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The Impact of Financial Education on Adolescents' Intertemporal Choices*

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Abstract

We examine the impact of a large high-school financial education program on the intertemporal choices of adolescents. We randomly assigned the program among a sample of almost 1,000 students and measured their intertemporal choices using an incentivized experiment. While intertemporal choices in the control group exhibit significant present bias, choices among treated students are time consistent on average. We structurally estimate individual preference parameters, explicitly allowing choices to be stochastic. Participation in the program increases time consistency and decreases error rates. These findings suggest that financial education can have significant effects on intertemporal choice already at a young age.

JEL codes: D14, D91, C93.

Keywords: Intertemporal Choice, Financial Education, Experiment.

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1 Introduction

Intertemporal choices are ubiquitous and central to economic decision-making. Examples include decisions such as how much to invest in education and save for retirement. An important phenomenon in intertemporal choice, documented in a large body of work (see, e.g., Frederick, Loewenstein and O’Donoghue, 2002), is that individuals often exhibit time-inconsistent behavior, contrary to the assumption of dynamic consistency of the standard economic model (Samuelson, 1937). Time-inconsistent preferences can explain why individuals fail to fulfill savings plans, do not save enough for retirement (Laibson, Repetto and Tobacman, 1998), and incur (unplanned) credit-card borrowing (Meier and Sprenger, 2010).

Thus far, existing empirical work has taken such behaviors as stable. In this paper we examine whether an educational intervention that deals extensively with intertemporal choice – in our case, an established financial education program – changes intertemporal choices. Strotz (1956), in his pioneering work on time inconsistency, and Becker and Mulligan (1997) argue that education can have important effects on intertemporal choice. While the human being, especially at an early age, can be very impatient, education has the potential to raise attention to the future, thereby decreasing present biased and impatient behavior.

Financial education initiatives, which have become increasingly popular in recent years, address intertemporal decision-making implicitly, as they cover such issues as impulse shopping, credit card borrowing, savings goals, and financial planning (e.g., Hastings, Madrian and Skimmyhorn, 2012; Lusardi and Mitchell, 2014).¹ Many of these educational interventions are aimed at adolescents. This may be an adequate age at which to provide such training, as recent evidence suggests that character and non-cognitive skills are still malleable during adolescence (for a detailed survey, see Heckman and Kautz, 2013). Also, already at a young age, behaviors such as savings are correlated with intertemporal preferences elicited using experimental tools (e.g., Sutter et al., 2013).²

We examine the effect of a financial education program that has been provided in recent years to over 35,000 thousand high-school students in Germany. The program we

¹A database of existing financial education programs can be found under the following address: <http://www.financial-education.org/gdofe.html>. It is estimated that 670 million US dollars are spent annually on financial education in the US (CFPB, 2013).

²Measures of time preferences elicited in the laboratory are correlated with intertemporal choices also among adults (Chabris et al., 2008).

study consists of three standardized modules on financial decision-making: shopping, planning and saving, which were developed by educational experts together with school principals. It discusses, among others, the role of reflection when making purchasing decisions as well as the use of financial planning to achieve savings goals. We measure the causal effect of financial education on adolescents' intertemporal choices following a randomized allocation of the program to treatment classes and using an incentivized experiment. Specifically, we measure intertemporal choices with an adapted version of the Convex Time Budget task, developed by Andreoni and Sprenger (2012a). This task allows us to precisely measure how adolescents trade off earlier and later monetary payments offered at different prices (or interest rates).

In total, almost 1,000 students participated in the experiment, about half of whom were randomly assigned to participate in the financial education program. A descriptive analysis of the data highlights three aspects of intertemporal choice. First, we obtain a measure of present bias by comparing allocations in situations when the earlier payment is made immediately with allocations when the earlier payment is delayed into the future. In the control group, adolescents are on average more impatient when early payments are immediate. In the treatment group, in contrast, the effect of immediacy is insignificant. Further, the share of present-biased choices decreases in the treatment group. Overall, these results indicate that participation in the program increases time consistency.

Second, we investigate how allocations change when the delay between the earlier and later payments is increased, which we term delay sensitivity. We do not find a significant change in delay sensitivity. At the same time, we do not find an increase in the average allocation to earlier payments, suggesting that the treatment had no significant effects on patience. Third, we examine the impact of the program on the consistency of choices. The program induces a small but significant increase in the share of choices that is consistent with the law of demand, i.e., as the price of choosing earlier payments increases, adolescents choose (weakly) smaller earlier payments. This finding is important in light of recent results suggesting that the quality of decision making, measured by consistency with utility maximization³, is strongly positively correlated with wealth accumulation (Choi et al., 2014).

Following a large body of empirical research on time preferences, we complement

³Choi et al. (2014) define consistency using a revealed preference method based on GARP and Afriat's (1972) Critical Cost Efficiency Index (CCEI).

these descriptive results with an estimation of the time preference parameters of adolescents.⁴ Recent contributions using multiple choice lists include Anderson et al. (2008), Benhabib, Bisin and Schotter (2010) and Tanaka, Camerer and Nguyen (2010), and those using the Convex Time Budget task include Andreoni and Sprenger (2012a, 2012b) and Kuhn, Kuhn and Villeval (2013). As in many studies involving price list tasks, some of the choices we observe are inconsistent with the law of demand. We thus allow subjects to make stochastic choices and extend the approach by von Gaudecker, van Soest and Wengström (2011) from the domain of risk elicitation to our setting with intertemporal choices. In the aggregate, the results confirm that students' choices in the control group exhibit significant present bias. In contrast, the choices of students who participated in the program do not exhibit present bias. In the treatment group, the hypothesis of time consistency cannot be rejected. For a variety of specifications and error models, this result remains robust.

When we allow for individual heterogeneity in preferences, we find that the educational program changes the distribution of the present bias parameter. There is a decrease in the share of students exhibiting (strong) present bias; there is an increase in the share of students classified as time consistent; and the share of those exhibiting future bias decreases. The estimated individual present bias parameter correlates significantly with a survey measure of savings, indicating that the experimental measures of intertemporal choice are externally valid. We also find that the program shifts the distribution of stochastic choices, as measured by trembling-hand errors (Harless and Camerer, 1994), and leads to a decrease in the average individual likelihood of a stochastic choice. Overall, our results suggest that financial education has a significant impact on intertemporal choice. Choices made by students who participated in the program are more consistent with respect to both time and price, i.e., they are less likely to violate the law of demand.

The impact of the program exhibits heterogeneity in three dimensions, cognitive ability, socio-economic status, and across the two age groups we consider (ages 13–14 and 14–15). Our results indicate that students with higher cognitive ability exhibited a stronger increase in time consistency. We also observe that students living with a single parent are less time consistent in the control group but exhibit a stronger increase in the treatment. Further, our results indicate that the effect of the treatment on time

⁴We interpret the parameters we estimate from observed choices in a revealed preference sense. We return to this issue in Section 7 when we discuss our findings.

consistency is stronger among younger students, while that on error rates is stronger among older students.

This paper makes three main contributions. Most importantly, we test for the first time the hypothesis that education may change intertemporal decision-making, as proposed by Strotz (1956) and Becker and Mulligan (1997). Variation in (financial) education is generated randomly, through the exogenous allocation of a widely taught financial education program. Intertemporal choice is measured with a controlled and incentivized task, following the most recent elicitation method developed by Andreoni and Sprenger (2012a). We find that an educational program focused on financial decision-making has significant effects on intertemporal choices.

A second contribution of this paper is towards the growing literature that documents – in quite diverse populations – low levels of financial literacy, studies its relation to poor financial decision-making, and discusses policy implications (see Lusardi and Mitchell, 2014, for a comprehensive review). Calls for policy action abound, and programs to improve financial literacy have been initiated in both industrialized and developing countries. Research on the effects of financial education interventions has, however, come to mixed conclusions. Several studies find that financial education yields weak, if any, effects on knowledge and behavior (see Lynch, Fernandes and Netemeyer, 2014, for a review). Skimmyhorn (2013), though, finds strong effects of a financial education program administered in the U.S. Army on retirement savings. Results on programs provided in adolescence are also mixed (e.g., Bechetti, Caiazza and Coviello, 2013; Berry, Karlan and Pradhan, 2013; Lührmann, Serra-Garcia and Winter, 2013). The strongest effects documented so far come from a large-scale study in Brazil: A year-long program increased knowledge and self-reported savings behavior in high schools (Bruhn et al., 2013). In contrast, the program we examine is short – it can be provided over the course of a week, so it is easily scalable. It is highly relevant whether such a short program can have significant effects on intertemporal choice, in particular in adolescence – a period during which individuals start to make spending and saving decisions and habits are potentially formed.

A third, perhaps broader, contribution of the paper is to suggest a way in which tools from experimental economics can be informative for the evaluation of educational interventions, and could be used in future studies in combination with surveys and administrative data. The CTB task has been used to measure changes in intertemporal choices in response to willpower manipulations (Kuhn, Kuhn and Villeval, 2013), after

the introduction of savings accounts (Carvalho, Prina and Sydnor, 2014), and around payday among low-income individuals (Carvalho, Meier and Wang, 2014). By using the CTB task, our paper provides complementary evidence to survey-based studies of the impact of financial education (e.g., Bruhn et al., 2013) or studies based on administrative data (e.g., Brown et al., 2013). Our findings suggest that the effects of financial education may be subtle and work through reductions of both, time-inconsistent choices and errors in decision-making. To the best of our knowledge, our study is the first to make this distinction in the analysis of interventions aimed at intertemporal choices.

The remainder of the paper proceeds as follows. In the next section, we describe the financial education program. In Section 3, we describe of the experimental task and methods used. Section 4 reports the descriptive results. In Section 5, we present the structural model, the estimation approach, and the estimates of preference parameters and error rates. Section 6 examines the heterogeneity of treatment effects. Section 7 concludes.

2 The Financial Education Program

The financial education program is provided by a non-profit organization, My Finance Coach, which since its startup in October 2010 has offered financial education to over 35,000 German high school students, aged mainly between 13 and 15 years (see My Finance Coach, 2012). We evaluate the impact of financial education offered through visits of “finance coaches” to schools. These coaches are employees of the (for-profit) firms that sponsor the (non-profit) provider, and they are not compensated for the training they provide to high-school students. They volunteer to conduct several visits of 90 minutes, each of which is dedicated to one of the training modules. The provider offers a set of materials for each module and trains the coaches; hence, visits are standardized.

This financial education program is well suited for studying the impact of educational interventions among adolescents. First, it is provided at schools, and hence all students in a class participate, avoiding selection problems (see, e.g., Meier and Sprenger, 2013). Second, the materials taught are standardized, have been developed by educational experts (ranging from education researchers to school directors), and have been extensively used in teaching for over four years in Germany. Third, this educational intervention is scalable.

We measure the joint impact of three training modules that are provided to all

treated students: Shopping, Planning, and Saving. Each module deals with the following topics as described in the official materials of the provider.⁵ The Shopping module deals with acting as an informed consumer. It focuses on prioritizing spending (“needs and wants”) and on criteria used in purchasing decisions. The module also addresses advertising and its objectives. Finally, it aims at helping adolescents critically reflect on personal purchasing decisions. The Planning module addresses aspects of conscious planning. It presents the concepts of income and expenditure as the basis of financial planning, and trains budgeting skills. The module then focuses on planning personal finances for the long term and discusses planning tools to help teenagers reach their financial goals, like buying a scooter. The last module, Saving, discusses different saving motives and various types of investment options. It also talks about conflicts of interest in everyday life as well as in relation to money.

Taken together, these three training modules deal at length with intertemporal choices in the domain of financial decisions, emphasizing the roles of reflection (e.g., while shopping) and planning. The training, however, does not take a normative position on saving – it explains why a person might want to save and how saving goals can be achieved, but it does not imply that every adolescent should save. Importantly, the training also does not involve any decision that directly resembles the tradeoffs in the Convex Time Budget task.

The existing literature suggests two potential effects this training might have on intertemporal choices. First, related to Becker and Mulligan (1997), the educational program may decrease the cost of imagining the future when making financial decisions. For example, it may make planning tools more accessible and hence reduce the cost of planning. This could increase patience among adolescents. Second, following Baumeister, Vohs and Tice (2007), the educational program we study can be viewed as an exercise strengthening self-control in purchasing decisions. Accordingly, should the importance of the present relative to the future weaken with the treatment, we would expect a decrease in present bias.

Whether adolescents’ intertemporal choices can be affected by a (relatively short) educational intervention is particularly interesting in the light of a wave of recent studies showing that while interventions aimed at increasing cognitive ability are most effective in childhood, character skills are still malleable among adolescents (Heckman and

⁵Further detailed information about the training materials can be found at <http://en.myfinancecoach.org/>.

Kautz, 2013). Evidence from neuroscience shows that adolescence is associated with increased connectivity and development of the prefrontal cortex which coordinates cognitive processes and executive functioning. This maturation of the brain continues until adulthood. Executive functioning and cognitive control are needed for “goal-directed behavior, including planning, response inhibition, working memory, and attention” (Johnson et al., 2009). They increase the capacity for reflection, assessment, and controlling impulse (see, Nurmi, 1991, for a review). The financial education program takes place during this developmental phase: it is targeted at 13 to 15 year old students to provide tools and a contextual framework for the exertion of goal-directed behavior with regard to money (without prescribing a specific financial goal). This training is further delivered in the years leading to apprenticeship or other career pathways and thus aims to prepare students for the first significant receipt of own financial resources.

3 Experimental Design

3.1 Setting and Randomization

The schools in our study pertain to the two lower tracks of the German high school system. Students in these two tracks typically continue with vocational training after graduation (rather than attending college).⁶ Dustmann (2004) shows that there is a strong association between family background (parents’ education as well as occupational status) and childrens’ school track. Moreover, children in the lower tracks also have lower income and occupational outcomes as adults.

The randomization of classes to the control and treatment group was conducted in the following manner: The provider contacted schools in the cities of Berlin, Düsseldorf and Munich. If a school was interested in the program, the provider entered the school’s information into a web interface designed by the research team. Upon submitting this information, the randomisation algorithm underlying the interface informed the provider and hence the school about the timing of the program. Schools in the treatment group were assigned to receive the training earlier in the school year, while schools in the control group were assigned to receive the program towards the end of the school year.

⁶The school system in Germany has three types of high schools, starting as of age 10. These tracks comprise schools in which students pursue vocational training (*Hauptschule*, *Sekundarschule*, *Mittelschule*), combine both vocational training with the option of accessing university later on (*Realschule*, *Gesamtschule*, *Werkrealschule*) or focus on preparation for university studies (*Gymnasium*). All participating students in our study belong to the first two types of schools.

Randomization occurred at the school level to avoid spillover effects. Randomization was stratified by city, so that differences in the educational systems in the different areas are orthogonal to the treatment allocation. Since we were bound by scheduling constraints, including that all participating schools receive the training by the end of the school year, the time between treatment and time preference elicitation was between 4 and 10 weeks. We thus measure medium-run effects of the program.

3.2 Method

The elicitation method we use, the Convex Time Budget (CTB), was developed by Andreoni and Sprenger (2012a, 2012b). This method asks individuals to allocate amounts of money to two points in time. The payment received at the earlier point in time, t , is x_t ; the amount received at a later point in time, $t + k$, is x_{t+k} . The delay between payments is k . The amounts x_t and x_{t+k} satisfy the budget constraint $(1+r)x_t + x_{t+k} = m$, where $1+r$ is the gross interest rate. In contrast to menu price lists in which monetary payments must be fully allocated to either the earlier or the later point in time, i.e., $(x_t, x_{t+k}) \in \{(\frac{m}{1+r}, 0), (0, m)\}$, the CTB method allows for inner choices in addition to corner solutions, which in turn allows for convex budgets. It is thus not necessary to assume linear utility when estimating discount rates from the observed allocations (an assumption which leads to biased discount rate estimates if utility is concave).⁷

We elicit choices using three different combinations of t and $t + k$; the tasks for each of these combinations are presented on a separate decision sheet. The first sheet offers payments immediately after the CTB ($t = 0$, “today”) and three weeks later, i.e., the delay is $k = 3$ weeks. The second sheet offers payments today and six weeks later, i.e., the delay is $k = 6$ weeks. The last sheet offers payments in three and in six weeks, i.e., the delay between payments is $k = 3$ weeks but there is also a “front-end delay” as $t > 0$. On each decision sheet, seven budget constraints – i.e., seven different interest rates – were presented to students. Going from top to bottom, the price for the earlier payment increases. An overview of the design is displayed in Table 1.

Comparing decisions with identical delay k but different front-end delay, i.e., $t = 0$ vs. $t > 0$, provides identification of the degree of present bias. Further, comparing decisions with a delay of 3 and 6 weeks allows identification of the degree of impatience.

⁷An alternative method to correct the bias associated with the assumption of linear utility was developed by Andersen et al. (2008) who estimate discounting and curvature parameters jointly but using data from separate choice lists for intertemporal payments and lotteries.

Decision sheet	Earlier payment (t)	Later payment	Delay (k)
(1)	Today	In 3 weeks	3 weeks
(2)	Today	In 6 weeks	6 weeks
(3)	In 3 weeks	In 6 weeks	3 weeks

Note: Within each decision sheet seven decisions were elicited with the following gross interest rates ($P = 1 + r$): 1.00, 1.025, 1.05, 1.08, 1.18, 1.33 and 2.00, on the budget constraint $Px_t + x_{t+k} = m$.

Table 1: Elicitation of time preferences – Design

Variation in the interest rates within each decision sheet tilts the budget constraint and thus allows identification of the concavity of utility. We note that, to generate sufficient variation in choices within the relatively short delay time, we offer high interest rates.^{8,9}

We adapt the elicitation task to ensure that our sample of adolescents understands it. In the first paper, Andreoni and Sprenger (2012a) offer a choice set with 100 choices within each budget to split between the earlier and later date. In a follow-up study, Andreoni, Kuhn and Sprenger (2013) limit the choice set to seven choices. Both studies are conducted among university students. To reduce complexity in our adolescent sample, we offer four combinations of money at the earlier and later points in time for each budget constraint. In each choice situation, participants can either allocate 100%, 66.6%, 33.3% or 0% of the budget to the earlier point in time. To make the variation in the time horizons salient, color-coding was used for each point in time. Additionally, the students saw a calendar at the top of each sheet on which the relevant payment dates were marked. The date on the calendar and the amounts of money referring to today were colored in green, those referring to payments in three weeks were blue, while those in 6 weeks were marked dark pink. An example of a decision sheet is provided in Figure 1. We randomized the ordering of the three decision sheets across classes to balance any potential order effects.

⁸For example, for a delay of three weeks, the effective yearly interest rate, assuming quarterly compounding, ranges from 0%, for gross rate 1.00, to 752.9%, for gross rate 1.18, and goes up to 27128%, for gross rate 2.00.

⁹An important discussion in the elicitation of choices over monetary payments paid at different points in time is the role of extra-experimental savings and credit options and liquidity constraints (Coller and Williams, 1999). Within the age group we study, access to the market is practically absent (see, Sutter et al., 2013, among others). Also, we do not find a significant difference in reported spending by students between the treatment and control group (as discussed in Section 5.3).

TODAY and 3 WEEKS from today								
		April			May			June
		1 2 3 4 5 6 7			6 7 8 9 10 11 12			3 4 5 6 7 8 9
		8 9 10 11 12 13 14			13 14 15 16 17 18 19			10 11 12 13 14 15 16
		15 16 17 18 19 20 21			20 21 22 23 24 25 26			17 18 19 20 21 22 23
		22 23 24 25 26 27 28			27 28 29 30 31			24 25 26 27 28 29 30
		29 30						
<p>Choose in each decision (A1 to A7) the amounts that you want to receive with certainty today and in 3 weeks, by crossing the corresponding box. Do not forget to cross only one box for each decision!</p>								
A1.	Amount TODAY ...	€6.00	€4.00	€2.00	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A2.	Amount TODAY ...	€5.85	€3.90	€1.95	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A3.	Amount TODAY ...	€5.70	€3.80	€1.90	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A4.	Amount TODAY ...	€5.55	€3.70	€1.85	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A5.	Amount TODAY ...	€5.10	€3.40	€1.70	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A6.	Amount TODAY ...	€4.50	€3.00	€1.50	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A7.	Amount TODAY ...	€3.00	€2.00	€1.00	€0.00			
	AND amount in 3 WEEKS	€0.00	€2.00	€4.00	€6.00	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 1: Example of a decision sheet (translated from German)

3.3 Implementation of Payments

We followed a number of procedures to ensure trust and to address issues of risk and transaction costs that typically arise when implementing delayed payments. All procedures were explained in the instructions before any decisions were taken by the adolescents.

Transaction costs. Students were given a “participation” fee of 2 Euro to thank them for their participation. They were informed that the participation fee would be split equally across both payment dates. Hence, independent of the exact choice of each student, he or she received always at least one Euro at each point in time.

Record of payments. After students made their 21 (7×3) choices, one decision was drawn for payment. The random draw was performed by one volunteer student for the entire class and this draw was noted on the classroom board. Subsequently, based on the student’s choice and the decision drawn for payment, each student received a payment card that recorded her exact payments and payment dates. Hence, students did not have to remember when the future payment would occur and how much they would receive. The payment card also served as a written confirmation of each students’ payment entitlement. The card format was designed to fit into students’ wallets, and students were requested to keep it there. At the same time, each student wrote her name onto a payment list, which also contained the payments she had chosen to receive at each point in time. This list was given to the teacher in the presence of the class. Both act as records for delayed payments and the backup copy kept by the teacher ensured that payments can be made even when individual payment cards are lost.

Delivery of payments. Payments were made in cash, in class, to each student individually. Immediate payments were made after the survey complementing the CTB experiment was completed, if today was drawn for payment. Delayed payments were made exactly three or six weeks later in class at the dates noted on the payment cards. The exact appointment for the future payment was discussed with the teacher and then announced in class. Our instructions clearly explained that we would come back into class once (or twice, depending on the draw) at the date(s) indicated on the calendars on their decision sheets and on payment cards to make the delayed payments. The teachers, who were present during the experiment, acted as witnesses of this commitment.

Consent. Only students whose parents had consented to participate are included in the study. The consent forms provided to parents included the researchers' contact information, which the teacher also obtained. Almost all students (97%) provided a signed consent form to participate in the study.

3.4 Procedures

In each session, the time preference elicitation task was conducted first, followed by a survey. The instructions for the time preference elicitation task were read aloud in front of the class. A copy of the instructions can be found in the Online Appendix. All class visits were conducted by the same two experimenters. One of them always presented the instructions in each session, using multiple examples and giving students plenty of time and opportunities to ask questions. After all questions were answered, students were asked to complete four control questions before starting their decisions. These questions were designed to test the understanding of the task. Each student's answers were checked by the experimenters before she could start making her 21 decisions.

The presentation of the instructions took on average 25 minutes, while students made their decisions in 5 to 10 minutes. When they finished with the task, students were asked to complete a survey. We asked students for their gender and age, their math grade as well as three questions regarding their socio-economic background. We elicited their household composition (i.e., who they live with), the language they speak at home and the amount of books at home. These are standard questions in the PISA survey (Frey et al., 2009). They are considered proxies of the socio-economic status of students' family and hence important family inputs into a student's education (for a review, see Hanushek and Woessmann, 2011). Our survey also included four of Raven's progressive matrices (Raven, 1989), selected to capture heterogeneity in cognitive skills, based on a previous study in Germany by Heller et al. (1998). The survey also included several questions on financial knowledge and financial behavior. The impact of the training on standard financial literacy questions is similar to the findings in Lührmann, Serra-Garcia and Winter (2013).¹⁰ We also elicited savings behavior in order to examine the relationship between savings decisions and estimated time preference parameters

¹⁰We observe an increase in knowledge about what stocks are, as measured by the question designed by van Rooij et al. (2011), which is a subject dealt with in the educational program. We do not find spillover effects on to questions about interest compounding, the time value of money and risk diversification (based on standard financial literacy questions, see, e.g., Lusardi and Mitchell, 2014), concepts not taught in the program. Detailed results are available from the authors.

(see Section 5.3). In total sessions lasted between 45 and 60 minutes. In each city, all sessions were scheduled to take place during the same week, for both treatment and control groups.¹¹

3.5 Sample

Our sample consists of 994 students from 55 classes in 25 schools (12 treatment, 13 control). These students completed first the CTB task and then a survey. As mentioned above, we conducted the CTB task using pen and paper. When encoding the answers electronically, we found that 80 students provided answers that could not be attributed a clear value, due to either a missing answer or multiple crossing of answers, in one to three of the 21 choices. We exclude these students from the sample and hence examine the choices of 914 students.¹² Their average age is 14.3 years and 39.8% of the students are female. A substantial share of students have a migrant background. Specifically, 46.4% speak a language other than German at home. Also, 58% report having less than 25 books at home. Individual characteristics were balanced across treatment and control, supporting the randomization method used in this study (details are provided in the Online Appendix).

4 Descriptive Results

This section provides a descriptive analysis of students' choices in the CTB task. We first examine the consistency of the choices. We then describe the allocation choices of students, providing evidence on time consistency and delay sensitivity, and on allocations between corner and interior choices which give a first indication of the curvature of the utility function. Throughout this section and the next two sections, we report two-sided tests (parametric and non-parametric) unless otherwise noted.

¹¹To avoid any time effects, we scheduled the experiment to take place in each city during the same week in April. This was possible for 46 out of 55 classes. For a small group of nine classes the class was scheduled to be at a practical training out of school for the week, and hence we conducted the experiment 3 weeks later in eight classes and 6 weeks later for one class. We control for any potential time effects by adding a month dummy for April (as 46 out of 55 were scheduled in April) in our regression analysis.

¹²Specifically, one out of 21 choices cannot be told apart for 71 students, two for 7 students and three for 2 students. Results remain the same if the students are included in the sample.

4.1 Consistency of Choices

The consistency of choices is a central issue in experiments using choice lists as the method of elicitation. A first measure of inconsistency is whether a student who chose to allocate 100% of his budget to the later point in time switches to allocating 0% (and thus 100% to the earlier point) as the interest rate increases. In multiple price lists this is the central measure of inconsistency (e.g., Andersen et al., 2008) and represents a violation of the law of demand. We find that 782 out of 914 students never make such an inconsistent choice. The rate of inconsistent individuals, 14.4%, is similar to that found in experimental tasks with children and adolescents (e.g., Bettinger and Slonim, 2007, Castillo et al., 2011) and does not differ across treatment and control (Mann-Whitney test, $p=0.1339$).

With CTB tasks, students may also display smaller decreases than a 100% shift in the share allocated to the later point in time as the interest rate increases. These changes are again violations of the law of demand.¹³ In our sample the average share of choices that is consistent with the law of demand is 80.8% in the control and 82.9% in the treatment group. These rates are very similar to those found by Gine et al. (2012) in individual interviews with farmers in Malawi (81%) and by Carvalho, Meier and Wang (2014) in the American Life Panel (82% before payday and 84% after payday). The consistency of choices in our experiment exhibits a 2 percentage point increase in the treatment group. The difference across treatment and control is statistically significant (Mann-Whitney test, $p=0.0258$). In the analysis of intertemporal choices that follows we thus adopt two approaches. First, we control for the fraction of choices that is consistent, i.e., does not violate the law of demand, in the descriptive results. Second, we allow for stochastic choice in the econometric model, since the estimation of preference parameters is biased unless the presence of inconsistencies is taken into account. Our model builds on previous work of Loomes, Moffatt and Sugden (2002), Andersen et al. (2008) and von Gaudecker, van Soest and Wengström (2011).

¹³Precisely, within each of the three decision sheets, students made seven choices. A choice is consistent if the share allocated to the earlier point in time decreases or stays unchanged as the interest rate increases. Excluding the first choice in each sheet, the fraction of consistent choices is the sum of consistent choices over 18.

4.2 Intertemporal Choices

A. Time Consistency

Figure 2 displays the mean share of the budget allocated to the earlier point in time for the control and treatment group by immediacy of the earlier payment, i.e., keeping delay k constant but varying t . The solid blue line shows the mean budget share allocated to earlier when the earlier payment is made instantly, i.e., today, and the dashed red line shows the same for the intertemporal choice when the earlier payment occurs in 3 weeks. In both, the treatment and control group, the earlier share decreases with increasing gross interest rates.

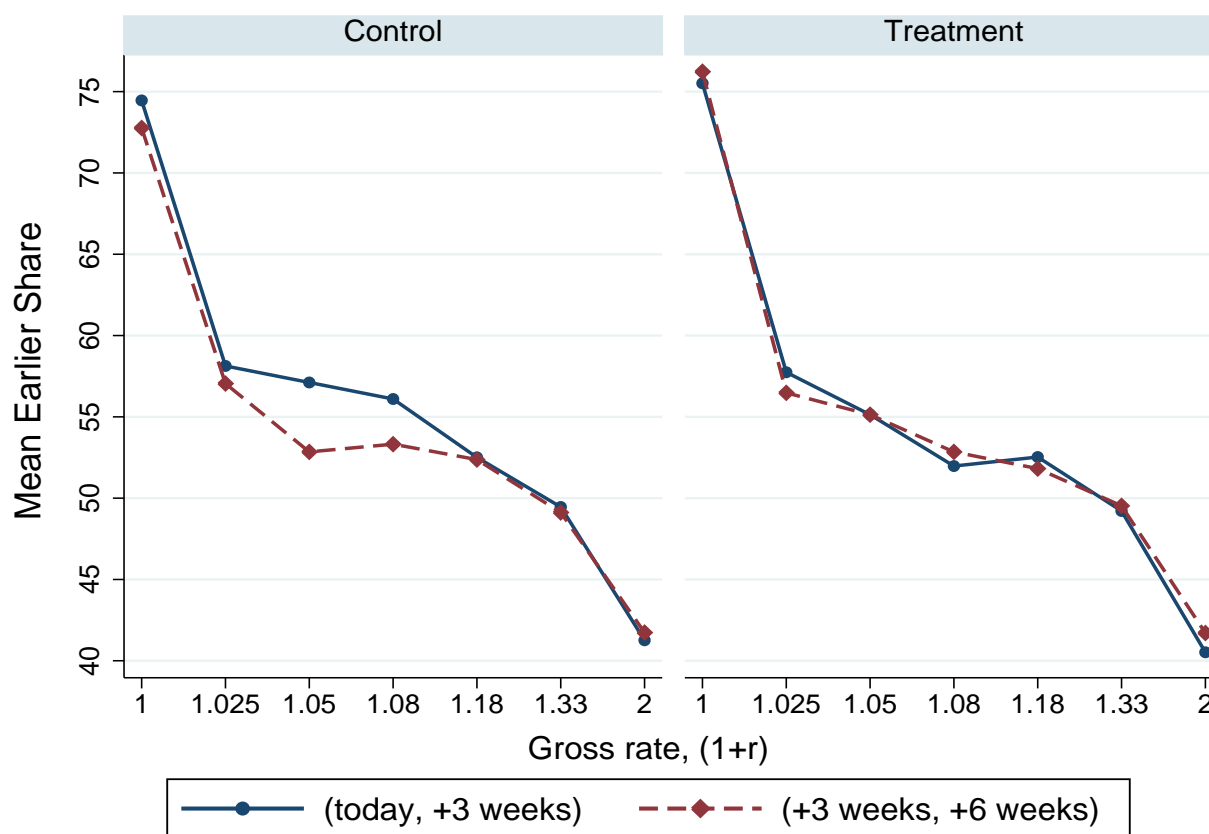


Figure 2: Allocations chosen for (today, 3 weeks) and (3 weeks, 6 weeks), by treatment

Figure 2 reveals that students in the control group allocate a larger budget share to earlier if the earlier point in time is today. This is an indicator of present bias in intertemporal allocations. On average, controlling for interest rates and interaction

effects, we find that students in this group allocate 6.73% more of their budget to the earlier point when the earlier point is today compared to in three weeks ($p=0.015$), as shown in Table 2, column (1).¹⁴

Table 2: Determinants of earlier share chosen

	(1)	(2)	(3)	(4)
	Control	Treatment	Time since treatment:	
			<5 weeks	>5 weeks
Today	6.73** [2.763]	1.93 [2.972]	3.82 [3.857]	-0.48 [4.636]
Delay = 6 w.	-3.51 [2.873]	2.31 [3.028]	1.86 [3.996]	3.05 [4.632]
Interest rate	-24.44*** [2.253]	-27.97*** [2.574]	-23.97*** [3.188]	-33.02*** [4.251]
Interest rate * Today	-3.92** [1.939]	-1.75 [2.143]	-3.23 [2.896]	0.14 [3.193]
Interest rate * Delay = 6 w.	2.15 [2.178]	0.11 [2.303]	0.65 [3.019]	-0.75 [3.551]
Constant	68.55*** [3.012]	74.07*** [3.511]	71.11*** [4.489]	77.87*** [5.577]
Observations	10,332	8,862	4,599	4,263
Nr. of students	492	422	219	203

Note: Interval data regression results with robust standard errors clustered at the student level. The dependent variable is the share of money allocated to the earlier payment time, ranging from 0 to 100. Today is a dummy variable that takes the value 1 if the earlier payment occurred immediately after the students completed the task and survey. Delay time = 6 w. is a dummy variable that takes the value 1 if the delay between the earlier and later payment was 6 weeks and not 3 weeks.

The effect of immediacy, i.e., the earlier payment being today, in the control group is present for small and medium gross interest rates. The difference in budget allocations is between 1.47% and 5.74% for rates up to 1.08. It drops to below 0.25% for rates of 1.18 and above. An explanation is that, as the interest rate increases, a much stronger degree of present bias is necessary for immediacy to affect choices. Rates higher than 1.25 are also uncommon in related studies, but were included to ensure sufficient variance in

¹⁴The estimates are obtained using an interval regression model to account for the fact that students were offered four possible choices. The cutoffs are defined assuming the student is most patient. Results remain qualitatively similar if a simple linear regression model is used or different cutoffs are defined.

choices.

In contrast to the control group, choices in the treatment group do *not* exhibit significant present bias. Treated students allocate 1.93% more of their budget to the earlier point when the earlier point is today, which is not significantly different from zero ($p=0.517$), as shown in Table 2, column (2).¹⁵ This result remains stable as the distance (in weeks) from the treatment increases. Columns (3) and (4) in Table 2 display estimation results splitting the sample by the median delay between the treatment and the experiment (5 weeks). Students who participate in the experiment at least 6 weeks later exhibit the same behavior: immediate earlier payments are not treated differently than delayed earlier payments.

An alternative measure of the effect of immediacy is obtained by comparing the proportion of present-biased choices, instead of the share of money allocated to the earlier payment. In the control group, on average, individuals make present-biased choices, i.e., allocate more money to the earlier payment when it is immediate, in 22.2% of the cases. In the treatment group, this percentage is 19.9% (Mann-Whitney test, $p=0.0288$). At the same time, the frequency of time consistent choices increases from 58.2% to 61.5% (Mann-Whitney test, $p=0.0799$), and there is a small non-significant decrease from 19.7% to 18.6% in the percentage of choices in which the students allocate less money when payments are immediate (Mann-Whitney test, $p=0.1758$).

B. Delay Sensitivity

Figure 3 below displays the mean earlier share chosen comparing changes in the delay of later payments, by 3 vs. 6 weeks. If students discount the future at a positive rate, the mean share of the budget allocated to earlier should increase as the delay increases. In the control group, students do not systematically chose a higher share of money earlier when the delay increases. The average difference in allocations is -3.51%, as shown in Table 2, column (1). It is smaller when the delay is six weeks instead of three, but not significantly different from zero ($p=0.221$). In contrast, in the treatment group, students allocate a larger share of money to the earlier point when the delay increases. The average difference in allocations is 2.31%, though this again is not significantly different from zero ($p=0.446$).¹⁶

¹⁵In the Online Appendix, we confirm this result using a regression with individual characteristics and share of consistent choices as controls.

¹⁶Results are similar if we focus on the proportion of choices in which the earlier share increases as delay increases (consistent with positive time discounting), stays the same as delay increases (consistent

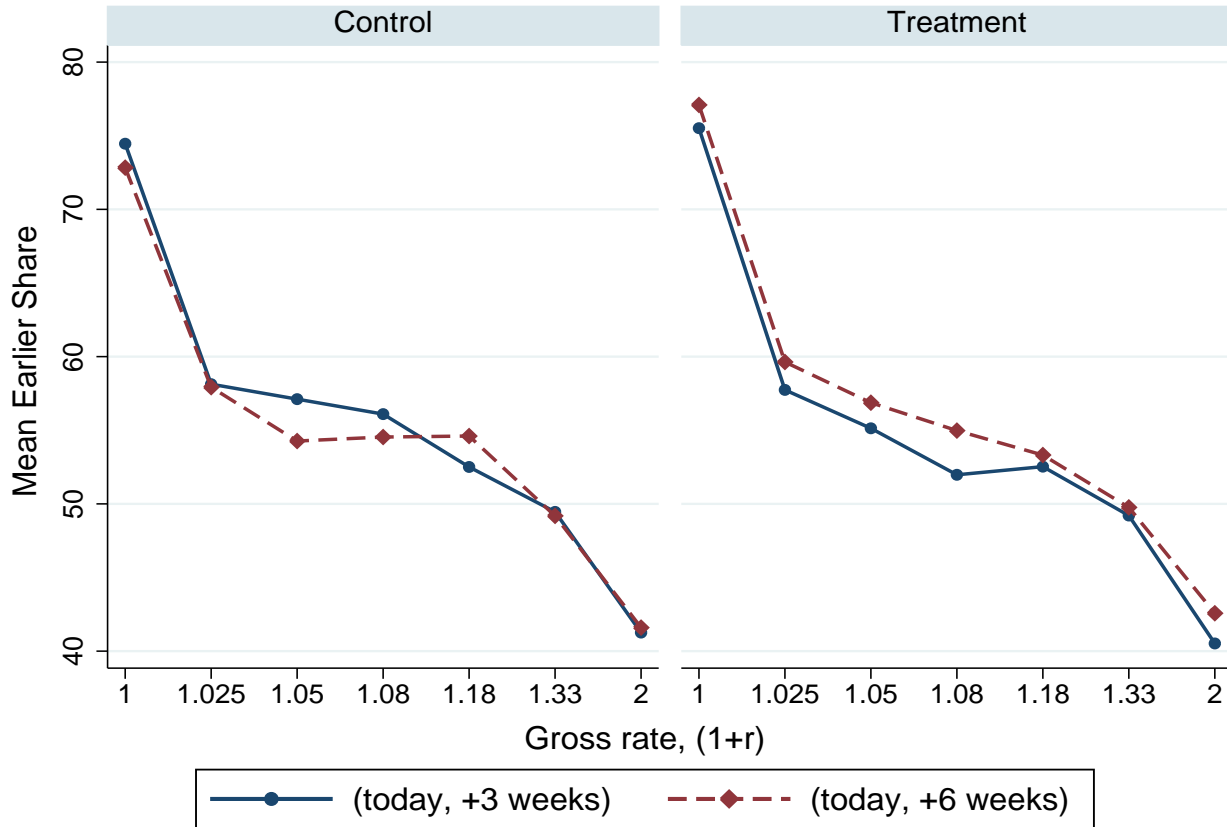


Figure 3: Allocations chosen for (today, 3 weeks) and (today, 6 weeks), by treatment

Overall, we find no evidence that the treatment changes the share of payment allocated to the earlier payment date. The average share allocated to earlier is 54.9% in the control group, while that in the treatment group is 55.26%. The difference is not statistically significant (Mann-Whitney test, $p=0.9618$).

C. Interior versus corner choices

A further dimension of choices is whether students choose to allocate positive amounts to both the earlier and the later points of time, which is an indication of the curvature

with no discounting), and decreases as delay increases (consistent with negative discounting). The proportion of choices consistent with positive discounting is 19.2% in the control group and 19.6% in the treatment group (Mann-Whitney test, $p=0.8883$). The proportion of choices consistent with no discounting is 61.0% in the control group and 62.7% in the treatment group (Mann-Whitney test, $p=0.4019$), and that consistent with negative discounting is 19.9% and 17.7% in the control and treatment groups, respectively (Mann-Whitney test, $p=0.1019$).

of students' utility. We find that a majority of choices are for interior allocations, 56.5% in the control group and 52.4% in the treatment group. The difference between groups is not significant, $\chi^2(1) = 2.69$ ($p=0.1007$).

5 Estimation of Time Preferences

5.1 Theoretical Framework and Empirical Model

We assume a time separable CRRA utility function within the $\beta - \delta$ model of quasi-hyperbolic discounting (e.g., Laibson, 1997),

$$U(x_t, x_{t+k}) = \begin{cases} x_t^\alpha + \delta^k x_{t+k}^\alpha & \text{if } t > 0 \\ x_t^\alpha + \beta \delta^k x_{t+k}^\alpha & \text{if } t = 0 \end{cases} \quad (1)$$

where the individual receives monetary amounts x_t and x_{t+k} at time t and $t+k$. The preference parameters of interest are the curvature parameter α , present bias β and discount rate δ . Individuals maximize utility subject to the budget constraint, $Px_t + x_{t+k} = Y$, where $P = 1 + r$ and Y is the available budget. This yields the standard Euler equation, which can be written in logs as:

$$\ln\left(\frac{x_t}{x_{t+k}}\right) = \frac{\ln(\beta)}{\alpha - 1} I_{t=0} + \frac{\ln(\delta)}{\alpha - 1} k + \frac{1}{\alpha - 1} \ln(P), \quad (2)$$

where $I_{t=0}$ is an indicator variable that takes value one if payments are immediate (or today), i.e., $t = 0$. The Euler equation establishes the optimal log ratio of payoffs across t and $t+k$, $x_j^* = \ln\left(\frac{x_{t,j}}{x_{t+k,j}}\right)$, in decision j , given the vector of preference parameters $\mu = \left(\frac{\ln(\beta)}{\alpha-1}, \frac{\ln(\delta)}{\alpha-1}, \frac{1}{\alpha-1}\right)$ and the vector of decision characteristics $X = (I_{t=0}, k, P)$ which we vary experimentally using the CTB method. β is identified through changes in whether the earlier payment is today or not, while changes in the delay between the earlier and the later point in time identify the discount factor δ . An individual i is offered four possible log ratios $s_m = \ln\left(\frac{x_{m,t}}{x_{m,t+k}}\right)$ in each decision problem j , where $m \in \{1, \dots, M\}$ and $M = 4$. Hence, we estimate an interval data model (Wooldridge, 2001, p. 509).¹⁷

We expand the standard interval model to allow choices to be stochastic.¹⁸ A per-

¹⁷We specify the cell limits taking the perspective of the individual being most patient.

¹⁸Details regarding this econometric model and the Luce Model, described below, are provided in the Appendix.

fectly rational decision maker would choose x^* based solely on X , μ and the available ratios s_m . First, we introduce Fechner errors, $\tau\varepsilon$, where ε is assumed to be i.i.d. across choices and individuals, and to follow a standard logistic distribution. This stochastic specification allows that errors may be made when evaluating the distance between the optimal ratio of consumption and the available ratio. A larger τ implies that this distance is given less weight and hence that errors are more likely. Second, we introduce a trembling-hand error (Harless and Camerer, 1994), which allows for a probability ω that a random choice is made in a given decision. This implies that the likelihood that s_m is chosen, if it is an interior choice, is

$$\begin{aligned} \mathcal{L}(s = s_m | X, \mu, \omega, \tau, s) &= P(s_m > x^* > s_{m+1}) = P(s_m > X'\mu + \tau\varepsilon > s_{m+1}) \\ &= (1 - \omega) \left(\Lambda\left(\frac{1}{\tau}(s_m - X'\mu)\right) - \Lambda\left(\frac{1}{\tau}(s_{m+1} - X'\mu)\right) \right) + \frac{\omega}{4}. \end{aligned} \quad (3)$$

The likelihood is adapted correspondingly if s_m is a corner choice. We estimate all parameters jointly and, in what follows, focus on the time preference parameters β and δ and the error term ω .¹⁹

As a robustness check, we estimate preference parameters using a different model of stochastic decision-making, based on Luce (1959), and adopted by Andersen et al. (2008). Under this model, the utility “index” of each option is the ratio of that option’s utility, exponentiated by a noise term $1/\sigma$, relative to the sum of all options’ exponentiated utilities. A drawback of this model is that it does not allow choices that are inconsistent with the law of demand (Loomes, Moffatt and Sugden, 2002). Hence, we consider the first model, with trembling-hand errors, more adequate in our context.

5.2 Aggregate Parameters

We begin by presenting estimates obtained from the pooled treatment and control group samples, assuming homogenous preference parameters within each sample. Following Andreoni and Sprenger (2012a), we use the term “aggregate parameters” for these estimates. Table 3 displays these aggregate preference parameters, implied by students’ choices in the control and treatment group. Columns (1) and (2) display estimated parameters following equation (3). We assume Fechner errors to be homogeneous within

¹⁹Because of the discrete nature of the data, the parameter α is only identified up to a constant and thus this estimate is unlikely to be accurate (see, also, Andreoni, Kuhn and Sprenger, 2013).

each group and allow trembling-hand errors to be school-specific.²⁰ The estimated β is 0.928 in the control group, which is significantly different from 1 (χ^2 -test, $p=0.0051$). In contrast, in the treatment group, $\hat{\beta}$ is 0.994, which is not different from 1 (χ^2 -test, $p=0.8422$). The estimated β is significantly larger in the treatment group than in the control group (t -test, $p=0.0459$, one-sided).

Table 3: Estimated Aggregate Time Preference Parameters, by Control and Treatment

	(1)	(2)	(3)	(4)
<i>Model:</i>	Interval Regression		Luce Model	
<i>Group:</i>	Control	Treatment	Control	Treatment
$\hat{\beta}$	0.928 [0.026]	0.994 [0.029]	0.943 [0.018]	0.989 [0.021]
$\hat{\delta}$	0.997 [0.001]	0.993 [0.002]	0.991 [0.001]	0.99 [0.002]
$\hat{\alpha}$	0.571 [0.030]	0.453 [0.056]	0.821 [0.026]	0.876 [0.027]
$\hat{\tau}$	0.499 [0.046]	0.612 [0.052]		
$\hat{\sigma}$			0.05 [0.005]	0.059 [0.007]
Observations	10332	8862	10332	8862
Nr. of students	492	422	492	422
$H_0 : \hat{\beta} = 1$	$\chi^2(1)= 7.83$ $p=0.0051$	$\chi^2(1)= 0.04$ $p=0.8422$	$\chi^2(1)=9.73$ $p=0.0018$	$\chi^2(1)= 0.28$ $p=0.5956$

Note: Columns (1) and (2) report the estimated preference parameters from the interval data model based on eq. (3). We allow for a school-specific trembling-hand error to capture school heterogeneity. The predicted value of ω is 0.54 in the control group and 0.50 in the treatment group. Columns (3) and (4) report the estimated preference parameters from the probability choice model, based on Luce (1959) and used in Andersen et al. (2008). Details are provided in Appendix A.2. All parameters are computed as nonlinear combinations, using the Delta method, of parameters estimated using maximum likelihood. Robust standard errors are presented, clustered at the individual level.

Columns (3) and (4) of Table 3 display the estimated parameters assuming a Luce

²⁰The trembling-hand error should be estimated at the individual level, such that it accounts for noise specific to the decisions of an individual. We follow this approach in the next subsection. In this specification we allow it to vary at the school level, where there is a substantial degree of variation. Results remain robust to estimating a single trembling-hand error.

probabilistic choice model. In this case, $\hat{\beta} = 0.943$ in the control group, which is significantly different from 1 (χ^2 -test, $p=0.0018$). In the treatment group, $\hat{\beta} = 0.989$, which is not significantly different from 1 (χ^2 -test, $p=0.5956$). In the Online Appendix, we report further robustness checks and show that the main result, that students do not exhibit significant present bias after the treatment while control students do, remains robust.

The estimated value of β in the control group, between 0.928 and 0.943, indicates significant present bias. It is slightly larger than $\hat{\beta}$ for effort choices in Augenblick, Niederle and Sprenger (2013), which is between 0.877 and 0.900. In Kuhn, Kuhn and Villeval (2013), where some present bias has been found over money, $\hat{\beta}$ is closer to 1, 0.979. In Andreoni and Sprenger (2012a), where no evidence of present bias is found, $\hat{\beta}$ is between 1.00 and 1.03. Hence, the magnitude of present bias in the control group is of significant magnitude, given the estimates found in related studies. In contrast, in the treatment group, $\hat{\beta}$ is no longer significantly different from 1 and similar to the value of $\hat{\beta}$ found for money in similar studies.

The value of the discount factor, $\hat{\delta}$, is smaller than 1, indicating positive discounting. We observe a small marginally significant decrease in its value in the treatment group (t -test, $p=0.0752$), which is consistent with the directional increase in delay sensitivity observed in Section 4. Based on the estimates in columns (1) and (2) in Table 3, including both $\hat{\beta}$ and $\hat{\delta}$, the estimated yearly discount rate is 2.71 (s.e. 1.49) in the control group, and 10.51 (s.e. 8.87) in the treatment group. The difference between these two estimates is not statistically significant (t -test, $p=0.3869$).²¹

Overall, we observe that participation in the financial education program decreases aggregate present bias. However, we do not observe an increase in the discount factor. Instead, we observe a small marginally significant increase in impatience. Since the discount factor is identified through changes in the delay between the earlier and later payment dates, the decrease in the discount factor is driven by the increase in delay sensitivity observed in the descriptive results above.

²¹The estimated yearly discount rate is similar to that found in Sutter et al. (2013), 3.3, among adolescents for delays of 3 weeks. These relatively large discount rates are in part due to the gross interest rates offered for a 3 week delay, which imply large (much larger than market) yearly interest rates between 0 and 271. See footnote 8 for further details.

5.3 Individual Parameters

To examine whether and how the treatment has affected the distribution of preference parameters, we estimate these at the individual level. The identification of these parameters using eq. (3) requires that an individual does not always choose the same allocation. Out of 914, 77 always make the same choice and hence they are excluded. Due to the limited number of choices and options for each individual, we obtain extreme values of β for some individuals. We trim the observations, dropping the lower and upper 2.5% of the distribution, as is done in Kuhn, Kuhn and Villeval (2013).²² This leaves us with 784 students. Table 4 displays the summary statistics for the estimated individual parameters, including the median and several other percentiles (5th, 25th, 75th, 95th).²³

Table 4: Descriptive statistics for the estimated individual parameters

	Percentile					N
	5 th	25 th	Median	75 th	95 th	
Control						
$\hat{\beta}_i$	0.464	0.830	1.000	1.166	2.239	433
$\hat{\delta}_i$	0.974	0.993	1.001	1.013	1.042	433
$\hat{\omega}_i$	0.000	0.000	0.130	0.358	0.585	433
Treatment						
$\hat{\beta}_i$	0.464	0.859	1.000	1.142	2.075	351
$\hat{\delta}_i$	0.957	0.994	1.002	1.014	1.036	351
$\hat{\omega}_i$	0.000	0.000	0.000	0.219	0.581	351

Note: The subscript i indicates individual i .

Figures 4 and 5 display the kernel densities of the estimated present bias parameter and discount factor for treatment and control. The distribution of $\hat{\beta}_i$ changes significantly in the treatment group (Kolmogorov Smirnov test, $p=0.017$). The distribution of $\hat{\delta}_i$ in treatment and control is marginally different (Kolmogorov Smirnov test, $p=0.063$).

²²Specifically, there are 21 individuals with $\hat{\beta}_i > 3.15$ (upper 2.5%) and 18 students with $\hat{\beta}_i < 0.13$ (lower 2.5%). These students stem equally from the treatment and control group ($\chi^2 = 0.0534$, $p=0.817$). For an additional 14 students, the estimation did not converge. Hence, these students are not included.

²³The estimated individual parameters correlate significantly with the underlying choices, as one would expect. The Spearman rank correlation coefficient between $\hat{\beta}_i$ and the difference between the share allocated to the earlier date when the earlier date is immediate compared to delayed is $\rho = -0.2029$ ($p < 0.01$). The Spearman rank correlation coefficient between $\hat{\delta}_i$ and share allocated to the earlier point in time is -0.0773 ($p=0.0305$), and between the share of consistent choices and $\hat{\omega}_i$ is -0.0914 ($p=0.0105$). Detailed results for the estimates of $\hat{\alpha}_i$ and $\hat{\tau}_i$ are presented in the Online Appendix.

We define students as time consistent following Augenblick, Niederle and Sprenger (2013), i.e., $0.99 < \hat{\beta}_i < 1.01$. We find a significant increase in the share of time consistent students in the treatment group. While 7.9% of the students are time consistent in the control treatment, the share is more than double, 16.0%, in the treatment group. Among students who are present biased, i.e. $\hat{\beta}_i < 0.99$, we observe a change in the density of students with strong present bias. Using $\hat{\beta}_i < 0.70$ as a cutoff, a value of present bias found in previous studies (e.g., Brown, Chua and Camerer, 2009)²⁴, we find there are significantly fewer students with $\hat{\beta}_i < 0.7$ in the treatment group, 11.7%, compared to 18.0% in the control group (χ^2 -test, $p=0.014$). As found in previous studies, there is a fraction of students who exhibit future bias, i.e., are more impatient when all payments are delayed in the future, compared to when the earlier payment is immediate. In the control group, 33.4% of the students exhibit moderate levels of future bias, $1.01 < \hat{\beta}_i < 1.3$. This share falls to 23.4% in the treatment group. The prevalence of future bias is similar to that in Andreoni and Sprenger (2012a), where 20 out of 86 students (23.3%) have an estimated $\hat{\beta}_i > 1.01$. Among adolescents, Sutter et al. (2013) also find 37% of the students to be more impatient between payments distributed in either three or six weeks, compared to payments offered today or in three weeks, for low stakes (based on calculations using their data).

Table 5, column (1), shows that, controlling for individual characteristics, the share of time consistent students increases by more than 7%.²⁵ This implies almost a 100% increase relative to the share of time consistent students in the control treatment. The mean $\hat{\beta}_i$ however does not change significantly with the treatment, as shown in Table 5, column (2). This is consistent with the evidence presented in Figure 4, namely that the changes in β_i occur on two margins, both among those students exhibiting strong present bias and those exhibiting future bias.

At the same time, there is a marginally significant decrease in the mean discount factor ($\hat{\delta}_i$), as shown in Table 5, column (3). This is in line with the increase in the share allocated to the earlier date as delay increases that we observed in Section 4.

The estimated error parameter ($\hat{\omega}_i$) falls significantly, by 0.06, as shown in Table 5, column (4). Further, the distribution of $\hat{\omega}_i$ changes across treatment and control (Kolmogorov Smirnov test, $p<0.01$). This evidence is in line with the finding that

²⁴Brown, Chua and Camerer (2009) also report estimates of present bias from previous studies, most of which lie between 0.55 and 0.9.

²⁵In Table 5 and Table 6 standard errors are clustered at the class level. Results remain qualitatively the same if standard errors are clustered at the school level.

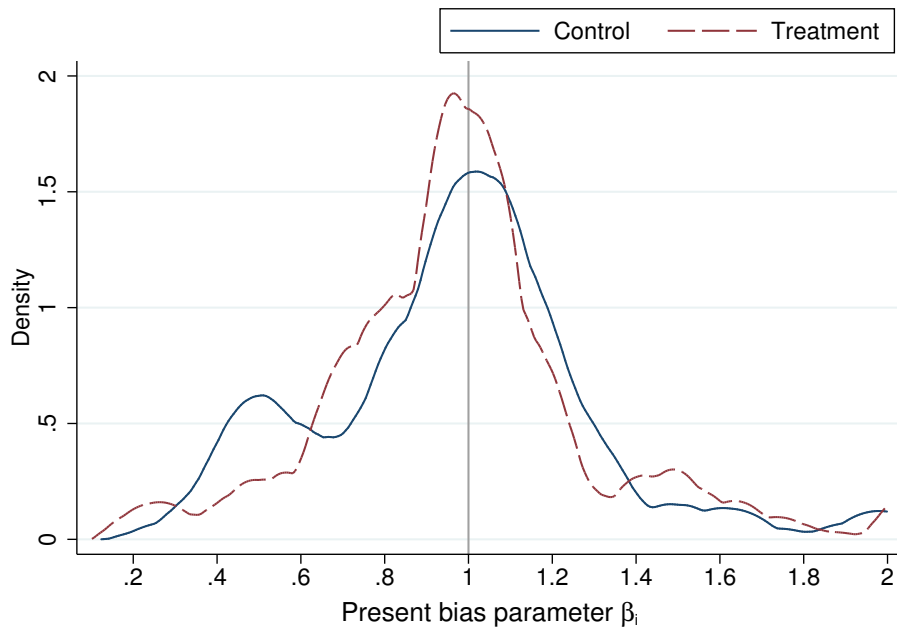


Figure 4: Distribution of individual present bias parameter ($\hat{\beta}_i$), by treatment

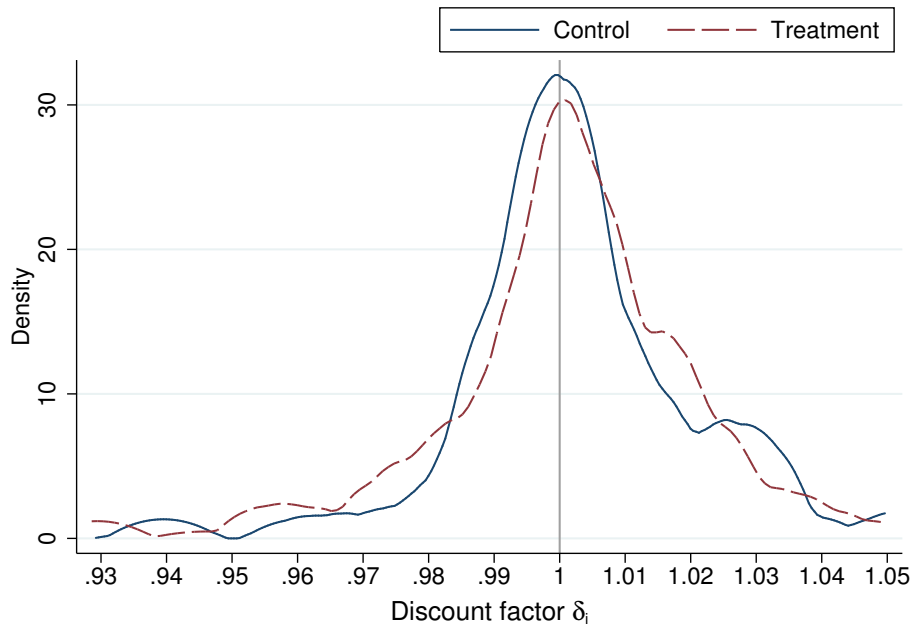


Figure 5: Distribution of the individual discount factor ($\hat{\delta}_i$), by treatment

Note: Figures 4 and 5 plot smoothed density functions, using the Epanechnikov kernel. Bandwidth is chosen according to Silverman's rule of thumb.

students' choices are more often consistent with the law of demand in the treatment group.

In addition to the treatment effects, Table 5 reveals interesting correlations between the estimated individual parameters and individual characteristics. In particular, we find that students from a poorer socio-economic background, as measured by migrant background, living with a single parent and having fewer books at home, exhibit somewhat stronger present bias. A potential explanation is that these students are in a different economic situation compared to other students. However, when we control for the student's spending in the last four weeks, we find similar results.²⁶ Also, we find no evidence of a difference in the average spending of students in the last four weeks before the experiment across treatment and control (t -test, $p=0.343$). This suggests that the strength of present bias is not only explained by the immediate economic situation of the student. These correlations are suggestive of the importance of socioeconomic background.

In the survey conducted after the CTB task, we included a question eliciting savings, with the objective of examining whether the estimated individual time preference parameters are significantly correlated with savings outside the experiment, as in Sutter et al. (2013). We measure savings by asking students whether they saved in the past four weeks and if so how much. Regression results show that a higher present bias parameter (lower present bias) and a higher discount factor (lower impatience) predict higher savings amounts (details shown in the Online Appendix), consistent with existing evidence.

In line with previous studies (e.g., Lührmann, Serra-Garcia, Winter, 2013), we do not find a significant effect of the treatment itself on self-reported savings, both including the estimated time preference parameters as additional regressors and without (t -tests, $p=0.452$ and 0.179 , respectively). There are several potential explanations for this result. Self-reported survey measures of savings are subject to imperfect recall and other response biases and thus likely to be more noisy than experimental measures of behavior (Browning, Crossley and Winter, 2014). Moreover, we would expect the educational program's impact on time consistency to translate into more successful financial planning, i.e. a larger share of students achieving their financial goals. If these goals include savings, effects on savings might arise in the long run. Such increases in savings may however be hard to detect, as saving decisions are influenced by a variety

²⁶Results are shown in the Online Appendix.

Table 5: Treatment effect on time consistency and time preference parameters

	(1)	(2)	(3)	(4)
	Time consistency $0.99 < \hat{\beta}_i < 1.01$	Present bias $\hat{\beta}_i$	Discount factor $\hat{\delta}_i$	Trembling-hand error $\hat{\omega}_i$
Treatment	0.074*** [0.028]	-0.024 [0.058]	-0.011* [0.006]	-0.060** [0.024]
Girl	0.014 [0.026]	0.017 [0.039]	-0.001 [0.004]	-0.023 [0.021]
Grade 8	-0.059* [0.033]	0.074 [0.086]	0.008 [0.006]	0.002 [0.030]
Cognition score	0.004 [0.015]	0.004 [0.019]	0.001 [0.001]	-0.013 [0.009]
Math grade	0.018 [0.012]	0.006 [0.016]	0.000 [0.001]	0.006 [0.009]
Migrant background	-0.021 [0.028]	-0.068* [0.035]	-0.002 [0.003]	-0.001 [0.016]
Single parent	0.021 [0.026]	-0.079*** [0.028]	-0.000 [0.002]	0.003 [0.018]
< 25 books at home	-0.018 [0.027]	-0.034 [0.029]	-0.001 [0.002]	-0.028* [0.014]
Constant		0.903*** [0.170]	1.006*** [0.013]	0.163*** [0.073]
Observations	719	719	719	719
Method	Probit	OLS	OLS	Tobit

Note: Column (1) reports the marginal effects of a probit model on the likelihood that an individual is time consistent, i.e., $\hat{\beta}_i$ falls within $0.99 < \hat{\beta}_i < 1.01$. Columns (2) and (3) report OLS regression results on the present bias parameter ($\hat{\beta}_i$) and the discount factor ($\hat{\delta}_i$). Column (4) reports Tobit regression results for the trembling-hand parameter ($\hat{\omega}_i$), allowing for censoring at 0. Treatment is a dummy variable that takes value 1 if the student participated in the education program. Girl takes value 1 if the gender of the participant is feminine. Grade 8 takes value 1 if the student is in grade 8, 0 if in grade 7. Cognition score is the number of correct answers provided in 4 of Raven's progressive matrices. Math grade is defined relative to the average math grade in the class. A positive value indicates that the student performs better than the class average. Migrant background and single parent are dummy variables that take value 1 when the student speaks another language other than german at home and lives with a single parent (mother or father), respectively. The variable < 25 books at home is a dummy variable that takes value 1 when the student has fewer than 25 books at home. Fixed effects are included to account for the city, month and day of the week the experiment took place, as well as the order of the decision sheets. Robust standard errors, clustered at the class level, are computed.

of other factors, e.g., income shocks.

6 Heterogeneity of the Treatment Effect

In this section, we examine whether the estimated treatment effect varies with students' cognitive ability and other individual characteristics. Recent evidence suggests that cognitive ability is important for financial decision-making. For example, low numerical ability predicts mortgage default (Gerardi, Goette and Meier, 2013). Also, low cognitive ability correlates with mistakes in credit card borrowing (Agarwal and Mazdumer, 2013). Some studies evaluating the impact of financial education programs find that individuals with low education are most strongly affected (Cole, Sampson and Zia, 2011).

In Table 6 we estimate heterogeneous treatment effects using the estimated individual preference parameters. In addition to estimating the interaction effect between the treatment and cognitive ability, we allow for heterogeneity of the treatment effect on all other individual characteristics. We observe that the treatment increases time consistency, and has a stronger effect among students with higher cognitive ability, though this effect is only marginally significant (column (1)). The interaction effect with present bias in column (2) is also positive, though very small and far from significant. However, we do not find a heterogeneous treatment effect with respect to numerical ability as measured by the math grade.

The treatment effect on time consistency is also significantly stronger for two other groups, younger students and students living with a single parent. The estimates in Table 6 suggest that students who lived with a single parent are somewhat less time consistent than those living with both parents, and are more strongly affected by financial education. We also find that the treatment effect on trembling-hand errors varies by age: Students in grade 8 (14 to 15 years old) exhibit a stronger decrease in the error rate than younger students.

Taken together, these results suggest that the effects of the treatment varied strongly depending on the student's socio-economic background and age. We cannot distinguish between differential financial management styles and differential parental education by socio-economic status, hence further research is needed to understand the underlying mechanism. The differential susceptibility to treatment by age may be influenced by the brain maturation process discussed in Section 2. The results also provide some

Table 6: Heterogeneous Treatment Effects

	(1) Time consistency $0.99 < \hat{\beta}_i < 1.01$	(2) Present bias $\hat{\beta}_i$	(3) Discount factor $\hat{\delta}_i$	(4) Trembling-hand error $\hat{\omega}_i$
Treatment	0.145*	0.023	-0.004	0.018
	[0.079]	[0.102]	[0.007]	[0.051]
Girl	0.037	0.038	-0.001	-0.017
	[0.028]	[0.053]	[0.004]	[0.030]
Grade 8	0.022	0.117	0.013*	0.066
	[0.035]	[0.128]	[0.008]	[0.040]
Cognition score	-0.018	0.004	-0.001	-0.011
	[0.015]	[0.019]	[0.001]	[0.010]
Math grade	0.021*	0.010	0.000	0.015*
	[0.013]	[0.022]	[0.001]	[0.009]
Migrant background	0.012	-0.060	-0.002	0.002
	[0.032]	[0.050]	[0.002]	[0.019]
Single parent	-0.055**	-0.114***	0.000	0.001
	[0.022]	[0.042]	[0.003]	[0.020]
< 25 books at home	0.025	-0.032	0.003	-0.019
	[0.034]	[0.041]	[0.002]	[0.019]
Girl * Treatment	-0.049	-0.048	0.001	-0.015
	[0.061]	[0.077]	[0.008]	[0.042]
Grade 8 * Treatment	-0.151**	-0.098	-0.011	-0.140***
	[0.066]	[0.160]	[0.014]	[0.052]
Cognition score * Treatment	0.065*	0.001	0.003	-0.004
	[0.034]	[0.039]	[0.004]	[0.019]
Math grade * Treatment	-0.015	-0.016	0.000	-0.026
	[0.026]	[0.032]	[0.002]	[0.018]
Migrant b. * Treatment	-0.070	0.010	-0.009	-0.001
	[0.061]	[0.056]	[0.007]	[0.028]
Single parent * Treatment	0.193***	0.077	-0.001	-0.002
	[0.058]	[0.063]	[0.005]	[0.035]
< 25 books at home * Treatment	-0.077	-0.022	0.001	-0.013
	[0.055]	[0.077]	[0.005]	[0.032]
Constant	0.133	0.888***	1.002***	0.147**
	[0.094]	[0.178]	[0.013]	[0.069]
Observations	719	719	719	719
R-squared	0.112	0.122	0.072	0.102

Note: This table presents estimated coefficients from linear probability models (column (1)) and ordinary least square models (columns (2) to (4)). The variables are defined as in Table 5. Additionally, interaction effects are included between each background characteristic and the treatment dummy. Fixed effects are included to account for the city, month and day of the week the experiment took place, as well as the order of the decision sheets. Robust standard errors, clustered at the class level, are computed.

evidence that cognitive ability is important in the context of this intervention. A possible interpretation of this result is that the program did not deal with tasks similar to the CBT task, but dealt with intertemporal choices when making shopping and saving decisions. Thus, exhibiting a change in the CBT task requires a transfer of knowledge that may have been easier for students with higher cognitive ability.

7 Discussion and Conclusion

This paper examines the effect of a financial education intervention on intertemporal choices in adolescence. Following random assignment to the intervention, we measure intertemporal choices using a controlled and incentivized experiment based on the CTB task. Our main finding is that the financial education intervention leads to a significant increase in time consistency. We obtain this result in a descriptive analysis of the data, and it is reflected in the time preference parameters we estimate using a stochastic choice model. It is also supported by a number of robustness checks.

The use of the CTB task allows us to document an important change in *revealed* preferences. The revealed-preference paradigm is central in economics, also in the design of experimental tools to measure individual preference parameters. However, as has been recognized early on in the discrete choice literature, not all observed choices are consistent with utility maximization. The random utility maximization paradigm, originally developed for the microeconomic analysis of field data (see McFadden, 2000, for a review), is increasingly used in experimental economics as well (e.g., Loomes, Moffatt and Sugden, 2002). We consider random variation in observed choices important and hence estimate time preference parameters using a stochastic model with two types of errors. We find that our main result is robust to different modeling assumptions. This supports our conclusion that the revealed preferences of students who participated in the financial education program are more time consistent.

An important question concerns the mechanisms underlying the increase in time consistency. As highlighted by Strotz (1956), the effect of the educational intervention we observe may have had two different sources. On the one hand, the intervention may have changed the underlying time preferences. On the other hand, students may have become more aware that their underlying time preferences are not time-consistent, and have learnt to choose more consistently. Both would translate into more time-consistent revealed preferences. The main aim of this study is to document the effects

of financial education on intertemporal choices, which had been unexplored so far, using an incentivized experimental task. We believe it would be interesting for future research to examine the two sources in more detail.

As is common in experiments eliciting time preferences, our experiment used monetary rewards. In models of intertemporal choice, the assumption is that of immediate consumption (for a discussion see, e.g., Chabris, Laibson and Schuldt, 2008). If the received monetary rewards are partly stored, the estimated values of the present bias parameter might themselves be biased upward, leading to an under-estimation of the degree of present bias. Among adolescents, we believe that the assumption of immediate consumption is realistic, perhaps more so than for adults. Choices in experimental tasks using monetary rewards have also been found to correlate with field behaviors such as exercising or smoking both among adults and adolescents (e.g., Chabris et al., 2008, Sutter et al., 2013).

Our findings suggest that, when presented with intertemporal trade-offs in the monetary domain, financially educated adolescents are likely to be more time-consistent. Increased time consistency could lead to better management of financial plans and help achieving savings goals. It could also lead to less under-saving and over-borrowing. To the extent that correlations between present bias and credit card borrowing (Meier and Sprenger, 2010) and retirement saving (Laibson, Repetto and Tobacman, 1998) reflect a causal relationship, changes in time consistency could lead to changes in these important financial decisions.

The educational intervention whose effects we study is relatively brief and easily scalable. We find that it leads to significant changes in the time consistency of choices in the medium term. An important issue for future research is to examine whether the effects of financial education on intertemporal choices persist also over longer time horizons. If the effects that financial education programs administered to adolescents have on intertemporal choices persisted over time, they could have important effects on financial decision-making in adulthood as well.

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Appendix: Econometric Models

A.1. Interval Model Estimation

We start from equation (2) in the text. The Euler equation establishes the optimal log ratio of payments across t and $t + k$, $x_j^* = \ln(\frac{x_{t,j}}{x_{t+k,j}})$, in decision j , given the vector of preference parameters $\mu = (\frac{\ln(\beta)}{\alpha-1}, \frac{\ln(\delta)}{\alpha-1}, \frac{1}{\alpha-1})$ and the vector of decision characteristics $X = (I_{t=0}, k, P)$. An individual i is offered four possible log ratios s_m in each decision problem j , where $m \in \{1, \dots, M\}$ and $M = 4$. Hence, we estimate an interval data model (Wooldridge, 2001, p. 509).

More specifically, let us denote the vector of possible ratios as $s = (s_1, s_2, s_3, s_4)$. To simplify notation we drop the subscripts for each individual i and choice j . For each decision problem, an individual chooses

$$s = \begin{cases} s_1 & \text{if } x^* > s_2. \\ s_2 & \text{if } s_2 > x^* > s_3. \\ s_3 & \text{if } s_3 > x^* > s_4. \\ s_4 & \text{if } s_4 > x^*. \end{cases} \quad (4)$$

The probability that $s = s_m$, where $m \in \{1, 2, 3, 4\}$, depends on $X'\mu$. Additionally, as in von Gaudecker, van Soest and Wengström (2011) and Loomes, Moffatt and Sugden (2002), two forms of stochastic choice are modeled. First, Fechner errors, which enter as weight τ on ε , which is assumed to be i.i.d across choices and individuals, and follow a standard logistic distribution. Second, a trembling-hand error (e.g., Harless and Camerer, 1994), which allows for a probability ω that a student makes a random choice in a given decision. Hence, we have that,

$$\begin{cases} P(s = s_1|X, \mu, \tau, \omega, s) &= (1 - \omega)(1 - \Lambda(\frac{1}{\tau}(s_2 - X'\mu))) + \frac{\omega}{4}, \\ P(s = s_2|X, \mu, \tau, \omega, s) &= (1 - \omega)(\Lambda(\frac{1}{\tau}(s_3 - X'\mu)) - \Lambda(\frac{1}{\tau}(s_2 - X'\mu))) + \frac{\omega}{4}, \\ P(s = s_3|X, \mu, \tau, \omega, s) &= (1 - \omega)(\Lambda(\frac{1}{\tau}(s_4 - X'\mu)) - \Lambda(\frac{1}{\tau}(s_3 - X'\mu))) + \frac{\omega}{4}, \\ P(s = s_4|X, \mu, \tau, \omega, s) &= (1 - \omega)(\Lambda(\frac{1}{\tau}(s_4 - X'\mu))) + \frac{\omega}{4}, \end{cases}$$

where $\Lambda(t) = (1 + e^{-t})^{-1}$. Thus, the conditional log-likelihood is

$$\ln L(\mu, \tau, \omega; X, s_m) = \sum_i \sum_j \ln(P_{ij}(s = s_m | \mu, \tau, \omega; X, s) I_{(s=s_m)})$$

where $I_{(s=s_m)}$ is an indicator variable that takes value one if $s = s_m$.

A.2. Luce Model

An alternative stochastic choice model, which is frequently used in related studies, is the Luce model (e.g., Andersen et al., 2008). According to this model, the utility “index” of option m is the ratio of its utility, weighted by an “error” parameter σ , over the sum of the utilities of all other options. In particular,

$$u_m = \frac{U(x_{m,t}, x_{m,t+k})^{\frac{1}{\sigma}}}{\sum_{n=1}^M U(x_{n,t}, x_{n,t+k})^{\frac{1}{\sigma}}} \quad (5)$$

As $\sigma \rightarrow 0$ choice collapses to the deterministic choice model, while as σ increases choices become random. In this case, the likelihood that an individual chooses m is $P(s = s_m) = P(u_m + \varepsilon > 0) = \Phi(-u_m)$, where $\Phi(\cdot)$ is the cumulative standard normal distribution.