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The baking of preferences throughout the high school^{*}

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Abstract

The purpose of this study is to examine whether girls and boys exhibit different risk and time preferences and how this difference evolves during the critical phase of adolescence. To achieve this, we use a large and powered sample of 4830 non-self-selected teenagers from 207 classes across 22 Spanish schools with very different socioeconomic backgrounds. Alongside time and risk preferences, we also collected additional information about class attributes, social network measures, students' characteristics, and the average level of economic preferences of friends. These measures enable us to account for potentially omitted variables that were not considered in previous studies. The results indicate that there are no significant gender differences in time and risk preferences, but older subjects exhibit more sophisticated time preferences and higher risk aversion. We also perform an exploratory heterogeneity analysis, which unveils two important results: first, cognitive abilities play a critical role in the development of time and risk preferences; second, interaction within the class social network does matter.

Keywords: developmental decision-making; field experiment; economic preferences; teenagers.

JEL-codes: C91, D81.

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1 Introduction

Some recent studies have shown that economic preferences have an impact on important life outcomes (Angerer et al., 2023; Dohmen et al., 2011; Falk et al., 2018; Golsteyn et al., 2014). For instance, risk and time preferences have been shown to influence behaviors related to health (Chabris et al., 2008; Sutter et al., 2013), educational achievements (Castillo et al., 2011, 2019; Golsteyn et al., 2014), labor outcomes (Bandiera, Barankay, & Rasul, 2010; Bandiera et al., 2005; Deming, 2017) and financial success (Meier & Sprenger, 2010; Meier & Sprenger, 2013). This research has led the scientific community to wonder how these preferences are formed and, particularly, to ask how they are shaped throughout the life cycle. In this line, the literature has identified different heterogeneity sources: genetic variations (Cesarini et al., 2009; Zyphur et al., 2009), cultural transmission from parents to children (Bisin & Verdier, 2000; Brañas-Garza et al., 2022; Samek et al., 2021; Stoklosa et al., 2018) and maturation of children and adolescents during the years of schooling (Booth & Nolen, 2012; Brocas & Carrillo, 2020, 2022; Sutter et al., 2018).

Additionally, studies based on different types of intervention have provided crucial insights into how malleable are these economic preferences during school age. For instance, Bruhn et al. (2013) and Lührmann et al. (2018) found that financial education increases savings, and time consistency in teenagers. In line with these results, Sutter et al. (2023) find that increasing financial literacy of 16-year-old high-school students makes them behave more patiently, more time-consistent, and more risk averse, and these results are stable after five years. Alan and Ertac (2018) found that an intervention aimed to improve the ability to act in a forward-looking manner and to exercise self-control in inter-temporal decision contexts increased the patience of children, with this result maintained three years later.

This study focuses on examining whether girls and boys exhibit different risk and time preferences and if so, how this difference evolves during the critical phase of adolescence. Although the literature in this domain is recent, this paper is closely related to several studies that have examined adolescent preferences. Some of them analyzed whether time preferences develop with age (Angerer et al., 2015; Bettinger & Slonim, 2007; Sutter et al., 2015) or whether males are more or less patient than females (Bettinger & Slonim, 2007; Castillo et al., 2011; Deckers et al., 2015; Golsteyn et al., 2014; Horn et al., 2022). Similarly, some other papers study if risk preferences change with age (Eckel et al., 2012; Harbaugh et al., 2002; Munro, Tanaka, et al., 2014; Piovesan & Willadsen, 2021; Sutter et al., 2013) and if there are differences between genders (Andreoni et al., 2020; Booth & Nolen, 2012; Borghans et al., 2009; Eckel et al., 2012; Khachatryan et al., 2015; Piovesan & Willadsen, 2021; Sutter et al., 2013) or even between countries and cultures like Cárdenas et al. (2012). Some of the most important findings of these papers are that patience increases with age and that older children become less risk lovers, but these relations are not significant during adolescence¹. Regarding gender differences, evidence finds that girls are more risk averse than boys but the findings are inconclusive for time preferences: some studies indicate that boys display less patience than girls (Bettinger & Slonim, 2007; Castillo et al., 2011), while others report the opposite pattern (Deckers et al., 2015; Golsteyn et al., 2014), and still others find no statistically significant differences (Horn et al., 2022; Sutter et al., 2013, 2015)².

 $^{^{1}}$ For a comprehensive review of the effects of age and gender on various economic preferences, see Sutter et al. (2019).

 $^{^{2}}$ One must be cautious in generalizing these results since Filippin and Crosetto (2016) and Niederle (2016) note that gender difference might be context and task sensitive.

To revise the development of preferences during adolescence (and gender differences), we conducted a lab-in-the-field experiment in 22 Spanish schools. We gathered data from 4,830 adolescents from 12 to 17 years old distributed in 207 different classrooms, of whom 49% were female. Two additional elements make our study unique. First, we collected data on the class enmity and friendship network, which allows for the assessment of social isolation(Ruiz-García et al., 2023). Second, we are able to compute the mean value of time and risk preferences for each subject's friends inside a classroom. It is also important to emphasize that the tasks to elicit time and risk preferences were designed specifically for adolescents. The time preference task constitutes a simplified and visual version with six decisions of Coller and Williams (1999) (see Alfonso et al. (2023) for details). Similarly, the risk preferences task is a simplified version with six decisions adapted from the Holt and Laury (2002) lottery task (for details, see Vasco and Vazquez (2023)). In both tasks, we used hypothetical payments since using economic incentives with children and adolescents requires a signed consent of parents. In a recent paper, we validated the use of hypothetical incentives as a reliable alternative to real incentives for similar tasks to measure risk and time preferences in adolescents (see Alfonso et al. (2023) for details).

This paper complements previous research on gender differences in economic preferences in three ways. First, we are able to detect a minimum gender difference of 0.12 SD, while in previous studies the minimum detectable gender difference ranges from 0.33 SD to 0.97 SD. Typically, those papers involve experiments conducted in a limited number of educational institutions, usually ranging from one to six³ and smaller sample sizes across ages (which range from 16 to 305 for time preferences and 12 to 293 for risk preferences)⁴. This means that, even if they consider the measurement of cognitive abilities (such as GPA and Raven's Progressive Matrices) and socioeconomic factors as controls, those studies can only find medium to large gender differences, while our dataset allows us to find statistically significant smaller differences.

Second, given our rich and wide dataset, we measure and explore the role of different external factors that could affect gender differences and economic preferences and, consequently, bias the estimations. Social interactions at the school do not necessarily involve all classmates but may be limited to a subset of them – the friends that the teenager voluntarily chooses, forming his or her social network. In other words, not only does the classroom environment where the individual spends at least thirty-five hours a week play a role, but also the network of friends could also influence the formation of economic preferences since there is evidence that risk and time preferences are shaped by environmental factors (see Alem et al. (2023), Booth and Nolen (2012), Lucks et al. (2020), and Zárate (2023)). Hence, not including them in the regression models could lead to omitted variables problems. To solve this problem, this dataset allows us to control not only for schools' fixed characteristics but also for classroom specific factors (such as size, number of repeaters, cohesion, among others). Additionally, we consider the student's social position within the class network, including measures of popularity and centrality in the network, and the average level of patience or risk of each subject's friends, which indicates whether preferences are aligned with the average level of preferences of friends⁵. Students' cognitive abilities are also assessed, including Cognitive Reflection Test

³Except for Horn et al. (2022) which involved 9 schools.

⁴See Tables OA.1.1a and OA.1.2a in the Online Appendix that summarize the mean sample sizes per age group in each study for time and risk preferences, respectively.

 $^{^{5}}$ The relationship between adolescent's preferences and the average preferences of friends should be interpreted with caution. It will be considered as a correlational analysis since it is not possible to distinguish between peer effects and/or homophily (the tendency of individuals with similar preferences to interact with each other in social groups, rather than with those who have different preferences). Furthermore, this measure might be affected by the reflection effect (Manski, 1993), which could mean either that an adolescent could be more patient because his/her

(CRT) scores, the number of A grades in the last academic year, and proficiency in probabilities understanding.

Third, the existing literature studying gender differences has not usually delved into individuals' cognitive abilities and friendship formation in explaining gender differences in economic preferences. As pointed out by Dasgupta et al. (2019), regression analyses commonly employ the binary gender variable to measure the variation in economic preferences between males and females after accounting for other factors. However, these regressions assume that the impact of these characteristics on economic preferences is the same for both genders, which is often not the case. So, we explore various sources of heterogeneity in time and risk preferences using the most important determinants of these economic preferences. Specifically, we investigate the interaction between the gender dummy variable and various measures of subjects' cognitive abilities, as well as the average level of risk and time preferences among friends. Our findings strongly support the significance of these variables in explaining gender and age differences.

The results of this research can be summarized as follows. After controlling for class and individual's and network measures, we find that girls and boys do not differ in patience at younger ages. We also find that older teens become less present-oriented and more sophisticated in their time preferences, and that the latter effect is higher for girls. Regarding risk preferences, we do not find gender differences in the number of risky options at lower grades, but we find that older teens choose fewer risky choices on average. However, in upper grades, we find some gender differences in the different risk types: girls become less risk averse and more risk neutral than boys.

In addition, the heterogeneity analysis unveils two new results to the existing literature concerning cognitive abilities and interaction with the social network. First, cognitive abilities play a critical role in the development of time and risk preferences. We find that cognitive abilities are positively correlated with patience but this relation varies according to age and gender: in lower grades, boys with higher cognitive abilities become less present-oriented than girls, but in upper grades, girls with higher cognitive abilities become less present-oriented and more sophisticated than boys. Regarding risk preferences, cognitive abilities also explain age and gender differences. We find that higher levels of cognitive abilities make boys less willing to take risks at lower grades, while girls with higher cognitive abilities become less risky at upper grades.

Second, interaction within the social network of the class also matters. We find that the average level of patience (risk) of friends is also correlated with adolescents' preferences. Interestingly, we observe that the higher the average level of patience (risk) of friends, the smaller the probability of becoming present-oriented (risk averse), and the higher the probability of choosing all future options (all risky options). However, none of these interactions with gender or age (grade) are significant, which means that all these effects are the same across genders and ages.

The structure of this paper is as follows: section 2 presents the experimental protocol and dataset; section 3 presents the econometric approach used in the paper; section 4.1 presents the main results of the research; section 4.2 explores different mechanisms behind the results; and section 6 concludes.

friends are more patient, or that friends are more patient because an adolescent is more patient

2 Dataset

2.1 Protocol

We collected data from 22 Spanish secondary schools by contacting the principals. The purpose was to include the experiment as part of the regular class activities. Participants could opt-out, as required by our institutional review board (IRB), but none of them exerted this option, eliminating any selection effect. Only children absent on the day of the experiment did not participate, leading to an overall participation rate of $83\%^6$ and a final sample of 4,830 subjects. The data for replication is available at https://github.com/teenslab/datateenslab⁷. The experiment was conducted as a regular class activity using a self-administered questionnaire programmed in a tailored online platform named SAND. Subjects answered it on computers, tablets, or mobile phones with guaranteed anonymity. The Ethical Committee of Universidad Lovola Andalucía approved the study and the experiment was pre-registered in AsPredicted⁸. Our sample consists of schools from very different backgrounds, although most of them were located in intensely deprived areas of Andalusia. These socio-demographic differences are reflected in our dataset, with students' expectations of achieving a university degree varying enormously across the sample: only 5% students of the bottom 10% schools thought they would achieve it, while this number increased to 50% in a school of the first quartile, 75% in the median school, 95% in a school of the third quartile and almost 100% in schools of the top 10%. We also observed differences in the average number of repeaters across schools varying from 0% to 33.6% with an average value of 12.8%, and the average number of A grades⁹ varying from 0.53 to 1.21 with an average value of 1.05.

2.2 The truck and the gumball tasks

This study employs tailored tasks explicitly designed for non-adult population. The truck task is a visual version of the Multiple Price List task of Coller and Williams (1999) used to elicit time preferences as developed by Alfonso et al. (2023). The gumball machine is a graphical version of the risk preferences task of Holt and Laury (2002), introduced by Vasco and Vazquez (2023). Figure 1 provides a view of the second decision screens for participants in the truck task (top) and the gumball task (bottom). In both tasks, subjects must take six consecutive decisions. In the truck task, they must choose in each decision between $10 \\mathcal{C}$ tomorrow or $10+x \\mathcal{C}$ one week later, with x = 0, 2, 4, 6, 8, 10. In the gumball task, subjects must choose between two paired lotteries (A and B), each of them with varying high and low payoffs. Lottery A is initially better than Lottery B, until p_{high} becomes sufficiently large to make Lottery B more rewarding. Appendix A provides detailed explanations about both tasks.

Under consistency¹⁰, the truck task allows us to compute several measures of time preferences. These include the number of future (#Future) allocations ranging from 0 to 6 choices¹¹. Additionally, we created three dummy variables: subjects who always choose the early period, indicating present-oriented preferences (*AllPresent*, 22.6% of participants); subjects who

⁸See the following link https://aspredicted.org/blind.php?x=af3rw7

 $^{^{6}}$ This percentage is similar to the 15.3% of early leavers from high school in Andalusia (Ministerio de Educación y Formación Profesional, 2023).

⁷Data on networks is not available yet, but it can be requested from the authors.

 $^{^{9}}$ This variable takes values between 0 and 3 since we asked the subjects if they had any A in English (English as a Foreign Language, EFL), Mathematics, and Spanish during the last year.

¹⁰Consistent subjects in the truck tasks are those who do not switch back.

 $^{^{11}}$ In the literature it is common to use discount factors or rates, however, following Chowdhury et al. (2022) we use the number of future allocations.

always choose the later period, indicating future-oriented preferences (*AllFuture*, 11.7% of participants); and subjects who choose both the early and the later periods, indicating interior preferences (*Interior*, 65.7% of participants). We used this nomenclature in reference to Andreoni et al. (2015).

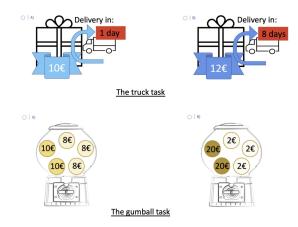


Figure 1: The truck and gumball tasks

Similarly, the gumball task allows us to compute several measures of risk preferences under subject consistency.¹². The number of risky choices (#Risky) represents the count of instances when subjects choose lottery B (the risky lottery) over lottery A between 0 and 6 times. The dummy *Averse* takes value 1 if the subject indicates risk-aversion by choosing lottery A at least in the first three decisions and 0 otherwise (44.6% of participants), the dummy *Neutral* takes value 1 if the subject indicates risk-neutrality by choosing Lottery A two times (45.4% of the sample) and the dummy *Lover* takes value 1 if the subject indicates risk-love by choosing Lottery A once (10.0% of participants).

It is important to note that for the first 11 schools, the tasks were presented in a fixed order, with subjects answering the time elicitation task before the risk elicitation task. Subsequently, we randomized the order of the tasks across schools. Five schools continued with the original order (truck \rightarrow gumball), while the remaining six schools followed the reversed order (gumball \rightarrow truck). This randomization resulted in 23.88% of participants answering the risk elicitation task before the time elicitation task. The order of tasks may have an impact on how teenagers make decisions, particularly concerning consistency. However, it is important to note that since the order was assigned to the entire school, it becomes a part of the school's fixed effect.

 $^{^{12}}$ There are three types of inconsistency: i) *Lack of understanding*, when subjects selected lottery B in the first decision since there is no uncertainty in probabilities and B is dominated by A; ii) *Switch back*, when subjects switched back from lottery B to A; and iii) *Lack of attention* when subjects chose lottery A in the sixth decision since there is no uncertainty and A is dominated by B.

2.3 Sources of heterogeneity

2.3.1 Class heterogeneity

Our experiment was conducted in 207 classes. In addition to our primary variables of interest (gender and grade), our dataset includes several class characteristics, such as $size^{13}$, the number of *repeaters* within the class, the number of students who did not complete the experiment (hereafter *slackers*), the number of *migrants* within the class, and the level of cohesion within the class (hereafter *cohesivity*). The last variable is defined as the difference between the density of friends and enemies at the class level (see Ruiz-García et al. (2023)). Each density is defined as the number of connections a participant has divided by the total possible connections a participant could have¹⁴. Additionally, the variable grade can take values 7, 8, 9, and 10.¹⁵ For simplicity, we will decompose them into two categories: *lower* when grade =7 or 8 and *upper* when grade =9 or 10. To avoid perfect collinearity, we only incorporate in our analysis the dummy variable *upper* (with value 1 when grade = 9 or 10, and 0 otherwise).

Figure 2 displays the correlations between our variables of interest. More detailed information is available in the Appendix in Table B.1.1. The diagonal in Figure 2 illustrates the distribution of the respective variable. All the variables were standardized using the max-min method ¹⁶. The first notable feature of our dataset is the great diversity in class characteristics, as shown in Table B.1.1. We have classes of varying sizes, ranging from 17 to 34 students, and varying percentages of repeaters (0% to 67%), slackers (0% to 76%), and migrants (0% to 60%). These classes also exhibit diverse social network structures, with *cohesivity* levels ranging from -0.01 to 0.75 and *popularity* f and *popularity*.e (popularity in the network of friends and enemies is the number of classmates that name subject i as a friend or enemy) varying from 0 to 22. We observe interesting correlations for time and risk preferences of subjects. First, we find positive correlations between the #Future allocations and female (p < 0.05), class size (p < 0.01) and class cohesivity (p < 0.05). Additionally, we observe that #Risky choices are negatively correlated with being in an upper grade (p < 0.05). Focusing on class characteristics, we also obtain interesting correlations. We observe that upper classes are smaller in size (p < 0.01) and cohesivity (p < 0.01). They also have a higher number of repeaters (p < 0.01), and a smaller number of migrants (p < 0.01) and slackers (p < 0.05). Classes with more repeaters tend to have fewer female $(p < 0.05)^{17}$, lower cohesivity (p < 0.01) and a higher number of migrants (p < 0.01). Finally, we also observe that classes with a higher number of migrants have a smaller number of slackers (p < 0.01), and that cohesivity is negatively linked with the number of slackers (p < 0.01) and migrants (p < 0.01).

 $^{^{13}}$ We define class size as the number of students in the class on the day of the experiment. This variable is important to control because Bandiera, Larcinese, and Rasul (2010) reported negative effects on student outcomes, particularly for students at the top of the test score distribution.

 $^{^{14}}$ The value of each density ranges from 0 to 1 and gives an idea of how connected the network is compared to how connected it could be. The difference between both densities ranges from -0.1 to 0.75, where negative and low values of the variable indicate a higher level of conflict within the class.

¹⁵These values correspond to the American educational system. In the Spanish system, they correspond to 1st to 4th year of Compulsory Secondary Education (Educación Secundaria Obligatoria).

¹⁶The max-min method of standardization involves re-scaling the range of features to scale the data between 0 and 1. For each variable, the formula used is $(x - \min)/(\max - \min)$, where x is the original value, min is the minimum value of the variable, and max is the maximum value of the variable.

 $^{^{17}}$ Which is consistent with the lower likelihood of *female* being *repeaters* (see Figure 4)

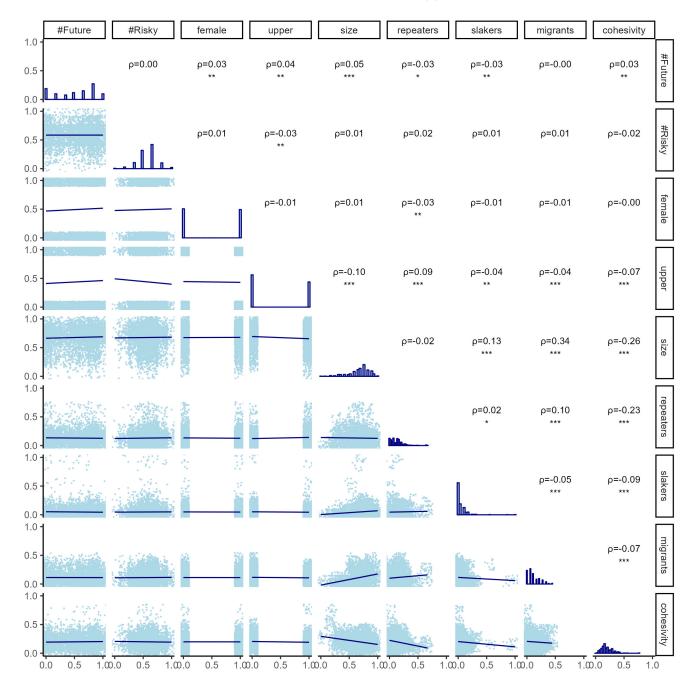


Figure 2: Class heterogeneity: Correlations (ρ)

2.3.2 Network heterogeneity

We employ network analysis for two distinct purposes: i) to assess the integration of students within the classroom, measuring factors such as *popularity* and *centrality* in the network, to which we propose a metric based on Gower and Legendre, 1986; and ii) to examine student relationships, probing potential peer effects on time and risk preferences stemming from direct friends. As mentioned above, we measure popularity in the network of friends and enemies (hereafter *popularity.f* and *popularity.e*) as the number of classmates that name subject i as a friend or enemy, respectively¹⁸. In addition, using the friendship networks, we computed the betweenness *centrality* measure for each subject. This variable measures how central to the network each subject is by counting the number of shortest paths connecting any pair of nodes in the network that pass through that particular subject (Branas-Garza et al., 2010). To calculate this index, we need to examine the entire network architecture rather than just considering the local properties of a specific node. Finally, we also computed the average level of patience and risk preferences of each subject's friends (hereafter *friendsAP* and *friendsAR*)¹⁹. Table B.1.1 provides some summary statistics for these variables.

Figure 3 shows the distribution (and correlations) of each relevant variable and the social network measures. There are some interesting results. First, we observe that *popularity.f* (in friends) is positively correlated with the #Future allocations (p < 0.05) and *centrality* in the class network (p < 0.01), but it is negatively correlated with *female* (p < 0.01), being in an *upper* grade (p < 0.01), *popularity.e* (p < 0.01) and *friendsAR* (p < 0.05). It means that having more risk-loving friends makes you less popular. Regarding popularity in enemy networks, we also observe that it is negatively correlated with being in an *upper* grade (p < 0.01), *centrality* in the class network (p < 0.01), and *friendsAP* (p < 0.01). This means that more popular subjects in enemy networks have more impatient friends.

It is worth noting that risk preferences do not correlate with the network position of a subject (i.e. centrality in friends' and enemies' networks). We also see that *popularity* (both positive and negative) is negatively correlated with *upper* grade, meaning that teenagers become less popular when they grow up (p < 0.01 for both variables). Additionally, we find that girls exhibit less *centrality* in the class network (p < 0.01).

Finally, we observe that the #Future allocations are highly and positively correlated with friendsAP (p < 0.01). And we can see the same phenomenon between #Risky choices and friendsAR (p < 0.01). These results indicate that patient individuals have patient friends and risk-loving subjects have risk-loving friends. In the end, individuals have friends with whom they share similar economic preferences. We also remark that the variable #Future allocations is negatively correlated with friendsAR (p < 0.05) and that #Risky choices is negatively correlated with friendsAR (p < 0.05) and that #Risky choices is negatively correlated with friendsAP (p < 0.01). It might suggest that having risk-loving friends makes the subject more present-oriented and having impatient friends makes the subject more risk-loving. Finally, we remark that female and friendsAP are positively correlated (p < 0.05), which suggests that females have more patient friends.

 $^{^{18}}$ This measure is known as in-degree, while out-degree measures the number of friends named by subject *i*. We use the former because it depends more on the choices of others than on the choices of the subjects themselves, which reduces any potential endogeneity problem.

¹⁹These variables will not capture the causal effect of peers, as there is an endogeneity problem: adolescents may exhibit assortative matching in their choice of friends, or attending the same friendship group may lead to convergence in economic preferences over time. Additionally, this measure is affected by the reflection effect defined by Manski (1993)

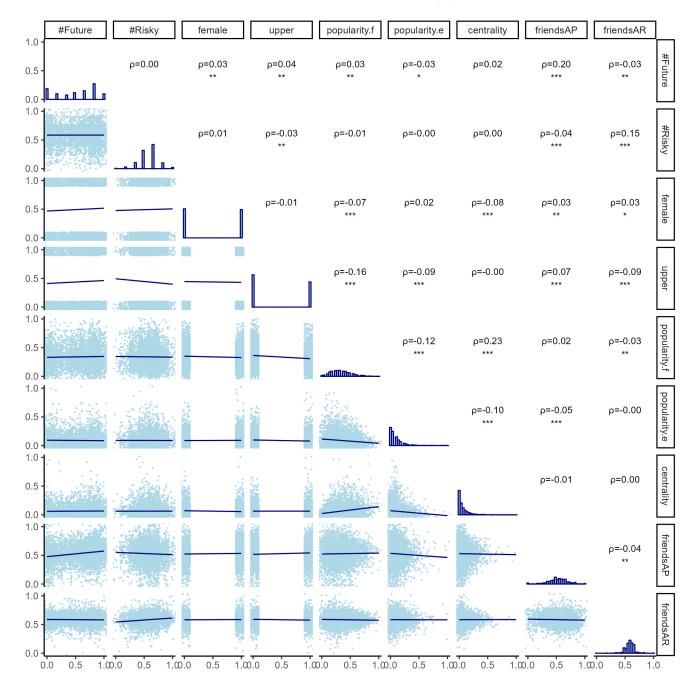


Figure 3: Network characteristics: Correlations (ρ)

2.3.3 Individual heterogeneity

For each student, we have a set of variables related to academic performance and cognitive abilities. There is evidence that time and risk preferences are correlated with academic outcomes (Castillo et al., 2011; Oreopoulos & Salvanes, 2011) and with cognitive abilities (Benjamin et al., 2013; Burks et al., 2009). This suggests a non-trivial interaction between schooling and unobserved abilities. First, we administered the Cognitive Reflection Test (CRT) of Frederick (2005), with a version adapted for teenagers. Second, we included six questions to assess subjects' accuracy in probability understanding, as outlined in Delavande and Kohler $(2009)^{20}$. We also have a dummy variable to identify *repeaters* and the expectations of subjects to achieve a university degree (expect). It is important to note that, due to Spanish regulations, we lack certain crucial variables such as the academic background of the student and their family income (SES). To fill the gap, we asked the students to report whether they obtained an A grade in the subjects of Spanish, Mathematics and English²¹ during the last academic year. We obtained three dummy variables with value 1 if the individual answered "Yes", and 0 otherwise. We then captured academic performance by summing these three variables in the number of A grades (#As). We also asked subjects to indicate the position of their family in the 1 to10 income stair to have a proxy of the family SES. However, several schools did not approve this question. Therefore, 18.07% of the sample did not provide this information and consequently, we decided to not use this variable in out analysis.

Figure 4 shows the distribution and the correlations between these variables and Appendix B.2 provides some summary statistics. First, concerning economic preferences, we observe that more #Future choices are associated with higher cognitive abilities in terms of CRT score, #As grades, and *accuracy* in probability understanding (p < 0.01 in all cases). We also see that more #Future allocations are correlated with a lower likelihood of being repeaters (p < 0.01) and with higher *expectations* of going to the university (p < 0.01). Regarding risk preferences, we observe that more #Risky choices are negatively correlated with CRT score (p < 0.01) and accuracy in probability understanding (p < 0.05). Second, if we look at gender differences, we observe that *female* obtain higher #As grades, are less likely to be *repeaters* and have higher *expectations* of going to the university (p < 0.01 in all cases). However, they have a lower CRT score (p < 0.01). Third, we focus on age differences. We see that subjects in upper grades have higher CRT scores and *accuracy* in the probabilities test. They are also more likely to be repeaters and less likely to have #As grades or to hold expectations of attending university (p < 0.01 in all cases). It suggests that despite being endowed with larger cognitive abilities, older subjects are worse in academic performance. Finally, we observe interesting correlations that validate our measures: CRT score and accuracy in probabilities are highly and positively correlated with the #As grades and expectations to go to the university, but negatively correlated with being repeaters $(p < 0.01 \text{ inall cases})^{22}$.

2.4 Important remarks

Before presenting the econometric approach, we would like to mention some final and important remarks about the dataset.

 $^{^{20}}$ For more details on the CRT and the probability understanding task, see sections 3 and 4 of Appendix A. $^{21}Spanish$ as native language in Spain and *English* as foreign language in Spain (EFL).

²²And they are also positively correlated between themselves (p < 0.01).

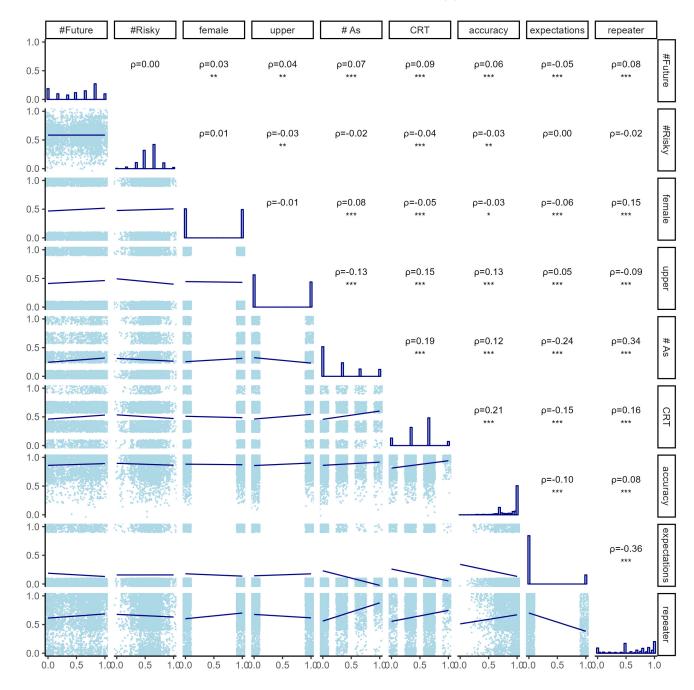


Figure 4: Individual characteristics: Correlations (ρ)

Power: our sample consists of a large number of adolescents in grades 7 to 10: we account for

2,751 students (56.96%) in grades 7-8 (49.4% females), and 2,079 students (43.04%) in grades 9-10 (48.6% females). With an effect size of 0.12 standard deviations, our study achieves a statistical power of 0.88 for the first sample and 0.78 for the second sample. This means that our research can detect significantly smaller differences compared to previous studies (for more details, see Tables OA.1.1a and OA.1.2a of the Appendix).

Non-self-selected subjects: data were obtained in schools that participated in the project. Students were not invited to participate in an experiment but were asked by their teachers to complete a survey as an in-class regular activity. Only 0.39% (19 out of 4,830) of subjects refused to participate in the experiment. These students did not sign the consent form and were automatically expelled from the platform. Additionally, 5.57% (269 out of 4,830) of students did not fill the last task of the experiment (a creativity task), but the fraction varies across schools. This non-completion rate varied across schools, ranging from 0% to 16.58%. Only one school had an exceptionally high non-completion rate of 68.89%.

Hypothetical incentives: the entire project was conducted without monetary incentives to make it easier to obtain the IRB (Institutional Review Board) approval and to involve a larger number of schools. In the previous phase of the project, we employed both monetary and hypothetical incentives to test the impact of incentives on eliciting time and risk preferences. We found a null result, as detailed in Alfonso et al. (2023). Similarly, recent papers with adults have shown that hypothetical payments yield similar results to real payments for time (see Brañas-Garza et al. (2023)) and risk preferences (see Brañas-Garza et al. (2021)).

These features make our dataset different from: i) other experimental studies with teenagers, since we did not use monetary incentives; therefore, our dataset is considerably larger and the schools are more diverse in background; ii) other experimental studies, which involve standard subjects, usually university students, since our participants were not not self-selectes and a significant portion of them may not pursue a higher education degree.

3 Econometric approach

To study if females behave differently than males and whether their preferences develop differently across adolescence, we employed the following regression $model^{23}$:

$$y_i^j = \beta_0 + \beta_1 \times female_i + \beta_2 \times upper_i + \beta_3 \times female_i \times upper_i + \epsilon_i \tag{1}$$

The term y_i^j refers to one variable from our set of outcome variables $j = \{\#Future, AllPresent, Interior, AllFuture, \#Risky, Averse, Neutral, Lover\}$. We are interested in the dummy variables $female_i$ and $upper_i$ (used as a proxy for age), as well as the interaction term $female_i \times upper_i$. Since we use the binary variable upper, this discretization may have unintended consequences and we will need to check the results with the original variable. The error term is denoted by ϵ_i .

First, we analyze the outcome variables of time and risk preferences. Figure 5 displays the distributions of these variables for subjects that are consistent in the respective task. Histograms A and B display the outcome variables related to *time* preferences. It is important to remark that our analysis is focused on *subjects that exhibit consistency in the task*, reducing

 $^{^{23}}$ We do not study the same individual across adolescence (like in a panel), but different teens in different cohorts.

our sample from 4,736 to 3,923 (82.8%) observations. Panel A of Figure 5 displays the distribution of the #*Future* allocations (standardized) for consistent subjects, while the inset graph includes all subjects (consistent and inconsistent). Both graphs have a similar distribution. Panel B shows the distribution of the different dummies: 22.7% of the consistent subjects allocate all to the present (*AllPresent*), 65.6% use interior allocations (*Interior*), which we name sophisticated individuals, and 11.7% allocate all to the future (*AllFuture*)²⁴. Similarly, Panels C and D of Figure 5 display the various outcome variables related to *risk* preferences. As for *time* preferences, we limited the analysis to consistent subjects, reducing the sample from 4,685 to 3,727 observations (79.6% of the original sample). Panel C displays the distribution of the #*Risky* choices (standardized) for consistent subjects, with the inset graph showing the distribution for all subjects. Again, both distributions are quite similar. Additionally, Panel D shows that 44.6% of subjects are risk-*averse*, 45.4% are risk-*neutral*, and 10.0% are risk-*lovers*.

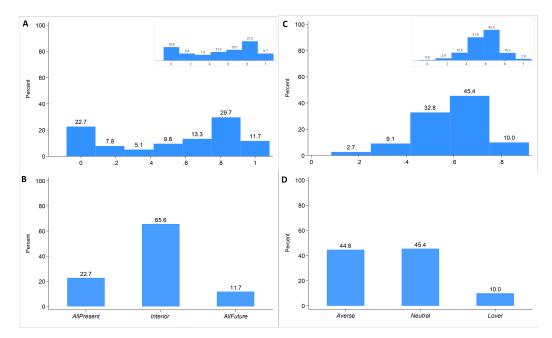


Figure 5: Distribution of time and risk preferences

We estimate equation 1 for each outcome variable using OLS. We use four different specifications to analyze the robustness of the estimations. First, we estimate equation 1 with *school fixed effects* (S) to account for unobserved heterogeneity across schools (such as socioeconomic status, teachers quality, etc.). We will use this model as a reference. In our second specification (SC), we add class controls such as class *size*, number of *repeaters*, number of *slackers*, number of *migrants*, and class *cohesivity*, to take into consideration class heterogeneity (such as selection of students into different classes, differences in effort doing the experiment, and class environment). Third, we add social networks measures (SCN) such as popularity in friends (*popularity.f*) and enemies (*popularity.e*) networks, *centrality*, and the average level of time and risk preference of subject's friends (*friendsAP* and *friendsAR*) to control for

 $^{^{24}\}mathrm{For}$ summary statistics of these variables see Table B.1.1

social hierarchies (Alem et al., 2023; Branas-Garza et al., 2010) and peers effect that might be correlated with the economic preferences of subjects (Lucks et al., 2020; Zárate, 2023). Finally, we add individual controls (SCNI) related to cognitive abilities such as #As grades, CRTscore, *accuracy* in probabilities, *expectations* to go to the university, and whether the subject is a *repeater*. It is worth noting that we estimate the different specifications using the same sample; that is, we restricted the sample to those subjects with all the information for all the control variables. In doing so, we lost 186 (4,74%) and 137 (3.68%) observations in the *time* and *risk* outcome variables regressions, respectively.

4 Results

4.1 Economic preferences

4.1.1 Time preferences

Figure 6 displays the estimated coefficients of the variables of interest (in columns), along with their corresponding 95% confidence intervals, for each outcome variable related to time preferences (in rows). It shows that the variable *female* is not significant for all specifications under scrutiny (p > 0.20), which means that girls are not more and not less patient than boys at lower grades. The use of school fixed effects (S), class controls (SC), social network controls (SCN), and individual controls (SCNI) does not change this result on the #*Future* allocations. We find identical results for the type of allocations used by younger males and females (p > 0.60). Therefore, it suggests that there are no gender differences in time preferences at younger ages.

On the other hand, when we compare the #Future allocations between older and younger males, we observe in specification SC that *upper* is positive and statistically significant. This result indicates that older boys tend to choose more future options (p = 0.04). However, this variable is no longer significant once we add social networks (SCN) and individual (SCNI) controls.Regarding the types of allocations used by subjects, we find some significant differences. Young teens select all present (*AllPresent*) allocations more often than old ones in specifications S (p = 0.04) and SC (p = 0.02) but this result is not robust to the inclusion of additional controls in specifications SCN and SCNI (p > 0.05). Additionally, while older teens are more likely to make *Interior* choices (p < 0.05 for all specifications), *upper* is not significant (p > 0.35) on whether they allocate everything to the future (*AllFuture*). Finally, the interaction term *female* × *upper* is never significant.

For a better understanding of the interaction terms, we compute the marginal effects of *female* and *male* on each outcome variable for *lower* and *upper* grades and their 95% confidence intervals. Figure 7 summarizes these results using the SCNI specification since it has the lowest AIC statistic and the highest adjusted R-squared. This figure reveals no gender differences in patience (Panel A), and *AllFuture* allocations (Panel D) across lower and upper grades. However, we find significant differences in allocating everything to the present (Panel B) and choosing interior allocations (Panel C). We find that older teens are less present oriented and more sophisticated than younger ones. In addition, we find that females become even more sophisticated than males in upper grades. This difference is significant (p = 0.05) and represents an increase in the probability of using interior solutions of 4.6 percentage points (7.4%) for females compared to males. However, since the interaction of *female × upper* in Figure 6 is not significant, we conclude that girls and boys become more sophisticated with age and there is weak evidence that this effect is higher for girls than for boys.

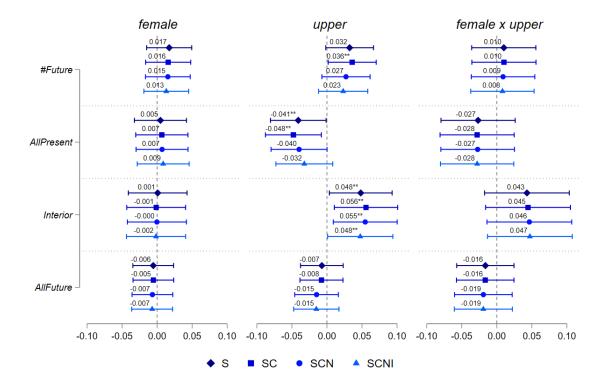


Figure 6: OLS estimations for time preferences outcomes

While the null results on patience are in line with Horn et al. (2022) and Sutter et al. (2013), the sophistication results, to the best of our knowledge, have not been found previously in the literature. We therefore conclude:

Result 1: Girls and boys do not differ in patience at younger ages, while older teens are less present oriented but more - especially girls – sophisticated.

Table B.2.1 shows all the regressions with the estimated coefficients of all the control variables. We highlight the following results:

• From the class controls, class size has a positive effect on the #Future allocations (p = 0.01 in SC and p < 0.10 in SCN and SCNI) with this effect being driven by a reduction in AllPresent allocations (p = 0.01 in SC and p < 0.10 in SCN and SCNI). We also find that cohesivity is positively related to the #Future allocations (p = 0.04 in SC specification)with this effect being driven by a reduction in AllPresent allocations (p = 0.01 in SC)and an increase in AllFuture allocations (p = 0.03 in SCN and SCNI). We also remark that the significance of size decreases and the significance of cohesivity disappears when we control for friendsAP, suggesting that the effect driving the result is the likeliness of finding similar friends in larger classes. These results suggest that patience is positively correlated with large classes.

- From the networks controls, popularity f is positively correlated with the use of Interior solutions (p = 0.02 in SCN and p < 0.10 in SCNI) and negatively related to AllFuture allocations (p < 0.05 in SCN and SCNI), suggesting that more popular subjects are more likely to make sophisticated choices at the expense of making more patient choices. Interestingly, friendsAP is positively correlated with patience (p < 0.01 for all the specifications and variables), with this effect being driven by a reduction in AllPresent and an increase of both Interior and AllFuture. It, therefore, suggests that teens with friends who have higher patience are more patient, some sort of social contagion (see Christakis and Fowler (2009)).
- From the *individual controls*, we find a strong and positive effect of cognitive abilities on the #Future allocations, specifically in #As grades (p = 0.02), CRT score (p < 0.01)and accuracy in probabilities (p < 0.10). This effect seems to be driven by a reduction in AllPresent allocations resulting in Interior allocations, since AllPresent is negatively correlated to #As (p = 0.02), CRT (p < 0.01) and accuracy (p = 0.02) while Interior is positively correlated with CRT (p = 0.03) and accuracy (p = 0.02). It suggests that subjects with higher cognitive abilities are more sophisticated in their allocations of time preferences.

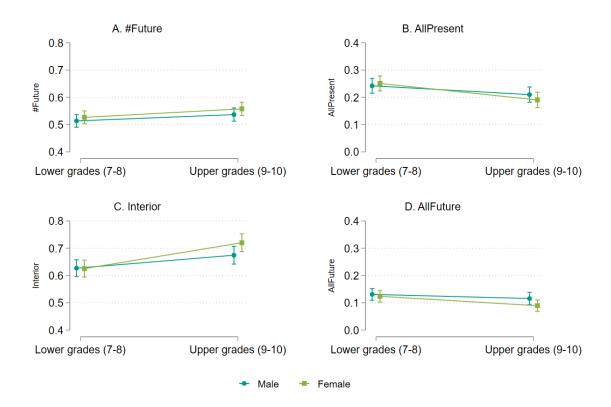


Figure 7: Linear prediction of female and male on time preferences by lower and upper grades

We therefore conclude that:

Result 2: Subjects with higher cognitive abilities are more patient, sophisticated, and less present oriented. Those who are friends of patient mates are more patient, sophisticated, and less present or more future oriented.

4.1.2 Risk preferences

Figure 8 focuses on risk attitudes and displays the same regression analysis across various control specifications as Figure 6. We observe that being *female* does not have a significant effect on #Risky choices (p > 0.50), being risk Averse (p > 0.30) or risk Neutral (p > 0.70). However, we observe in the SCNI specification that young females are more likely to have risk Lover preferences than males (p = 0.04). It should be noted that this result applies only to one specification and for a small fraction of the sample, as 11.7% of the subjects are risk-lovers. Results, therefore, indicate that there is no gender effect on risk preferences for young subjects. Additionally, we find a negative and significant effect of upper (p < 0.05 for all specifications) on the #Risky choices, indicating that older males take fewer risks than young ones. When we focus on the different types of risk preferences, we find a strong positive impact of upper (p < 0.01 for all specifications) on the fraction of risk Averse teens and a negative effect of upper (p < 0.01 for all specifications) on the fraction of risk Neutral. It suggests that older males are more risk-averse and less risk-neutral than young ones. Finally, we find that the interaction term is never significant $(p \ge 0.2)$, suggesting that these results also apply to girls.

As before, we calculate the marginal effects of *female* and *male* on each outcome variable by *upper* and *lower* grades to analyze better the significance of the interaction terms. Figure 9 provides these results for the specification with all the control variables (SCNI) ²⁵. Panel A confirms that girls and boys choose fewer #Risky choices at upper grades than lower grades and that this effect is not different across genders. This effect is driven by an increase in the proportion of being risk *Averse* and a reduction in the proportion of being risk *Neutral* as shown in Panels B and C. In addition, Panel B also suggests that risk aversion evolves differently across genders: we find that the probability of being risk *Averse* does not differ between girls and boys at lower grades (p > 0.20), but at upper grades, it is 0.06 percentage points (13.2%) higher for boys compared to girls (p = 0.02). Although this difference is significant, the interaction of *female* × *upper* in the graph 8 is not significant. Therefore, we conclude that teens become more risk *Averse* and less risk *Neutral* at upper grades, but there is also weak evidence that the increase in the proportion of risk *Averse* is higher for boys than for girls. Finally, Panel D shows that there is a small difference in the probability of being risk *Lover* between males and females at lower grades, this difference disappears at upper grades.

Overall, we conclude that girls and boys do not differ in risk preferences, however, teens in upper grades prefer fewer risks than those in lower grades. This maturity effect is explained by an increase in the fraction of risk-averse and a reduction of risk-neutral subjects. We also find weak evidence that this maturation process is different between girls and boys: the increase in risk aversion is higher for males than for females. Therefore, our result 3 is:

Result 3: Older teens are more risk averse and less risk neutral. There are no gender differences at younger ages, but older girls are less risk averse than older boys.

 $^{^{25}\}mathrm{Again},$ this specification has the lowest AIC statistic and the highest adjusted R-squared.

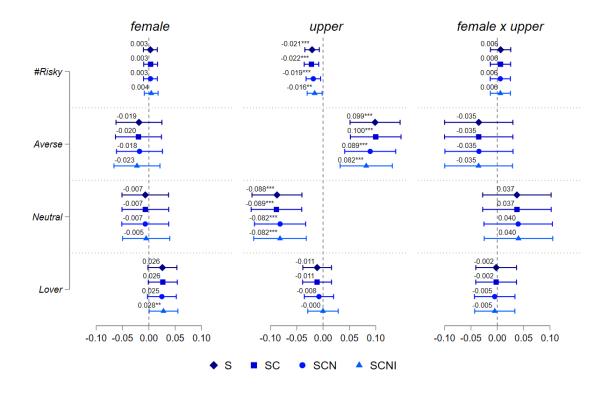


Figure 8: OLS estimated coefficients

While the first part of result 3 is in line with Harbaugh et al. (2002) and Deckers et al. (2015), the second part is new and requires a more detailed analysis of what could be the potential mechanisms. This will be addressed in the next section.

Table B.2.2 of the Appendix displays the estimated coefficients of the variables of interest along with all the controls. Some results are quite revealing:

- From the class controls, we observe that class size reduces the likelihood of being risk Neutral (p < 0.10 in SC, p = 0.04 in SCN and SCNI) and increases the likelihood of being risk Lover (p < 0.10 in SC and SCN, p = 0.03 in SCNI). We conclude that teenagers in larger classes tend to be more risk-lover and less risk-neutral. As before we find evidence of social contagion.
- From the *network controls*, we observe that *friendsAR* has a positive effect on #Risky choices (p < 0.01), with this effect being driven by a reduction in risk *Averse* preferences and an increase in both risk *Neutral* and risk *Lover* preferences (p < 0.01 for all specifications and outcomes variables). We also remark that *popularity.f* decreases the likeliness of being risk *Lover* in the SCN specification (p = 0.04), this result is most likely driven by higher cognitive abilities since such subjects are generally more popular. We conclude that teenagers with risk-prone friends have higher preferences for risk.
- From the *individual controls*, we observe that the #Risky choices are negatively correlated

with cognitive abilities, specifically with the #As grades (p < 0.01), the CRT score (p < 0.01) and the accuracy in probabilities (p < 0.01). This effect is driven by an increase in the proportion of risk Averse (p < 0.01) for the three variables) and a reduction in the proportion of risk Lover individuals (p < 0.01) for the three variables).

- We therefore conclude that:
- **Result 4:** Subjects with higher cognitive abilities choose fewer risky options, are more averse and less risk lovers. Those who are friends of risky mates choose more risky options, are less averse and are more risk lovers.

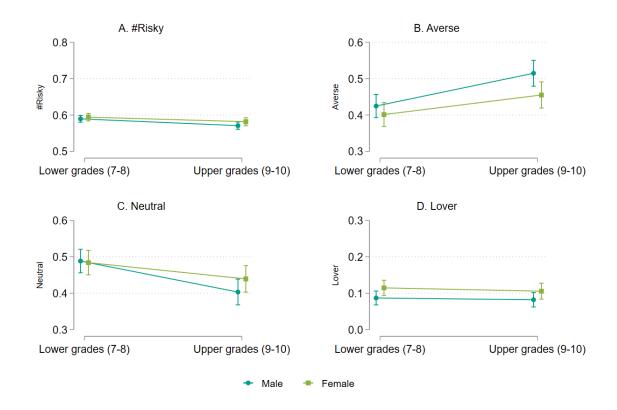


Figure 9: Linear prediction of female and male on risk preferences by lower and upper grades

4.1.3 Robustness checks

To assess the robustness of our results, Sections B.3 and B.4 extend the analysis by using the original variable *grade* instead of the discrete variable *upper* grade. Table B.4.1 in Section B.3 replicates the results presented in Table B.2.1 for time preferences. Similarly, Table B.4.2 in Section B.4 reproduces the findings of Table B.2.2 for risk preferences. We find that results are robust to an alternative specification of the grade variable.

Additionally, Section OA.2 extends the analysis by employing alternative regression models

according to the different nature of the outcome variables. In this line, columns (1) to (4) of Table OA.2.1 and OA.2.2 deliver the corresponding Tobit regression for the #Future allocations and #Risky options, respectively. The same tables also provide Probit estimations in columns (5) to (16) where the dependent variables are binary. We find that results hold, demonstrating the robustness of our findings to these alternative specifications.

Finally, in Section OA.3, we analyze whether inconsistency depends on gender and grade. The results are displayed in Figure OA.3.1. We found that there are no gender differences in consistency regarding time preferences for younger teens (p > 0.20). However, older males perform more consistently in the task (p < 0.01 in all specifications), while older females are less consistent (p = 0.02 in all specifications). These results suggest that consistency matures for boys but not for girls. As for risk preferences, we found that young females are less consistent (p = 0.02 in all specifications) than young males, while older males are more consistent than young males (p < 0.05 in all specifications). The interaction term not being significant in any specification (p > 0.10) implies that older females are also more consistent than young females. Considering that these differences in consistency could introduce selection bias if disregarded, Table OA.3.1 presents the regressions for the number of future allocations and the number of risky choices when including inconsistent subjects. We observe similar results than before when including inconsistent subjects, except that cognitive abilities do not influence the #Risky choices anymore. Overall, we conclude that our results are robust to alternative specifications.

4.2 Heterogeneity analysis

In the previous sections, we found evidence of no gender differences and certain maturity effects on risk and time preferences. Additionally, we observed the significant influence of cognitive abilities and the average level of patience and risk among friends on economic preferences. Based on these results, in this section, we will conduct an exploratory analysis to further investigate these findings and determine if the maturity effects can be attributed to any change in these (significant) control variables. Specifically, we will estimate the following interaction model:

$$y_{i}^{j} = \beta_{0} + \beta_{1} \times female_{i} + \beta_{2} \times upper_{i} + \beta_{3} \times female_{i} \times upper_{i} + \beta_{4} \times V_{i}^{j} + \beta_{5} \times V_{i}^{j} \times female_{i} + \beta_{6} \times V_{i}^{j} \times upper_{i} + \beta_{7} \times V_{i}^{j} \times female_{i} \times upper_{i} + \epsilon_{i}$$

$$(2)$$

Equation 2 is similar than equation 1 but adding to the regression the variable V_i^j and their interactions with $female_i$ and $upper_i$. As before, the term y_i^j refers to one variable from our set of outcome variables, and $female_i$ and $upper_i$ are dummy variables. The term V_i^j refers to one variable from our set of control variables that have a significant coefficient in Tables B.2.1 and B.2.2, that is $j=\{CRT, accurcy, \#As, friendsAP \text{ or } friendsAR\}$. The error term is denoted by ϵ_i . We estimate equation 2 using OLS for the specification with full controls (SCNI).

Subsections B.5 and B.6 of the Appendix display the regression results for the heterogeneity analysis for time and risk preferences, respectively. In the following subsections, we will focus on the marginal effects of V_i^j on each outcome variable by gender and for lower and upper grades separately. This analysis will allow us to understand better the mechanisms behind the maturity process found in the previous section and the significance of the interaction terms.

4.2.1 Heterogeneity in time preferences

Panels A to D from Figure 10 show the linear prediction of CRT, accuracy, #As, or friendsAP on the different outcome variables by gender. Within each panel, different plots are shown from left to right with these results for each outcome variable (#Future, AllPresent, Interior, or AllFuture, respectively), by lower and upper grades separately. For example, Panel A shows the results when the interacting variable (V_i^j) is the CRT score. The first graph on the left shows the linear prediction of this variable on the number of future allocations (#Future) for lower and upper grades. It suggests that at lower ages there are no gender differences at any level of CRT (p > 0.07), but boys with higher levels of reflection allocate more to the future (p = 0.03), while this variable does not affect girls' time preferences (p > 0.40). In upper grades, there are also no gender differences (p > 0.40), but now CRT increases the number of future allocations for girls but not for boys (p = 0.03 and p > 0.10). These results suggest that reflective abilities increase the patience of young boys and older girls, but do not explain gender differences.²⁶

We now explore the effect of CRT on AllPresent, Interior, and Allfuture allocations types. The second graph from the left of Panel A refers to the first type and unveils some interesting findings. First, boys with higher levels of reflection become less present-oriented (p < 0.01) at lower grades. Still, the percentage of girls allocating everything to the present remains the same, independent of their level of reflection become less present-oriented (p = 0.03) while present orientation for boys is unaffected by reflection levels (p > 0.07). The third graph from the left of Panel A shows the results for Interior allocations. It shows that in lower grades there is no significant effect of CRT on this outcome variable for either girls or boys (p > 0.20). However, at upper grades higher levels of reflection make girls more sophisticated (p = 0.02) while do not affect boys (p > 0.10). Finally, the fourth graph from the left of Panel A focuses on AllFuture allocations. It shows that reflection levels have no significant effect on this outcome variable at any grade for either boys or girls (p > 0.06).

The same analysis using *accuracy* as the interacting variable is shown in Panel B of figure 10. The first graph on the left shows that at lower grades, this variable has no significant effect on #*Future* allocations for either boys or girls (p > 0.09). At upper grades, we find that boys with low accuracy start with a higher patience level than girls (p = 0.05), but as *accuracy* increases, girls choose more future allocations (p = 0.03) while this cognitive ability does not affect boys' patience (p > 0.30). From the second graph, we can see that *accuracy* does not affect *AllPresent* allocations for girls and boys at lower grades (p > 0.06), but at upper grades, higher *accuracy* levels induce only girls -and not boys (p > 0.50)- to choose fewer *AllPresent* options (p = 0.03). Looking at the third graph, we find that there is no effect of *accuracy* levels on *Interior* allocations. This is true for both girls and boys in all grades (p > 0.06). Finally, from the fourth graph from the left, we observe that this variable does not affect *Allfuture* allocations at earlier grades (p > 0.26). In contrast, for upper grades, we find interesting results across genders. Older boys with low probability understanding are more future-oriented than girls with the same cognitive level (p = 0.04), but as probability understanding increases this future orientation of boys decreases (p = 0.01) while for girls is unaffected by *accuracy* (p > 0.90).

Panel C of figure 10 uses the #As as the interacting variable and shows that this variable has no effect on any of the outcome variables for lower grades (p > 0.10). However, for upper

 $^{^{26}}$ All these results and those described below for the other outcome variables, come from the estimation using OLS of equation 2. The regression results are shown in Figures B.5.1 and B.5.2 of Appendix B.5.

grades the results are different. First, girls with higher #As become more patient (p = 0.05) while it doesn't affect #Future allocations for boys (p > 0.20). Second, this increase in patience for girls is explained by a reduction in the probability of allocating everything to the present (AllPresent, p < 0.01) and an increase in sophistication (Interior, p < 0.01); while for boys, there is no evidence that these variables are affected by #As (p > 0.20). Finally, there is no effect of #As on the development of AllFuture allocations at any grade for either boys or girls (p > 0.06).

Finally, Panel D shows the results when friendsAP is used as the interacting variable. We observe that for all subjects, regardless of age and gender, this variable increases #Future, *Interior*, and *AllFuture* allocations, while it also decreases the allocation to *AllPresent* (p < 0.01 for all the mentioned outcome variables).

Overall, our results suggest that higher cognitive abilities –measured by CRT, accuracy, or #As– increase teens' patience for boys at lower grades, while at upper grades only increase girls' patience. This last effect is explained by the fact that girls with a higher cognitive ability become less present-oriented and more sophisticated than boys. Finally, we also found that a higher average level of patience of friends makes all subjects more future-oriented. Therefore, we can summarize this evidence in the following result:

Result 5: Cognitive ability is positively correlated with patience. However, the effect varies according to age and gender: in lower grades, boys with higher cognitive ability become less present-oriented than girls, but in upper grades, girls with higher cognitive ability become less present and more sophisticated than boys. A higher average level of patience with friends makes all subjects more future-oriented.

4.2.2 Heterogeneity in risk preferences

Similar to the previous subsection, we now study risk preferences. Figure 11 replicates the same analysis as Figure 10 for the different outcome variables. Panel A of Figure 11 uses the CRTas the interacting variable. The first graph from the left shows the results for the number of risky options (#Risky). It suggests that at lower grades, higher reflective abilities make boys choose fewer risky options (p = 0.04) but there is no significant effect for girls (p > 0.90). At upper grades the results are quite different: girls with low reflective abilities choose more risky options (p = 0.04) than boys, but this gender difference tends to zero since girls choose fewer risky options than boys for higher levels of reflection (p < 0.01 and p > 0.08, respectively). The second graph from the left shows the results for the Averse variable. At lower grades, males with higher cognitive ability become more risk averse (p = 0.04), while the probability of being this type for girls is stable across different levels of reflection (p > 0.90). However, at upper grades the results are different: boys start being more risk-averse than girls (p = 0.01) at low reflection levels, but girls become more risk-averse than boys as their cognitive ability increases, suggesting a convergence of girls' risk aversion levels with those of boys (p < 0.01 and p > 0.50, respectively). The third graph shows the results for *Neutral*: while for lower and upper grades the linear prediction of CRT looks different across boys and girls, these differences are not significant (p > 0.10).

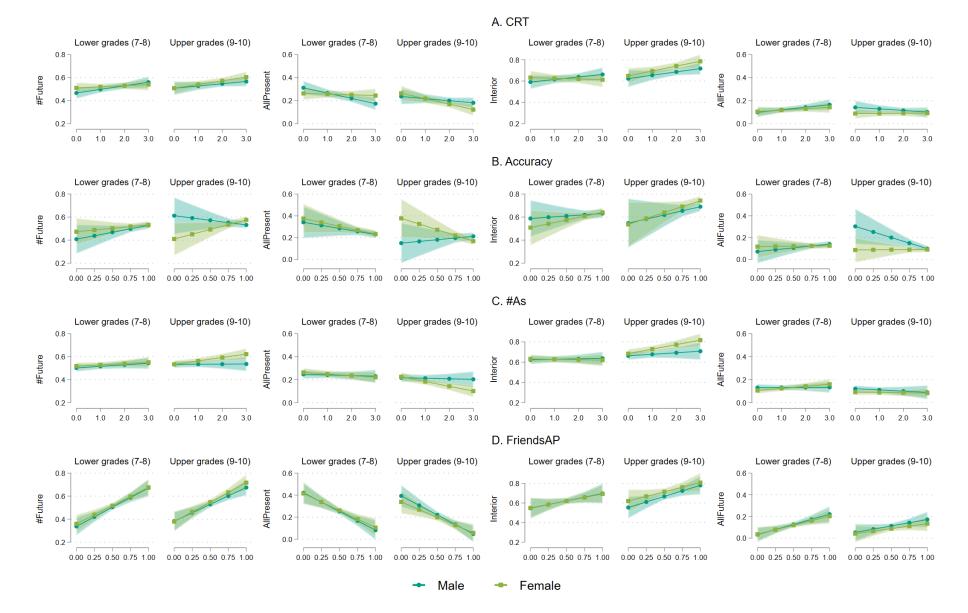


Figure 10: Linear prediction of V_i^j on time preferences for male and female by lower and upper grades

Finally, the fourth graph from the left suggests that CRT does not explain gender differences in the probability of being risk *Lover* at lower grades (p > 0.10). However, at upper grades, we observe that girls with higher levels of reflection become less risk *Lover* (p = 0.03), while for boys the probability of being risk lovers remains the same at any level of CRT (p > 0.10)²⁷.

We now look at Panel B of Figure 11, where accuracy in probability is used as the interacting variable. As before, the first graph shows the results for #Risky and we observe that boys with higher levels of accuracy choose fewer risky options (p = 0.04) at lower grades. However, for girls, this effect is not significant (p > 0.60). At upper grades, this negative effect of accuracy on #Risky is no longer significant (p > 0.10) neither for girls nor for boys. The second graph shows the same analysis for risk Averse. It suggests that at lower grades, higher levels of accuracy in probability make boys more risk Averse (p < 0.01), but has no effect on girls (p > 0.08). This effect of accuracy remains for boys at upper grades (p < 0.01), while higher levels of accuracy make girls now more risk Averse (p = 0.04). The third graph shows that at lower grades, girls with low accuracy in probability are less risk Neutral than boys (p = 0.02), but as this cognitive ability increases, they become more risk Neutral (p = 0.02), while it does not affect to boys (p > 0.09). At upper grades, we do not observe an effect of accuracy on risk neutrality for either girls or boys (p > 0.20). Finally, the fourth graph shows that girls at lower grades become less risk Lover as their accuracy in probability increases (p < 0.01) but it has no effect on boys (p > 0.17). As before, at upper grades, we do not observe any effect of this cognitive ability on being risk lover for either girls or boys (p > 0.07).

Panel C of Figure 11 shows the same analysis using the #As as the interacting variable. The first graph from the left shows the results for the number of risky options (#Risky). It suggests that for lower grades, the #As does not affect #Risky for either girls or boys (p > 0.08). However, at upper grades emerges some interesting differences: boys with fewer #As grades choose fewer risky choices than girls with similar grades (p = 0.02). However, as #As increases, girls choose fewer risky choices (p < 0.01) but boys remain at the same level (p > 0.60). The same analysis is presented in the second graph for the variable Averse. As before, we observe that #As does not affect the probability of being risk Averse either for girls or boys (p > 0.30). However, at upper grades the results are different. Males without any A are more risk averse than girls with the same condition (p = 0.02), but they become more risk averse than boys as #As increases (p = 0.02). At the same time, we observe that academic excellence does not affect the risk aversion of males (p > 0.70). The third graph shows that, at lower grades, the #As does not affect risk neutrality (*Neutral*) for either girls or boys (p > 0.13). At upper grades, girls without any A are more risk Neutral than boys with the same condition (p = 0.03), but as #As increases, girls become less risk Neutral (p = 0.02). However, this outcome variable remains at the same level for boys across independently the number of As (p > 0.70). Finally, we observe in the fourth graph that higher values of #As make boys less risk lovers (Lover) at lower grades (p < 0.01), while it does not affect this outcome variable for girls (p > 0.50). At upper grades, We observe the opposite pattern: girls with higher #As grades become less risk Lover (p < 0.01) while it does not affect boys (p > 0.13).

 $^{^{27}}$ As before, all these results and those presented below, come from the different estimated coefficients using equation 2. Figures B.6.1 and B.6.2 of the Appendix B.6 displays the results for #Risky and the different risk types respectively, using each of the interacting variables separately (rows).

Finally, Panel D of Figure 11 shows the results when friendsAR is used as the interacting variable. We observe that for all subjects, regardless of age and gender, this variable increases the number of risky options chosen by teens (#Risky). Also, it reduces the probability of being risk *Averse* and increases the probability of being risk *Lover* (p < 0.01 for all the mentioned outcome variables).

Overall, our results suggest that cognitive abilities explain differences in the maturity process of risk preferences: higher levels of cognitive abilities make boys less prone to take risk at lower grades, while girls with higher cognitive abilities become less risky at upper grades. We, therefore, conclude:

Result 6: Cognitive abilities are inversely associated with risk taking. However, the effect is different according to age and gender: higher levels of cognitive abilities make boys less willing to take risk at lower grades, while girls with higher cognitive abilities become less risky at upper grades. Friends who choose more risky options on average make all subjects more risky.

5 Conclusion

We use a large and powered sample of n = 4830 non-self-selected teenagers from 22 Spanish schools with diverse socioeconomic backgrounds to study whether females behave differently than males, and whether their preferences for time and risk develop differently across adolescence.

In addition to measuring time and risk preferences and including fixed effects to account for school characteristics, we also collected information on several variables that characterize the different 207 classes in our dataset. These data include factors such as the selection of students into different classes, variations in effort during the experiment, and the level of cohesion at the class level. In doing so, we aimed to control for class-specific heterogeneity.

We also collected a large array of students' characteristics including controls regarding cognitive abilities that are strongly related to economic preferences (Horn et al., 2022). These controls include the CRT score, the number of A grades, and the accuracy in understanding probability.

Last but not least, we compute several measures that allow us to identify patterns and trends that go beyond individual decisions and shed light on the influence of social networks on decision-making. Specifically, we compute measures of popularity in friends' and enemies' networks for each participant, as well as the average level of economic preferences of our subjects' friends. These new variables provide valuable insights not explored in the existing literature and serve as valuable controls for potentially omitted variables that have been shown to be significant determinants in recent studies (Alem et al., 2023; Branas-Garza et al., 2010; Lucks et al., 2020).

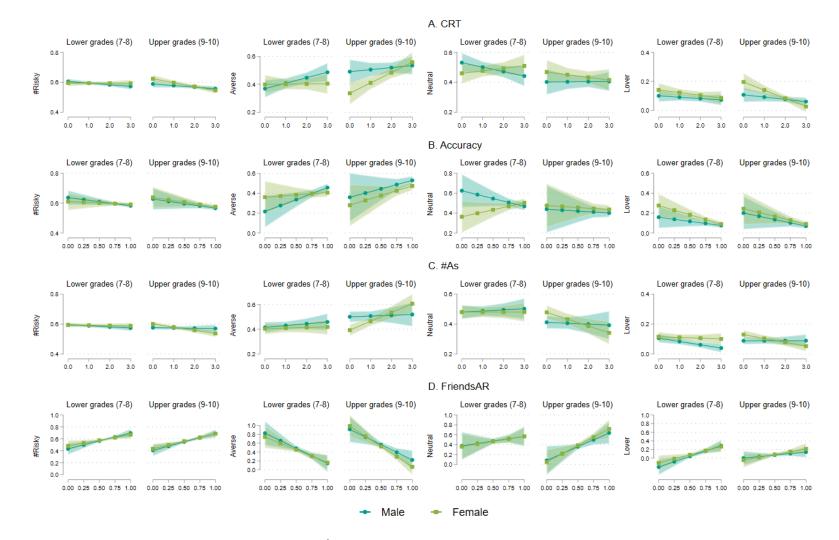


Figure 11: Linear prediction of V_i^j on risk preferences for male and female by lower and upper grades

By taking all these factors as exogenous, we find that girls and boys do not differ in patience at younger ages while older teens are less present-oriented and more sophisticated in their time preferences because they choose more interior solutions and are less likely to allocate everything to present. However, this effect is higher for girls. Regarding risk preferences, we do not find gender differences in the number of risky choices at younger ages, but we find that older teens choose fewer risky choices on average. However, we find at upper grades some gender differences in the different risk types: girls become less risk averse and more risk neutral than boys.

To better understand this maturation process in time and risk preferences, we perform an exploratory heterogeneity analysis. We find two new results to the existing literature. First, cognitive abilities play a critical role in the development of time and risk preferences. We find that cognitive abilities increase patience but the effect varies according to age and gender: in lower grades, boys with higher cognitive abilities become less present-oriented than girls, but in upper grades, girls with higher cognitive abilities become less present-oriented and more sophisticated than boys. Regarding risk preferences, cognitive abilities also explain age and gender differences. We find that higher levels of cognitive abilities make boys less prone to take risk at lower grades, while girls with higher cognitive abilities become less risky at upper grades.

Second, interaction within the social network of the class also matters. We find that the average level of patience (risk) of friends also impacts adolescents' preferences. Interestingly, we observe that the higher the average level of patience (risk) of their ties, the smaller the probability of becoming present-oriented (risk averse) and the higher the probability of taking all patient options (and all risky options). However, none of these interactions with gender or age (grade) are significant, implying that all these effects are the same across genders and ages.

These results have important implications for future research. First, it is essential to consider the interactions between gender, age, and cognitive abilities, as failing to do so may introduce bias when analyzing gender differences in risk and time preferences. Second, these interactions underscore the importance of cognitive abilities in understanding gender differences. We discovered that increasing cognitive abilities among females, particularly knowledge of probabilities, may lead to lower present orientation, potentially bringing them in line with males in terms of time preferences. Concerning risk preferences, higher cognitive abilities will make females more risk-averse, offering a possible explanation for why women often exhibit greater risk aversion than men in standard experiments involving university students.

Similarly, the strong and positive relationship between friends' preferences – that we cannot call homophily since, among others, we cannot even isolate the reflection effect – has also two important implications. The first one refers to common habits since good (bad) habits are commonly shared by friends and in turn, this could have an impact on future outcomes. Second, since there is evidence of successful interventions on time preferences (see Alan and Ertac, 2018; Lührmann et al., 2018; Rueda et al., 2012; Sutter et al., 2023) an interesting study might be to intervene in a random number of students to test whether their friends change their preferences as well. And if these spillovers in preferences appear then interventions might be even more beneficial.

Additionally, these results have important policy implications for reducing gender differences.

While prior studies have demonstrated the impact of financial literacy on participants' risk and time preferences (e.g., Sutter et al. (2023), Alan and Ertac (2018) and Lührmann et al. (2018)), our findings highlight the significance of including probability calculus in efforts to reduce gender differences in patience. This suggests the necessity of incorporating probability education into such interventions and even into standard school curricula.

Before closing the paper it is necessary to acknowledge its limitations. The first limitation of this study is that we do not have treatments, therefore the entire analysis is purely correlational. Therefore, although our results are suggestive still we cannot discard that certain variables may co-evolve jointly. Second, it's also important to note that both time and risk preferences are elicited with simplified (and visually formatted) versions of classical tasks - Alfonso et al. (2023) and Vasco and Vazquez (2023) respectively. While these tasks provide very good results in terms of consistency (higher than 80% in both cases), still is true that our results are valid for these tasks only and therefore we cannot extrapolate them to other experimental settings. Lastly, the entire study is based on hypothetical rewards. Besides our previous experience shows that hypothetical tasks – in this particular dominion – are informative (see Alfonso et al., 2023; Brañas-Garza et al., 2021, 2023) still we could be missing relevant information.

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Appendix

A Experimental tasks

A.1 Time preferences

We measured time preferences with a modified version of the Multiple Price Lists task. Subjects were asked to take six decisions between two amounts of money. Option A allowed them to obtain money tomorrow, and option B allowed them to obtain money at the later date of one week and one day. The amount of money at the early date is always $\in 10$, and the amount of money at the later date increases from decision to decision: $\in 10$, $\in 12$, $\in 14$, $\in 16$, $\in 18$ and $\in 20$. Subjects should initially select option A and the trial at which they switch from option A to option B gives an interval of potential values for their discount rate. See Alfonso et al. (2023) for details about how we built the task through different versions. Figure A.1.1 provides an example of a decision screen for the second decision.

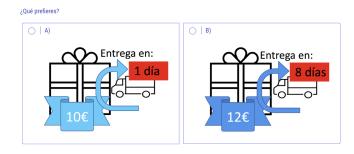


Figure A.1.1: Example of decision screen for the time preferences task

Monetary amounts are represented by a gift for the participant with a blue ribbon indicating their value. Using a gift symbol should help subjects understand that they make a choice for themselves. Figure A.1.2 shows how the ribbon darkens proportionally to the increase in the monetary value in order to help subjects understand the concept of interest rate. Waiting times are represented by a van surmounted with the text "Delivery in: 1 day / 8 days". A curved arrow represents the truck movement and points at the time delay to help subjects understand the meaning of the van symbol. Instructions above the answers say: "What do you prefer?". We used an emotional vocabulary following the advice of psycho-pedagogical teams that it would make subjects comfortable with answering the experiment.



Figure A.1.2: Monetary values in late period used in the experiment

A.2 Elicitation of risk preferences

We measured risk preferences with a modified version of the Holt-Laury task. Subjects were asked to make six decisions between two paired lotteries where they have p_h to obtain the highest payoff and p_l to obtain the lowest payoff. The first decision in the standard Holt-Laury task is taken with probabilities $p_h=0$ and $p_l=1$, then p_h increases by 0.2 in each following decision. Lottery A is initially better than lottery B until p_h becomes sufficiently high and it reverses, but subjects might continue to pick lottery A because it is less risky than lottery B. The trial at which they switch to lottery B gives an interval of estimated values for their risk-aversion parameter. Because inconsistency in the Holt-Laury task is usually high, we expected teenagers to face serious problems in this task. We, therefore, reduced the number of trials to six to limit the number of potentially inconsistent choices. We also added the $(p_h=0, p_l=1)$ trial to get an additional measurement testing the consistency of subjects. Figure A.2.1 displays an example of a decision screen for the second decision.

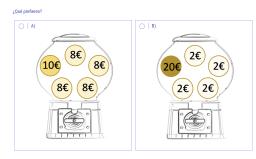


Figure A.2.1: Example of decision screen for the risk preferences task

We used the visual representation of a gumball machine to help teenagers understand the concept of risk since the functioning of a gumball machine is to insert a coin and turn the crank to receive one of the balls inside the tank. Each ball represents one potential outcome of the lottery. Balls from the safe lottery are represented in yellow, and balls from the risky lottery are represented in brown, with balls of lower values being clear and balls of higher values being darker. Figure A.2.2 shows how the number of higher values balls increases from trial to trial for lottery B. Figure A.2.3 does the same for lottery A.



Figure A.2.2: Lottery B used in the experiment

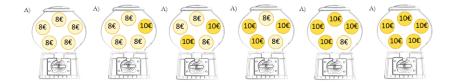


Figure A.2.3: Lottery A used in the experiment

A.3 Cognitive Reflection Test

We use two complementary tasks to study the abilities of teenagers: the Cognitive Reflection Test (CRT) adapted to teenagers to measure cognitive abilities. We used the following questions:

- CRT1: In a library, the number of books doubles every month. If the library takes 48 months to fill, how long will it take to fill it halfway? Indicate with a number. (reflective: 47; intuitive: 24).
- CRT2: If you are running a race and you pass the person in second place, what place are you in? Indicate with a number. For example: 1 (first), 2 (second), etc. (reflective: second; intuitive: first).
- CRT3: The father of Emilia has 3 daughters. The first two are named April and May. What is the name of the third daughter ? (reflective: Emilia; intuitive: June).

Subjects answered the three CRT questions on the same screen and were instructed that there were correct answers to all questions.

A.4 Probability knowledge

To elicit probabilistic expectations, we follow the approach suggested by Delavande and Kohler (2009) and adapted to Spanish by Estepa et al. (2021). We asked students to allocate a slider between 0 and 100 to express the likelihood that an event will be realized. We called this the "Delavande Test". We first elicit the understanding of our participants on probabilities. The first two questions allow us to test teenagers' ability to calculate a known probability with the slider. We used the following questions:

- Q1 Imagine I have a basket with five apples: 1 green and four red. If I ask you to pick one of the apples without looking at the inside of the basket, how likely do you think it is that you will pick the green apple?
- Q2 Imagine I have a basket with 10 apples: 1 green and 9 red. If I ask you to pick one of the apples without looking at the inside of the basket, how likely do you think you will pick the green apple?

The third and fourth questions inquire about events that are very close to 0 and 100 (absolute certainty), aiming to assess whether teenagers can accurately represent probabilities of zero and one.

- Q3 How likely do you think it is that you are not going to attend school during the entire next month (including today)?
- Q4 How likely do you think it is that you are going to take a shower at least once in the next month (including today)?

Finally, questions five and six jointly assess whether teenagers respect a fundamental property of probability by examining nested events.

- Q5 How likely do you think it is that you will eat rice in the next week (including today)?
- Q6 How likely do you think it is that you will eat rice in the next month (including today)?

In this paper, we use the two first questions to define a measure of accuracy. Specifically, using the true values of Q1 and Q2, we first define a variable called *inaccuracy* as follows: $Inacc_i = (Y_{i1} - TV_1)^2 + (Y_{i2} - TV_2)^2$, where Y_{ij} is the value given by individual *i* in question j = [1, 2]; and TV_j is the true value for question *j*. We then standardize this variable between 0 and 1 using a max-min procedure. Next, we compute our outcome variable, *accuracy* as *accuracy_i* = $1 - std(Inacc_i)$. Higher values of these variables indicate answers that are closer to the true values, while lower values reflect higher errors in computing objective probabilities. In addition, we introduce the following question: "How likely are you to attend UNIVERSITY?". This question was designed to elicit students' perceptions of their likelihood of enrolling in university. The responses obtained were used to quantitatively assess expectations of university attendance, referred to in our analysis as *expectations*.

B Additional analysis

B.1 Summary statistics

Variables	Obs	Mean	Std. dev.	Min	Max
Variables of interest					
female	4792	0.49	0.50	0.00	1.00
upper	4811	0.43	0.49	0.00	1.00
Class level					
size	4811	28.50	3.10	17.00	34.00
repeaters	4811	3.71	3.24	0.00	20.00
slackers	4811	1.23	2.56	0.00	22.00
migrants	4811	2.17	2.41	0.00	18.00
cohesivity	4807	0.20	0.10	-0.01	0.75
Social networks					
popularity.f	4811	7.51	3.91	0.00	22.00
popularity.e	4811	1.98	2.39	0.00	22.00
centrality	4811	18.21	26.41	0.00	288.62
friendsAP	4792	3.15	1.00	0.00	6.00
friendsAR	4789	3.51	0.47	0.00	6.00
Individual level					
#As	4811	0.28	0.35	0.00	1.00
CRT	4719	0.49	0.27	0.00	1.00
accuracy	4535	0.88	0.17	0.00	1.00
expectations	4573	0.65	0.33	0.00	1.00
repeater	4811	0.16	0.37	0.00	1.00
Time preferences					
#Future	4730	3.14	2.06	0.00	6.00
AllPresent	4730	0.19	0.39	0.00	1.00
Interior	4730	0.72	0.45	0.00	1.00
AllFuture	4730	0.10	0.30	0.00	1.00
Risk preferences					
#Risky	4684	3.50	1.01	0.00	6.00
Averse	4687	0.46	0.50	0.00	1.00
Neutral	4687	0.42	0.49	0.00	1.00
Lover	4687	0.12	0.33	0.00	1.00

Table B.1.1: Summary statistics of the variables without standardizing.

B.2 Regression tables

$\frac{\#Future}{female} \\ 0.017 \\ (0.016) \\ upper \\ 0.032* \\ (0.017) \\ female \times upper \\ 0.010 \\ (0.023) \\ size \\ repeaters \\ slackers \\ migrants \\ cohesivity \\ \hline \\ popularity.f \\ popularity.e \\ centrality \\ \hline \end{cases}$	$\begin{array}{c} 0.016\\ (0.016)\\ 0.036^{**}\\ (0.018)\\ 0.010\\ (0.023)\\ \hline \\ 0.125^{**}\\ (0.051)\\ -0.112^{*}\\ (0.061)\\ -0.065\\ \end{array}$	#Future 0.015 (0.016) 0.027 (0.018) 0.009 (0.023) 0.095* (0.052) -0.092	$\begin{array}{c} \#Future \\ 0.013 \\ (0.016) \\ 0.023 \\ (0.018) \\ 0.008 \\ (0.023) \\ \hline 0.087^* \end{array}$	$\begin{array}{c} 0.005 \\ (0.019) \\ -0.041^{**} \\ (0.020) \\ -0.027 \\ (0.027) \end{array}$	0.007 (0.019) -0.048** (0.020) -0.028	$\begin{array}{c} 0.007 \\ (0.019) \\ -0.040^{*} \\ (0.020) \end{array}$	$\begin{array}{c} 0.009 \\ (0.019) \\ -0.032 \\ (0.021) \end{array}$	$\begin{array}{c} 0.001 \\ (0.021) \\ 0.048^{**} \\ (0.023) \end{array}$	-0.001 (0.021) 0.056**	-0.000 (0.022) 0.055**	-0.002 (0.022) 0.048**	-0.006 (0.015) -0.007	-0.005 (0.015) -0.008	-0.007 (0.015) -0.015	-0.007 (0.015)
(0.017) female × upper 0.010 (0.023) size repeaters slackers migrants cohesivity popularity.f popularity.e	$(0.018) \\ 0.010 \\ (0.023) \\ \hline \\ 0.125^{**} \\ (0.051) \\ -0.112^{*} \\ (0.061) \\ \end{cases}$	$(0.018) \\ 0.009 \\ (0.023) \\ \hline 0.095^{*} \\ (0.052) \\ \end{cases}$	(0.018) 0.008 (0.023)	(0.020) -0.027	(0.020)						0.048**	-0.007	-0.008	0.015	
(0.023) size repeaters slackers migrants cohesivity popularity.f popularity.e	(0.023) 0.125^{**} (0.051) -0.112^{*} (0.061)	$(0.023) \\ 0.095^{*} \\ (0.052)$	(0.023)		-0.028		(- /=-)	(0.023)	(0.023)	(0.023)	(0.024)	(0.016)	(0.016)	(0.015)	-0.015 (0.017)
repeaters slackers migrants cohesivity popularity.f popularity.e	(0.051) -0.112* (0.061)	(0.052)	0.087*		(0.027)	-0.027 (0.027)	-0.028 (0.027)	$\begin{array}{c} 0.043 \\ (0.031) \end{array}$	$\begin{array}{c} 0.045 \\ (0.031) \end{array}$	$\begin{array}{c} 0.047 \\ (0.031) \end{array}$	$\begin{array}{c} 0.047 \\ (0.031) \end{array}$	-0.016 (0.021)	-0.017 (0.021)	-0.019 (0.021)	-0.019 (0.021)
slackers migrants cohesivity popularity.f popularity.e	(0.061)	-0.092	(0.052)		-0.148^{**} (0.059)	-0.111^{*} (0.061)	-0.102^{*} (0.060)		0.097 (0.067)	$\begin{array}{c} 0.047 \\ (0.069) \end{array}$	$0.038 \\ (0.069)$		$\begin{array}{c} 0.051 \\ (0.044) \end{array}$	0.064 (0.045)	$\begin{array}{c} 0.064 \\ (0.045) \end{array}$
migrants cohesivity popularity.f popularity.e	-0.065	(0.061)	-0.025 (0.065)		$\begin{array}{c} 0.114 \\ (0.073) \end{array}$	0.095 (0.072)	$\begin{array}{c} 0.051 \\ (0.077) \end{array}$		-0.139^{*} (0.079)	-0.130 (0.079)	-0.105 (0.086)		$\begin{array}{c} 0.024 \\ (0.054) \end{array}$	$\begin{array}{c} 0.035\\ (0.054) \end{array}$	$\begin{array}{c} 0.055\\ (0.058) \end{array}$
cohesivity popularity.f popularity.e	(0.005)	-0.064 (0.085)	-0.079 (0.086)		0.083 (0.113)	0.081 (0.111)	$0.099 \\ (0.111)$		-0.055 (0.115)	-0.054 (0.115)	-0.068 (0.115)		-0.028 (0.053)	-0.027 (0.053)	-0.031 (0.053)
popularity.f	-0.047 (0.082)	-0.035 (0.081)	-0.037 (0.081)		-0.059 (0.093)	-0.071 (0.092)	-0.071 (0.092)		$\begin{array}{c} 0.118 \\ (0.107) \end{array}$	$\begin{array}{c} 0.131 \\ (0.108) \end{array}$	$\begin{array}{c} 0.131 \\ (0.108) \end{array}$		-0.059 (0.073)	-0.059 (0.073)	-0.061 (0.074)
popularity.e	0.149^{**} (0.073)	$0.095 \\ (0.088)$	$0.108 \\ (0.088)$		-0.201^{**} (0.082)	-0.120 (0.099)	-0.127 (0.099)		$\begin{array}{c} 0.120 \\ (0.097) \end{array}$	-0.049 (0.117)	-0.048 (0.117)		$0.080 \\ (0.068)$	0.169^{**} (0.081)	0.174^{**} (0.082)
		$0.032 \\ (0.050)$	-0.006 (0.050)			-0.058 (0.058)	-0.021 (0.059)			0.155^{**} (0.067)	0.128^{*} (0.067)			-0.098^{**} (0.045)	-0.107** (0.045)
centrality		$\begin{array}{c} 0.067 \\ (0.062) \end{array}$	$\begin{array}{c} 0.089\\ (0.062) \end{array}$			-0.071 (0.071)	-0.094 (0.071)			$\begin{array}{c} 0.068 \\ (0.083) \end{array}$	$\begin{array}{c} 0.086\\ (0.084) \end{array}$			$\begin{array}{c} 0.002\\ (0.058) \end{array}$	$\begin{array}{c} 0.008\\ (0.058) \end{array}$
		0.088 (0.069)	0.071 (0.069)			-0.076 (0.080)	-0.056 (0.080)			$\begin{array}{c} 0.002 \\ (0.090) \end{array}$	-0.016 (0.090)			0.074 (0.060)	$\begin{array}{c} 0.072\\ (0.060) \end{array}$
friends AP		$\begin{array}{c} 0.334^{***} \\ (0.039) \end{array}$	$\begin{array}{c} 0.319^{***} \\ (0.039) \end{array}$			-0.335^{***} (0.046)	-0.319^{***} (0.046)			$\begin{array}{c} 0.189^{***} \\ (0.053) \end{array}$	$\begin{array}{c} 0.176^{***} \\ (0.052) \end{array}$			$\begin{array}{c} 0.146^{***} \\ (0.036) \end{array}$	$\begin{array}{c} 0.144^{***} \\ (0.036) \end{array}$
#As			0.041^{**} (0.018)				-0.047^{**} (0.020)				$0.036 \\ (0.024)$				$0.012 \\ (0.017)$
CRT			0.069^{***} (0.023)				-0.087^{***} (0.027)				0.067^{**} (0.031)				$\begin{array}{c} 0.020\\ (0.021) \end{array}$
accuracy			0.074^{*} (0.038)				-0.109^{**} (0.045)				$\begin{array}{c} 0.121^{**} \\ (0.051) \end{array}$				-0.013 (0.035)
expectations			$\begin{array}{c} 0.029\\ (0.022) \end{array}$				-0.030 (0.025)				$\begin{array}{c} 0.032\\ (0.029) \end{array}$				-0.001 (0.020)
repeater			-0.013 (0.019)				-0.011 (0.023)				$\begin{array}{c} 0.022\\ (0.026) \end{array}$				-0.011 (0.016)
$\begin{tabular}{ c c c c c }\hline \hline $constant$ & 0.580^{***} & (0.026) \\ \hline N & 3737 \\ $Adj. R^2$ & 0.033 \\ \hline \end{tabular}$	0.478*** (0.052) 3737 0.036	$\begin{array}{c} 0.298^{***} \\ (0.054) \\ 3737 \\ 0.057 \end{array}$	0.183^{***} (0.064) 3737 0.064	$\begin{array}{c} 0.162^{***} \\ (0.028) \\ 3737 \\ 0.024 \end{array}$	$\begin{array}{c} 0.302^{***} \\ (0.059) \\ 3737 \\ 0.028 \end{array}$	0.482^{***} (0.064) 3737 0.043	0.635^{***} (0.076) 3737 0.051	$\begin{array}{c} 0.695^{***} \\ (0.035) \\ 3737 \\ 0.020 \end{array}$	$\begin{array}{c} 0.608^{***} \\ (0.068) \\ 3737 \\ 0.021 \end{array}$	0.509^{***} (0.073) 3737 0.025	$\begin{array}{c} 0.354^{***} \\ (0.085) \\ 3737 \\ 0.029 \end{array}$	$\begin{array}{c} 0.143^{***} \\ (0.027) \\ 3737 \\ 0.012 \end{array}$	0.090^{*} (0.047) 3737 0.011	$\begin{array}{c} 0.009 \\ (0.048) \\ 3737 \\ 0.017 \end{array}$	$\begin{array}{c} 0.010 \\ (0.056) \\ 3737 \\ 0.016 \end{array}$
Adj. R ² 0.033 AIC 2926	0.036 2920	0.057 2844	0.064 2820	0.024 4023	0.028 4015	0.043 3960	$0.051 \\ 3934$	0.020 4984	$\frac{0.021}{4985}$	$\frac{0.025}{4972}$	0.029 4961	2088	2095	2078	0.016 2086
School Fixed Effect (S) Yes Class controls (SC) No Networks controls (SCN) No Individual controls (SCNI) No		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table B.2.1: OLS estimations on time preferences

	(1) #Risky	(2) #Risky	(3) #Risky	(4) #Risky	(5) Averse	(6) Averse	(7) Averse	(8) Averse	(9) Neutral	(10) Neutral	(11) Neutral	(12) Neutral	(13) Lover	(14) Lover	(15) Lover	(16) Lover
female	0.0028 (0.0067)	0.0033 (0.0067)	0.0029 (0.0067)	0.0045 (0.0067)	-0.0188 (0.0222)	-0.0198 (0.0223)	-0.0178 (0.0223)	-0.0226 (0.0223)	-0.0068 (0.0226)	-0.0067 (0.0226)	-0.0069 (0.0227)	-0.0051 (0.0228)	0.0257^{*} (0.0140)	0.0264^{*} (0.0140)	0.0247* (0.0140)	0.0277** (0.0139)
upper	-0.0209^{***} (0.0070)	-0.0221^{***} (0.0071)	-0.0185^{***} (0.0071)	-0.0160^{**} (0.0073)	0.0987^{***} (0.0242)	0.0999^{***} (0.0245)	0.0895^{***} (0.0247)	0.0819^{***} (0.0253)	-0.0875^{***} (0.0242)	-0.0885^{***} (0.0245)	-0.0816^{***} (0.0248)	-0.0818^{***} (0.0254)	-0.0112 (0.0138)	-0.0114 (0.0140)	-0.0078 (0.0142)	-0.0002 (0.0148)
$female \times upper$	$\begin{array}{c} 0.0064 \\ (0.0098) \end{array}$	$\begin{array}{c} 0.0061 \\ (0.0098) \end{array}$	$\begin{array}{c} 0.0057 \\ (0.0098) \end{array}$	$\begin{array}{c} 0.0059 \\ (0.0097) \end{array}$	-0.0352 (0.0331)	-0.0353 (0.0331)	-0.0348 (0.0330)	-0.0355 (0.0328)	$\begin{array}{c} 0.0373 \\ (0.0331) \end{array}$	$\begin{array}{c} 0.0374 \\ (0.0332) \end{array}$	$\begin{array}{c} 0.0397 \\ (0.0331) \end{array}$	$\begin{array}{c} 0.0402 \\ (0.0332) \end{array}$	-0.0021 (0.0197)	-0.0021 (0.0197)	-0.0049 (0.0196)	-0.0048 (0.0194)
size		0.0120 (0.0216)	0.0085 (0.0221)	0.0128 (0.0220)		0.0575 (0.0715)	0.0650 (0.0733)	0.0511 (0.0731)		-0.132* (0.0714)	-0.152^{**} (0.0736)	-0.149** (0.0737)		0.0745^{*} (0.0439)	0.0871^{*} (0.0455)	0.0976^{**} (0.0452)
repeaters		0.0419^{*} (0.0253)	$\begin{array}{c} 0.0376 \\ (0.0247) \end{array}$	0.0082 (0.0265)		-0.1000 (0.0858)	-0.0861 (0.0846)	-0.0008 (0.0904)		-0.0051 (0.0857)	-0.0140 (0.0852)	-0.0446 (0.0920)		0.105^{**} (0.0515)	0.100^{*} (0.0512)	$\begin{array}{c} 0.0454 \\ (0.0558) \end{array}$
slackers		-0.0074 (0.0405)	-0.0011 (0.0402)	$\begin{array}{c} 0.0032\\ (0.0414) \end{array}$		-0.0064 (0.114)	-0.0248 (0.112)	-0.0360 (0.114)		-0.0304 (0.113)	-0.0183 (0.113)	-0.0123 (0.114)		$\begin{array}{c} 0.0368\\ (0.0748) \end{array}$	$\begin{array}{c} 0.0431 \\ (0.0739) \end{array}$	$\begin{array}{c} 0.0483 \\ (0.0733) \end{array}$
migrants		-0.0157 (0.0348)	-0.0244 (0.0347)	-0.0247 (0.0346)		-0.0906 (0.117)	-0.0668 (0.117)	-0.0647 (0.117)		$0.106 \\ (0.119)$	0.0938 (0.119)	$\begin{array}{c} 0.0916 \\ (0.119) \end{array}$		-0.0158 (0.0674)	-0.0270 (0.0676)	-0.0269 (0.0668)
cohesivity		-0.0555^{*} (0.0315)	-0.0525 (0.0385)	-0.0557 (0.0383)		$\begin{array}{c} 0.148 \\ (0.106) \end{array}$	$\begin{array}{c} 0.147 \\ (0.128) \end{array}$	0.154 (0.127)		-0.0467 (0.105)	-0.159 (0.128)	-0.165 (0.128)		-0.101 (0.0625)	$\begin{array}{c} 0.0121\\ (0.0788) \end{array}$	$\begin{array}{c} 0.0109 \\ (0.0781) \end{array}$
popularity.f			$0.0054 \\ (0.0214)$	0.0214 (0.0214)			-0.0202 (0.0711)	-0.0670 (0.0715)			$0.110 \\ (0.0717)$	0.125^{*} (0.0726)			-0.0894** (0.0434)	-0.0581 (0.0432)
popularity.e			$\begin{array}{c} 0.0122\\ (0.0284) \end{array}$	-0.0001 (0.0280)			-0.0264 (0.0916)	0.0098 (0.0902)			-0.0515 (0.0915)	-0.0631 (0.0915)			0.0780 (0.0573)	$\begin{array}{c} 0.0532 \\ (0.0570) \end{array}$
centrality			-0.0232 (0.0274)	-0.0161 (0.0272)			$\begin{array}{c} 0.122\\ (0.0954) \end{array}$	$\begin{array}{c} 0.0991 \\ (0.0951) \end{array}$			-0.0978 (0.0948)	-0.0927 (0.0948)			-0.0238 (0.0529)	-0.0064 (0.0526)
friends AR			$\begin{array}{c} 0.250^{***} \\ (0.0399) \end{array}$	0.242^{***} (0.0396)			-0.746^{***} (0.118)	-0.720^{***} (0.117)			0.406^{***} (0.120)	0.398^{***} (0.120)			0.340^{***} (0.0797)	0.322^{***} (0.0784)
#As				-0.0227^{***} (0.0075)				0.0667^{***} (0.0256)				-0.0266 (0.0258)				-0.0401^{***} (0.0140)
CRT				-0.0339^{***} (0.0097)				$\begin{array}{c} 0.0938^{***} \\ (0.0326) \end{array}$				-0.0243 (0.0331)				-0.0695^{***} (0.0201)
accuracy				-0.0458^{***} (0.0171)				0.157^{***} (0.0536)				-0.0201 (0.0542)				-0.137^{***} (0.0369)
expectations				-0.0175^{*} (0.0093)				0.0604^{**} (0.0300)				-0.0119 (0.0305)				-0.0485** (0.0200)
repeater				-0.0001 (0.0081)				$\begin{array}{c} 0.0066\\ (0.0269) \end{array}$				$\begin{array}{c} 0.0053 \\ (0.0274) \end{array}$				-0.0118 (0.0176)
constant	0.609^{***} (0.0108) 3590	0.609^{***} (0.0214) 3590	0.459^{***} (0.0319) 3590	0.535^{***} (0.0356) 3590	0.399^{***} (0.0373) 3590	0.347^{***} (0.0720) 3590	0.791^{***} (0.101) 3590	0.543^{***} (0.112) 3590	0.465^{***} (0.0381) 3590	0.560^{***} (0.0723) 3590	0.324^{***} (0.101) 3590	0.373^{***} (0.112) 3590	0.136^{***} (0.0260) 3590	0.0929^{**} (0.0471) 3590	-0.115^{*} (0.0653) 3590	0.0841 (0.0737) 3590
Adj. \mathbb{R}^2	0.0163	0.0170	0.0297	0.0430	0.0244	0.0246	0.0345	0.0451	0.0199	0.0197	0.0227	0.0223	0.00973	0.0116	0.0195	0.0368
AIC	-3593	-3591	-3633	-3678	5107	5111	5079	5044	5137	5143	5136	5143	1444	1442	1417	1358
School Fixed Effect (S) Class controls (SC)	Yes No	Yes Yes	Yes Yes	Yes Yes	Yes No	Yes Yes	Yes Yes	Yes Yes	Yes No	Yes Yes	Yes Yes	Yes Yes	Yes No	Yes Yes	Yes Yes	Yes Yes
Networks controls (SC)	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Individual controls (SCNI)	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

B.3 Time preferences and grade variable

In this section, we analyze the robustness of results shown in Table B.2.1, considering all the values of the variable grade (1, 2, 3, and 4). Table B.4.1 shows the results for the regression of the outcomes on our variables of interest. Results remain almost the same: we do not see that older teens make more allocations to the future, but we see in all specifications that younger teens are more likely to allocate everything to the present (p < 0.10) while older teens are more likely to choose at least one interior allocation (p < 0.05).

B.4 Risk preferences and grade variable

We now proceed to assess the robustness of the results presented in Table B.2.2 by considering all possible values of the variable grade. Table B.4.2 displays these results. Notably, the findings regarding risk preferences remain consistent: there are no gender differences in terms of risk preferences, except that young females exhibit a higher propensity for risk-loving behavior compared to young males. Additionally, older teenagers tend to make less risky choices (p < 0.05), a trend driven by their greater risk aversion (p < 0.01) and reduced risk-neutrality (p < 0.01).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
<u> </u>	#Future 0.0398	#Future 0.0379	#Future 0.0383	#Future 0.0352	AllPresent	AllPresent -0.00522	-0.00520	AllPresent	-0.0144	-0.0172	-0.0186	-0.0214	AllLater 0.0223	AllLater 0.0225	AllLater 0.0238	AllLater 0.0231
female	(0.0398) (0.0291)	(0.0379) (0.0291)	(0.0383) (0.0288)	(0.0352) (0.0287)	-0.00793 (0.0334)	(0.00522) (0.0334)	(0.00520 (0.0331)	-0.00171 (0.0330)	(0.0144)	(0.0382)	(0.0186) (0.0382)	(0.0214) (0.0382)	(0.0223) (0.0272)	(0.0225) (0.0272)	(0.0238) (0.0271)	(0.0231) (0.0272)
grade	$\begin{array}{c} 0.0111 \\ (0.00791) \end{array}$	$\begin{array}{c} 0.0122\\ (0.00796) \end{array}$	$\begin{array}{c} 0.0115 \\ (0.00790) \end{array}$	$\begin{array}{c} 0.00905 \\ (0.00809) \end{array}$	-0.0185^{**} (0.00924)	-0.0208^{**} (0.00928)	-0.0203^{**} (0.00922)	-0.0166^{*} (0.00941)	$\begin{array}{c} 0.0250^{**} \\ (0.0104) \end{array}$	$\begin{array}{c} 0.0275^{***} \\ (0.0105) \end{array}$	$\begin{array}{c} 0.0285^{***} \\ (0.0105) \end{array}$	$\begin{array}{c} 0.0254^{**} \\ (0.0108) \end{array}$	-0.00645 (0.00716)	-0.00673 (0.00719)	-0.00813 (0.00726)	-0.00880 (0.00759)
$female \times grade$	-0.00773 (0.0107)	-0.00747 (0.0106)	-0.00810 (0.0105)	-0.00780 (0.0105)	$\begin{array}{c} 0.000456 \\ (0.0123) \end{array}$	-0.000107 (0.0122)	$\begin{array}{c} 0.000183 \\ (0.0121) \end{array}$	$\begin{array}{c} -0.000715 \\ (0.0121) \end{array}$	$\begin{array}{c} 0.0143 \\ (0.0141) \end{array}$	$0.0148 \\ (0.0141)$	$\begin{array}{c} 0.0161 \\ (0.0141) \end{array}$	$\begin{array}{c} 0.0168 \\ (0.0141) \end{array}$	-0.0147 (0.00982)	-0.0147 (0.00983)	-0.0163^{*} (0.00984)	-0.0160 (0.00990)
size		0.122^{**} (0.0510)	0.0957^{*} (0.0521)	0.0878^{*} (0.0518)		-0.149^{**} (0.0592)	-0.116^{*} (0.0607)	-0.106^{*} (0.0602)		$0.105 \\ (0.0669)$	$0.0568 \\ (0.0691)$	$\begin{array}{c} 0.0470 \\ (0.0688) \end{array}$		$0.0439 \\ (0.0441)$	$\begin{array}{c} 0.0592 \\ (0.0451) \end{array}$	$0.0586 \\ (0.0451)$
repeaters		-0.103^{*} (0.0608)	-0.0857 (0.0606)	-0.0184 (0.0647)		0.107 (0.0729)	$\begin{array}{c} 0.0894 \\ (0.0726) \end{array}$	$\begin{array}{c} 0.0444 \\ (0.0771) \end{array}$		-0.134^{*} (0.0791)	-0.126 (0.0792)	-0.101 (0.0855)		$\begin{array}{c} 0.0276 \\ (0.0536) \end{array}$	$\begin{array}{c} 0.0364 \\ (0.0536) \end{array}$	$\begin{array}{c} 0.0565 \\ (0.0579) \end{array}$
slackers		-0.0777 (0.0854)	-0.0719 (0.0849)	-0.0868 (0.0855)		$\begin{array}{c} 0.0959\\ (0.113) \end{array}$	$\begin{array}{c} 0.0903 \\ (0.112) \end{array}$	$0.108 \\ (0.111)$		-0.0649 (0.115)	-0.0628 (0.115)	-0.0769 (0.114)		-0.0310 (0.0524)	-0.0276 (0.0520)	-0.0307 (0.0520)
migrants		-0.0800 (0.0811)	-0.0592 (0.0802)	-0.0600 (0.0800)		-0.0216 (0.0917)	-0.0438 (0.0909)	-0.0452 (0.0909)		$0.0866 \\ (0.106)$	$0.103 \\ (0.106)$	$0.107 \\ (0.106)$		-0.0649 (0.0721)	-0.0595 (0.0721)	-0.0613 (0.0722)
cohesivity		0.142^{*} (0.0729)	$\begin{array}{c} 0.100 \\ (0.0880) \end{array}$	$\begin{array}{c} 0.114 \\ (0.0879) \end{array}$		-0.190^{**} (0.0815)	-0.119 (0.0991)	-0.127 (0.0992)		0.107 (0.0963)	-0.0617 (0.117)	-0.0586 (0.117)		$\begin{array}{c} 0.0833 \\ (0.0683) \end{array}$	0.180^{**} (0.0814)	0.185^{**} (0.0818)
popularity.f			$0.0197 \\ (0.0500)$	-0.0181 (0.0503)			-0.0485 (0.0579)	-0.0121 (0.0586)			0.153^{**} (0.0663)	0.126^{*} (0.0670)			-0.105^{**} (0.0451)	-0.114^{**} (0.0454)
popularity.e			$\begin{array}{c} 0.0599 \\ (0.0620) \end{array}$	$\begin{array}{c} 0.0821 \\ (0.0624) \end{array}$			-0.0678 (0.0710)	-0.0911 (0.0712)			$0.0708 \\ (0.0829)$	$\begin{array}{c} 0.0890\\ (0.0835) \end{array}$			-0.00298 (0.0576)	$\begin{array}{c} 0.00218 \\ (0.0578) \end{array}$
centrality			$\begin{array}{c} 0.0937\\ (0.0688) \end{array}$	$\begin{array}{c} 0.0764 \\ (0.0688) \end{array}$			-0.0791 (0.0803)	-0.0589 (0.0804)			-0.000836 (0.0899)	-0.0187 (0.0902)			$\begin{array}{c} 0.0799 \\ (0.0601) \end{array}$	$\begin{array}{c} 0.0776 \\ (0.0601) \end{array}$
friends AP			$\begin{array}{c} 0.341^{***} \\ (0.0384) \end{array}$	$\begin{array}{c} 0.326^{***} \\ (0.0386) \end{array}$			-0.346^{***} (0.0461)	-0.329*** (0.0460)			0.203^{***} (0.0521)	$\begin{array}{c} 0.189^{***} \\ (0.0520) \end{array}$			$\begin{array}{c} 0.143^{***} \\ (0.0357) \end{array}$	$\begin{array}{c} 0.140^{***} \\ (0.0359) \end{array}$
#As				0.0397^{**} (0.0178)				-0.0484^{**} (0.0202)				0.0407^{*} (0.0239)				0.00762 (0.0169)
CRT				$\begin{array}{c} 0.0711^{***} \\ (0.0232) \end{array}$				-0.0867^{***} (0.0267)				0.0630^{**} (0.0309)				$\begin{array}{c} 0.0237 \\ (0.0211) \end{array}$
accuracy				$\begin{array}{c} 0.0774^{**} \\ (0.0385) \end{array}$				-0.108^{**} (0.0450)				0.115^{**} (0.0509)				-0.00621 (0.0350)
expectations				$0.0286 \\ (0.0217)$				-0.0301 (0.0254)				$\begin{array}{c} 0.0316 \\ (0.0287) \end{array}$				-0.00151 (0.0200)
repeater				-0.0137 (0.0192)				-0.0100 (0.0231)				$\begin{array}{c} 0.0214 \\ (0.0256) \end{array}$				-0.0114 (0.0161)
constant	0.557^{***} (0.0303)	0.460^{***} (0.0544)	0.274^{***} (0.0570)	0.161^{**} (0.0654)	0.197^{***} (0.0326)	0.336^{***} (0.0623)	0.523^{***} (0.0667)	0.670^{***} (0.0775)	0.653^{***} (0.0401)	0.562^{***} (0.0712)	0.453^{***} (0.0759)	0.309^{***} (0.0870)	0.150^{***} (0.0306)	0.102^{**} (0.0489)	0.0239 (0.0506)	0.0207 (0.0570)
N Adj. R ²	$3737 \\ 0.0317$	$3737 \\ 0.0345$	$3737 \\ 0.0557$	3737 0.0634	$3737 \\ 0.0224$	3737 0.0254	3737 0.0416	$3737 \\ 0.0496$	3737 0.0197	3737 0.0207	3737 0.0256	3737 0.0296	3737 0.0135	3737 0.0129	3737 0.0184	3737 0.0177
School Fixed Effect (S)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class controls (SC)	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Networks controls (SCN) Individual controls (SCNI)	No No	No No	Yes No	Yes Yes	No No	No No	Yes No	Yes Yes	No No	No No	Yes No	Yes Yes	No No	No No	Yes No	Yes Yes
	110	110	110	162	110	110	110	162	110	110	110	162	110	110	110	105

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) N - ()	(10)	(11)	(12)	(13)	(14)	(15)	(16)
female	#Risky 0.00164 (0.0122)	$\frac{\#Risky}{0.00219}$ (0.0122)	$\frac{\#Risky}{0.000904}$ (0.0122)	#Risky 0.00271 (0.0121)	Averse -0.0124 (0.0398)	Averse -0.0136 (0.0399)	Averse -0.00858 (0.0398)	Averse -0.0141 (0.0396)	<u>Neutral</u> -0.0311 (0.0405)	<u>Neutral</u> -0.0309 (0.0406)	<u>Neutral</u> -0.0355 (0.0407)	<u>Neutral</u> -0.0338 (0.0407)	$\frac{Lover}{0.0434^{*}}$ (0.0250)	$\frac{Lover}{0.0445^{*}}$ (0.0250)	$\frac{Lover}{0.0441^{*}}$ (0.0249)	$\frac{Lover}{0.0479^{*}}$ (0.0246)
grade	-0.00875^{***} (0.00323)	-0.00890^{***} (0.00324)	-0.00793^{**} (0.00323)	-0.00687^{**} (0.00334)	$\begin{array}{c} 0.0410^{***} \\ (0.0111) \end{array}$	$\begin{array}{c} 0.0413^{***} \\ (0.0111) \end{array}$	$\begin{array}{c} 0.0384^{***} \\ (0.0112) \end{array}$	$\begin{array}{c} 0.0354^{***} \\ (0.0115) \end{array}$	-0.0327^{***} (0.0111)	-0.0334^{***} (0.0112)	-0.0315^{***} (0.0112)	-0.0315^{***} (0.0116)	-0.00829 (0.00603)	-0.00791 (0.00606)	-0.00691 (0.00612)	-0.00392 (0.00644)
female imes grade	0.00165 (0.00449)	$\begin{array}{c} 0.00157 \\ (0.00449) \end{array}$	$\begin{array}{c} 0.00190 \\ (0.00448) \end{array}$	$\begin{array}{c} 0.00183 \\ (0.00445) \end{array}$	-0.00915 (0.0151)	-0.00901 (0.0151)	-0.0102 (0.0151)	-0.0102 (0.0150)	$\begin{array}{c} 0.0170 \\ (0.0152) \end{array}$	$\begin{array}{c} 0.0170 \\ (0.0152) \end{array}$	$\begin{array}{c} 0.0193 \\ (0.0152) \end{array}$	$\begin{array}{c} 0.0194 \\ (0.0152) \end{array}$	-0.00785 (0.00885)	-0.00795 (0.00885)	-0.00909 (0.00881)	-0.00916 (0.00875)
size		0.00985 (0.0216)	0.00617 (0.0220)	$\begin{array}{c} 0.0108 \\ (0.0219) \end{array}$		0.0683 (0.0716)	0.0763 (0.0733)	$\begin{array}{c} 0.0613 \\ (0.0731) \end{array}$		-0.136^{*} (0.0717)	-0.158** (0.0737)	-0.155^{**} (0.0738)		$\begin{array}{c} 0.0672 \\ (0.0440) \end{array}$	0.0820^{*} (0.0454)	0.0937^{**} (0.0451)
repeaters		$\begin{array}{c} 0.0404 \\ (0.0253) \end{array}$	0.0365 (0.0247)	$\begin{array}{c} 0.00720 \\ (0.0265) \end{array}$		-0.0942 (0.0858)	-0.0817 (0.0845)	$\begin{array}{c} 0.00326 \\ (0.0904) \end{array}$		-0.0143 (0.0855)	-0.0223 (0.0850)	-0.0526 (0.0920)		0.109^{**} (0.0518)	0.104^{**} (0.0514)	$\begin{array}{c} 0.0493 \\ (0.0559) \end{array}$
slackers		-0.00444 (0.0405)	$\begin{array}{c} 0.00107 \\ (0.0402) \end{array}$	$\begin{array}{c} 0.00510 \\ (0.0413) \end{array}$		-0.0177 (0.114)	-0.0337 (0.112)	-0.0446 (0.114)		-0.0167 (0.113)	-0.00652 (0.113)	-0.000813 (0.113)		$\begin{array}{c} 0.0344 \\ (0.0749) \end{array}$	$\begin{array}{c} 0.0402 \\ (0.0740) \end{array}$	$\begin{array}{c} 0.0454 \\ (0.0734) \end{array}$
migrants		-0.00754 (0.0341)	-0.0183 (0.0341)	-0.0200 (0.0340)		-0.123 (0.116)	-0.0922 (0.116)	-0.0857 (0.115)		$\begin{array}{c} 0.145 \\ (0.118) \end{array}$	$\begin{array}{c} 0.127\\ (0.118) \end{array}$	$\begin{array}{c} 0.125 \\ (0.118) \end{array}$		-0.0222 (0.0660)	-0.0347 (0.0663)	-0.0388 (0.0653)
cohesivity		-0.0523* (0.0315)	-0.0507 (0.0385)	-0.0542 (0.0383)		$\begin{array}{c} 0.134 \\ (0.107) \end{array}$	$\begin{array}{c} 0.137\\ (0.128) \end{array}$	$\begin{array}{c} 0.146 \\ (0.128) \end{array}$		-0.0361 (0.106)	-0.161 (0.128)	-0.167 (0.128)		-0.0980 (0.0625)	$\begin{array}{c} 0.0234 \\ (0.0788) \end{array}$	$\begin{array}{c} 0.0206 \\ (0.0781) \end{array}$
popularity.f			0.00634 (0.0214)	$\begin{array}{c} 0.0222\\ (0.0214) \end{array}$			-0.0234 (0.0711)	-0.0700 (0.0714)			0.122^{*} (0.0717)	0.137^{*} (0.0725)			-0.0983** (0.0432)	-0.0671 (0.0429)
popularity.e			$\begin{array}{c} 0.0126 \\ (0.0283) \end{array}$	$\begin{array}{c} 0.000203 \\ (0.0279) \end{array}$			-0.0278 (0.0913)	$\begin{array}{c} 0.00924 \\ (0.0899) \end{array}$			-0.0431 (0.0914)	-0.0550 (0.0914)			$\begin{array}{c} 0.0709 \\ (0.0572) \end{array}$	0.0458 (0.0570)
centrality			-0.0234 (0.0274)	-0.0163 (0.0272)			0.122 (0.0956)	$\begin{array}{c} 0.0994 \\ (0.0952) \end{array}$			-0.103 (0.0950)	-0.0974 (0.0951)			-0.0191 (0.0528)	-0.00192 (0.0525)
friends AR			0.253^{***} (0.0399)	0.244^{***} (0.0396)			-0.757^{***} (0.118)	-0.730^{***} (0.117)			0.421^{***} (0.120)	0.413^{***} (0.120)			0.336^{***} (0.0794)	0.317^{***} (0.0782)
#As				-0.0234^{***} (0.00752)				0.0704^{***} (0.0257)				-0.0263 (0.0260)				-0.0442^{***} (0.0141)
CRT				-0.0336^{***} (0.00973)				0.0922^{***} (0.0327)				-0.0269 (0.0332)				-0.0653^{***} (0.0201)
accuracy				-0.0447^{***} (0.0171)				0.151^{***} (0.0539)				-0.0212 (0.0545)				-0.130*** (0.0370)
expectations				-0.0175^{*} (0.00929)				$\begin{array}{c} 0.0604^{**} \\ (0.0300) \end{array}$				-0.0112 (0.0305)				-0.0492** (0.0200)
repeater				$\begin{array}{c} -0.000191 \\ (0.00813) \end{array}$				$\begin{array}{c} 0.00687\\ (0.0269) \end{array}$				$\begin{array}{c} 0.00527 \\ (0.0274) \end{array}$				-0.0121 (0.0176)
constant	0.622*** (0.0126)	0.622*** (0.0223)	0.469*** (0.0324)	0.544^{***} (0.0360)	0.341^{***} (0.0431)	0.286*** (0.0757)	0.740^{***} (0.104)	0.501^{***} (0.113)	0.514^{***} (0.0437)	0.608^{***} (0.0761)	0.361*** (0.104)	0.411*** (0.114)	0.145^{***} (0.0283)	0.106^{**} (0.0485)	-0.101 (0.0660)	0.0881 (0.0739)
N Adj. R ²	3590 0.0161	3590 0.0166	3590 0.0297	3590 0.0430	3590 0.0241	3590 0.0242	3590 0.0345	3590 0.0452	3590 0.0183	3590 0.0182	3590 0.0217	3590 0.0213	3590 0.0112	3590 0.0129	3590 0.0209	3590 0.0378
School Fixed Effect (S)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class controls (SC)	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Networks controls (SCN)	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Individual controls (SCNI)	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

B.5 Heterogeneity in time preferences

Figure B.5.1 presents the estimated coefficients of equation 2 and their 95% CI for the heterogeneity analysis on time preferences. The first row replicates model (4) from Table B.2.1, corresponding to the SNCI specification with full controls. The second row uses the CRT score as the interacting variable, the third row uses the #As grades, the fourth row uses accuracy in probability understanding and the fifth row uses friendsAP in time preferences. In each row, the coefficient of the interacting variable is displayed in column V, the coefficient of the interaction of this variable with female is shown in column $F \times V$, the coefficient of the interaction with upper grade is displayed in column $U \times V$ and the triple interaction between the interacting variable, female and upper is presented in column $F \times U \times V$.

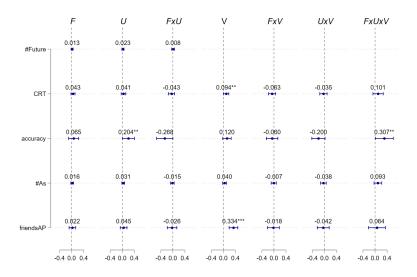


Figure B.5.1: Estimated coefficients from the heterogeneity analysis in time preferences (where: V = CRT, #As, accuracy, friendsAP). Dependent variable: #Future.

Figure B.5.2 replicated the same analysis for each allocation type: *AllPresent*, *Interior*, and *AllFuture*. In this case, our reference models are respectively (8), (12), and (16) of Table B.2.1, and their results are plotted in the first row.

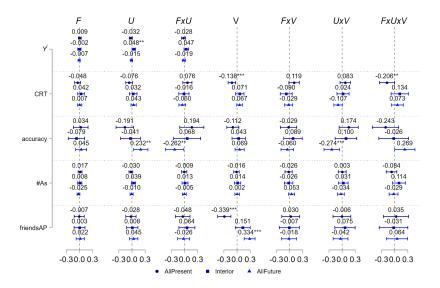


Figure B.5.2: Estimated coefficients from the heterogeneity analysis in time preferences (where: V = CRT, #As, accuracy, friendsAP). Dependent variables: AllPresent, Interior and AllFuture.

B.6 Heterogeneity in risk preferences

Similarly to the previous subsection, Figure B.6.1 replicates the same analysis as Figure B.5.1 for the number of risky choices (#Risly), where our reference model is column (4) of Table B.2.2.

Similarly, Figure B.6.2 replicates the analysis for the different categories of risk preferences. Our reference models are columns (8), (12), and (16) in Table B.2.2.

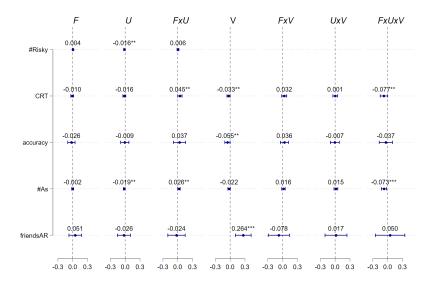


Figure B.6.1: Estimated coefficients from the heterogeneity analysis in risk preferences (where: V = CRT, #As, accuracy, friendsAR). Dependent variable: #Risky.

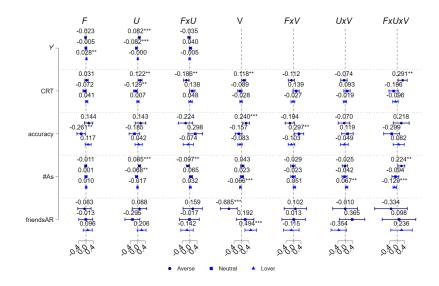


Figure B.6.2: Estimated coefficients from the heterogeneity analysis in risk preferences (where: V = CRT, #As, accuracy, friendsAP).Dependent variables: Averse, Neutral and Lover

Online Appendix

OA.1 Literature review

Paper	n	n equivalent	Schools	Grades	Classes	n average	3 4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Angerer et al. (2015)	561	0	2	5	N/A	112,2				112	112	112	112	112										
Bettinger and Slonim (2007)	191	80	N/A	12	N/A	15,92		16	16	16	16	16	16	16	16	16	16	16	16					
Castillo et al. (2019)	878	878	4	3	N/A	292,67										293	293	293						
Golsteyn at al. (2014)	661	661	N/A	1	N/A	661										661								
Horn et al. (2022)	1088	465	9	7	53	155,43												155	155	155	155	155	155	155
Luhrmann et al. (2018)	914	914	25	3	55	304,67										305	305	305						
Sutter et al. (2013)	661	438	3	9	28	$73,\!44$							73	73	73	73	73	73	73	73	73			
Our paper	4830	N/A	22	4	207	23,33									807	1270	1028	949	492	114				

Table OA.1.1:	Papers on	time preferences
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(a) Note: N/A refers when there is no information or the sample was targeted to a specific population that it is not a school, for example: the targeted population of a public program.

Paper	n	n equivalent	Schools	Grades	Classes	n average	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Andreoni et al. (2020)	1.295	398	3	13	N/A	99.62	99	99	99	99	99	99	99	99	99	99	99	99	99						
Booth and Nolen (2012)	260	260	8	2	N/A	130													130	130					
Borghans et al. (2009)	347	347	1	2	N/A	347													174	174					
Cárdenas et al. (2012)	1240	0	N/A	3	54	413,33	413	413	413																
Castillo et al. (2019)	878	878	4	3	N/A	292,67											293	293	293						
Eckel et al. (2012)	490	490	8	4	N/A	490												123	123	123	123				
Glätzle-Rützler and Lergetporer (2015)	755	566	4	8	N/A	94,38									94	94	94	94	94	94	94	94			
Harbaugh et al. (2014)	187	72	N/A	15	N/A	75			12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	
Horn et al. (2022)	1088	466	9	7	53	155,43													155	155	155	155	155	155	155
Khachatyran et al. (2015)	824	412	2	10	N/A	82,4					82	82	82	82	82	82	82	82	82	82					
Munro and Tanaka (2014)	412	353	N/A	7	N/A	58,86										58	58	58	58	58	58	58			
Piovesan and Willadsen (2021)	340	170	N/A	10	19	34					34	34	34	34	34	34	34	34	34	34					
Samek et al. (2021)	500	250	N/A	4	N/A	125														125	125	125	125		
Sutter et al. (2013)	661	440	3	9	28	73,44								73	73	73	73	73	73	73	73	73			
Tymula (2019)	33	33	N/A	6	N/A	33										6	6	6	6	6	6				
Our paper	4830	N/A	22	4	207	23,33										807	1270	1028	949	492	114				

Table OA.1.2: Papers on risk preferences

(a) Note: N/A refers when there is no information or the sample was targeted to a specific population that it is not a school, for example: the targeted population of a public program.

OA.2 Nonlinear models

	(1) #Future	(2) #Future	(3) #Future	(4) #Future	(5) AllPresent	(6) AllPresent	(7) AllPresent	(8) AllPresent	(9) Interior	(10) Interior	(11) Interior	(12) Interior	(13) AllFuture	(14) AllFuture	(15) AllFuture	(16) AllFuture
female	0.0155 (0.0237)	0.0134 (0.0236)	0.0125 (0.0235)	0.00973 (0.0234)	0.0186 (0.0610)	0.0258 (0.0611)	0.0270 (0.0617)	0.0386 (0.0622)	0.00124 (0.0569)	-0.00473 (0.0570)	-0.00224 (0.0573)	-0.00723 (0.0578)	-0.0262 (0.0718)	-0.0252 (0.0717)	-0.0341 (0.0722)	-0.0371 (0.0725)
upper	0.0443^{*} (0.0259)	0.0493^{*} (0.0261)	0.0344 (0.0261)	0.0275 (0.0266)	-0.139^{**} (0.0682)	-0.173^{**} (0.0694)	-0.158^{**} (0.0705)	-0.131^{*} (0.0727)	0.133^{**} (0.0628)	0.158^{**} (0.0637)	0.158^{**} (0.0646)	0.140^{**} (0.0663)	-0.0382 (0.0789)	-0.0394 (0.0799)	-0.0823 (0.0818)	-0.0816 (0.0846)
female \times upper	$\begin{array}{c} 0.0138 \\ (0.0351) \end{array}$	$\begin{array}{c} 0.0146 \\ (0.0350) \end{array}$	$\begin{array}{c} 0.0120 \\ (0.0347) \end{array}$	$\begin{array}{c} 0.0108\\ (0.0346) \end{array}$	-0.0938 (0.0935)	-0.0975 (0.0939)	-0.0917 (0.0947)	-0.107 (0.0952)	$\begin{array}{c} 0.123 \\ (0.0864) \end{array}$	$0.128 \\ (0.0866)$	$0.133 \\ (0.0870)$	$\begin{array}{c} 0.138 \\ (0.0873) \end{array}$	-0.103 (0.110)	-0.101 (0.110)	-0.111 (0.111)	-0.111 (0.111)
size		0.193^{**} (0.0758)	0.151^{*} (0.0776)	0.140^{*} (0.0773)		-0.521^{***} (0.199)	-0.399* (0.207)	-0.362* (0.207)		0.288 (0.185)	0.151 (0.192)	0.124 (0.192)		0.234 (0.235)	0.332 (0.243)	0.334 (0.243)
repeaters		-0.143 (0.0888)	-0.112 (0.0879)	-0.0221 (0.0948)		0.436^{*} (0.234)	0.389^{*} (0.236)	0.248 (0.256)		-0.400* (0.216)	-0.381^{*} (0.217)	-0.316 (0.235)		$\begin{array}{c} 0.105 \\ (0.271) \end{array}$	0.168 (0.279)	0.284 (0.298)
slackers		-0.103 (0.128)	-0.0994 (0.126)	-0.123 (0.126)		0.234 (0.342)	$\begin{array}{c} 0.208 \\ (0.334) \end{array}$	$\begin{array}{c} 0.270 \\ (0.335) \end{array}$		-0.131 (0.312)	-0.121 (0.309)	-0.157 (0.309)		-0.176 (0.335)	-0.221 (0.357)	-0.245 (0.359)
migrants		-0.0541 (0.124)	-0.0372 (0.122)	-0.0405 (0.122)		-0.197 (0.330)	-0.260 (0.334)	-0.255 (0.336)		$\begin{array}{c} 0.327 \\ (0.304) \end{array}$	$\begin{array}{c} 0.369 \\ (0.306) \end{array}$	$\begin{array}{c} 0.375 \\ (0.308) \end{array}$		-0.288 (0.383)	-0.320 (0.383)	-0.325 (0.384)
cohesivity		0.236^{**} (0.111)	$\begin{array}{c} 0.180 \\ (0.133) \end{array}$	$0.198 \\ (0.132)$		-0.735^{**} (0.302)	-0.439 (0.361)	-0.466 (0.366)		$\begin{array}{c} 0.349 \\ (0.272) \end{array}$	-0.131 (0.329)	-0.128 (0.331)		$\begin{array}{c} 0.375 \\ (0.330) \end{array}$	0.891^{**} (0.406)	0.923^{**} (0.408)
popularity.f			0.0212 (0.0746)	-0.0329 (0.0752)			-0.211 (0.204)	-0.0889 (0.208)			0.444^{**} (0.187)	0.372** (0.189)			-0.531** (0.237)	-0.584** (0.240)
popularity.e			0.0967 (0.0932)	$0.130 \\ (0.0930)$			-0.256 (0.250)	-0.350 (0.255)			$0.196 \\ (0.232)$	0.246 (0.235)			-0.00616 (0.289)	$\begin{array}{c} 0.0211 \\ (0.289) \end{array}$
centrality			$\begin{array}{c} 0.146 \\ (0.0999) \end{array}$	0.123 (0.0995)			-0.230 (0.287)	-0.147 (0.288)			$\begin{array}{c} 0.00434 \\ (0.253) \end{array}$	-0.0504 (0.254)			$\begin{array}{c} 0.416 \\ (0.300) \end{array}$	$\begin{array}{c} 0.409 \\ (0.300) \end{array}$
friendsAP			$\begin{array}{c} 0.517^{***} \\ (0.0567) \end{array}$	0.496^{***} (0.0566)			-1.095^{***} (0.152)	-1.046^{***} (0.152)			$\begin{array}{c} 0.505^{***} \\ (0.141) \end{array}$	$\begin{array}{c} 0.470^{***} \\ (0.141) \end{array}$			0.738^{***} (0.188)	$\begin{array}{c} 0.726^{***} \\ (0.188) \end{array}$
#As				0.0607^{**} (0.0269)				-0.195^{***} (0.0755)				0.109 (0.0681)				0.0549 (0.0838)
CRT				0.106^{***} (0.0346)				-0.306^{***} (0.0922)				0.186^{**} (0.0860)				$0.0895 \\ (0.111)$
accuracy				0.110^{**} (0.0552)				-0.361** (0.145)				0.332^{**} (0.136)				-0.0870 (0.175)
expectations				$\begin{array}{c} 0.0409 \\ (0.0315) \end{array}$				-0.0916 (0.0837)				$\begin{array}{c} 0.0860\\ (0.0782) \end{array}$				-0.00391 (0.103)
repeater				-0.0138 (0.0285)				-0.0417 (0.0763)				$\begin{array}{c} 0.0641 \\ (0.0704) \end{array}$				-0.0659 (0.0879)
constant	0.580^{***} (0.0397)	0.416^{***} (0.0764)	0.135^{*} (0.0815)	-0.0356 (0.0947)	-0.985*** (0.110)	-0.495** (0.205)	0.0742 (0.219)	0.585^{**} (0.255)	0.509^{***} (0.0982)	0.254 (0.187)	-0.0117 (0.201)	-0.437* (0.234)	-1.066*** (0.119)	-1.311*** (0.235)	-1.753*** (0.256)	-1.727*** (0.294)
var(e.#Future)	0.263*** (0.00830)	0.261^{***} (0.00826)	0.255*** (0.00805)	0.252^{***} (0.00796)				. *				. ,	. ,		. ,	
N	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737
School Fixed Effect (S)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class controls (SC)	No No	Yes No	Yes Yes	Yes Yes	No	Yes	Yes	Yes Yes	No No	Yes	Yes	Yes	No	Yes	Yes Yes	Yes
Networks controls (SCN)		NO	Yes	res	No	No	Yes	Yes	INO	No	Yes	Yes	No	No	res	Yes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
C 1	#Risky	#Risky	#Risky	#Risky	Averse	Averse	Averse	Averse	Neutral	Neutral	Neutral	Neutral	Lover	Lover	Lover	$\frac{Lover}{0.156^{**}}$
female	0.00282 (0.00662)	0.00332 (0.00662)	$\begin{array}{c} 0.00294 \\ (0.00660) \end{array}$	0.00446 (0.00658)	-0.0491 (0.0580)	-0.0515 (0.0581)	-0.0473 (0.0586)	-0.0590 (0.0591)	-0.0177 (0.0575)	-0.0173 (0.0576)	-0.0179 (0.0580)	-0.0133 (0.0583)	0.131^{*} (0.0767)	0.138^{*} (0.0771)	0.127 (0.0772)	(0.156^{-1})
upper	-0.0209^{***} (0.00719)	$\begin{array}{c} -0.0221^{***} \\ (0.00727) \end{array}$	-0.0185^{**} (0.00729)	-0.0160^{**} (0.00743)	$\begin{array}{c} 0.254^{***} \\ (0.0625) \end{array}$	$\begin{array}{c} 0.257^{***} \\ (0.0632) \end{array}$	$\begin{array}{c} 0.231^{***} \\ (0.0641) \end{array}$	$\begin{array}{c} 0.214^{***} \\ (0.0661) \end{array}$	-0.225^{***} (0.0624)	-0.228^{***} (0.0632)	-0.212^{***} (0.0640)	-0.212^{***} (0.0657)	-0.0915 (0.0908)	-0.0954 (0.0924)	-0.0764 (0.0947)	-0.0366 (0.101)
female \times upper	0.00637 (0.00979)	$0.00605 \\ (0.00979)$	$\begin{array}{c} 0.00573 \\ (0.00973) \end{array}$	0.00586 (0.00968)	-0.0886 (0.0852)	-0.0887 (0.0854)	-0.0879 (0.0857)	-0.0919 (0.0862)	$0.0966 \\ (0.0851)$	$\begin{array}{c} 0.0971 \\ (0.0852) \end{array}$	$\begin{array}{c} 0.103 \\ (0.0854) \end{array}$	$0.104 \\ (0.0856)$	0.0227 (0.118)	$\begin{array}{c} 0.0190 \\ (0.118) \end{array}$	-0.00188 (0.119)	-0.0196 (0.121)
size		$0.0120 \\ (0.0211)$	0.00848 (0.0217)	0.0128 (0.0215)		$\begin{array}{c} 0.153 \\ (0.183) \end{array}$	0.173 (0.190)	$0.135 \\ (0.191)$		-0.342* (0.183)	-0.395^{**} (0.190)	-0.386** (0.190)		0.446^{*} (0.251)	0.535^{**} (0.263)	0.638^{**} (0.271)
repeaters		$\begin{array}{c} 0.0419^{*} \\ (0.0250) \end{array}$	$\begin{array}{c} 0.0376 \\ (0.0249) \end{array}$	$\begin{array}{c} 0.00817\\ (0.0267) \end{array}$		-0.249 (0.221)	-0.212 (0.220)	$\begin{array}{c} 0.00979 \\ (0.238) \end{array}$		-0.0146 (0.219)	-0.0408 (0.219)	-0.119 (0.237)		0.643^{**} (0.272)	0.597^{**} (0.277)	$\begin{array}{c} 0.326 \\ (0.317) \end{array}$
slackers		-0.00743 (0.0335)	-0.00110 (0.0333)	$\begin{array}{c} 0.00318 \\ (0.0331) \end{array}$		-0.0163 (0.291)	-0.0649 (0.290)	-0.0957 (0.297)		-0.0799 (0.291)	-0.0487 (0.291)	-0.0335 (0.292)		$\begin{array}{c} 0.166 \\ (0.385) \end{array}$	$\begin{array}{c} 0.206 \\ (0.381) \end{array}$	$\begin{array}{c} 0.242 \\ (0.383) \end{array}$
migrants		-0.0157 (0.0350)	-0.0244 (0.0348)	-0.0247 (0.0346)		-0.239 (0.305)	-0.182 (0.307)	-0.179 (0.309)		$\begin{array}{c} 0.280 \\ (0.304) \end{array}$	$\begin{array}{c} 0.246 \\ (0.305) \end{array}$	$\begin{array}{c} 0.240 \\ (0.306) \end{array}$		-0.0895 (0.405)	-0.132 (0.408)	-0.220 (0.414)
cohesivity		-0.0555^{*} (0.0313)	-0.0525 (0.0377)	-0.0557 (0.0375)		$\begin{array}{c} 0.380 \\ (0.272) \end{array}$	$\begin{array}{c} 0.386 \\ (0.331) \end{array}$	$\begin{array}{c} 0.403 \\ (0.333) \end{array}$		-0.125 (0.271)	-0.416 (0.329)	-0.431 (0.330)		-0.642 (0.398)	0.0978 (0.481)	$\begin{array}{c} 0.0623 \\ (0.494) \end{array}$
popularity.f			$0.00536 \\ (0.0209)$	0.0214 (0.0210)			-0.0548 (0.185)	-0.173 (0.188)			0.284 (0.184)	0.324^{*} (0.186)			-0.589^{**} (0.263)	-0.390 (0.268)
popularity.e			$\begin{array}{c} 0.0122\\ (0.0269) \end{array}$	-0.0000738 (0.0267)			-0.0698 (0.239)	$\begin{array}{c} 0.0276 \\ (0.238) \end{array}$			-0.133 (0.237)	-0.165 (0.238)			$\begin{array}{c} 0.410 \\ (0.308) \end{array}$	$\begin{array}{c} 0.245 \\ (0.320) \end{array}$
centrality			-0.0232 (0.0279)	-0.0161 (0.0277)			$\begin{array}{c} 0.325 \\ (0.247) \end{array}$	$\begin{array}{c} 0.270 \\ (0.248) \end{array}$			-0.251 (0.246)	-0.237 (0.246)			-0.102 (0.354)	-0.0168 (0.357)
friendsAR			$\begin{array}{c} 0.250^{***} \\ (0.0354) \end{array}$	$\begin{array}{c} 0.242^{***} \\ (0.0352) \end{array}$			-1.947^{***} (0.320)	-1.898^{***} (0.319)			$\begin{array}{c} 1.055^{***} \\ (0.313) \end{array}$	$\begin{array}{c} 1.034^{***} \\ (0.313) \end{array}$			$\begin{array}{c} 1.952^{***} \\ (0.436) \end{array}$	1.901^{***} (0.432)
#As				-0.0227^{***} (0.00759)				$\begin{array}{c} 0.174^{***} \\ (0.0673) \end{array}$				-0.0690 (0.0669)				-0.331*** (0.0993)
CRT				-0.0339^{***} (0.00969)				$\begin{array}{c} 0.244^{***} \\ (0.0863) \end{array}$				-0.0633 (0.0853)				-0.436^{***} (0.115)
accuracy				-0.0458^{***} (0.0156)				$\begin{array}{c} 0.417^{***} \\ (0.143) \end{array}$				-0.0524 (0.139)				-0.719^{***} (0.178)
expectations				-0.0175^{**} (0.00884)				$\begin{array}{c} 0.161^{**} \\ (0.0794) \end{array}$				-0.0326 (0.0783)				-0.254^{**} (0.105)
repeater				-0.000148 (0.00792)				$\begin{array}{c} 0.0178 \\ (0.0713) \end{array}$				$\begin{array}{c} 0.0123\\ (0.0702) \end{array}$				-0.0771 (0.0932)
constant	$\begin{array}{c} 0.609^{***} \\ (0.0111) \end{array}$	$\begin{array}{c} 0.609^{***} \\ (0.0213) \end{array}$	$\begin{array}{c} 0.459^{***} \\ (0.0300) \end{array}$	$\begin{array}{c} 0.535^{***} \\ (0.0330) \end{array}$	-0.256^{***} (0.0969)	-0.395^{**} (0.186)	0.759^{***} (0.266)	0.114 (0.296)	-0.0880 (0.0957)	$0.160 \\ (0.185)$	-0.453^{*} (0.262)	-0.326 (0.291)	-1.111^{***} (0.116)	-1.370^{***} (0.246)	-2.587^{***} (0.366)	-1.579*** (0.402)
var(e.# <i>Risky</i>)	$\begin{array}{c} 0.0212^{***} \\ (0.000501) \end{array}$	$\begin{array}{c} 0.0212^{***} \\ (0.000500) \end{array}$	$\begin{array}{c} 0.0209^{***} \\ (0.000493) \end{array}$	$\begin{array}{c} 0.0206^{***} \\ (0.000485) \end{array}$												
N Adj. R ²	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590

OA.3 Consistency

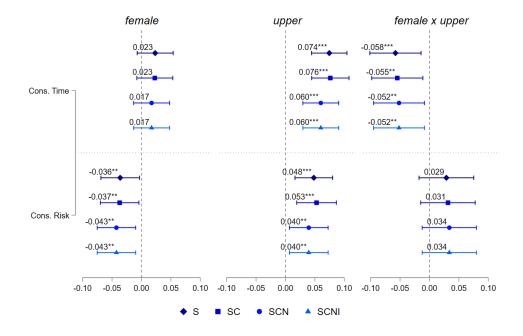


Figure OA.3.1: OLS estimations on Consistency

	(1) #Future	$\begin{array}{c} (2) \\ \#Future \end{array}$	$ \begin{array}{c} (3) \\ \#Future \end{array} $		(5) #Risky	(6) #Risky	(7) #Risky	
female	$\begin{array}{c} 0.0186 \\ (0.0134) \end{array}$	$\begin{array}{c} 0.0161 \\ (0.0134) \end{array}$	$\begin{array}{c} 0.0135 \\ (0.0133) \end{array}$	$\begin{array}{c} 0.0143 \\ (0.0138) \end{array}$	-0.00170 (0.00666)	-0.00154 (0.00668)	-0.00257 (0.00667)	-0.00140 (0.00685)
upper	0.0307^{**} (0.0147)	$\begin{array}{c} 0.0317^{**} \\ (0.0149) \end{array}$	$\begin{array}{c} 0.0239 \\ (0.0150) \end{array}$	$\begin{array}{c} 0.0230 \\ (0.0156) \end{array}$	-0.0189^{***} (0.00703)	-0.0199^{***} (0.00714)	-0.0156^{**} (0.00717)	-0.0136^{*} (0.00748)
female \times upper	$\begin{array}{c} 0.00409 \\ (0.0198) \end{array}$	$\begin{array}{c} 0.00558 \\ (0.0198) \end{array}$	$\begin{array}{c} 0.00599 \\ (0.0196) \end{array}$	0.00486 (0.0200)	0.0121 (0.00987)	$\begin{array}{c} 0.0122\\ (0.00989) \end{array}$	$\begin{array}{c} 0.0124 \\ (0.00982) \end{array}$	$\begin{array}{c} 0.00973 \\ (0.00995) \end{array}$
size		0.120^{***} (0.0426)	0.0924^{**} (0.0436)	0.0764^{*} (0.0449)		0.0197 (0.0220)	0.0181 (0.0222)	0.0239 (0.0229)
repeaters		-0.0941^{*} (0.0513)	-0.0788 (0.0514)	-0.0275 (0.0560)		$0.0399 \\ (0.0251)$	0.0333 (0.0246)	$0.0362 \\ (0.0270)$
slackers		-0.0932 (0.0604)	-0.0788 (0.0603)	-0.0599 (0.0713)		-0.00192 (0.0340)	$\begin{array}{c} 0.00344 \\ (0.0340) \end{array}$	-0.00699 (0.0396)
migrants		-0.0468 (0.0520)	-0.0392 (0.0517)	-0.0137 (0.0701)		-0.0124 (0.0296)	-0.0150 (0.0296)	-0.0339 (0.0348)
cohesivity		0.142^{**} (0.0632)	$\begin{array}{c} 0.0814 \\ (0.0751) \end{array}$	$\begin{array}{c} 0.0904 \\ (0.0764) \end{array}$		-0.00469 (0.0319)	$\begin{array}{c} 0.00263 \\ (0.0382) \end{array}$	$\begin{array}{c} 0.00884 \\ (0.0387) \end{array}$
popularity.f			0.0335 (0.0413)	0.0105 (0.0426)			-0.000613 (0.0213)	0.00299 (0.0218)
popularity.e			0.0245 (0.0517)	0.0664 (0.0535)			-0.00223 (0.0272)	-0.0174 (0.0278)
centrality			0.0584 (0.0588)	0.0517 (0.0608)			0.00575 (0.0280)	0.00628 (0.0282)
friendsAP			0.306^{***} (0.0328)	0.296^{***} (0.0337)				
friendsAR							0.269^{***} (0.0393)	0.270^{***} (0.0400)
#As				0.0411^{***} (0.0157)				-0.0115 (0.00765)
CRT				0.0607^{***} (0.0198)				-0.0111 (0.00987)
accuracy				0.0581^{*} (0.0320)				-0.0246 (0.0175)
expectations				0.0227 (0.0182)				-0.0117 (0.00937)
repeater				-0.0192 (0.0157)				-0.0104 (0.00830)
constant	0.571^{***} (0.0219)	0.472^{***} (0.0437)	0.313^{***} (0.0460)	0.219^{***} (0.0547)	0.608^{***} (0.0109)	0.591^{***} (0.0216)	0.429^{***} (0.0315)	0.465^{***} (0.0365)
N Adj. R ² School Fixed Effect (S)	4713 0.0273 Yes	4710 0.0308 Yes	4710 0.0495 Yes	4498 0.0580 Yes	4666 0.0127 Yes	4663 0.0123 Yes	4663 0.0256 Yes	4499 0.0280 Yes
Class controls (SC) Networks controls (SCN) Individual controls (SCNI)	No No No	Yes No No	Yes Yes No	Yes Yes Yes	No No No	Yes No No	Yes Yes No	Yes Yes Yes

Table OA.3.1: OLS estimations on time and risk preferences using all subjects. Robust standard errors in brackets. Asterisk denote significance levels:*** p<0.01, ** p<0.05, * p<0.1