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DEBT AVERSION EXPERIMENT: A REPLICATION WITH SOPHISTICATED PARTICIPANTS

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Debt aversion experiment: A replication with sophisticated participants[*]

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Abstract

We conduct a replication experiment, with sophisticated student participants, of the three main treatments of the debt aversion experiment by Martínez-Marquina and Shi (2024). While participants in our experiment have chosen return maximizing strategies much more frequently than those in Martínez-Marquina and Shi (2024), our findings partially corroborate their observations that participants burdened with debt tend to forego, at least initially, the "certain and maximum profit investment opportunity" in favor of prioritizing debt repayment.

Keyword: Replication, Debt Aversion, Portfolio Allocation

JEL Code: C91, D91, G51

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1 Introduction

Debt aversion is a person's attitude toward debt, characterized by, for example, a reluctance to borrow even for investments in human capital (Eckel et al., 2007). Several empirical studies have demonstrated how this attitude influences financial decisions. For instance, entrepreneurs who are debt-averse show less interest in COVID-19 support policies if these involve debt financing (Paaso et al., 2023). Similarly, debt-averse homeowners with limited access to capital are less likely to adopt retrofit measures compared to their non-debt-averse counterparts who also have poor access to capital (Schleich et al., 2021). Moreover, debt-averse students often hesitate to take out loans to finance their college education (See, e.g. Boatman et al., 2017; Callender and Mason, 2017; Callender and Jackson, 2005). These findings suggest that debt aversion can lead to suboptimal financial decisions by causing individuals to forgo profitable investment opportunities.

Recently, Martínez-Marquina and Shi (2024, MMS2024 in below) showed, via their experiments conducted on Amazon Mechanical Turks (MTurks), that participants have a preference for prioritizing debt repayment over choosing the risk-free profit-maximizing investment opportunity. While some experimental studies provide evidence of debt aversion influencing consumption decisions,[1] prior to MMS2024, no research focused on its effects on portfolio allocation decisions. While their main result, i.e., one-third of their participants ignore risk-free high returns and focus on repaying the debt, is intriguing, there are some concerns. Namely, the experiments have been conducted on MTurks together with the obser-

[1]For example, Meissner (2016), Ahrens et al. (2022), and Duffy and Orland (2023) have observed debt-averse behavior in borrowing decisions, where individuals hesitate to borrow even when it would be beneficial to increase consumption.

vations in their baseline treatment without the debt that, on average, less than 75% of the funds were initially allocated to the risk-free maximum-return account, and less than 40% of the participants made such a risk-free return maximizing choices in all the decisions, makes us question how much of this finding can be replicated in other populations.

The literature suggests that while the point estimates vary, the comparative static results, such as the comparison of behavior between the treatments with and without debt, tend to be robust regardless of the participant pools (see, e.g, Snowberg and Yariv, 2021; Hanaki et al., 2024). Yet, the magnitude of the effect of debt aversion reported in MMS2024 should be evaluated in various populations to have a better understanding of its economic consequences. In this paper, therefore, we conduct a replication experiment of the three main treatments of MMS2024 with students from a highly selective university in Japan.

The participants in our experiment have significantly higher cognitive ability and are significantly more prudent and less loss averse compared to the Japanese adult population (Hanaki et al., 2024). Their cognitive abilities are as high as, although their score on the financial literacy test is significantly lower than, certified financial professionals (Bao et al., 2024). And, participants in our experiment misperceive the risk associated with a complex financial product which financial professionals do not (Hanaki, 2021). These characteristics of our participants provide a good test of the robustness of the results of MMS2024 when the experiment is conducted with sophisticated participants.[2]

[2]Numerous studies have investigated the relationship between behavioral biases and the cognitive abilities of participants. For example, Frederick (2005), Burks et al. (2005), Oechssler et al. (2009), and Benjamin et al. (2013) report that individuals with higher Cognitive Reflection Test (CRT) scores tend to make more rational choices, exhibit less risk aversion, show less loss aversion, and demonstrate greater patience.

In the experiment, participants are required to allocate experimental currency –points– to several virtual accounts with different interest rates and balances. This allocation occurs four times over a week, and the virtual accounts generate returns over time. The points available for allocation in each decision depend on the accounts' balances and interests they generate. The payoff of participants depends on the sum of the final balance and the interest earned at the end of the experiment. To maximize the payoff, therefore, participants should always allocate all experimental currency to the account with the highest interest rate.

The experiment includes three treatments, with the initial balances being the only difference among them. In the first treatment, referred to as "No Debt," participants can allocate points only to accounts that start with positive balances, providing a baseline for the fraction of participants who follow the return-maximizing strategy in the absence of debt. In the second and third treatments, labeled "Low Debt" and "High Debt" respectively, two of the accounts start with a negative balance: in the "Low Debt" treatment, it is possible for participants to fully repay the debts, while in the "High Debt" treatment, full repayment is not possible. Since the interest rates for each account remain constant across these three treatments, the return-maximizing action remains the same regardless of the presence of debt.

The findings of MMS2024 from these three treatments can be summarized as follows:

- In the first allocation, on average, 73% of the fund is allocated to the account with the highest interest rate in the No Debt treatment, while it is 47% in the Low Debt treatment.

- Instead, in the Low Debt treatment, 32% of the initial allocations are used to repay the debt with the highest interest rate (although doing so would lower the return compared to allocating the same amount to the account with the highest interest rate).

- While 38% of their participants consistently allocated all the funds to the account with the highest interest rate across four decisions in the No Debt treatment, it is only 13% who did so in the Low Debt treatment.
- These differences between No Debt and Low Debt are due to many participants in Low Debt treatment trying to repay the debt fully before maximizing the returns. Indeed, 38% of participants in Low Debt treatment fully repaid at least one debt, and 20% repaid all.
- There are heterogeneous responses when debt cannot be fully repaid in High Debt treatment. Namely, while fewer participants try to repay the debt in High Debt treatment compared to Low Debt treatment, there remain those trying to do so with larger financial losses.

While a much higher proportion of our participants maximized return, our data partially replicated the findings of MMS2024. Namely, in Low Debt treatment, initially, participants allocate significantly less to the account with the highest interest rate compared to No Debt treatment. On average, while 90% of initial allocation in the No Debt treatment was in the account with the highest return, it was 69% in the Low Debt treatment. Instead, 26% of the initial allocation in Low Debt treatment was to repay the debt with a higher interest rate. However, other results summarized above are not replicated. Although our data indicate, just as in MMS2024, that the proportion of participants who maximize returns in all decisions is lower in Low Debt treatment (57%) than in No Debt treatment (70%), this difference is not statistically significant. Additionally, we do not observe heterogeneous responses in High Debt treatment. The proportion of participants who maximize the return in all the treatments is not significantly different between High- and Low Debt treatments. In our experiment, there was no participant fully repaying any of the debt in the High Debt treatment. Finally, we observe that regardless of the size of the debt, there is a clearer tendency to prioritize repaying the high-interest debt account in MMS2024 compared to our study.

The rest of the paper is organized as follows: Section 2 describes the experimental design, Section 3 provides an analysis of the data, and Section 4 offers some conclusions.

2 Experimental design

Our experiment replicates the main experimental setup of MMS2024.

2.1 Basic Setting

In the experiment, participants manage several virtual accounts characterized by varying interest rates and balances, which yield returns over time. The balances fluctuate based on the participants' allocation decisions, while the interest rates are held constant throughout the experiment. Accounts with positive balances accrue positive returns, whereas those with negative balances incur negative returns. Accounts that start with positive balances are labeled as *Savings accounts*, and those beginning with non-positive balances are termed *Debt accounts*.

Specifically, each participant owns six accounts with different interest rates:

four of them are allocatable accounts and two of them are locked accounts. Participants allocate points—the experimental currency—to the allocatable accounts four times over the course of a week. The timeline is structured as follows: participants are initially assigned virtual accounts and receive an initial endowment of 500 points. All these points must be allocated to their allocatable accounts. Two days after the first allocation decision, participants receive returns generated from their accounts and must allocate these points to their accounts once again. This process continues for one week, culminating in a total of four allocation decisions.

Participants are paid based on the sum of total balances and the returns after the final allocation. To maximize the payoff, participants should allocate all points to the account with the highest interest rate, regardless of the distribution of balances, including the presence of accounts with negative balances.

2.2 Treatments

There are three treatments with varying initial balances across six accounts: *No Debt*, *Low Debt*, and *High Debt*. They are summarized in Table 1. In the table, allocatable accounts are shown in black and locked accounts are shown in gray.

No Debt Treatment This serves as the baseline for analyzing return-maximizing behavior. In this treatment, all the allocatable accounts are Savings accounts. Panel (a) of Table 1 provides detailed information about each account's interest rate and balance. Account Savings 1 has the highest interest rate among the four accounts, suggesting the return maximizing allocation strategy would be to direct all the points to this account. Accounts Debt 1 and Debt 2 are locked accounts with a zero balance and do not generate any returns. This setup controls for the

Table 1: Initial balance of three treatments

(a) **No Debt**

	Savings 1	**Savings 2**	**Debt 1**	**Debt 2**	**Savings 3**	**Savings 4**
Interest Rate	20%	10%	15%	5%	15%	5%
Balance	1100	700	0	0	900	1500

(b) **Low Debt**

	Savings 1	**Savings 2**	**Debt 1**	**Debt 2**	**Savings 3**	**Savings 4**
Interest Rate	20%	10%	15%	5%	15%	5%
Balance	1100	700	-900	-1500	1800	3000

(c) **High Debt**

	Savings 1	**Savings 2**	**Debt 1**	**Debt 2**	**Savings 3**	**Savings 4**
Interest Rate	20%	10%	15%	5%	15%	5%
Balance	1100	700	-2900	-3500	3800	5000

potential influence of the existence of the term "debt" on participants' allocation decisions.

Low Debt and High Debt treatments Two of the four unlocked accounts have negative initial balances and generate negative returns before subsequent allocations. Panels (b) and (c) of Table 1 provides detailed information about each account's interest rate and balance for these treatments. Unlike in the *No Debt* treatment, participants can allocate points to Debt 1 and Debt 2. However, Savings 3 and Savings 4, which have similar interest rates, are locked to maintain the same number of investment opportunities. Moreover, the initial balances are such that the sum of the balances of Savings 3 and Debt 1, both sharing the same interest rate of 15%, is equal to 900 in all three treatments. The same adjustment is applied between Savings 4 and Debt 2, their interest are both 5% and the sum of the initial balances are 1500 in all three treatments. Thus, despite the presence of negative balances in the two treatments with debt, the return-maximizing strategy is the same as in the No Debt treatment, and participants can earn the same final payoff if they follow the same allocation strategy in the three treatments.

Note that, on the one hand, in the Low Debt treatment, participants can accrue sufficient points during the experiment to completely repay both outstanding debt balances. Namely, participants can fully repay both Debt 1 and Debt 2 within three allocation rounds. In the High Debt treatment, on the other hand, full repayment of debt is not possible. Thus, the comparison of participants' behavior in these two treatments allows us to investigate the impact of repayability of debt.

2.3 Initial Survey, Additional Questions, and One-shot allocation

During the experiment, participants are asked additional questions designed to control and elicit their risk preferences and time preferences. Immediately following the fourth (final) allocation decision, participants engage in a separate brief experiment consisting of a one-shot allocation. This brief experiment aims to test the robustness of the results using a within-participant design. By answering these questions and participating in the short experiment, participants have the opportunity to earn additional points or money. While these additional inquiries and the short experiment may influence the participants' payments, they do not affect the implications of the main experiment, as they do not alter the payoff-maximizing behavior.

Initial Survey To mitigate withdrawal rates and control for baseline risk and time preferences, participants are required to complete an initial survey before

Table 2: Initial Survey on Time and Risk Preferences

Question	**Option A**		**Option B**
Initial Risk	50% chance: 100 yen within 24 hours	vs.	Receive X yen within 24 hours
Initial Time	Next Wednesday: 100 yen	vs.	Receive X yen within 24 hours

participating in the first allocation decision. This survey ensures participation by verifying that participants regularly check their emails, which is necessary for accessing links to subsequent allocation decisions. The initial survey employs the Becker-DeGroot-Marschak (Becker et al., 1964, BDM for short) mechanism, as outlined by Healy (2020), to elicit initial risk and time preferences. Each survey item presents a price list offering two options. To assess risk preferences, participants choose between a guaranteed monetary amount or a 50 percent chance of winning 100 Japanese Yen (yen) within 24 hours. For time preferences, the choice is between receiving JPY today or 100 yen next week (details provided in Table 2). Each set of price lists consists of 85 variations of these scenarios, with the guaranteed amounts, X, ranging from 15 to 100 yen in a step of 1 yen. It is important to highlight that, in contrast to the initial survey conducted by MMS2024, which comprised 100 questions ($X \in \{1, 2, .., 99, 100\}$), our survey includes only 85 questions ($X \in \{15, 16, .., 99, 100\}$). This modification was necessary due to the way we paid participants.[3]

When responding to these questions, participants are required to identify the point on the list where their preference switches from one option to the other. Based on the chosen switching point, responses to all subsequent questions are inferred. One question from the list is then randomly selected and implemented.

[3]Namely, participants are paid with Amazon Gift Cards (email type) and 15 yen was the minimum amount that could be issued.

Table 3: Additional Questions on Time and Risk Preferences

Question	**Option A**		**Option B**
Risk (Points vs. Points)	50% chance: 500 points	vs.	100% chance: X points
Risk (Points vs. Money)	50% chance: 500 points	vs.	Receive X yen today
Time (Points vs. Points)	The next allocation: 500 points	vs.	The current allocation: X points
Time (Points vs. Money)	The next allocation: 500 points	vs.	Receive X yen today

Note: Except for "The next allocation: 500 points", participants must allocate the points received from the additional questions to their accounts in the same decision day.

Additional Questions In addition to the Initial Survey, participants are required to answer another series of questions on risk and time preferences after the initial allocation decisions in each decision day. These questions are designed not only to elicit each participant's risk and time preferences but also to test whether bearing debt alters their allocation behavior. By responding to these questions, participants have the opportunity to earn additional points or money. Utilizing the same BDM mechanism as in the initial survey, participants are asked four risk and time trade-off questions —- two for risk preferences and two for time preferences (see details in Table 3). These questions are presented in random order within the risk or time blocks. From these four lists, one question is randomly selected and implemented. After completing these additional questions, participants can once again allocate their earned points across their four available accounts. To ensure that all participants have additional points to allocate, everyone receives 100 additional points regardless of the implemented question.

One-shot allocation Immediately after the final allocation decision, participants face three one-shot scenarios to check the robustness of the week-long results. Each one-shot scenario corresponds to either No Debt, Low Debt, or High Debt

Table 4: The initial balances of One-shot allocation

(a) One-shot No Debt account

	Savings 1	**Savings 2**	**Savings 3**	**Savings 4**
Interest Rate	20%	10%	15%	5%
Balance	200	100	300	200

(b) One-shot Low Debt account

	Savings 1	**Savings 2**	**Debt 1**	**Debt 2**
Interest Rate	20%	10%	15%	5%
Balance	1000	1200	-600	-800

(c) One-shot High Debt account

	Savings 1	**Savings 2**	**Debt 1**	**Debt 2**
Interest Rate	20%	10%	15%	5%
Balance	2000	2400	-1700	-1900

accounts, but there are no locked accounts, and all decisions are made consecutively. The initial balances of each account in each scenario are shown in Table 4. The initial balances are the same (800 points), but their net returns differ. Additionally, the One-shot Low Debt scenario allows for full repayment in at least one debt account, whereas the One-shot High Debt scenario does not allow for full repayment in any debt accounts. In all these scenarios, participants must allocate 1000 points among the four available accounts. Scenarios are presented in a random order. After completing all the one-shot allocations, one of the scenarios is randomly selected for payment; participants are paid according to the total balance and returns in the chosen scenario. As in the week-long experiment, the payoff-maximizing behavior is to allocate all points to the account with the highest interest rate (20 percent).

Table 5: Summary of Experimental Procedure

	Day 1	**Day 2**	**Day 3**	**Day 4**
Part 0	Initial Survey	–	–	–
Part 1	Allocation Decision	Allocation Decision	Allocation Decision	Allocation Decision
Part 2	Risk and Time Elicitation	Risk and Time Elicitation	Risk and Time Elicitation	Risk and Time Elicitation*
Part 3	Additional Allocation Decision	Additional Allocation Decision	Additional Allocation Decision	Additional Allocation Decision
Part 4	-	–	–	One-shot
Part 5	-	–	–	End Survey

*Only Risk Question #1

2.4 Experimental procedures

A total of 153 undergraduate students from Osaka University were recruited through ORSEE (Greiner, 2015) for this experiment, and 134 of them completed the entire study.[4] Participants were required to complete an online survey for a week-long study. To prevent dropouts, reminders were sent every 6 hours (at 12 a.m., 6 a.m., 12 p.m., and 6 p.m.) on the days of allocation decisions. Only participants who completed the initial survey were assigned to one of the three treatments in the main experiment.[5] As a result, each treatment included 42 to 47 participants (47 in the No Debt, 42 in the Low Debt, and 45 in the High Debt) who completed the experiment.

Our experiment was programmed in oTree (Chen et al., 2016) and conducted from October 11-18 and November 15-22, 2023. The daily schedule of the ex-

[4]The sample size is determined by a power analysis with a significance level of 5% and statistical power of 80%, calculated from the No Debt and Low Debt treatment shown in Figure 2 of MMS2024. Additionally, there were no statistically significant differences in completion rates among treatments ($p = 0.572$) based on F-test based on the linear regression.

[5]The eligibility criteria for participating differ from those in MMS2024, who required participants to respond to a follow-up email from the initial survey.

periment is reported in Table 5. At the beginning of each allocation day in the main experiment, participants were required to read the instructions and complete a quiz to ensure they understood and remembered the experiment rules. Since all treatments involved allocating points, the instructions and the quiz were identical across all treatments. The quiz was based on several examples, and participants could not proceed to the main decisions unless they answered all quiz correctly. After completing all decisions on the final day, participants were required to fill out a series of demographic and feedback questions, identical to those used by MMS2024. On average, participants took approximately 1 hour and 20 minutes to complete all parts of the experiment across one week.

Each participant's final payment includes a show-up fee of 500 Japanese Yen and a bonus based on their performance and luck. All points earned during the experiment are converted to Yen at a rate of 500 points to 100 Yen.[6] These points include the total final balance and the return generated from it in the main experiment, as well as in the one-shot experiment. The median payments to participants were 3061 JPY in the No Debt, 3044 JPY in the Low Debt, and 3084 JPY in the High Debt.

Table 6 shows the descriptive statistics of our participants in three treatments. Compared to MMS2024, our sample comprised undergraduate and graduate students, who are generally younger. Additionally, the majority of our participants identified as Asian in terms of ethnicity. Moreover, our sample included a few participants with experience holding debt or student loans. Finally, our participants

[6] 100 Yen $\approx$ 0.67 USD based on the exchange rate at the time of the experiment. MMS2024 used 500 points = 1 USD exchange rate together with 10 USD participation fee. In terms of purchasing power parity, 1 USD is about 95 Yen; thus, participants in our experiment are rewarded at a similar rate as those in MMS2024.

Table 6: Sample characteristics in three treatments

	No Debt Mean	Low Debt Mean	High Debt Mean	P-Value
Age	23	22.8	22.2	0.38
Male	0.64	0.60	0.62	0.92
Asian	0.96	0.95	1	0.35
Undergraduate student	0.43	0.52	0.67	0.07
Hold Student Loan	0.21	0.07	0.18	0.17
Hold Debt	0.19	0.17	0.18	0.96
Impact Covid	3.30	3.24	3.09	0.56
Initial Risk	0.53	0.49	0.52	0.66
Initial Time	0.97	0.93	0.91	0.46
Duration (hours)	2.72	1.91	2.48	0.57
Median Duration (hours)	1.33	1.45	1.33	0.37
Observations	47	42	45	

*Notes:*This table shows the results from a balance test between our treatments. We report the p-values of an F-test of equivalence of the three treatment means. Additionally, we use Kruskal-Wallis test for computing the p-value of Median Duration (hours).

exhibited risk-neutral behavior, small time-discounting behavior, and completed the experiment faster than those in MMS2024. The samples' characteristics are balanced across the treatments.

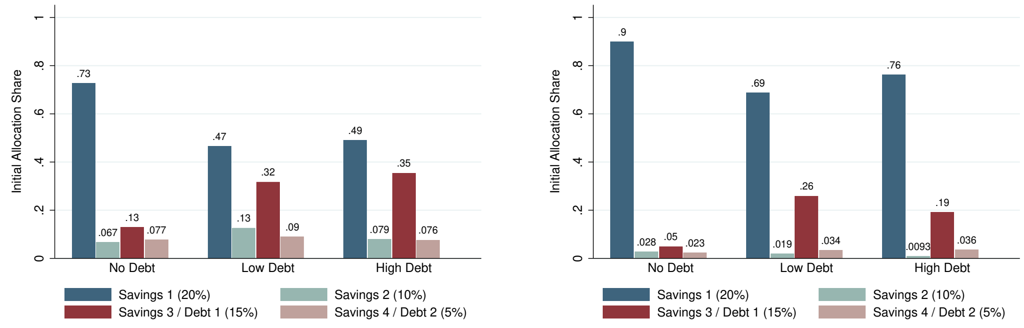
3 Results

We first compare the initial allocation across four allocatable accounts in three treatments. We then compare the frequency of participants following the return-maximizing strategy in all the decisions.

3.1 Initial allocation

Figure 1 shows the average share of initial allocation in each of the four allocatable accounts in No Debt (left most), Low Debt (middle), and High Debt (right

Figure 1: The average initial allocation share



(a) MMS2024

(b) This study

most) treatment. Panel (a) shows the result of MMS2024 and Panel (b) shows the result of the current study. The average, the standard error, as well as p-values for comparison between allocations in each account observed in No Debt and others with debt, and p-values for comparison between the two studies, are summarized in Table 7. Figure 1 and Table 7 are created based on the linear regression, without individual controls, reported in Table B1 in Appendix B.[7]

The following observations can be made about the result of the current study.

- Initial allocation to the account with the highest return (Savings 1) is significantly higher ($p = 0.003$ in Low Debt, $p = 0.033$ in High Debt) in No debt treatment (90%) compared to two treatments with debt (69% and 76% in Low- and High Debt treatment, respectively) replicating the result of MMS2024.
- The difference in the allocations to Savings 1 between No debt and two treatments with debt can be explained by the significant difference($p =$

[7]The results of treatment comparisons are robust against the inclusion of individual controls. See Table B2 in Appendix B.

Table 7: Summary statistics and p-values for various comparisons associated with Figure 1.

	Account	MMS2024					This study					p-value++
		Mean	SE	p-value+		n	Mean	SE	p-value+		n	
No Debt	Saving1(20%)	0.73	0.031	-	-	86	0.90	0.029	-	-	47	0.000
	Saving2(10%)	0.07	0.010	-	-	86	0.03	0.009	-	-	47	0.006
	Saving3(15%)	0.13	0.016	-	-	86	0.05	0.015	-	-	47	0.000
	Saving4(5%)	0.08	0.016	-	-	86	0.02	0.008	-	-	47	0.003
Low Debt	Saving1(20%)	0.47	0.035	0.000	-	86	0.69	0.065	0.004	-	42	0.003
	Saving2(10%)	0.13	0.017	0.003	-	86	0.02	0.010	0.491	-	42	0.000
	Debt1(15%)	0.32	0.034	0.000	-	86	0.26	0.062	0.001	-	42	0.407
	Debt2(5%)	0.09	0.012	0.513	-	86	0.03	0.013	0.477	-	42	0.002
High Debt	Saving1(20%)	0.49	0.044	0.000	0.663	86	0.76	0.057	0.034	0.389	45	0.000
	Saving2(10%)	0.08	0.017	0.537	0.046	86	0.01	0.005	0.076	0.382	45	0.000
	Debt1(15%)	0.35	0.042	0.000	0.499	86	0.19	0.049	0.005	0.397	45	0.013
	Debt2(5%)	0.08	0.016	0.980	0.494	86	0.04	0.015	0.450	0.932	45	0.068

Notes: + The first column shows the comparison with results in No Debt of the same account type, while the second column shows the comparison with results in Low Debt for High Debt. ++ Comparing two studies. P-values are computed using F test based on the linear regression without individual controls reported in Table B1 in Appendix B.

0.001 in Low Debt, $p = 0.005$ in High Debt) in the allocations to Savings 3 (5% in No debt) and Debt 1 (26% and 19% in Low Debt and High Debt, respectively) as in MMS2024.

- The allocation to Savings 1 is significantly higher($p < 0.001$ in No Debt,$p = 0.003$ in Low Debt, $p < 0.001$ in High Debt) in all the treatments in the current study compared to MMS2024 (90% vs.73%, 69% vs.47%, and 76% vs.49% in No Debt, Low Debt, and High Debt treatment respectively). The initial allocations to the accounts other than Savings 1 and Debt 1 are all no greater than 5% in the current study.

Thus, our study replicates the significantly lower initial allocations in the account with the highest interest rate in the presence of debt observed in MMS2024. This is, as in MMS2024, due to participants initially allocating more points to repay the debt. Overall, however, participants in our study were more likely to follow the return-maximizing strategies from the beginning compared to those in MMS2024.

3.2 Return maximizing behavior

Figure 2 displays the percentage of participants who maximize returns in all decisions in three treatments, No debt (left most), Low debt (middle), and High debt (right most). Panels (a) and (b) show the results of MMS2024 and the current study, respectively. The average, the standard error, and the p-values for treatment comparisons, as well as for comparison between the two studies, are reported in Panel (c). This figure is created based on the linear regression reported in Table C1 in Appendix C.

Our observations can be summarized as follows:

- Fractions of participants who allocate exclusively to Savings 1 in all the decisions are significantly higher($p < 0.001$ in No Debt,$p < 0.001$ in Low Debt,$p = 0.002$ in High Debt)) in the current study than MMS2024 (70% vs. 38% in No debt, 57% vs. 13% in Low debt, and 53 vs. 26% in High debt treatment).

- While the fraction of participants who allocate exclusively to Savings 1 is higher in No debt than in two treatments with debt, these fractions are not significantly different across three($p = 0.202$ in No debt vs Low Debt, $p = 0.094$ in No debt vs High Debt) treatments in the current study.

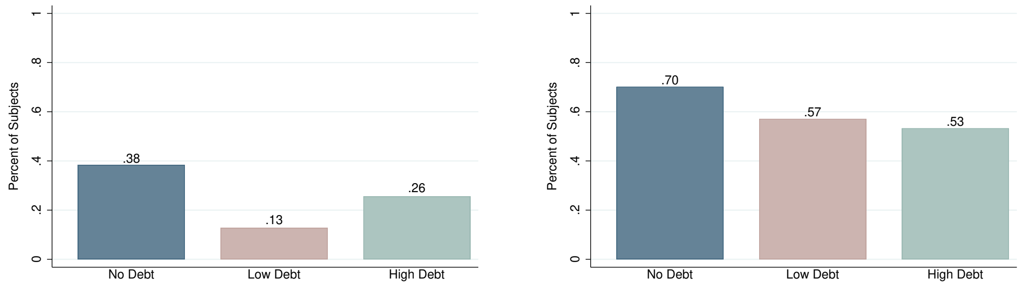
Thus, we fail to replicate the significant difference in the fraction of participants who consistently follow the return maximizing strategy between No Debt and Low Debt observed in MMS2024.

3.3 Prioritizing the debt repayment and heterogeneous response

Figure 3 shows the distribution of the total points allocated to the with 15% (Savings 3/Debt 1, Panels (a) and (b)) and 5% (Savings 4/Debt 2, Panels (c) and (d)) interest rates, respectively, as a share of the initial amount of debt in the three treatments. Panels (a) and (c) show the results of MMS2024, and panels (b) and (d) show the results of the current study. Panel (e) summarizes them in a table. Several observations can be made.

- The fractions of the participants who have allocated 0 points to the Savings 3/Debt 1 and Savings 4/Debt 2 are significantly higher ($p < 0.001$ in Saving

Figure 2: Percent of participants that Maximize Returns in All Decisions



(a) MMS2024

(b) This study

(c) Summary statistics and p-values for various comparisons.

	MMS2024					This study					p-value^{++}
	Mean	SE	p-value^{+}		n	Mean	SE	p-value^{+}		n	
No Debt	0.38	0.053	–	–	86	0.70	0.067	–	–	47	0.000
Low Debt	0.13	0.036	0.000	–	86	0.57	0.077	0.202	–	42	0.000
High Debt	0.26	0.047	0.072	0.033	86	0.53	0.075	0.094	0.723	45	0.002

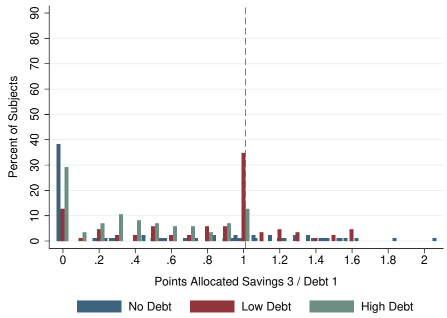
Notes: $+$ The first column shows the comparison with results in No Debt of the same account type, while the second column shows the comparison with results in Low Debt for High Debt. $++$ Comparing two studies. P-values are computed using F test based on the linear regression without individual controls reported in Appendix C1.

3/Debt 1, $p < 0.001$ in Saving 4/Debt 2) in our study than in MMS2024 in all the treatments.

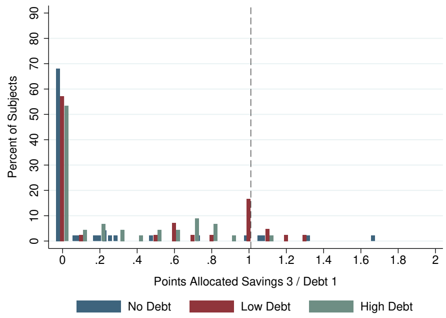
- For Savings 3/Debt 1, they are 68%, 57%, and 51% for No Debt, Low Debt, and High Debt treatments in our study, while they are 38%, 13%, and 27% for MMS2024, respectively.
- For the Savings 4/Debt, they are 77%, 79%, and 78% for our data, while they are 51%, 28%, and 57% for MMS2024.

• There is no significant difference across treatments in the fraction of those allocated 0 points in Saving 3/Debt 1 ($p = 0.235$) nor Saving 4/Debt 2

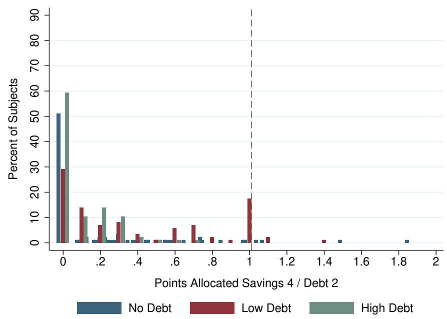
Figure 3: The distribution of the total points allocated to the with 15% (top) and 5% (bottom) interest rates as a share of the initial amount of debt in the three treatments



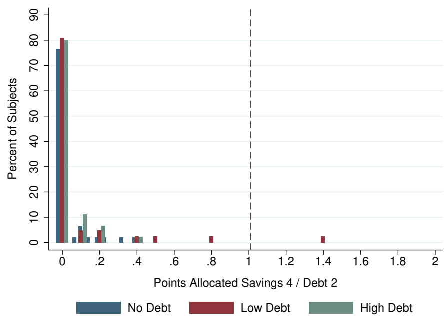
(a) MMS2024



(b) This study



(c) MMS2024



(d) This study

Notes:Vertical dashed lines indicate 100% of the repayment.

(e) Percentage of participants with various allocated amounts (as a share of initial amount of saving/debt)

	MMS2024				This study			
	$X = 0$	$0 < X < 1$	$X = 1$	$1 < X$	$X = 0$	$0 < X < 1$	$X = 1$	$1 < X$
No Debt								
Saving 3/ Debt 1	38%	35%	0%	27%	68%	23%	2%	6%
Saving 4/ Debt 2	51%	45%	0%	3%	77%	23%	0%	0%
Low Debt								
Saving 3/ Debt 1	13%	34%	34%	20%	57%	17%	17%	10%
Saving 4/ Debt 2	28%	51%	17%	3%	79%	19%	0%	2%
High Debt								
Saving 3/ Debt 1	27%	63%	10%	0%	51%	47%	0%	2%
Saving 4/ Debt 2	57%	43%	0%	0%	78%	22%	0%	0%

Notes: X = total point allocated / initial amount of saving or debt (900 in case of No Debt and Low Debt, 2900 in case of High Debt on Saving 3/Debt 1. 1500 in case of No Debt and Low Debt, 3500 in case of High Debt on Saving 4/Debt 2).

($p = 0.975$) in our study. In MMS2024, on the contrary, these fractions were significantly lower ($p < 0.001$ in Saving 3/Debt 1, $p < 0.001$ in Saving 4/Debt 2) in Low Debt treatment compared to the other two.[8]

- The fractions of participants who fully repay the initial debt, for both Debt 1 and 2, are significantly lower ($p = 0.001$ in Debt 1, $p < 0.001$ in Debt 2) in our studies than in MMS2024.
  - For Debt 1, they are 17% (vs 34% in MMS2024) and 0% (vs 10% in MMS2024) in Low Debt and High Debt treatment, respectively
  - For Debt 2, they are both 0% (vs 17% and 0% in MMS2014) in Low Debt and High Debt treatment.
- Participants in our study who tried to fully repay the debt in Low Debt treatment, only did so for the one with a higher interest rate.

Thus, unlike MMS2024, where some participants tried to repay the debt fully even in High Debt treatment, none of the participants in our study did not do so. Thus, we do not observe the heterogeneous responses in High Debt treatment reported by MMS2024.

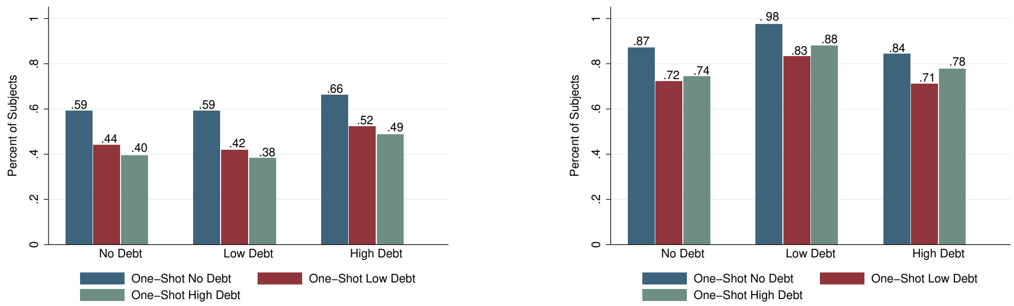
3.4 Robustness Analysis Through One-Shot Scenarios

We analyze the data from the three one-shot scenarios encountered by participants after the final allocation decision. This analysis aims to address the following two questions: 1) whether the data replicate the findings from the one-shot scenarios

[8] p-values are based on the Fisher exact test.

]

Figure 4: Percentage of Participants Who Maximize Returns in One-Shot Scenarios



(a) MMS2024

(b) This study

reported by MMS2024, and 2) whether the data are consistent with the results of our main experiment.

Figure 4 displays the percentage of participants who maximize returns in each one-shot scenario. Panel (a) shows the results of MMS2024, Panel (b) shows those of the current study. Table 8 provides the summary statistics and p-values for various treatment comparisons. The figure and table are generated based on the linear regression reported in Table D1 in Appendix D.

Let us first summarize the results of MMS. There is a significant difference between One-shot No Debt and One-shot Low Debt, irrespective of the treatment experienced by participants in the main experiment. Specifically, the fractions of participants who maximized returns in One-shot No Debt and One-shot Low Debt treatments are 59% vs 44% ($p = 0.047$) in No Debt, 59% vs 42 % ($p = 0.021$) in Low Debt, and 66% vs 52% ($p = 0.062$) in High Debt treatment, respectively.[9] However, no statistically significant difference was observed between One-shot

[9] p-values are based on F-test comparison of the estimated coefficients of the treatment dummies in the linear regression. See the notes of Panel (c) of Figure 4.

Table 8: Summary statistics and p-values for various comparisons on one-shot treatments

		MMS2024					This study					p-value^{++}
	One-shot	Mean	SE	p-value^{+}		n	Mean	SE	p-value^{+}		n	
No Debt	No Debt	0.59	0.053	-	-	86	0.87	0.049	-	-	47	0.000
	Low Debt	0.44	0.054	0.047	-	86	0.72	0.066	0.070	-	47	0.001
	High Debt	0.40	0.053	0.009	0.539	86	0.74	0.064	0.114	0.817	47	0.000
Low Debt	No Debt	0.59	0.053	-	-	86	0.97	0.024	-	-	42	0.000
	Low Debt	0.42	0.054	0.021	-	86	0.83	0.058	0.023	-	42	0.000
	High Debt	0.38	0.053	0.005	0.643	86	0.88	0.050	0.087	0.535	42	0.000
High Debt	No Debt	0.66	0.051	-	-	86	0.84	0.054	-	-	45	0.015
	Low Debt	0.52	0.054	0.062	-	86	0.71	0.068	0.126	-	45	0.031
	High Debt	0.49	0.054	0.020	0.650	86	0.78	0.062	0.421	0.471	45	0.001

Notes: + The first column shows the comparison with results in One-shot No Debt of the same One-shot account type, while the second column shows the comparison with results in One-shot Low Debt for One-shot High Debt. ++ Comparing two studies. P-values are computed using F test based on the linear regression reported in Table D1 in Appendix D

Low Debt and One-shot High Debt ($p = 0.539$ in No Debt, $p = 0.643$ in Low Debt, $p = 0.650$ in High Debt), regardless of the treatment experienced by participants in the main experiment. In addition, the fraction of participants who maximized the return in each of the one-shot treatments is not significantly different across the three main treatments these participants experienced ($p = 0.550$ in One-shot No Debt, $p = 0.356$ in One-shot Low Debt,$p = 0.322$ in One-shot High Debt).[10]

While the former results align with the findings of the main experiment, suggesting that participants with debt are less likely to allocate points to the accounts that would maximize their financial benefits, the latter observations are inconsistent with the results of the main experiment and do not replicate the heterogeneous effects.

We replicate both results of MMS2024. Namely, the fraction of participants who maximize returns in the One-shot No Debt treatment is 13% to 15% percentage points higher than the One-shot Low Debt (and One-shot High Debt) treatment. Although the difference is significant at 5% level only for Low Debt treatment ($p = 0.023$) and not for No Debt and High Debt treatments ($p = 0.070$ and $p = 0.126$, respectively). See Panel (c) of Figure 4.

Furthermore, there is no significant difference ($p = 0.299$ in One-shot Low Debt, $p = 0.195$ in One-shot High Debt) in the magnitude of difference One-Shot treatment with debt across the treatments participants have experienced as the main part of the experiment. The difference across the treatments is significant at the 5% level only for One-shot No Debt ($p = 0.026$).[11] Finally, as in the

[10] p-values are based on F-test comparison of the estimated coefficients of the treatment dummies in the linear regression.

[11] p-values are based on the F tests comparing the estimated coefficients of treatment dummies

main experiment, a significantly higher fraction of participants in our study made return-maximizing choices in one-shot scenarios than those in MMS2024.

3.5 Estimation of Debt Aversion

We also estimate how much agents overweight debt using the MMS2024 model, which is based on the experimental design (see Appendix E.1 for the detail).

According to the MMS2024 estimation, about 47% of the participants did not overweight debt, while 24% of the subjects overweighted debt by at least 4% or 14%. Moreover, on average, participants in the Low Debt treatment trade off \$1 of debt for \$1.035 in savings.

Our estimation results, are weaker compared to the debt attitude shown by MMS2024. In this study, about 60% of participants did not overweight debt, and only about 10% of participants overweighted debt by at least 4% or 14%. On average, in the Low Debt treatment, participants trade off \$1 of debt for \$1.016 in savings. See Appendix E.2 for the detailed results.

4 Conclusions and Discussion

In this paper, we conducted an online experiment using Japanese participants, which aims to replicate the findings of MMS2024, who provide evidence of the existence of debt aversion and its negative implications for financial decisions.

The data partially replicated the findings of MMS2024: there are more points used to repay the debt instead of maximizing the returns when participants hold debt, showing debt-biased decisions. However, although our data show a lower

in a linear regression.

percentage of participants maximizing returns when holding debt compared to when not holding debt in the main experiment, these differences are not statistically significant over the entire week, inconsistent with the finding of MMS2024.

In conditions where participants' debts cannot be fully repaid, MMS2024 reports heterogeneous effects of holding debt: more participants opt to maximize returns throughout the main experiment, but some allocate more points to fully repay one of the debt balances, compared to conditions where the debt can be fully repaid. Our experiment fails to replicate this result. Specifically, our data do not show any statistically significant differences in the proportions of participants maximizing returns between this Low and High debt treatment. According to MMS2024, one-quarter of all participants in the Low debt treatment took a repayment strategy in which they repaid their high-interest debts and then repaid their low-interest debts, but such our result was not observed. In our results, the participants with debts maximized their returns after repaying their high-interest debt regardless of the amount of their initial negative balance. Finally, in accordance with these results, in our experiment, significantly smaller fraction of participants overweighted the debt compared to MMS2024.

One possible explanation for these discrepancies may lie in the participant pool. The participants recruited for our study are students at Osaka University, who generally possess high academic aptitude scores, suggesting a potentially higher average cognitive ability with lower variance compared to the participants recruited via Amazon Mechanical Turk by MMS2024. Across both the main treatments and the one-shot scenarios, our data reveal a higher allocation share to the account with the highest interest rate and a higher proportion of participants maximizing returns in all treatments compared to those in MMS2024. This difference in the participant pool could attenuate the observed effects of debt.

Finally, the mechanism underlying debt-biased behavior has not yet been fully elucidated. MMS2024 attribute such bias to factors including loss aversion (See, e.g., Tversky and Kahneman, 1991), narrow framing (See, e.g., Barberis et al., 2006), and mental accounting (See, e.g., Thaler, 1999). They hypothesize that participants exhibiting debt-biased behavior do not aggregate balances across accounts and tend to perceive negative interest as a loss, prioritizing its elimination. Additionally, Meissner and Albrecht (2022), who investigates debt-biased behavior using a different framework, reports a significant positive correlation in their experiment. However, no research has yet demonstrated a causal relationship between these factors, presenting a valuable avenue for future studies.

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A Description of control variables

Variable	Description
Error Instruction	The amount of errors of all the understanding questions in a whole experiment.
Above Median Age	Whether the participant's age is above or equal to the median age [22 in this study, 36 in MMS]. (Above or same median = 1, Below median = 0)
Male	Gender (Male=1, Female=0)
Asian	Ethnicity (Asian=1, The other ethnicity=0)
White	Ethnicity (White=1, The other ethnicity=0)
College Education	Education level (College degree or higher = 1,Less than a college education = 0)
Undergraduate Student	(Graduated high school but not yet graduated college or university = 1, Graduated college or university or higher = 0)
Student Loan	Holding Studnet Loan (Yes=1, No=0)
Holding Debt	Holding a debt (Yes=1, No=0)
Covid Little Impact	Little impact from Covid19 (Yes=1, Not impacted by Covid19=0)
Covid Moderate	Moderate impact from Covid19 (Yes=1, Not impacted by Covid19=0)
Covid A lot	Significant impact from Covid19 (Yes=1, Not impacted by Covid19=0)
Covid Great	Severe impact from Covid19 (Yes=1, Not impacted by Covid19=0)

B Regression results: Initial allocation share

Table B1: Comparison between MMS2024 and This study

		Saving 1	**Saving 2 Debt 1**	**Saving 3/ Debt 2**	**Saving 4/**
(a) MMS2024					
	No Debt	0.73^{***}	0.07^{***}	0.13^{***}	0.08^{***}
		(0.031)	(0.010)	(0.016)	(0.016)
	Low Debt	0.47^{***}	0.13^{***}	0.32^{***}	0.09^{***}
		(0.035)	(0.017)	(0.034)	(0.012)
	High Debt	0.49^{***}	0.080^{***}	0.35^{***}	0.08^{***}
		(0.044)	(0.017)	(0.042)	(0.016)
(b) This study					
	No Debt	0.90^{***}	0.03^{**}	0.05^{**}	0.02^{**}
		(0.029)	(0.009)	(0.015)	(0.008)
	Low Debt	0.69^{***}	0.02	0.26^{***}	0.03^{*}
		(0.065)	(0.010)	(0.062)	(0.013)
	High Debt	0.76^{***}	0.01	0.19^{***}	0.04^{*}
		(0.057)	(0.005)	(0.049)	(0.015)
	Observations	392	392	392	392

Note: Results from linear regression with robust standard errors in parentheses. The dependent variable is the share of the initial endowment of 500 points that subjects allocate to each account. $^{*}p < 0.05;^{**} p < 0.01;^{***} p < 0.001$.

Table B2: Initial Allocation Share on Day 1

	Savings 1	**Savings 2**	**Savings 3/ Debt 1**	**Savings 4/ Debt 2**
Low Debt	-0.19^{*}	-0.01	0.19^{**}	0.01
	(0.075)	(0.014)	(0.066)	(0.016)
High Debt	-0.11	-0.02	0.12^{*}	0.01
	(0.070)	(0.013)	(0.055)	(0.019)
Error Instruction	0.00	0.00	-0.00	-0.00
	(0.006)	(0.001)	(0.005)	(0.001)
Above Median Age	0.04	-0.01	-0.04	-0.01
	(0.077)	(0.012)	(0.064)	(0.019)
Male	0.08	-0.01	-0.05	-0.02
	(0.074)	(0.012)	(0.065)	(0.017)
Asian	-0.16	0.01	0.15	-0.00
	(0.103)	(0.012)	(0.092)	(0.015)
Undergraduate Student	0.01	0.01	-0.04	0.01
	(0.074)	(0.011)	(0.060)	(0.021)
Student Loan	0.01	-0.00	-0.01	-0.00
	(0.100)	(0.013)	(0.090)	(0.024)
Holding Debt	0.03	-0.01	-0.02	-0.00
	(0.092)	(0.014)	(0.087)	(0.015)
Covid Little Impact	-0.11	-0.02	0.17	-0.03
	(0.231)	(0.036)	(0.155)	(0.058)
Covid Moderate	0.01	-0.04	0.07	-0.04
	(0.217)	(0.033)	(0.133)	(0.057)
Covid A lot	-0.02	-0.04	0.06	0.00
	(0.223)	((0.034)	(0.139)	(0.061)
Covid Great	0.04	-0.02	-0.01	-0.01
	(0.223)	(0.035)	(0.135)	(0.061)
Constant	0.94^{***}	0.06	-0.06	0.06
	(0.242)	(0.035)	(0.167)	(0.059)
Observations	134	134	134	134

Note: Results from linear regression with robust standard errors in parentheses.
$^{*}p < 0.05;^{**} p < 0.01;^{***} p < 0.001$.

C Regression results: Return maximizing choice across all the decisions

Table C1: The percentage of return-maximizing in the whole experiment

		(1)	(2)	(3)
(a) MMS2024				
	No Debt	0.38^{***}	-0.30^{*}	-0.10^{*}
		(0.053)	(0.137)	(0.044)
	Low Debt	0.13^{***}	-1.14^{***}	-0.37^{***}
		(0.036)	(0.172)	(0.048)
	High Debt	0.26^{***}	-0.67^{***}	-0.22^{***}
		(0.047)	(0.146)	(0.044)
(b) This study				
	No Debt	0.70^{***}	0.53^{**}	0.17^{**}
		(0.067)	(0.193)	(0.062)
	Low Debt	0.57^{***}	0.18	0.06
		(0.077)	(0.195)	(0.064)
	High Debt	0.53^{***}	0.08	0.03
		(0.075)	(0.187)	(0.062)
	Observations	392	392	392

Note: (1) shows the linear regression results; (2) presents the probit regression results; (3) indicates the marginal effects.All parentheses are robust standard errors; $^{*}p < 0.05;^{**} p < 0.01;^{***} p < 0.001$.

Table C2: The percentage of return-maximizing in the whole experiment with individual attribution

	MMS2024			This study		
	(1)	(2)	(3)	(4)	(5)	(6)
Low Debt	-0.25^{***}	-1.02^{***}	-0.25^{***}	-0.09	-0.25	-0.09
	(0.062)	(0.254)	(0.055)	(0.106)	(0.291)	(0.100)
High Debt	-0.13	-0.53^{*}	-0.13^{*}	-0.15	-0.43	-0.15
	(0.066)	(0.228)	(0.053)	(0.104)	(0.290)	(0.098)
Error Instruction	-0.02^{***}	-0.13^{***}	-0.03^{***}	-0.01	-0.02	-0.01
	(0.002)	(0.024)	(0.005)	(0.009)	(0.025)	(0.009)
Above Median Age	-0.03	-0.18	-0.04	-0.01	-0.02	-0.01
	(0.055)	(0.212)	(0.051)	(0.112)	(0.296)	(0.102)
Male	0.07	0.26	0.06	0.22^{*}	0.59^{*}	0.21^{*}
	(0.052)	(0.198)	(0.047)	(0.097)	(0.254)	(0.082)
White	0.13^{*}	0.62^{*}	0.15^{*}			
	(0.061)	(0.258)	(0.059)			
Asian				0.04	0.11	0.04
				(0.248)	(0.731)	(0.253)
College Education	0.11	0.47^{*}	0.11^{*}			
	(0.058)	(0.223)	(0.052)			
Undergraduate Student				-0.07	-0.22	-0.07
				(0.109)	(0.294)	(0.101)
Student Loan	0.03	0.04	0.01	0.15	0.54	0.19
	(0.056)	(0.214)	(0.051)	(0.123)	(0.409)	(0.141)
Holding Debt	-0.07	-0.19	-0.05	-0.07	-0.25	-0.09
	(0.057)	(0.209)	(0.409)	(0.121)	(0.378)	(0.131)
Covid Little Impact	0.11	0.37	0.08	-0.13	-0.35	-0.12
	(0.106)	(0.488)	(0.097)	(0.378)	(0.927)	(0.306)
Covid Moderate	0.14	0.51	0.11	-0.01	-0.01	-0.00
	(0.108)	(0.485)	(0.097)	(0.375)	(0.914)	(0.300)
Covid A lot	0.06	0.23	0.05	-0.13	-0.36	-0.13
	(0.115)	(0.526)	(0.106)	(0.382)	(0.938)	(0.309)
Covid Great	0.12	0.52	0.12	-0.23	-0.64	-0.23
	(0.136)	(0.616)	(0.136)	(0.382)	(0.946)	(0.312)
Constant	0.22	-0.75		0.64	0.42	
	(0.132)	(0.564)		(0.444)	(1.164)	
Observations	258	258	258	134	134	134

Note: (1) and (4) show the linear regression results; (2) and (5) present the probit regression results; (3) and (6) indicate the marginal effects. All parentheses are robust standard errors; $^{*}p < 0.05$;$^{**}p < 0.01$;$^{***}p < 0.001$.

D Regression results: One-Shot Scenarios

Table D1: The percentage of return-maximizing in One-Shot Scenarios

	Treatment groups	One-shot	(1)	(2)	(3)
(a) MMS2024					
	No Debt	No Debt	0.59^{***}	0.24	0.08
			(0.053)	(0.137)	(0.046)
		Low Debt	0.44^{***}	-0.15	-0.05
			(0.054)	(0.136)	(0.046)
		High Debt	0.40^{***}	-0.27	-0.09
			(0.053)	(0.137)	(0.047)
	Low Debt	No Debt	0.59^{***}	0.24	0.08
			(0.053)	(0.137)	(0.046)
		Low Debt	0.42^{***}	-0.21	-0.07
			(0.054)	(0.136)	(0.046)
		High Debt	0.38^{***}	-0.30^{*}	-0.10^{*}
			(0.053)	(0.137)	(0.047)
	High Debt	No Debt	0.66^{***}	0.42^{**}	0.14^{**}
			(0.051)	(0.140)	(0.047)
		Low Debt	0.52^{***}	0.06	0.02
			(0.054)	(0.135)	(0.046)
		High Debt	0.49^{***}	-0.03	-0.01
			(0.054)	(0.135)	(0.046)
(b) This study					
	No Debt	No Debt	0.87^{***}	1.14^{***}	0.39^{***}
			(0.049)	(0.233)	(0.077)
		Low Debt	0.72^{***}	0.59^{**}	0.20^{**}
			(0.066)	(0.195)	(0.066)
		High Debt	0.75^{***}	0.66^{***}	0.22^{***}
			(0.064)	(0.198)	(0.067)
	Low Debt	No Debt	0.98^{***}	1.98^{***}	0.68^{***}
			(0.024)	(0.420)	(0.140)
		Low Debt	0.83^{***}	0.97^{***}	0.33^{***}
			(0.058)	(0.230)	(0.077)
		High Debt	0.88^{***}	1.18^{***}	0.40^{***}
			(0.050)	(0.251)	(0.084)
	High Debt	No Debt	0.84^{***}	1.01^{***}	0.35^{***}
			(0.054)	(0.226)	(0.075)
		Low Debt	0.71^{***}	0.56^{**}	0.19^{**}
			(0.068)	(0.198)	(0.067)
		High Debt	0.78^{***}	0.77^{***}	0.26^{***}
			(0.062)	(0.208)	(0.070)
		Observations	1176	1176	1176

Note: (1) shows the linear regression results; (2) presents the probit regression results; (3) indicates the marginal effects. All parentheses are robust standard errors; $^{*}p < 0.05$;** $p < 0.01$;*** $p < 0.001$.

E Estimation : Debt aversion

In this appendix, we first introduce the estimation model developed in MMS2024 before presenting the results.

E.1 Set up

Let an agent make allocation decisions over multiple periods $t = (1, ..., T)$, distributing a given endowment X^t across multiple accounts $j = (1, ..., J)$. Each account has an initial balance of b_j^t, and the agent allocates an amount x_j^t to each account. In the next period, each account generates a return of $b_j^t i_j$ based on its balance following the previous allocation and the interest rate i_j. This return is reallocated to each account as the initial endowment. Every interest rate is positive and time-invariant. To ensure consistency with the experimental design, results of MMS2024 and this study, we introduce the following assumptions:

(A1) $\sum_{j=1}^{J} x_j^t = X^t, \forall t \in T$: The agent must exhaust her endowment.

(A2) $x_j^t \geq 0, \forall t \in T, \forall j \in J$: The agent cannot redistribute her balances.

(A3) When the agent has a negative balance (i.e.,$x_j^t + b_j^t < 0$), the agent has a debt aversion parameter λ affects the evaluation of the current negative balance.

Under the (A1)-(A3), the agent has a particular allocation $\sigma = ((x_1^1, ..., x_j^1), ..., (x_1^T, ...x_j^T))$ as follow :

$$U(\sigma) = \sum_{t=1}^{T} \sum_{j=1}^{J} (b_j^t + x_j^t)(1 + i_j)(1 + \lambda \mathbb{1}\{b_j^t + x_j^t < 0\}) \tag{1}$$

Deriving the first order condition, the following conditions are obtained from Eq.(1).

$$\frac{\partial U}{\partial x_j^t} = 1 + i_j \quad \text{for} \quad b_j^t + x_j^t \geq 0 \tag{2}$$
$$\frac{\partial U}{\partial x_j^t} = (1 + i_j)(1 + \lambda) \quad \text{for} \quad b_j^t + x_j^t < 0 \tag{3}$$

These conditions are independent of other periods; hence, the same return-maximizing strategy is used in all periods. These conditions yield that the agent's strategy behavior depends on the interest rate for positive balance accounts or the accounts where the negative balances are repaid, while it depends on both the interest rate and the debt aversion parameter λ for accounts with not repaid the negative balances. If λ is low, the agent allocates all endowments to the highest interest rate account each period. We call the group of agents with low λ is labeled the *Zero-*λ. If λ is sufficiently high, the agent prioritizes repaying a negative balance until the debt is repaid, after switching the allocation behavior that the agent allocates to the highest interest rate account in the remaining periods. The group of agents with sufficiently high λ is labeled the *Low-*λ. If λ is very high, the agent allocates all endowments to negative balances until all debts are repaid. After the agent fully repays all debts, they allocate the highest interest rate in the remaining period. The group of agents with very high λ is labeled the *High-*λ.

To estimate λ, we simplify the model. Assuming the agent has only four accounts: two with positive(non-negative) initial balances ($b_1, b_2 \geq 0$) and two with negative balances ($b_3, b_4 < 0$). In addition, let the highest interest rate correspond to the account with i_1. According to the first-order conditions, the range of λ can be derived by applying i_1 to Condition (2) and i_3 or i_4 to Condition (3) and comparing two conditions.

We apply these settings to our experiment design to specify the range of λ.[12] First, *Zero*-λ agents allocate all endowment to the account with i_1, thus, $\lambda < 0.05/(1+0.15) \simeq 0.04$. Next, *Low*-$\lambda$ agents repay only one debt account, thus, $0.04 < \lambda < 0.05/(1+0.05) \simeq 0.14$. Finally, *High*-$\lambda$ agents repay all debts account, thus, $0.05/(1+0.05) \simeq 0.14 < \lambda$.

Using the different types of λ, we compare the allocation predicted by each type of λ with the actual allocation behavior in our experiment by the mean squared error (MSE), as shown in eq (4).

$$\text{MSE} = \frac{1}{4}\sum_{t=1}^{4}\sum_{j=1}^{4}\left(\frac{x_j^t - \hat{x}_j^t}{X^t}\right)^2 \tag{4}$$

where $\hat{x}_j^t$ represents the allocation predicted by each type of λ. We calculate the deviations between the actual allocation and the predicted allocation of each type divided by the endowment. The participant is classified into the type with the smallest MSE (i.e., minimum distance estimation) among the three MSE calculated by the three types. The average $\hat{\lambda}$ is calculated using the number of participants classified into each type and the corresponding $1+\lambda$ for each type as shown in (5).[13]

$$\hat{\lambda} = \frac{(n_{\text{Zero}} \times 1) + (n_{\text{Low}} \times 1.04) + (n_{\text{High}} \times 1.14)}{n_{\text{Zero}} + n_{\text{Low}} + n_{\text{High}}} \tag{5}$$

In this estimation, we use experimental data from both treatments with and without debt, similar to MMS2024. The treatment without debt represents the Low

[12] The interest rates (i_1,i_2,i_3,i_4) correspond to (20%,10%,15%,5%) from our experimental design.

[13] *Low*-λ is calculated as $1 + \frac{0.2-0.15}{1+0.15} \simeq 1.04$, and *High*-$\lambda$ as $1 + \frac{0.2-0.05}{1+0.05} \simeq 1.14$

Debt treatment setting based on the allocation behavior in No Debt due to control for the noise in type classification and we conduct a placebo experiment using data from No Debt participants. The treatment with debt represents the Low Debt, High Debt, and One-shot scenarios, based on the allocation behavior in Low Debt.

E.2 Estimation results

Table E1 presents the percentages of *Zero*λ, *Low*λ, and *High*λ types, as well as average debt aversion parameter in both MMS2024 and this study. The summary of p-values that compare them across treatments is reported in Table E2.

First, let us summarize the results from MMS2024. In the Low Debt treatment, there is greater heterogeneity compared with the other treatments with debt. While no significant differences in fraction of *Low*λ are observed across the other treatments ($p = 0.055$ in No-Debt, $p = 0.473$ in High-Debt, $p = 0.317$ in One-shot), significant differences at the 5% level are observed for the fraction of *High*λ ($p = 0.025$ in No-Debt, $p < 0.001$ in High-Debt, $p = 0.025$ in One-shot). The 49% participants are classified into debt-averse types. The average $\hat{\lambda}$ calculated from each type in Low Debt is 0.044. To confirm the robustness of estimation, we conduct a placebo experiment that examines how allocations from the No-Debt treatment would be classified if they allocate points under the Low-Debt treatment.

The placebo experiment shows that while some percentage of participants' allocation behavior cannot be sufficiently explained (14% of Lowλ, 10% of Highλ), it also shows that when the MSE threshold is 0.054, participants are not classified into debt-averse types in Low Debt treatment. Under the MSE thresholds, 41%

Table E1: Percentage of Participants' Type and Average λ

		MMS20204				This Study					
		MSE ≥ 0	**Ave** $\hat{\lambda}$	**MSE** ≤ 0.054	**Ave** $\tilde{\lambda}$	**MSE** ≥ 0	**Ave** $\hat{\lambda}$	**MSE** ≤ 0.086	**Ave** $\tilde{\lambda}$	p-value^{++}	p-value^{--}
No Debt in Low Debt (Placebo)	Zeroλ	76%	0.021	100%	0.000	98%	0.001	100%	0.000	0.000	–
	Lowλ	14%		0%		2%		0%		0.006	–
	Highλ	10%		0%		0%		0%		0.002	–
	n	86		51 (Δ 35)		47		45 (Δ 2)			
Low Debt	Zeroλ	51%	0.044	59%	0.035	69%	0.016	71%	0.015	0.048	0.251
	Lowλ	26%		24%		29%		27%		0.724	0.803
	Highλ	23%		17%		2%		2%		0.000	0.023
	n	86		41 (Δ 45)		42		41 (Δ 1)			
High Debt	Zeroλ	76%	0.014	81%	0.014	87%	0.006	94%	0.002	0.102	0.078
	Lowλ	21%		14%		13%		6%		0.261	0.248
	Highλ	3%		6%		0%		0%		0.081	0.151
	n	86		36 (Δ 50)		45		35 (Δ 10)			
One Shot in Low Debt	Zeroλ	57%	0.029	64%	0.026	93%	0.003	93%	0.003	0.000	0.000
	Lowλ	33%		26%		7%		7%		0.000	0.013
	Highλ	10%		10%		0%		0%		0.002	0.021
	n	86		50 (Δ 36)		42		41 (Δ 1)			

Notes: All delta in parentheses are the number of data omitted by MSE thresholds. $++$ Comparison of two studies of average $\hat{\lambda}$ without MSE threshold. $--$ Comparison of two studies of average $\tilde{\lambda}$ with MSE threshold, where the participant in No Debt is not classified as Low and High types. P-values are computed using an F-test based on the linear regression without individual controls, as reported in Table E3. We also assess the significance of estimated average $\tilde{\lambda}$ using bootstrap simulations, see Figure E3 and Table E4.

Table E2: Summary of p-values computed across treatments.

(a) **MMS20204**

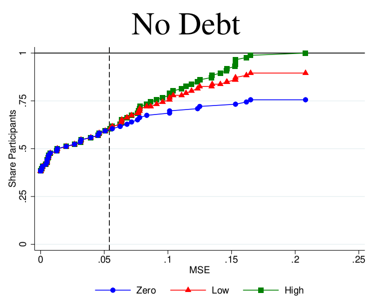
		MSE ≥ 0			MSE ≤ 0.054		
		Low Debt	**High Debt**	**One-shot**	**Low Debt**	**High Debt**	**One-shot**
Zeroλ	**No Debt**	0.001	1.000	0.009	0.000	0.004	0.000
	Low Debt	–	0.001	0.447	–	0.033	0.599
	High Debt	–	–	0.009	–	–	0.085
Lowλ	**No Debt**	0.055	0.230	0.004	0.000	0.018	0.000
	Low Debt	–	0.473	0.317	–	0.242	0.862
	High Debt	–	–	0.085	–	–	0.159
Highλ	**No Debt**	0.025	0.073	1.000	0.004	0.151	0.021
	Low Debt	–	0.000	0.025	–	0.105	0.336
	High Debt	–	–	0.073	–	–	0.442

(b) **This Study**

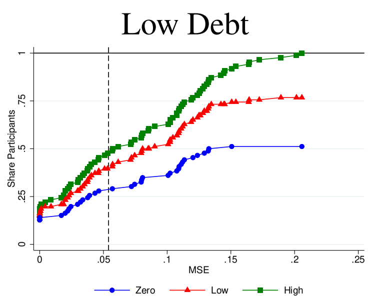
		MSE ≥ 0			MSE ≤ 0.086		
		Low Debt	**High Debt**	**One-shot**	**Low Debt**	**High Debt**	**One-shot**
Zeroλ	**No Debt**	0.000	0.043	0.269	0.000	0.151	0.076
	Low Debt	–	0.046	0.004	–	0.004	0.008
	High Debt	–	–	0.341	–	–	0.779
Lowλ	**No Debt**	0.000	0.043	0.269	0.000	0.151	0.076
	Low Debt	–	0.080	0.008	–	0.009	0.017
	High Debt	–	–	0.341	–	–	0.779
Highλ	**No Debt**	0.316	–	–	0.318	–	–
	Low Debt	–	0.316	0.316	–	0.318	0.318
	High Debt	–	–	–	–	–	–

Notes: P-values are computed using an F-test based on the linear regression without individual controls, as reported in Table E3.

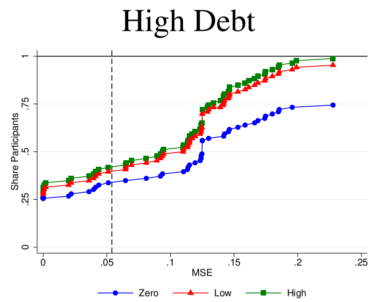
Figure E1: The λ types based on Goodness of fit



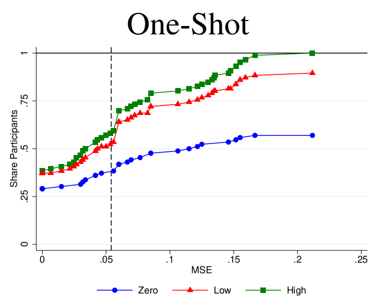
(a) MMS2024



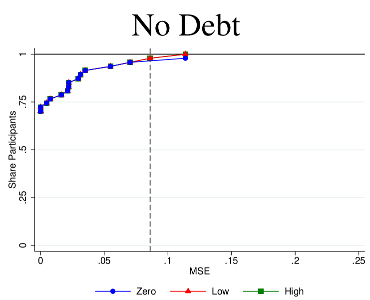
(b) MMS2024



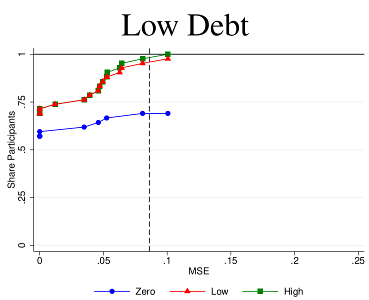
(c) MMS2024



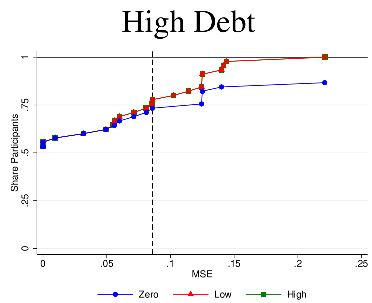
(d) MMS2024



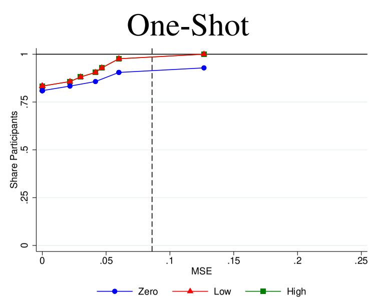
(e) This study



(f) This study



(g) This study



(h) This study

Note: Vertical dashed lines indicate the MSE threshold in the No Debt treatment (placebo experiment). (a) (b) (c) (d) The MSE threshold is 0.054, and (e) (f) (g) (h) the MSE threshold is 0.086, with no Low or High λ types in No Debt treatment.

Table E3: The percentage of types

		MSE ≥ 0			**MSE $\leq$ 0.054** or **0.086**		
		(1) Zeroλ	(2) Lowλ	(3) Highλ	(4) Zeroλ	(5) Lowλ	(6) Highλ
(a) MMS2024	No Debt	0.76^{***}	0.14^{***}	0.10^{**}	1.00^{***}	0.00	0.00
		(0.047)	(0.038)	(0.033)	(0.000)	(−)	(−)
	Low Debt	0.51^{***}	0.26^{***}	0.23^{***}	0.59^{***}	0.24^{***}	0.17^{**}
		(0.054)	(0.047)	(0.046)	(0.078)	(0.068)	(0.059)
	High Debt	0.76^{***}	0.21^{***}	0.03	0.81^{***}	0.14^{*}	0.06
		(0.047)	(0.044)	(0.020)	(0.067)	(0.058)	(0.039)
	One-shot	0.57^{***}	0.33^{***}	0.10^{**}	0.64^{***}	0.26^{***}	0.10^{*}
		(0.054)	(0.051)	(0.033)	(0.069)	(0.063)	(0.043)
(b) This study	No Debt	0.98^{***}	0.02	0.00	1.00^{***}	0.00	0.00
		(0.021)	(0.021)	(−)	(0.000)	(−)	(−)
	Low Debt	0.69^{***}	0.29^{***}	0.02	0.71^{***}	0.27	0.02
		(0.072)	(0.070)	(0.024)	(0.072)	(0.070)	(0.024)
	High Debt	0.87^{***}	0.13^{**}	0.00	0.94^{***}	0.06	0.00
		(0.051)	(0.051)	(−)	(0.040)	(0.040)	(−)
	One-shot	0.93^{***}	0.07	0.00	0.93^{***}	0.07	0.00
		(0.040)	(0.040)	(−)	(0.041)	(0.041)	(−)
	Observations	520	520	520	340	340	340

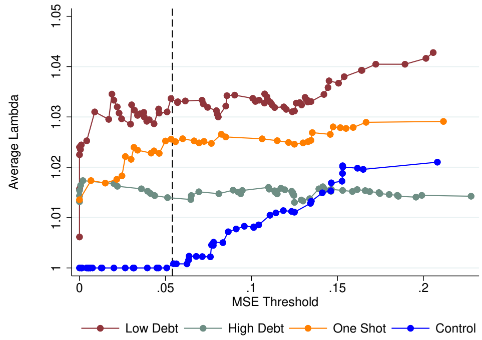
Notes: (1), (2), and (3) show the linear regression results without the MSE threshold; (4), (5), and (6) show the linear regression results with MSE thresholds of 0.054 and 0.086. All parentheses are robust standard errors; $^{*}p < 0.05;^{**}p < 0.01;^{***}p < 0.001$.

in Low debt, 20% in high debt, and 36% in one-shot are classified as debt-averse. These relative proportions of classified types are similar.

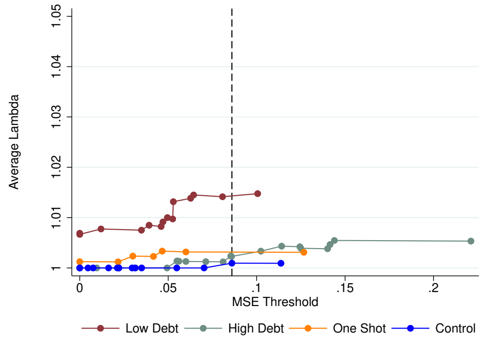
Furthermore, even when using data with an MSE below 0.05, the relative distribution of types in the treatments with debt is similar to the data with a large MSE (See, Figure E1). The average $\tilde{\lambda}$ are 0.035 for Low Debt, 0.014 for High Debt, and 0.026 for One-shot, respectively[14].

[14]Thses average $\hat{\lambda}$ for treatments with debt across different MSE thresholds (e.g., $0.05 \leq$

Figure E2: The average $\hat{\lambda}$ based on MSE thresholds.



(a) MMS2024



(b) This study

Notes: Vertical dashed lines indicate the MSE threshold in the No Debt treatment (placebo experiment). (a) The MSE threshold is 0.054, and (b) the MSE threshold is 0.086, with no Low or High λ types in No Debt treatment.

We replicate the greater heterogeneity in Low Debt compared with other treatments with debt. In the Low Debt treatment, 69%, 29%, and 2% of participants are classified into Zeroλ, Lowλ, and Highλ, respectively. Compared to MMS2024, Zeroλ is 18% lower ($p = 0.048$), Highλ is 21% lower ($p < 0.001$), but the difference for Lowλ is 2%, which is not significant ($p = 0.724$). Applying the MSE threshold (MSE ≤ 0.085) to the treatments with debt, the percentage of Zeroλ no longer shows a significant difference compared to MMS2024. However, 71% of Zeroλ is the lowest among the treatments with debt ($p = 0.004$ v.s. High Debt, $p = 0.008$ v.s. One-shot). Additionally, 27% of Lowλ types, which is the highest among the treatments with debt ($p = 0.009$ v.s. High Debt, $p = 0.017$ v.s. One-shot). The average $\tilde{\lambda}$ is 0.016 in Low Debt which is stable even using the different MSE threshold (See, Figure E2 (b)).

This indicates that the Low Debt treatment in this study has a higher propor-

MSE threshold ≤ 0.15) are similar to the average $\tilde{\lambda}$ with the MSE threshold is 0.054. Thus, these average $\tilde{\lambda}$ stable on different MSE thresholds (See, Figure E2 (a)) tion of participants showing debt-averse behavior than other treatments with debt. Moreover, unlike MMS2024, the Low Debt treatment in this study also shows a higher proportion of participants classified as debt-averse types compared to the other treatments with debt even the tendency of type classification between this study and MMS2024 is similar (See Figure E1). In the Low Debt treatment of MMS2024, participants perceive \$1 of debt as equivalent to \$1.035 in savings, whereas in this study, they perceive \$1 of debt as equivalent to \$1.016 in savings.

E.3 Bootstrap Simulations

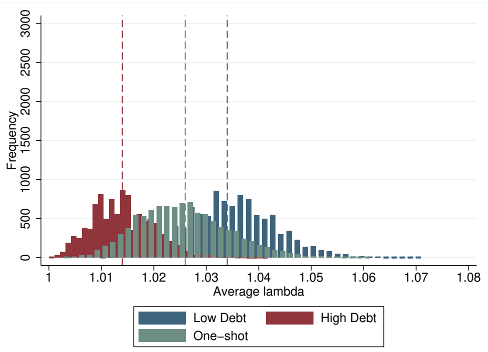
Similarly to MMS2024, we confirm the significance of the estimated average $\tilde{\lambda}$ using bootstrap simulations. We draw 10,000 samples from MMS2024 and this study experimental sample, controlling noise at the MSE threshold in the Low-Debt treatment where no participants exhibit debt aversion, and re-estimate λ^B for each type (Zeroλ, Lowλ, Highλ)[15]. In the No-Debt treatment, as no participants show debt aversion, the distribution of average $\tilde{\lambda}$ concentrates around 1. We use F-tests to check whether the re-estimated λ^B for the treatments with debt (Low, High, One-shot) are equal to 1.

Figure E3 and Table E4 present the distributions of the average λ^B for each treatment with debt, along with the results of linear regression analysis for the average λ^B of each treatment.

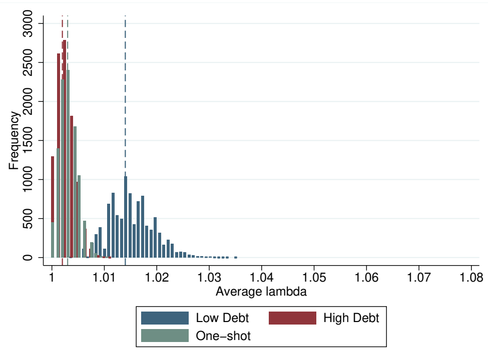
The results show that in MMS2024, the distribution of average $\tilde{\lambda}$ for treatments with debt (Low, High, One-shot) deviates from 1, with the largest difference observed in the Low-Debt treatment (See Figure E3 (a)). The F-test shows that the reestimated average λ^B significantly differs from 1 (p-value < 0.000).

[15] See Figure E1 (a)

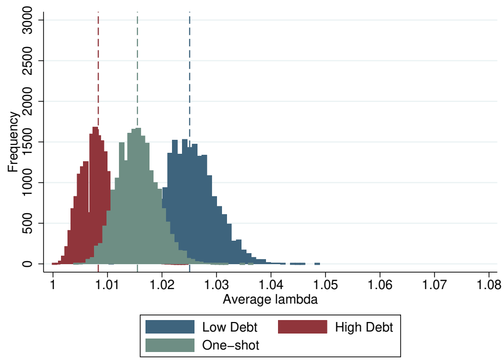
Figure E3: The distribution of average λ^B by Bootstrap simulations



(a) MMS2024



(b) This study



(c) MMS2024 $\times$ This study

Notes: Vertical dashed lines in (a) and (b) indicate the average $\tilde{\lambda}$ for our sample and the MMS2024 sample, controlled by the MSE threshold (see Table E1). Vertical dashed lines in (c) indicate the average $\tilde{\lambda}$ for the combined data from our sample and the MMS2024 sample, controlled by the MSE threshold. These average $\tilde{\lambda}$ in (c) are Low Debt 1.025, High Debt 1.008, and One-shot in Low Debt 1.015

In this study, compared to MMS2024, the distribution of average $\tilde{\lambda}$ is closer to 1, although,the distance from 1 is still observed in the Low Debt treatment. The reestimated average λ^B of treatments with debt differ from 1 (p-value < 0.000). Additionally, we combine the treatments with debt types (Zero, Low, High) from MMS2024 and this study, drawing 20,000 samples and reestimating λ^B. The results show a reduction in the distribution variance, and the reestimated average λ^B aligns with the average $\tilde{\lambda}$ calculated using each MSE threshold ($\tilde{\lambda}$ is 0.025 in Low Debt, High Debt $\tilde{\lambda}$ is 0.008 in High Debt, and $\tilde{\lambda}$ is 0.015 in One-shot in Low Debt). The reestimated average λ^B of treatments with debt significantly differ from 1 (p-value < 0.000).

Table E4: The linear regression of bootstrap simulations

		(1) Average λ^B	(2) Average λ^B	p-value$^+$
(a) MMS2024	**Low Debt**	1.035^{***}		0.0000
		(0.0001)		
	High Debt	1.014^{***}		0.0000
		(0.0001)		
	One shot	1.026^{***}		0.0000
		(0.0001)		
(b) This study	**Low Debt**	1.015^{***}		0.0000
		(0.0000)		
	High Debt	1.003^{***}		0.0000
		(0.0000)		
	One shot	1.003^{***}		0.0000
		(0.0000)		
(c) MMS2024$\times$ This study	**Low Debt**		1.025^{***}	0.0000
			(0.0000)	
	High Debt		1.008^{***}	0.0000
			(0.0000)	
	One shot		1.016^{***}	0.0000
			(0.0000)	
	Observations	60000	60000	

Notes: The p-value$^+$ is computed using an F-test based on linear regression. The p-value$^+$ shows the result of the F-test for the significant difference between the No Debt treatment with an average $\tilde{\lambda}$ of 1 and the average λ^B controlled by MSE threshold for the Low Debt, High Debt, and One-shot treatments calculated using the Bootstrap simulations. All parentheses are robust standard errors; $^*p < 0.05$;$^{**}\,p < 0.01$;$^{***}\,p < 0.001$.