Appendix for Online Publication

"The Opportunity Cost of Debt Aversion"

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A. Appendix for Online Publication

A. Instructions

– In this experiment, you will have accounts that generate positive and negative returns over the duration of the experiment

– At each decision, you will allocate points between different accounts

– There is a total of 4 decisions, one today, and another on Friday, Monday and next Wednesday

– You will only receive your payments if you successfully complete all four decisions

Accounts

– Accounts generate returns, based on their balance and interest rates

– Balances change over time based on your decisions

– Interest rates are constant throughout the experiment

– Accounts with positive balances generate positive returns

– Accounts with negative balances generate negative returns

– We label accounts with positive starting balances as Savings accounts

– We label accounts with negative starting balances as Debt accounts

For example, a Savings account with a balance of 150 points and an interest rate of 30% would generate a positive return of 150 x 0.30 = 45 points

Similarly, a Debt account with a balance of -120 points and an interest rate of 40% would generate a negative return of -120 x 0.40 = -48 points

Endowment

– At each decision, you will receive an endowment of points that you will have to allocate between the accounts

– The endowment is calculated as the sum of the returns of all your accounts

– You can allocate the points as you wish between your available accounts as long as the sum is equal to the endowment

– Points allocated to an account increase its balance for all subsequent decisions

Timeline of the experiment

Decision 1: Wednesday (Today)

- You receive an endowment of points based on the initial balances and interest rates
- You must allocate this endowment between the available accounts
- The accounts generate returns, based on their balances and interest rates

Decision 2: Friday (Two days from today)

- Balances on Friday will reflect your previous decisions
- The sum of the returns from Wednesday is your endowment for this decision
- You will allocate the new endowment between the available accounts

Decision 3: Monday (Five days from today)

- Balances on Monday will reflect your previous decisions
- The sum of the returns from Friday is your endowment for this decision
- You will allocate the new endowment between the available accounts

Decision 4: Next Wednesday (A week from now)

- Balances on next Wednesday will reflect your previous decisions
- The sum of the returns from Monday is your endowment for this decision
- You will allocate the new endowment between the available accounts
- The accounts will generate returns and the experiment will end

Payments:

- You will be paid a $10 participation fee as well as a bonus based on your decisions
- We will sum all your points, including your final balances and the returns on next Wednesday. You will earn $1 for every 500 points
- Payments will be disbursed within 2 days of the end of the study
- Throughout the study there will be additional opportunities to make earnings, so please pay close attention to all the instructions

You will only receive your final payment if you finish the experiment

Table A.9: Summary/Timeline of the Experimental Design

	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	–	–	–	One-shot
Part 4	–	–	–	End Survey

* Only Risk Question #1

B. Initial Survey/Additional Questions

During the experiment, subjects have the opportunity to obtain additional earnings by answering additional questions. While these questions may affect subjects' earnings, they do not alter the main implications of our experiment, as they do not change the payoff-maximizing action.

To prevent attrition and control for baseline risk and time preferences, subjects must complete an initial survey before making their first allocation decision. For our week-long experiment, and as with all longitudinal studies, attrition is an issue. The initial survey ensures that subjects who fail to check their emails, which is necessary to obtain the links to the subsequent decisions, are dropped before we randomize them into treatment groups. Furthermore, this reduces concerns about selective attrition by treatment.

Beyond our concerns with attrition, our initial survey also allows us to elicit starting risk and time preferences through a Becker–DeGroot–Marschak (BDM) mechanism following the guidelines in Healy (2016). For each question, subjects are shown a price list where they choose between two options. In the risk preferences case, subjects are asked whether they prefer dollars for sure versus a 50 percent chance at earning $1. In the time preferences case, subjects face a tradeoff between dollars today versus $1 next week.[46] In addition, subjects are asked a series of comprehension check questions beforehand that they have to answer correctly before they can respond to the lists to ensure that they understand the mechanism. This price list BDM mechanism is used again in our main decisions, so this is also a way to introduce

[46]Both price lists have 100 versions of this question, with the dollars for sure ranging from one cent to $1. Rather than have subjects answer all 100 questions, we ask them to indicate the spot on the list where they would switch from preferring one option to the other. We then fill in the assumed answers for all other questions based on their switching point. One question from one list is randomly selected and implemented.

subjects to these questions in advance.

Eliciting Time and Risk Preferences

After the initial allocation decisions each day, subjects have the opportunity to make additional gains by answering a series of risk and time preference questions. Using the same BDM mechanism as in our initial survey, we ask subjects four risk and time tradeoff questions, two for risk preferences and two for time preferences (see details in Table A.10). These questions are shown in random order within the risk or time block. Of these four lists, one question from one list is randomly selected and implemented. To ensure that all subjects have additional points to allocate, we give everyone 100 additional points regardless of the implemented question. Thus, after completing the additional questions, subjects are again able to allocate their earned points to their four available accounts.

Table A.10: Additional Questions on Time and Risk Preferences

	Option A		**Option B**
Risk Question #1:	50% chance of 500 points	vs.	X points for sure
Risk Question #2:	50% chance of 500 points	vs.	X dollars paid today
Time Question #1:	500 points for the next allocation decision	vs.	X points for the current one
Time Question #2:	500 points for the next allocation decision	vs.	X dollars paid today

- You have the opportunity to earn monetary payoffs by answering lists of questions
- In each list, you will indicate what you prefer between two options. For example, a 50% chance of earning $1 versus $0.40 for sure
- One of these lists will be randomly selected and one question from it implemented
- Before you answer these questions lists, you will go through an explanation of the setting and how to answer these questions

- This is an example to help you understand how the questions work
- Imagine that you are given the choice between a 50% chance to get $1 or dollars for sure and you have a list of questions like this one:

Q#		Option A		Option B
1	Would you rather have:	50% chance of $1	or	$0.01 for sure
2	Would you rather have:	50% chance of $1	or	$0.02 for sure
3	Would you rather have:	50% chance of $1	or	$0.03 for sure
...	...	...	...	...
98	Would you rather have:	50% chance of $1	or	$0.98 for sure
99	Would you rather have:	50% chance of $1	or	$0.99 for sure
100	Would you rather have:	50% chance of $1	or	$1 for sure

In each question, you pick either Option A (50% chance of $1) or Option B (dollars for sure)

- After you answer all 100 questions, I will randomly pick one question and pay you the option you chose on that one question
- Each question is equally likely to be chosen for payment. Obviously, you have no incentive to lie on any question, because if that question gets chosen for payment then you'd end up with the option you like less.

I assume you're going to choose Option A in at least the first few questions, and I assume you're going to choose Option B in at least the last few questions. So at some point, you will switch from preferring Option A to Option B. To save time, just tell when you would switch from preferring Option A to Option B.

- I can then 'fill out' your answers to all 100 questions based on your switch point (choosing Option A for all questions before your switch point, and Option B for all questions at and after your switch point).
- I'll still draw one question randomly for payment. Again, if you lie about your true switch point you might end up getting paid an option that you like less.

At which dollar value would you switch from Option A to Option B?

C. Redistribution/Borrowing Decisions

Redistribution Treatments:

- Before you decide how to allocate your initial endowment of points, you have the opportunity to withdraw points from the Savings 1 and Savings 2 accounts

- You can withdraw up to 2000 points from Savings 1 and up to 400 points from Savings 2
- Any amount that you withdraw will be added to your endowment of points and will reduce the balances of Savings 1 and Savings 2 accounts

Borrowing Treatments:

- Before you decide how to allocate your initial endowment of points, you have the opportunity to withdraw [borrow] points from any of the locked Savings [Debt] accounts
- You can withdraw [borrow] up to 900 points from Savings 5 [Debt 1] and up to 1500 points from Savings 6 [Debt 2]
- Any amount that you withdraw [borrow] will be added to your endowment of points and will affect the returns that locked Savings [Debt] accounts generate
- You will still not be able to allocate any points to the locked Savings [Debt] accounts. [Any amount that you borrow will be repaid at the end of the experiment]

D. One-shot Parameters

After the last allocation decision, subjects face these one-shot scenarios in random order. In each decision, they must allocate 1000 points between the four available accounts. In this simplified version of our main experiment, there are no locked accounts and all decisions are done back-to-back. Parameters are chosen to mimic the main treatments of our experiment. Initial wealth is kept constant across the three one-shot scenarios, but net returns differ. For *One-shot Low-Debt*, subjects can choose to fully repay at least one debt account, but this is not feasible in the *One-shot High-Debt*.

Table A.11: Accounts in One-shot Scenarios

One-shot No Debt:

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

One-shot Low Debt:

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

One-shot High Debt:

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

E. Hindsight Examples

At the end of the final day, subjects are asked to describe how they would behave if they could do the experiment again with the benefit of hindsight. Specifically, we ask "After completing the experiment and with the benefit of hindsight, what strategy would you follow in order to make as many points as possible and obtain a high payoff?". This elicitation is not incentivized. We present some examples of the responses that subjects wrote.

We categorize the hindsight into three categories. Based on subjects provided hindsight and performance during their allocation decision, we categorize subjects as either "maximizing returns", "debt then maximize", and "other". Subjects who mention maximizing their returns or focusing on the high interest account are put into the first category. These subjects also have allocation strategies that generally match their given hindsight. Similar to this group, there is also another group of subjects who mention first being concerned with debt and wanting to pay if off and then wanting to follow the return maximizing strategy. Interestingly, there are even some subjects in the *No-Debt* treatment who bring up similar concerns with debt even though in their cases debt has 0 balances and is only in the locked accounts. Finally, there are other subjects who do not describe either such type of strategy. These subjects either focus solely on debt, did not have coherent strategies, or describe behavior that is not necessarily reflected by their actions. When comparing *No-Debt* with *Low-Debt* and *High-Debt* treatments, we find a similar fraction of subjects who eventually maximize returns, i.e. in *Low-Debt* and *High-Debt*, the number of subjects who act optimally from the start, in addition to those who say they focused on debt and then acted optimally, roughly corresponds to the same fraction of subjects in the *No-Debt* who simply described optimizing.

Maximizing returns:

> "I would always put all the endowment in the account with the highest interest rate."
>
> "Allocate all to the savings account with highest interest rate. Of course if it has bigger percentage than my debt accounts."
>
> "I would go with the same strategy again, which was putting as much as I could in my highest interest account."

Paying debt first then maximize returns:

> "I think I would still pay off all debt first and then put all the rest of my points into the 20 percent allocation."

> “Get rid of the high interest debt and stick any gains in high interest savings.”

> “I probably could’ve completely ignored the low percentage debt, eliminated the high percentage debt, then just put everything into the 20% return account”

Other strategies:

> “I would invest in the account that had the least amount of debt, but gained the most interest.”

> “Make sure no accounts are falling into debt, and make sure there is some even spreading of the money even if it means less interest”

> “I ensure 40% of earns on paying debts “

Table A.12: Overview of Features of Selected Debt Related Papers

Authors (Chronologically)	Main mechanism	Decision	Sample Size	Country	Investment and Debt? (Y/N)	Investment Return	Borrowing Cost (APR)	Return > Borrowing (Y/N)	Estimate Debt Aversion (Y/N)	Type of Study	Notes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Martinez-Marquina, Shi (2023)	Debt-Aversion	Investment Allocation	578	US	Y	20%	5% & 15%	Y	Y	Lab Experiment	
Panel A. Determinants of Borrowing											
Meier and Sprenger (2010)	Present Focus	Credit Card Debt	541	US	N	-	-	-	N	Field Study	Measures of present focus correlate with credit card usage and total credit card debt.
Shah, Mullainathan, and Shafir (2012)	Scarcity Driven Attention	Family Feud and Wheel of Fortune	526	US	Y	[1]	0% & 100%	N	N	Lab Experiment	Participants with scarce resources borrow excessively. Attention is devoted to more pressing tasks while neglecting others.
Karlan, Mullainathan, and Roth (2019)	Present Focus, Shocks...	Moneylending	1951	India and Philippines	Y	65%[2]	13%[2]	Y	N	Field Experiment	Three field studies where they paid off high-interest debts of small businesses. Within six weeks, most are back to borrowing.
Allcott, Kim, Taubinsky, and Zinman (2022)	Naive Present Focus	Payday Loan	1205	US	N	-	3.91	-	N	Field Experiment	Among payday loan borrowers, experienced ones predict correctly future behavior.
Panel B. Suboptimal Debt Decisions											
Ponce and Seira (2017)	Limited Attention, Anchoring...	Credit Card Repayments	10,335	Mexico	N	-	35.12%	-	N	Observational Study	Consumers are insensitive to interest rates when paying their credit cards. However, consumers are sensitive to salient price reductions.
Gathergood, Mahoney,Stewart, and Weber (2019)	Balance-matching	Credit Card Repayments	1.4 million	UK	N	-	19.7% avg.	-	N	Observational Study	Half of individuals repay credit cards using a balance-matching heuristic rather than prioritizing high-interest cards.
Ozyilmaz and Zhang WP	Balance-matching and Debt Framing	Credit Card Repayments	165	US	N	-	3.4-5.9%	-	N	Lab Experiment	Participants struggle to minimize interest payments. Larger effects when balances are negative.
Panel C. Evidence on Debt Aversion											
Prelec and Loewenstein (1998)	Debt-Aversion and Mental Accounting	Pre-payment of Consumption	86	US	N	-	-	-	N	Theory and Survey	Theoretical model where people are reluctant to consume without paying beforehand as it diminishes the enjoyment of consumption.
Eckel, Johnson, and Rojas (2007)	Debt-Aversion	Hypothetical Student Loans/Grants	900	Canada	Y	-	0%[3]	-	N	Lab Experiment	Participants choose between cash or different types of financial aid for education. Little to no role of debt aversion.
Field (2009)	Psychological Responses to Debt	Career Choice after Graduation	270	US	Y	-	0%	-	N	Field Experiment	Field experiment offering different financial aid packages. Students who receive loans are less likely to work in public jobs.
Meissner (2016)	Debt-Aversion	Consumption-smoothing	76	Germany	N	-	0	N	N	Lab Experiment	Consumption/saving experiment where deviations from optimal behavior are higher when subjects have to borrow.
Caetano, Palacios, and Patrinos (2019)	Debt-Aversion and Debt Framing	Hypothetical Student Loans	1,422	Chile	Y	-	8%, 20% & 32%	-	-	Online Survey	Survey study where they offer different hypothetical options to finance education. Debt-labeled options are chosen 8% less.
Berkouwer and Dean (2022)	Credit Constrains	Cookstove Purchase	1,000	Kenya	Y	296%	14%	Y	N	Field Experiment	Charcoal cookstove experiment in Nairobi where access to loans doubles willingness to pay.

Notes:[1] Performance-based, overall lower than borrowing cost.[2] Based on the daily returns of their Philipinnes sample, 1.7% daily. [3] Real interest rate.

F. Robustness Treatment: Low-Debt-Reverse

In our *Low-Debt* treatment, we find that participants on day 1 allocate 32 percent of their initial endowment to the high-interest Debt account (figure 1). However, a potential confound is that the Debt 1 account also has a lower balance than Debt 2, and thus, it is easier to repay. To rule out this possibility, we ran a robustness treatment with an additional 80 subjects recruited again from Amazon Mechanical Turk. Since the goal of this additional treatment arm is to look at differences in allocations on day 1, we streamline the design and get rid of the additional questions after each decision and the one-shot questions at the end. In addition, rather than having 4 allocation decisions over a week, participants make all 4 allocations on the same day. The initial parameters, where we switch the balances of Debt accounts, are the following:

Table A.13: Accounts in Low-Debt Treatments

Low Debt Reverse (Robustness):

	Savings 1	**Savings 2**	**Debt 1**	**Debt 2**	Savings 3	Savings 4
Interest Rate	**20%**	**10%**	**15%**	**5%**	15%	5%
Balance	**1100**	**700**	**-1500**	**-900**	2400	2400

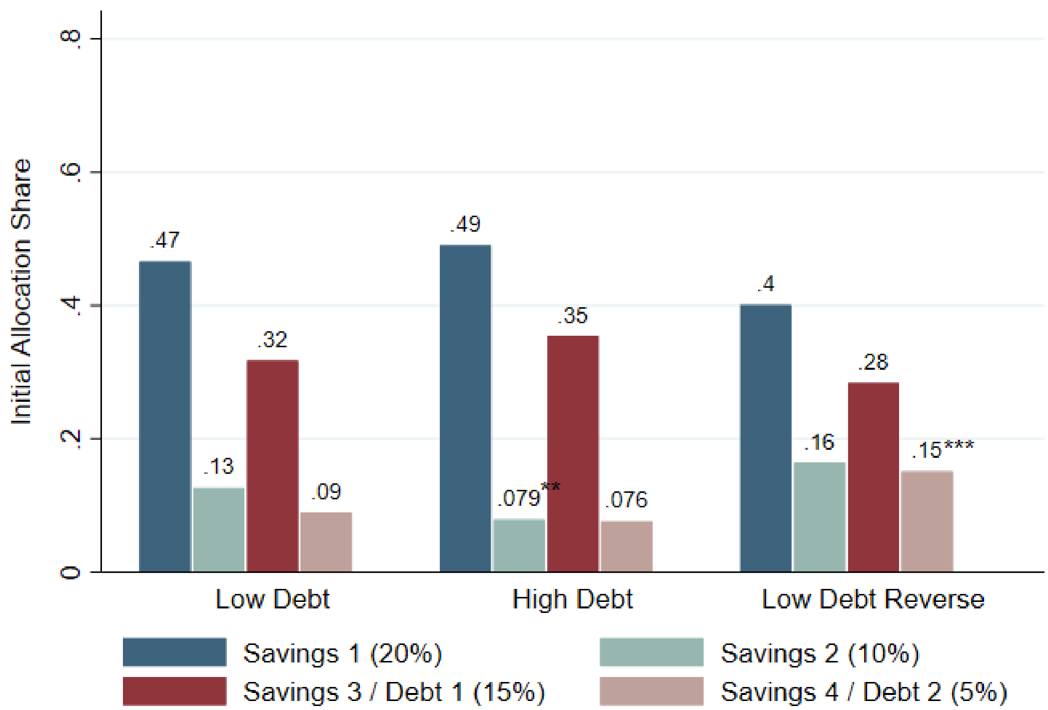
Low Debt (Main):

	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

Notes: In both cases, the sum of the balances is 4200 points, and the returns of these six accounts sum up to 500 points, which is the initial endowment that subjects must allocate.

To ease comparison, we also depict the original initial balances from our main *Low-Debt* treatment. Note that swapping the balances of the Debt accounts also impacts the total returns. Therefore, we also adjust the locked accounts, Savings 3 and Savings 4, to ensure that the net returns and total balances are also comparable across both conditions.

Figure A.9: Allocation Shares of the Initial Endowment in Day 1 [Debt Treatments]



Notes: Stars correspond to treatment differences using *Low-Debt* as a baseline.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Subjects were only randomized into treatments after completing the initial survey and responding to the follow-up email. At the end of the last day, subjects were asked a series of demographic questions on sex, race, and education. We also surveyed them on their past experiences with debt as well as their experiences during the Covid-19 pandemic. Below we present balance tables comparing means for these elicited characteristics across the *No-Debt*, *Low-Debt*, and *High-Debt* treatments. To create comparable categories, we collapsed the race question into White and non-White, and we also collapsed the education question into college-plus and non-college-plus. We also compare subjects initial risk and time preferences from the initial survey before they were sorted into treatment groups. The final total duration across all days is shown as well, for both the mean and median.

Table A.14: Main Treatments: Balance Table

	No Debt Mean	Low Debt Mean	High Debt Mean	P.value
Age	37.56	38.58	37.87	0.82
Male	0.60	0.56	0.57	0.82
White	0.73	0.85	0.73	0.11
College	0.73	0.67	0.72	0.68
Hold Student Loan	0.54	0.51	0.41	0.27
Hold Debt	0.66	0.61	0.60	0.67
Impact Covid	2.86	2.90	2.86	0.97
Initial Risk	0.62	0.64	0.63	0.87
Initial Time	0.85	0.88	0.89	0.52
Duration (hours)	2.31	2.17	2.13	0.79
Median Duration (hours)	1.68	1.70	1.60	0.38
Observations	86	86	86	

Notes: This table shows results from a balance test between our main treatments. We report the p.values of an F-test of equivalence of the three treatment means.

We also present the balance table for the two *Redistribution* and two *Borrowing* treatments. We compare the same elicited characteristics as from the three *Main* treatments.

Table A.15: Redistribution Treatments: Balance Table

	Redistribution No Debt	Redistribution Debt	
	Mean	Mean	P.value
Age	39.48	36.03	0.05
Male	0.54	0.60	0.49
White	0.77	0.75	0.86
College	0.80	0.77	0.58
Hold Student Loan	0.45	0.43	0.80
Hold Debt	0.61	0.74	0.09
Covid	3.05	3.17	0.51
Initial Risk	0.64	0.68	0.36
Initial Time	0.85	0.84	0.87
Duration (hours)	1.38	1.41	0.87
Median Duration (hours)	1.18	1.08	0.63
Observations	81	77	

Notes: This table shows results from a balance test between our redistribution treatments. We report the t-test p.values of equivalence of the two means.

Table A.16: Borrowing Treatments: Balance Table

	Borrowing No Debt	Borrowing Debt	
	Mean	Mean	P.value
Age	37.10	35.83	0.44
Male	0.70	0.56	0.07
White	0.77	0.74	0.65
College	0.68	0.79	0.09
Hold Student Loan	0.49	0.52	0.70
Hold Debt	0.66	0.67	0.82
Covid	3.04	3.10	0.70
Initial Risk	0.61	0.66	0.13
Initial Time	0.85	0.84	0.78
Duration (hours)	2.91	2.55	0.49
Median Duration (hours)	1.56	1.65	0.53
Observations	80	82	

Notes: This table shows results from a balance test between our borrowing treatments. We report the t-test p.values of equivalence of the two means.

Using the first allocation decision in our *Main* Treatments, we present the results from a regression on the share that subjects allocate to each account. In both *Low-Debt* and *High-Debt* subjects allocate less points to Savings 1 since they allocate a larger share to Debt 1.

Table A.17: Main Treatments: Estimation Output Using Initial Allocation

	(1) Allocation Share Savings 1	(2) Allocation Share Savings 2	(3) Allocation Share Savings 3/Debt 1	(4) Allocation Share Savings 4/Debt 2
Mean of dep.var	0.483***	0.160*	0.268**	0.268**
	(0.102)	(0.0769)	(0.100)	(0.100)
Low Debt	-0.259***	0.0553**	0.192***	0.0115
	(0.0457)	(0.0174)	(0.0399)	(0.0187)
High Debt	-0.233***	0.0130	0.224***	-0.00324
	(0.0511)	(0.0180)	(0.0465)	(0.0218)
Errors Instructions	-0.0101***	0.00806***	-0.00264	0.00472***
	(0.00183)	(0.000876)	(0.00160)	(0.000758)
Above Median Age	0.0313	-0.0167	-0.0290	0.0143
	(0.0447)	(0.0166)	(0.0424)	(0.0159)
Male	0.0451	-0.00328	-0.0232	-0.0186
	(0.0427)	(0.0143)	(0.0406)	(0.0169)
White	0.104*	-0.0309	-0.0119	-0.0616*
	(0.0509)	(0.0198)	(0.0467)	(0.0259)
College Education	0.0706	-0.00560	-0.0648	-0.000168
	(0.0505)	(0.0169)	(0.0478)	(0.0154)
Hold Student Loan	0.0140	-0.0268	0.0186	-0.00584
	(0.0485)	(0.0172)	(0.0467)	(0.0166)
Hold Debt	-0.0413	0.00975	0.0228	0.00874
	(0.0488)	(0.0159)	(0.0467)	(0.0143)
Covid - Little Impact	0.156	-0.112	-0.0221	-0.0212
	(0.0825)	(0.0664)	(0.0873)	(0.0225)
Covid - Moderate	0.100	-0.114	0.00526	0.00838
	(0.0836)	(0.0657)	(0.0868)	(0.0226)
Covid - A lot	0.0748	-0.113	0.0202	0.0178
	(0.0928)	(0.0672)	(0.0928)	(0.0291)
Covid - Great	0.236*	-0.120	-0.0753	-0.0401
	(0.0950)	(0.0671)	(0.0955)	(0.0277)
Batch FE	Y	Y	Y	Y
Observations	258	258	258	258

Notes: Results from a linear regression with robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the share of the initial endowment of 500 points that subjects allocate to each account.

Next, we look at the total amount of points that subjects allocate to each account by the end of the study. In both *Low-Debt* and *High-Debt* subjects allocate less points to Savings 1, although the difference is marginally significant. For *High-Debt*, subjects allocate 616 more points to the Debt 1 account. In *Low-Debt*, we also find a significant increase in the amount of points that subjects allocate to the Debt 2 account. This effect is mainly driven by subjects who repay Debt 2 after fully repaying Debt 1, which is an infeasible strategy in *High-Debt*.

Table A.18: Main Treatments: Estimation Output Using Total Allocation

	(1) Total Allocation Savings 1	(2) Total Allocation Savings 2	(3) Allocation Share Savings 3/Debt 1	(4) Allocation Share Savings 4/Debt 2
Mean of dep.var	3573.6***	642.4	479.9	213.1
	(509.3)	(344.7)	(254.3)	(135.9)
Low Debt	-417.6*	76.02	175.6*	241.8**
	(185.0)	(63.39)	(74.17)	(81.65)
High Debt	-451.4*	-34.97	616.0***	-26.85
	(214.4)	(71.79)	(128.5)	(68.48)
Errors Instructions	-82.11***	32.57***	11.51**	24.15***
	(9.089)	(3.509)	(4.007)	(3.752)
Above Median Age	80.01	-67.67	133.2	-13.55
	(174.8)	(59.85)	(95.12)	(68.29)
Male	137.7	-32.94	-38.43	-30.60
	(166.2)	(50.25)	(91.15)	(64.72)
White	482.6*	-172.3*	-127.8	-213.7*
	(202.0)	(69.64)	(111.3)	(91.48)
College Education	-0.0267	-41.46	-82.63	29.99
	(187.3)	(63.04)	(108.8)	(76.27)
Hold Student Loan	234.5	-7.336	-84.34	-136.7
	(182.6)	(62.63)	(108.2)	(78.73)
Hold Debt	-172.1	-90.02	176.2	107.9
	(186.0)	(57.94)	(103.9)	(74.73)
Covid - Little Impact	120.8	-366.4	7.356	92.57
	(429.4)	(295.2)	(212.3)	(73.19)
Covid - Moderate	-91.34	-247.9	23.99	135.3
	(433.6)	(292.5)	(212.5)	(77.53)
Covid - A lot	27.65	-281.5	-39.83	106.5
	(457.2)	(298.1)	(223.8)	(93.06)
Covid - Great	124.9	-255.8	-117.9	-55.60
	(452.8)	(296.7)	(236.7)	(102.1)
Batch FE	Y	Y	Y	Y
Observations	258	258	258	258

Notes: Results from a linear regression with robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19: Borrowing Treatments: Returns and Payments Estimation Output

	(1) Log Total Returns	(2) Log Total Returns	(3) Log Total Returns	(4) Final Payment	(5) Final Payment	(6) Final Payment
Sample	All Subjects	Max Returns	All Subjects	All Subjects	Max Returns	All Subjects
Mean of dep.var.	8.578***	8.847***	8.439***	23.131***	25.217***	21.793***
	(0.090)	(0.092)	(0.059)	(0.896)	(1.667)	(0.639)
Borrow Debt	-0.090***	-0.094**	-0.008	-0.860**	-1.279*	-0.069
	(0.031)	(0.043)	(0.027)	(0.355)	(0.667)	(0.335)
Borrow Max			0.184***			1.771***
			(0.027)			(0.358)
Errorts Instructions	-0.011***	0.001	-0.007***	-0.082***	0.111	-0.044**
	(0.002)	(0.008)	(0.002)	(0.021)	(0.113)	(0.020)
Above Median Age	-0.006	-0.013	0.002	-0.335	-0.782	-0.266
	(0.028)	(0.039)	(0.024)	(0.351)	(0.588)	(0.314)
Male	0.025	-0.114***	0.039	0.253	-1.115*	0.392
	(0.032)	(0.041)	(0.025)	(0.367)	(0.652)	(0.316)
White	0.013	-0.050	0.018	0.409	0.383	0.454
	(0.042)	(0.048)	(0.032)	(0.422)	(0.819)	(0.353)
College Education	-0.040	-0.045	-0.050*	-0.306	-0.513	-0.407
	(0.031)	(0.042)	(0.028)	(0.408)	(0.662)	(0.387)
Hold Student Loan	0.023	0.009	0.051*	0.555	0.284	0.816**
	(0.035)	(0.047)	(0.027)	(0.419)	(0.714)	(0.361)
Hold Debt	-0.001	-0.008	-0.015	0.020	-0.235	-0.112
	(0.032)	(0.040)	(0.027)	(0.440)	(0.675)	(0.401)
Covid - Little Impact	-0.046	-0.053	-0.084**	-0.434	0.251	-0.796*
	(0.075)	(0.066)	(0.041)	(0.733)	(1.133)	(0.444)
Covid - Moderate	-0.032	-0.090	-0.067*	-0.455	-0.477	-0.787**
	(0.075)	(0.059)	(0.038)	(0.714)	(0.884)	(0.395)
Covid - A lot	-0.013	-0.062	-0.051	-0.268	-0.312	-0.641
	(0.080)	(0.059)	(0.045)	(0.821)	(0.980)	(0.569)
Covid - Great	-0.083	-0.140	-0.093	-0.949	-1.855	-1.037*
	(0.096)	(0.089)	(0.065)	(0.810)	(1.237)	(0.527)
Observations	117	47	117	117	47	117

Notes: Results from a linear regression with robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the log of the cumulative returns in the four allocation decisions and the final payments that subjects obtained without the participation fee. Borrow Max is a dummy that equals 1 if the subject borrowed the maximum amount by the end of the experiment. Columns 2 and 6 focus on subjects who maximize returns in all allocation decisions, regardless of their borrowing behavior.

H. Risk and Time Preference Elicitation

Our measures of risk and time preferences do not show systematic differences between treatments, with the exception of risk preferences in one domain. As expected from an experimental population, our subjects are on average risk averse (see Table A.20).[47] Using all the elicitations after the allocation decisions, we find that subjects with debt exhibit more risk-taking behavior but only when both options involve points—even after initial responses and allocation decisions are controlled for. *Low-Debt* subjects require 5 percent more points to forgo the risky prospect of the lottery. Larger debt balances aggravate this effect, with *High-Debt* subjects requiring 7 percent more. However, these effects are no longer present when the tradeoff involves dollars for sure versus a lottery of points. Similarly, we find no significant differences for time tradeoffs when one option involves money. For the time tradeoffs between points vs. points, we find a similar pattern as in the risk question for that same domain: subjects with debt discount future payments more heavily, particularly when debt balances are higher, although these differences are significant only for the *High-Debt* group.[48]

While we may be concerned that people holding debt behave more erratically, our evidence suggests that this is not the case. For most tradeoffs, subjects with and without debt answer similarly. Despite the large differences in behavior observed in the previous subsections, these effects do not seem to extrapolate to risk or time choices, except for risk in the point domain. The latter suggests that in measuring risk preferences, the domain of the tradeoffs matters for people who hold debt.

[47] Experimental subjects are in general risk averse and often excessively so given the low stakes; see Rabin (2000).

[48] These results are in line with the findings of Meier and Sprenger (2010) that where people with credit card debt tend to be more present biased. However, our measure captures time discounting but not present bias.

Table A.20: Main Treatments: Estimation Output Using Risk and Time Elicitation Questions

	(1) Risk 1 Points vs Points	(2) Risk 2 Money vs Points	(3) Time 1 Points vs Points	(4) Time 2 Money vs Points
Mean of dep. var	0.240	0.202	0.249	0.194
	(0.058)	(0.066)	(0.063)	(0.063)
Low Debt	0.049	-0.018	0.035	-0.005
	(0.025)	(0.030)	(0.025)	(0.028)
High Debt	0.070	0.015	0.055	-0.006
	(0.024)	(0.028)	(0.027)	(0.026)
Initial Risk	0.182	0.200	0.085	0.059
	(0.056)	(0.060)	(0.050)	(0.058)
Initial Time	0.080	0.219	0.262	0.308
	(0.053)	(0.065)	(0.045)	(0.065)
Observations	1032	774	774	774

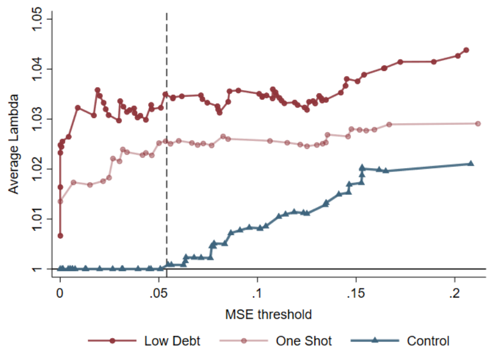
Notes: Results from a linear regression with clustered standard errors at the individual level in parentheses . The dependent variable is an index of risk and time preferences that ranges from 0 to 1. Higher numbers imply higher risk-seeking and time-discounting behavior. Low Debt is a treatment dummy that equals 1 if the subject participated in *Low Debt*. Similarly for High Debt dummy. The regression also includes responses to the initial survey, controls for order effects, dummy if participant maximize returns in all decisions, the number of errors in the instructions, demographic controls (Gender, Ethnicity, Age, and Schooling), controls for whether they hold debt or student loans, and the personal impacts from Covid-19. The full output is presented in Table A.18 in the Appendix.

I. Additional Results from the Structural Exercise

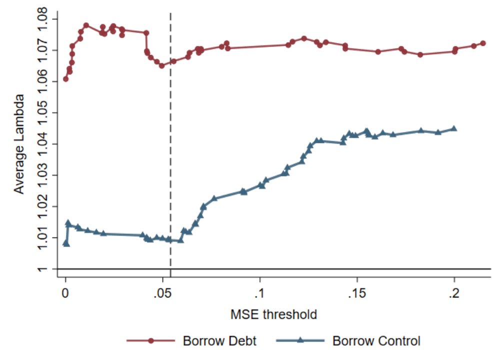
Figure A.10 depicts the average λ based on our type classification from section V. We see that the average λ in the control condition increases due to mistakenly classifying noisy subjects as debt-averse. However, this is not the case in *Low-Debt*, figure A.10a, where we observe a more stable average of 1.035. In our context, a relatively constant λ implies that the relative shares of types remain unchanged over different MSE thresholds. Although less restrictive thresholds increase the number of unclassified subjects. It is only at large MSE thresholds that we observe an increase in our estimated average. We also observe a large spike when moving from 0 MSE to values slightly positive. This spike is due to subjects that allocate 1 or 2 points to other accounts while paying debt or that they allocate 1 or 2 points above the zero debt threshold, possibly due to rounding.

Figure A.10: Subject λ Classification Based on Goodness of Fit [Main Treatments]

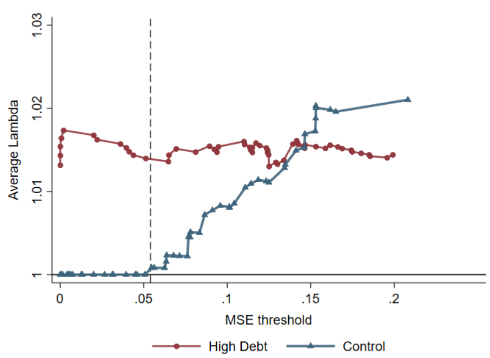
(a) Main Treatments



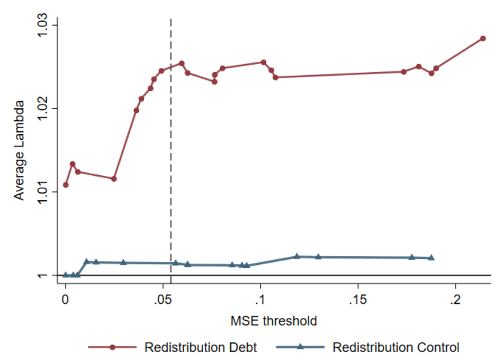
(b) Borrowing Treatments



(c) High Debt Treatment



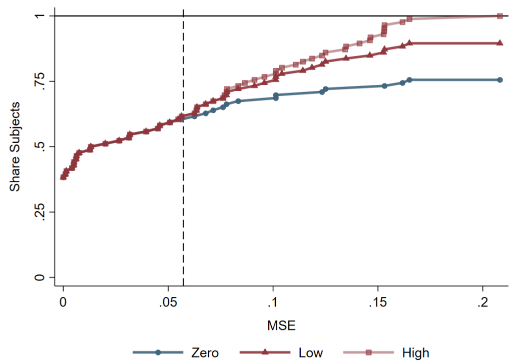
(d) Redistribution Treatments



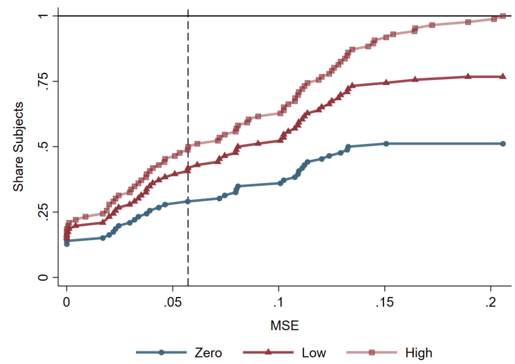
Notes: Vertical dashed lines indicate the MSE threshold in the *No-Debt* (Control) Treatment at which there are no Low or High λ types.

We also find a relatively constant average λ for *Borrow-Debt*, specially when compared to *Borrow-Savings*. For large MSE thresholds, we see values of λ around 1.07, not far from those at lower thresholds. Similarly, restricting to only subjects with a perfect type fit yields an average of 1.06, still far from the 1.015 from the control. Redistribution treatments also show a consistent difference between both conditions. However, in these treatments, we see a relatively sharp increase in the average lambda for larger MSE thresholds. This is because the type classification in *Borrowing* treatments also requires redistributing balances, which many subjects do noisily.

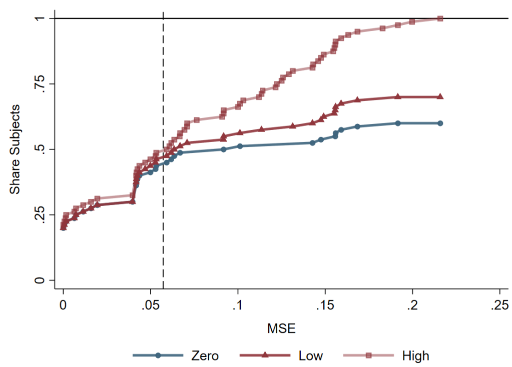
Figure A.11: Subject λ Classification Based on Goodness of Fit



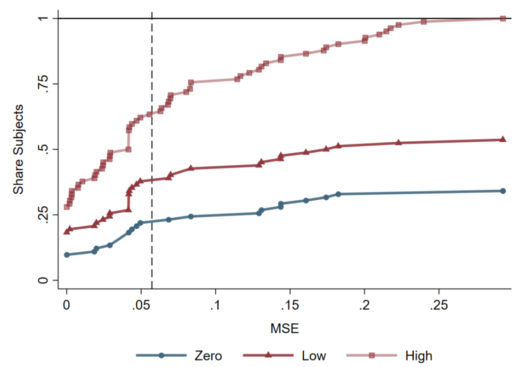
(a) No-Debt Treatment



(b) Low-Debt Treatment



(c) Borrow-Savings Treatment

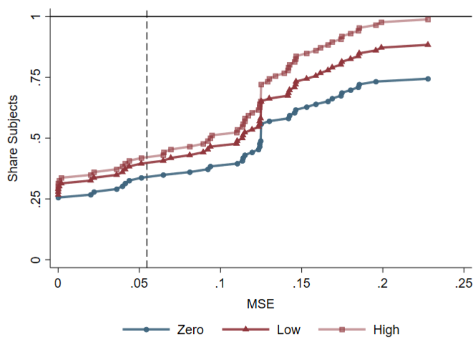


(d) Borrow-Debt Treatment

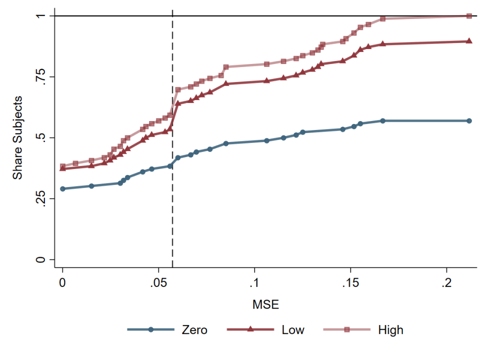
Notes: Vertical dashed lines indicate the MSE for the Control (No Debt) Treatment at which there are no Low or High types.

Figure A.12: Subject λ Classification Based on Goodness of Fit [Additional Treatments]

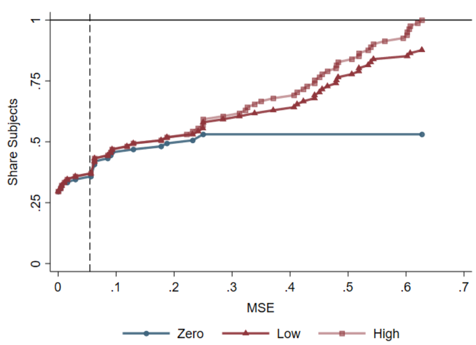
(a) High-Debt Treatment



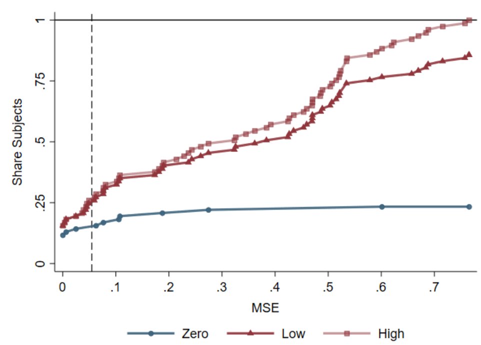
(b) One-Shot Treatment



(c) Redistribution No-Debt



(d) Redistribution Debt



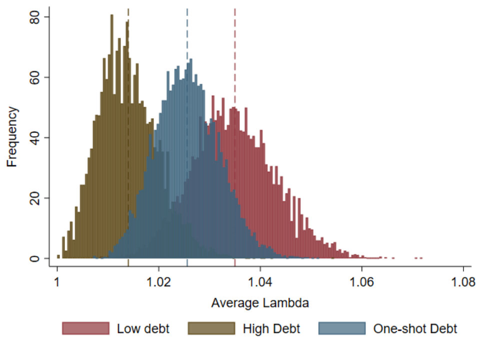
Notes: Vertical dashed lines indicate the MSE for the Control (No Debt) Treatment at which there are no Low or High types.

Figures A.11 and A.12 depict the type classification for all treatments. We find in all treatments a sizable fraction of participants classified as debt averse, i.e., $\lambda > 0$. While different treatments vary in the goodness of fit measures, with redistribution treatments being much noisier, differences arise even at lower MSE thresholds.

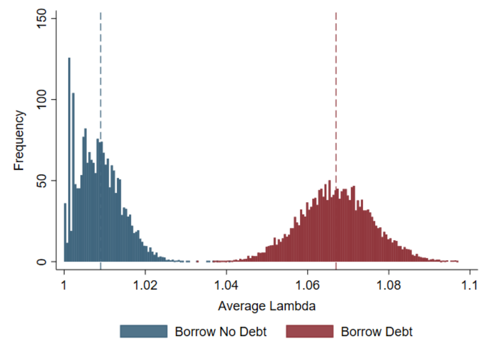
We assess the significance of our estimated average λ in a bootstrap exercise. Specifically, we draw 10,000 samples from our original experimental sample and re-estimate the average lambda. To control for overall noisiness, as in our main results, we estimate λ at the MSE threshold at which no participant is debt-averse in *Low-Debt*. This procedure provides a distribution of estimates for each treatment which we use to perform significance tests. One advantage of calculating the average at the *No-Debt* threshold is that by construction, the *No-Debt* treatment will have a distribution with all mass at one since all observations are non-debt-averse at that threshold. Hence, we can perform significance tests for our debt treatments by simply testing if the empirical 95% or 99% confidence interval encompasses 1.

Figure A.13: Distribution of Average λ in Bootstrap Simulations

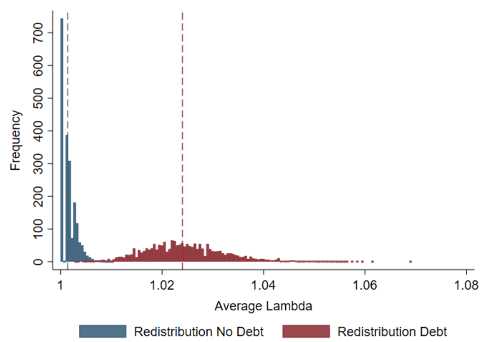
(a) Debt Treatments



(b) Borrowing Treatments



(c) Redistribution Treatments



Notes: Vertical dashed lines indicate the average λ from our original samples.

Figure A.13 provides compelling evidence that our estimates of debt-aversion do not arise due to randomness in our sample. In our treatments with debt (*Low, High* and *One-shot*), we find in all cases that the distribution of average λ is centered away from zero, with the largest difference in the *Low-Debt* treatment. These treatments have a mass much smaller than 1% for values close to one. Therefore, we can reject the null hypothesis that λ in the debt treatments are similar to the ones in the *No-Debt* treatment with a confidence level higher than 99%. A similar pattern arises when we look at the *Borrowing* and *Redistribution treatments*, figures A.13b and A.13c. For borrowing treatments, we see clearly how both distributions are quite far apart, with almost no overlap (p.value<0.000). Note that since the MPE threshold corresponds to the *No-Debt* treatment, we now have variance in the *Borrow No-Debt* condition. Finally, we also find significant differences for our *Redistribution* treatments when debt is present, although not as stark as in the previous cases. In the *Redistribution No-Debt* sample, the distribution is heavily skewed towards one, while in *Redistribution Debt* is centered around 1.024. Despite the large right tail, with some values higher than 1.06, the overlap between distributions is smaller than 1%.

J. Additional Details from Discussion on Present Focus vs. Debt Aversion

For our first example, we use a linear utility function based on Berkouwer and Dean (2022). In their setting, people can purchase a charcoal cookstove for a retail price of \$40, and loans offer a monthly interest rate of 14%

Concerning the benefits, they find that a household saves \$119 per year, which corresponds to \$9.91 per month. Hence, we consider the benefits of purchasing the new charcoal as \$9.91 per month for two years, corresponding to the estimated lifespan of the cookstove. In this setting, we assume an agent decides to borrow when the benefits outweigh the costs:

$$9.91 + \sum_{i=1}^{24} \beta\delta^i \times 9.91 \geq \sum_{i=1}^{3} \beta\delta^i \times 13.65(1+\lambda)$$

where x_t denotes the monetary flow in period t, which corresponds to a month. Note that this expression incorporates present focus and time discounting, i.e., β and δ, and debt-aversion similarly to Section V i.e., λ. We choose $\beta = 0.80$ and $\delta = 0.95$ for easy comparison with our next example and by having $\delta = 0.95$ corresponding to a yearly discount rate.

For our second example, inspired by Allcott et al. (2022), we consider a \$200 two-week payday loan to fund immediate consumption at a 15% interest rate. Here we consider both a linear and an exponential utility function. In the exponential case, we further need to assume whether debt aversion impacts the balance directly, i.e., $x(1+\lambda)$, or the disutility of the negative balance, i.e., $u(x)(1+\lambda)$. While we consider this distinction an interesting theoretical question, our results are robust to either. Hence, we report results when assuming it impacts balances directly, in line with our theoretical framework. The comparison is then:

$$u(200) \geq \beta\delta^{0.5}u(230(1+\lambda))$$

Note that here, we assume that $\delta = 1$ due to the short time horizon, as opposed to the yearly discount as in the previous case. Our results are qualitatively robust to using the same yearly discount rate in both examples.

Table A.21: Examples of Borrowing Decisions

(a) Example 1 - Charcoal Cookstove Investment

Row	Scenario	Present Focus & Time Discounting	Debt Aversion	Percentage Return
1	$\beta = 1, \delta = 1, \lambda = 0$	No	No	291%
2	$\beta = 0.80, \delta = 0.95, \lambda = 0$	Yes	No	259%
3	$\beta = 1, \delta = 1, \lambda = 0.15$	No	Yes	253%
4	$\beta = 1, \delta = 1, \lambda = 0.5$	No	Yes	194%
5	$\beta = 1, \delta = 1, \lambda = 1$	No	Yes	168%
6	$\beta = 0.80, \delta = 0.95, \lambda = 0.15$	Yes	Yes	225%
7	$\beta = 0.80, \delta = 0.95, \lambda = 0.5$	Yes	Yes	173%
8	$\beta = 0.80, \delta = 0.95, \lambda = 1$	Yes	Yes	148%

(b) Example 2 - Payday Lending with Linear Utility

Row	Scenario	Present Focus & Time Discounting	Debt Aversion	Percentage Return
1	$\beta = 1, \delta = 1, \lambda = 0$	No	No	87%
2	$\beta = 0.80, \delta = 1, \lambda = 0$	Yes	No	109%
3	$\beta = 1, \delta = 1, \lambda = 0.15$	No	Yes	76%
4	$\beta = 1, \delta = 1, \lambda = 0.5$	No	Yes	58%
5	$\beta = 1, \delta = 1, \lambda = 1$	No	Yes	43%
6	$\beta = 0.80, \delta = 1, \lambda = 0.15$	Yes	Yes	95%
7	$\beta = 0.80, \delta = 1, \lambda = 0.5$	Yes	Yes	72%
8	$\beta = 0.80, \delta = 10.95, \lambda = 1$	Yes	Yes	54%

Notes: Panel (a) simulates borrowing \$40 to purchase a charcoal cookstove using a 3-month loan at 14%, as in Berkouwer and Dean (2022). Percentage returns use their charcoal savings estimates without incorporating any additional health or environmental benefits. Panel (b) simulates a two-week payday loan of \$200 to finance an immediate expenditure/consumption at a 15% interest rate. Present focus parameter β is chosen based on Allcott et al. (2022) and we also assume risk-neutrality. A percentage return higher than 100% implies the acceptance of the loan, while a percentage lower than 100% implies a loss and hence declining the loan offer.