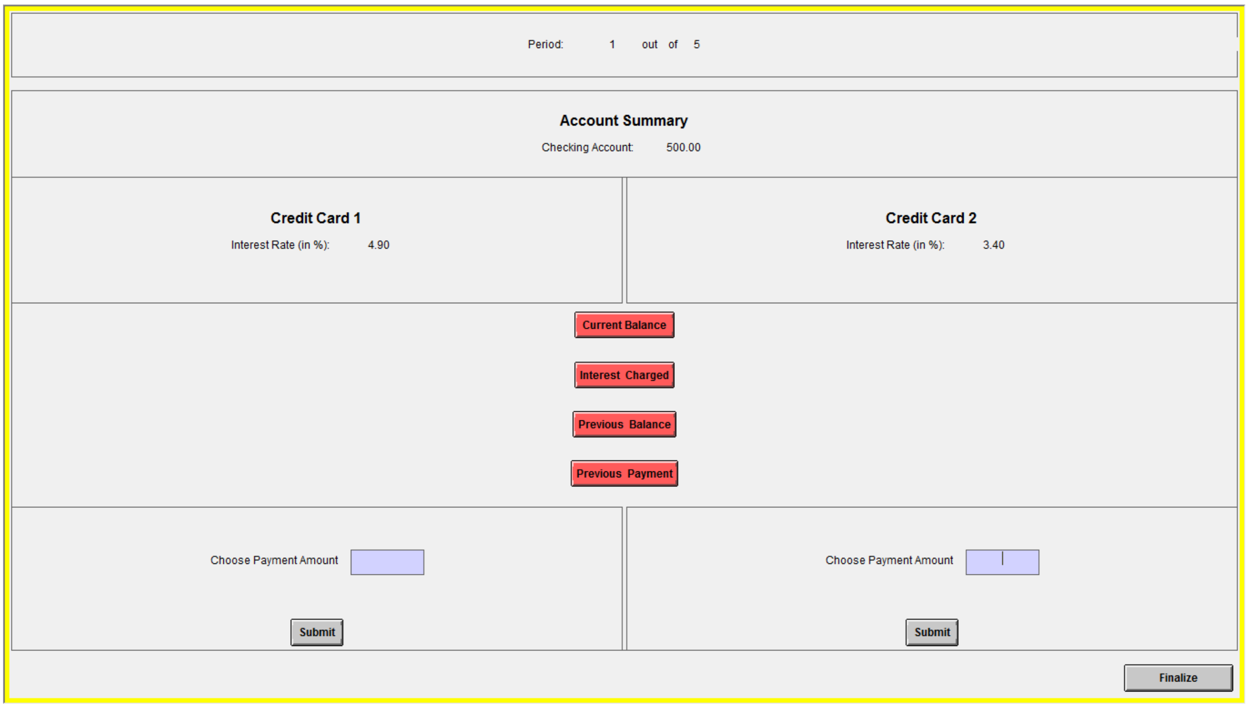


Figure D2: Experiment Interface for the treatment **DR**

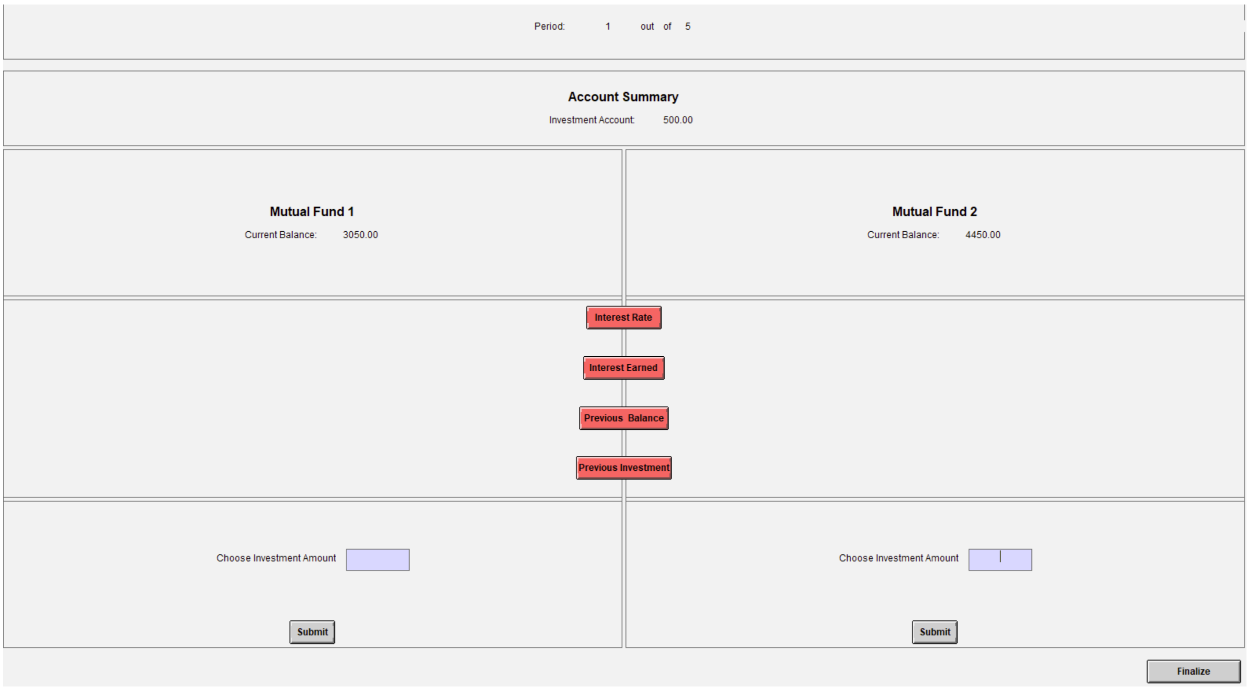


Figure D3: Experiment Interface for the treatment **IB**

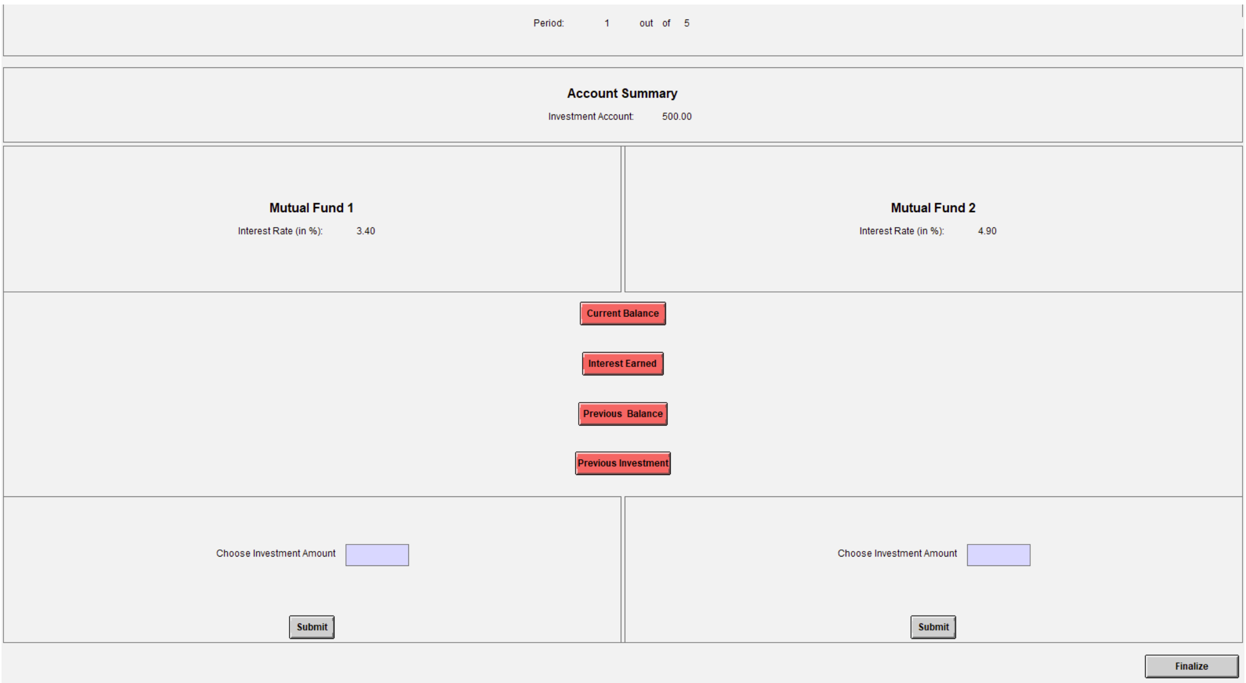


Figure D4: Experiment Interface for the treatment **IR**

Figure D5: Experiment Interface for the treatment DN

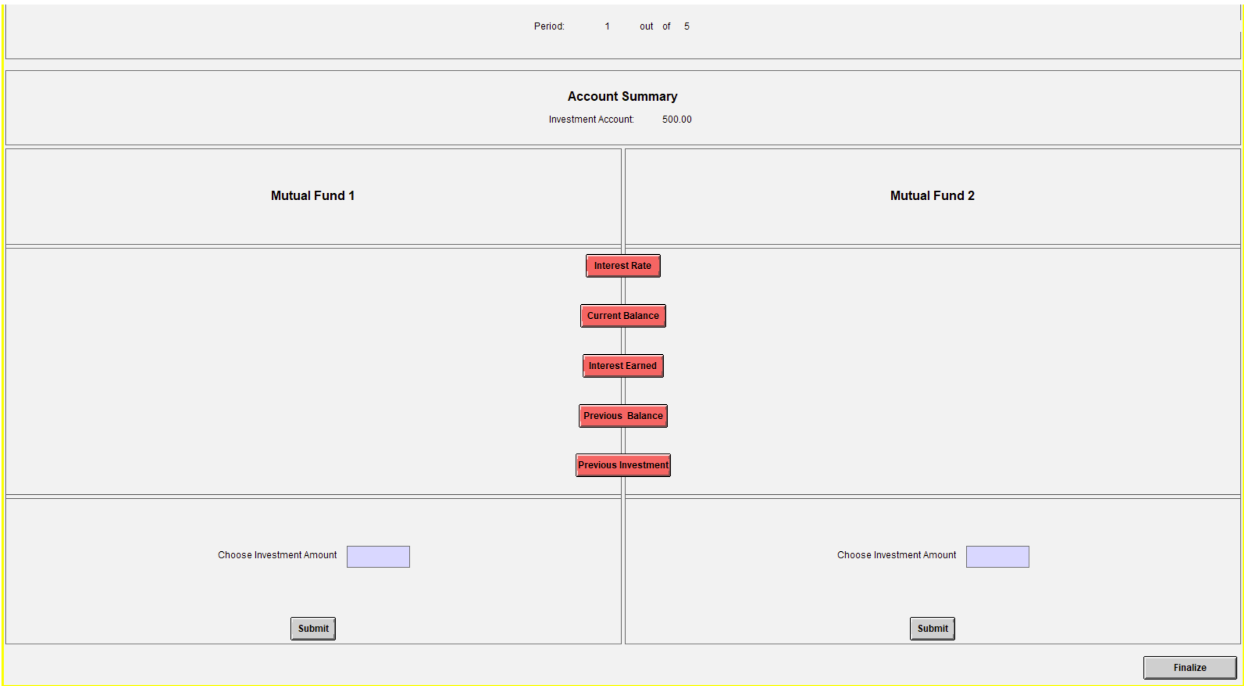


Figure D6: Experiment Interface for the treatment IN

Experiment Instructions for Debt Treatments

INSTRUCTIONS

Welcome

You are about to participate in a decision making experiment. In this experiment, you have the ability to earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The amount of money you earn will depend partly on your decisions. Therefore, it is in your best interest that you read these instructions carefully in order to have a clear understanding of the rules of the experiment. If you need assistance, please raise your hand quietly. Someone will come and answer your question in private.

This experiment is going to be conducted through computer terminals. The information provided to you on your terminal is private and it belongs only to you. It is very important that you do not communicate with other participants for the duration of the experiment. All necessary decision making information will be provided to you through your terminal. Please turn off your cell phone now, and refrain from opening any other programs or browsers on your computer during the experiment.

Economics experiments have a strict policy against deception. The rules you are going to read next will be implemented just as they are written.

The experiment should take no more than 60 minutes.

Background

This is a financial decision making experiment. In this experiment, you will be assigned two credit card accounts and a checking account. The experiment will be divided into stages and periods where you will be asked to make payments toward these credit card accounts.

Experiment Roadmap

The main experiment contains 6 Independent Stages. Each stage consists of 5 payment periods. You will be presented with different credit cards in each stage.

Your Task

At the beginning of each period, you will receive a fixed amount of money, called a deposit, in your checking account. Your task in each period is to make credit card payment decisions, using the amount of money you have available in your checking account.

A Period

There will be multiple periods in the experiment. An experimental period starts when you receive your deposit, and ends when you finalize your payments to each card for that period.

Level of Debt

At the beginning of the first period, each credit card will be assigned a level of debt. From the second period onward, the level of debt will be determined by two factors: interest rates and your previous period's payment decisions for each card. To illustrate this point, consider the following example:

Suppose that you have two credit cards, Left and Right. Your Left Card has a 4% per period interest rate and you owe 2,000 on that card. Your Right Card has a 5% per period interest rate and you owe 1,000 on that card. After you determine your payments on each card, your *Total Credit Card Debt in the following period* will be calculated as

(1+ 4%) (2,000 - Payment to Left Card) + (1+5%) (1,000 - Payment to Right Card)

Your *End of Stage Total Credit Card Debt* will be calculated as above once you make your last payment decision in that stage.

Your Payment

You will have an initial endowment of 6,500 experimental currency units (ECUs) at the beginning of each stage. To determine a *Stage Payoff*, we will subtract your End of Stage Total Credit Card Debt from your initial endowment. Your stage payoff will then be converted into US Dollars at the rate of 25 ECUs=$1. Only one stage payoff will be randomly selected as your cash payment in the end. All stage payoffs have the same chance of being selected.

Thank you for your participation in this experiment.

Key Features Recap

Setting:	Two credit card accounts
Task:	Make payment decisions on both cards
Duration:	5 periods per stage, 6 stages
Time:	No strict time restriction (as long as total time < 60 mins)
Payoff:	The less the total debt you have at the end of each stage, the more money you will make from the experiment

We will explain how the to use the interface next, please wait for further instructions.

Experiment Instructions for Balance Reallocation Periods

Instructions for Balance Reallocation

In this part of the experiment, you will go through the remaining two stages. The first 5 periods of these stages will be exactly the same as before. However, there is going to be an additional, sixth, period at the end of each stage. We will call these additional periods *Balance Reallocation Periods*. During these periods you will not be assigned a deposit, nor be asked to make a payment decision. Instead, your task will be reallocating your total debt between two cards.

Your stage payoff will be calculated similar to previous stages. We will subtract your End of Stage Total Credit Card Debt from your initial endowment. In this part of the experiment, we change your initial endowment to be 7,390 ECUs. Consider the following example:

Suppose that at the beginning of a Balance Reallocation period, your Left Card has 4% interest rate and you owe 2,000 on that card. Your Right Card has 5% interest rate and you owe 1,000 on that card. After you determine your new debt level on each card, your *End of Stage Total Credit Card Deb*t will be calculated as

(1 + 4%)(New Debt Level on Left Card) + (1 + 5%) (New Debt Level on Right Card)

To determine a Stage Payoff, we will subtract your End of Stage Total Credit Card Debt from your initial endowment of 7,390 ECUs. Your stage payoff will then be converted into US Dollars at the rate of 25 ECUs=$1 as before. Remember that each stage is equally likely to be selected for your payment.

You will go through an explanation period before you start making your decisions.

This explanation period will not count for money.

What Has Changed?

- Each stage has an additional Balance Reallocation period as a 6th period
- Your task in those periods is to adjust your balance levels on each card
- Your initial endowment is 7,390 ECUs

Experiment Instructions
for Investment Treatments

INSTRUCTIONS

Welcome

You are about to participate in a decision making experiment. In this experiment, you have the ability to earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The amount of money you earn will partly depend on your decisions. Therefore, it is in your best interest that you read these instructions carefully in order to have a clear understanding of the rules of the experiment. If you need assistance, please raise your hand quietly. Someone will come and answer your question in private.

This experiment is going to be conducted through computer terminals. The information provided to you on your terminal is private and it belongs only to you. It is very important that you do not communicate with other participants for the duration of the experiment. All necessary decision making information will be provided to you through your terminal. Please turn off your cell phone now, and refrain from opening any other programs or browsers on your computer during the experiment.

Economics experiments have a strict policy against deception. The rules you are going to read next will be implemented just as they are written.

The experiment should take no more than 60 minutes.

Background

This is a financial decision making experiment. In this experiment, you will be assigned two mutual funds and an investment account. The experiment will be divided into stages and periods where you will be asked to make investment decisions toward these mutual funds.

Experiment Roadmap

The main experiment contains 6 Independent Stages. Each stage consists of 5 investment periods. You will be presented with different mutual funds in each stage.

Your Task

At the beginning of each stage, you will be given a loan to be repaid so that you have some amount of money to invest. At the beginning of each period, you will receive a fixed amount of money, called a deposit, in your investment account. Your task in each period is to make investment decisions, using the amount of money you have available in your investment account.

A Period

There will be multiple periods in the experiment. An experimental period starts when you receive your deposit, and ends when you finalize your investment decisions on each fund for that period.

Level of Investment

At the beginning of the first period, each mutual fund will be assigned a level of investment. From the second period onward, the level of investment will be determined by two factors: interest rates and your previous period's investment decisions on each fund. To illustrate this point, consider the following example:

Suppose that you have two mutual funds, Left and Right. Your Left Fund has a 4% per period interest rate and you own 2,000 in that fund. Your Right Fund has a 5% per period interest rate and you own 1,000 in that fund. After you determine your investment decisions on each fund, your *Total Investment in the following period* will be calculated as

(1+4%) (2,000 + Investment to Left Fund) + (1+5%) (1,000 + Investment to Right Fund)

Your *End of Stage Total Investment* will be calculated as above once you make your last investment decision in that stage.

Your Payment

To determine a *Stage Payoff*, we will subtract a loan repayment of 12,000 experimental currency units (ECUs) from your End of Stage Total Investment. Your stage payoff will then be converted into US Dollars at the rate of 25 ECUs=$1. Only one stage payoff will be randomly selected as your cash payment in the end. All stage payoffs have the same chance of being selected.

Thank you for your participation in this experiment.

Key Features Recap

Setting:	Two mutual funds
Task:	Make investment decisions on both funds
Duration:	5 periods per stage, 6 stages
Time:	No strict time restriction (as long as total time < 60 mins)
Payoff:	The higher the total investment you have at the end of each stage, the more money you will make from the experiment

We will explain how to use the interface next, please wait for further instructions.