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The baking of preferences throughout the high school☆

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ABSTRACT

This study investigates gender differences in time and risk preferences and how this difference evolves during adolescence. Using a sample of 4,830 non-self-selected teenagers from 207 classes across 22 Spanish schools, we provide a detailed analysis of how boys and girls differ – or not – in economic preferences, and how these preferences change as they grow older. Our large and rich dataset includes information on class attributes, social networks, and friends' preferences, allowing us to control for a wide range of potentially confounding variables. We find no significant gender differences in patience or risk attitudes at younger ages. However, we find that older adolescents tend to exhibit different patterns than younger ones—girls in higher grades show more nuanced time preferences, and boys in higher grades appear more risk averse than girls. These patterns are shaped by cognitive abilities and the social environment within classrooms. Our findings underscore the importance of considering gender-specific developmental trajectories when studying economic preferences during adolescence.

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 et al., 2005; Bandiera, Barankay, & Rasul, 2010; Deming, 2017) and financial success (Meier & Sprenger, 2010, 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), 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 intertemporal 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 these differences

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evolve during the critical phase of adolescence. To investigate these research questions, we conducted a lab-in-the-field experiment in 22 Spanish schools. We gathered data from 4830 adolescents aged 12 to 17, distributed across 207 classrooms, of whom 49% were female. Two additional elements make our study unique. First, we collected data on class enmity and friendship networks, allowing us to assess social isolation (Ruiz-García et al., 2023). Second, we computed the average time and risk preferences of each subject's friends within their classroom. These two elements enable us to control for new variables and analyze whether social network measures and peer effects act as mediators for gender differences.

It is also important to emphasize that the tasks used to elicit time and risk preferences were specifically designed for adolescents. The time preference task is a simplified and visual version with six decisions, based on Coller and Williams (1999) (see Alfonso et al., 2023 for details). Similarly, the risk preference task is an adapted version with six decisions based on the Holt and Laury (2002) lottery task (for details, see Vasco & Francisco, 2025). In both tasks, we used hypothetical payments since economic incentives for children and adolescents require parental consent. In a recent paper, we showed that hypothetical incentives in similar tasks provide a reliable alternative to real incentives for measuring risk and time preferences in adolescents (see Alfonso et al., 2023 for details). Additionally, throughout the paper, we also show that these hypothetical measures are correlated with field behavior, as predicted in the literature.

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 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 more risk averse, but these relations are not significant during adolescence.[1] 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]

The results of this research can be summarized as follows. (i) After controlling for class, individual, and network measures, we find that girls and boys do not differ in time preferences at younger ages. However, for older teens we find that they are less present-oriented and exhibit more nuanced[3] time preferences—being this pattern significantly more pronounced among girls. (ii) Regarding risk preferences, we do not find gender differences at lower grades. In contrast, in upper grades girls are less likely to be risk averse but more likely to be risk neutral. We also find that older teens tend to choose fewer risky choices on average, e.g. are more risk averse.

These findings are broadly consistent with previous work showing that patience and risk aversion tend to increase with age (Deckers et al., 2015; Sutter et al., 2015). However, unlike prior studies that report no significant gender differences during adolescence (Horn et al., 2022; Sutter et al., 2013), our data suggest that such differences may be more salient in later grades. In our sample, girls in upper grades are more likely to exhibit nuanced intertemporal choices, while boys in the same grades appear more risk averse. These patterns, while not necessarily causal, indicate that gender gaps in economic preferences may vary throughout adolescence and are sensitive to both age and context.

Furthermore, we analyze interactions between the gender dummy and various measures of subjects' cognitive abilities separately, as well as with the average levels of risk and time preferences among friends. First, we find that cognitive abilities play a critical role in the development of time and risk preferences for consistent subjects. Specifically, results show that cognitive abilities are positively correlated with patience but this relationship varies by age and gender. In lower grades, boys with higher cognitive abilities are less present-oriented than girls. However, in upper grades, girls with higher cognitive abilities tend to be less present-oriented and more nuanced (i.e. they switch from option A to B) than boys. Regarding risk preferences, cognitive abilities also explain age and gender differences. We find that higher levels of cognitive abilities are associated with lower risk-taking among boys at lower grades, while girls with higher cognitive abilities tend to be less risk seeking at upper grades.

Second, interactions within the classroom's social network appear to be associated with adolescents' economic preferences. We observe that the average patience of friends is positively correlated with the student's own patience (patient students tend to be friends with other patient individuals.[4]) Similarly, friends' risk aversion is positively correlated with the student's own risk aversion (more risk-averse students tend to associate with similarly cautious peers). These associations do not vary significantly by gender or grade level, suggesting that the observed patterns are consistent across these groups.

This paper complements previous research on gender differences in economic preferences in three ways. First, we provide a well-powered analysis using a large and diverse sample of adolescents. While previous studies have examined these differences, their sample sizes and school coverage have typically been limited, usually ranging from one to six schools[5] and featuring smaller sample sizes across age groups.[6] These limitations may affect the ability to detect small gender differences. Our study, which includes 4830 adolescents across 22 schools, is designed to detect subtle gender differences in economic preferences. Specifically, we are able to identify minimum gender differences of 0.12 SD in the number of future and risky choices, which corresponds to a small effect size according to Cohen's classification. While some recent studies also feature large samples, our dataset is distinct in its broad coverage of multiple schools and its inclusion of additional measures such as social networks, cognitive abilities, and classroom characteristics. These features allow us to account for a richer set of factors when analyzing gender differences in time and risk preferences.

Second, given our rich and extensive dataset, we measure and account for various external factors that could influence gender differences and mediate economic preferences. Social interactions in school do not necessarily involve all classmates but may be limited to a

[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.

[3] By "nuanced", we refer to patterns of choice across multiple decisions (six choices in our case) that go beyond consistently choosing always A or B, potentially reflecting a more refined combination of both options. Along the paper we also use "interior" choices.

[4] Obviously, this association closely resembles *homophily*. However, since we only have a single observation in time, we cannot determine whether more patient (or risk-averse) individuals choose friends with similar traits, or whether they simultaneously shape each other's preferences.

[5] Except for Horn et al. (2022), which involved nine schools.

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

subset—the friends that a teenager voluntarily chooses, forming their social network. In other words, while the classroom environment, where individuals spend at least thirty-five hours a week, plays an important role, the network of friends may also shape economic preferences. There is evidence that risk and time preferences are influenced by environmental factors (see Alem et al., 2023; Booth & Nolen, 2012; Lucks et al., 2020; Zárate, 2023). To address this potential confounder, our dataset allows us to control not only for schools' fixed characteristics but also for classroom-specific factors (such as size, number of repeaters, and cohesion, among others). Additionally, we consider students' social positions within their class networks, including measures of popularity and centrality, as well as the average level of patience or risk-taking among their friends. This provides insight into whether an individual's preferences are aligned with the broader peer environment. [7] Students cognitive abilities are also assessed, including Cognitive Reflection Test (CRT) scores, the number of A grades in the last academic year, and proficiency in probability 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 each subject's friends. Our findings strongly support the significance of these variables in explaining gender and age differences.

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 presents the main results of the research; Section 5 explores different mechanisms behind the results; and Section 6 concludes.

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%[8] and a final sample of 4830 subjects. The data for replication is available at https://github.com/teenslab/datateenslab (see Mónica Vasco et al., 2025 for details). 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 Loyola Andalucía approved the study.

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 grades[9] 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 Francisco (2025). Fig. 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 make six consecutive decisions. In the truck task, they must choose in each decision between 10€ tomorrow or 10+x€ 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 B provides detailed explanations about both tasks.

Under consistency,[10] 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 choices.[11] Additionally, we created three dummy variables: subjects who always choose the early period, indicating present-oriented preferences ($AllPresent$, 22.6% of the consistent participants); subjects who always choose the later period, indicating future-oriented preferences ($AllFuture$, 11.7% of the consistent participants); and subjects who choose both the early and the later periods, indicating interior preferences ($Interior$, 65.7% of the consistent participants). We used this nomenclature in reference to Andreoni et al. (2015).

Similarly, the gumball task allows us to compute several measures of risk preferences under subject consistency.[12] The number of risky

[7] However, it is important to interpret these relationships with caution. The correlation between an adolescent's preferences and the average preferences of their friends does not necessarily imply a causal effect. This analysis remains correlational, as we cannot fully disentangle peer influence from homophily – the tendency of individuals with similar preferences to form social ties – nor can we rule out the reflection effect (Manski, 1993). This means that an adolescent could appear more patient because their friends are patient, or conversely, that their friends are patient because the adolescent is patient

[8] This percentage is similar to the 15.3% of early leavers from high school in Andalusia (Ministerio de Educación y Formación Profesional, 2023).

[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.

[10] Consistent subjects in the truck tasks are those who do not switch back. The consistency rate among those who completed the experiment was 83.1%.

[11] We follow Chowdhury et al. (2022) in using the number of future allocations as a summary measure of patience, rather than estimating discount rates. However, this measure may contain a potential measurement error in the case of $\#Future = 0$, as it is not possible to disentangle whether the choice reflects a genuine preference for immediacy or a lack of attention or understanding.

[12] There are three types of inconsistency: (i) *Lack of understanding*, when subjects selected lottery B in the first decision – with no uncertainty – given that B is dominated by A. Hence making this choices suggests that the subject may not have understood the task; (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, where there is again no uncertainty and A is dominated by B. Note that in this case, the most plausible explanation is inattention—for example, automatically clicking on the left side without noticing the change in dominance. Overall the rate of consistency among those who completed the experiment was 79.8%.

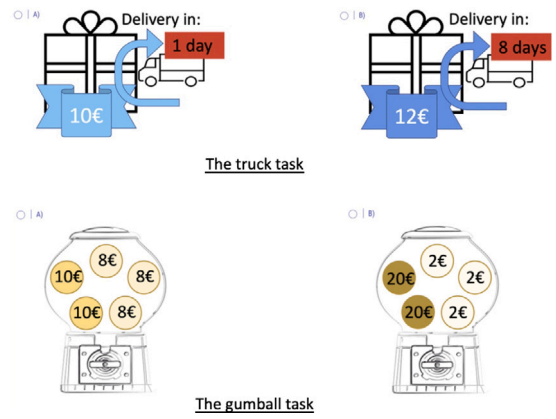


Fig. 1. The truck and gumball tasks.

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 the consistent participants), the dummy *Neutral* takes value 1 if the subject indicates risk-neutrality by choosing Lottery A two times (45.4% of the consistent subjects) and the dummy *Lover* takes value 1 if the subject indicates risk-love by choosing Lottery A once (10.0% of the consistent 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 → gumball), while the remaining six schools followed the reversed order (gumball → 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.[13]

2.3. Sources of heterogeneity

In this section, we describe a set of variables used to account for potential sources of heterogeneity that may influence individuals' decisions. We consider three main sources: the classroom in which the student is enrolled, the student's social network, and individual characteristics. The first source refers to the environment—for example, the composition of peers in a class may foster certain types of behavior. The second relates to the individual's network of friends, which may exert direct influence through peer effects. The third concerns the student's own characteristics, such as cognitive skills, which may differ from those of their classmates.

The purpose of this section is not to propose new research directions or hypotheses, but rather to control for the possible impact of unobserved factors and thereby reduce bias in our estimates. For clarity, Table A.0.1 of Appendix A summarizes all variable definitions and abbreviations used in the analysis.

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*,[14] 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*).[15] 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 have.[16] Additionally, the variable *grade* can take values 7, 8, 9, and 10.[17] 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).

Fig. 2 displays the correlations between our variables of interest. More detailed information is available in Table C.1.1 of Appendix C. The diagonal in Fig. 2 illustrates the distribution of the respective variable. All the variables were standardized using the max–min method.[18] The first notable feature of our dataset is the great diversity in class characteristics, as shown in Table C.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* ($p < 0.05$),[19] 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] While school fixed effects absorb this variation (rendering the task order dummy collinear and omitted in the main regressions), a separate analysis using only these 11 schools shows that presenting the HL task before the TD task reduces #*Future* allocations by 0.048 ($p < 0.05$), with no significant effect on consistency in this task ($p = 0.11$). For risk preferences, this order has no effect on #*Risky* choices ($p = 0.64$) but reduces the consistency in the risk task by 0.07 ($p < 0.01$).

[14] 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.

[15] Note that the variable *slackers* refers to the number of adolescents who did not complete the experiment in each class. We used it as a control at the class level. However, we exclude subjects who did not complete the experiment from the regression analysis, but we keep this variable as a control.

[16] 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.

[17] These 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).

[18] The 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.

[19] Which is consistent with the lower likelihood of *female* being *repeaters* (see Fig. 4)

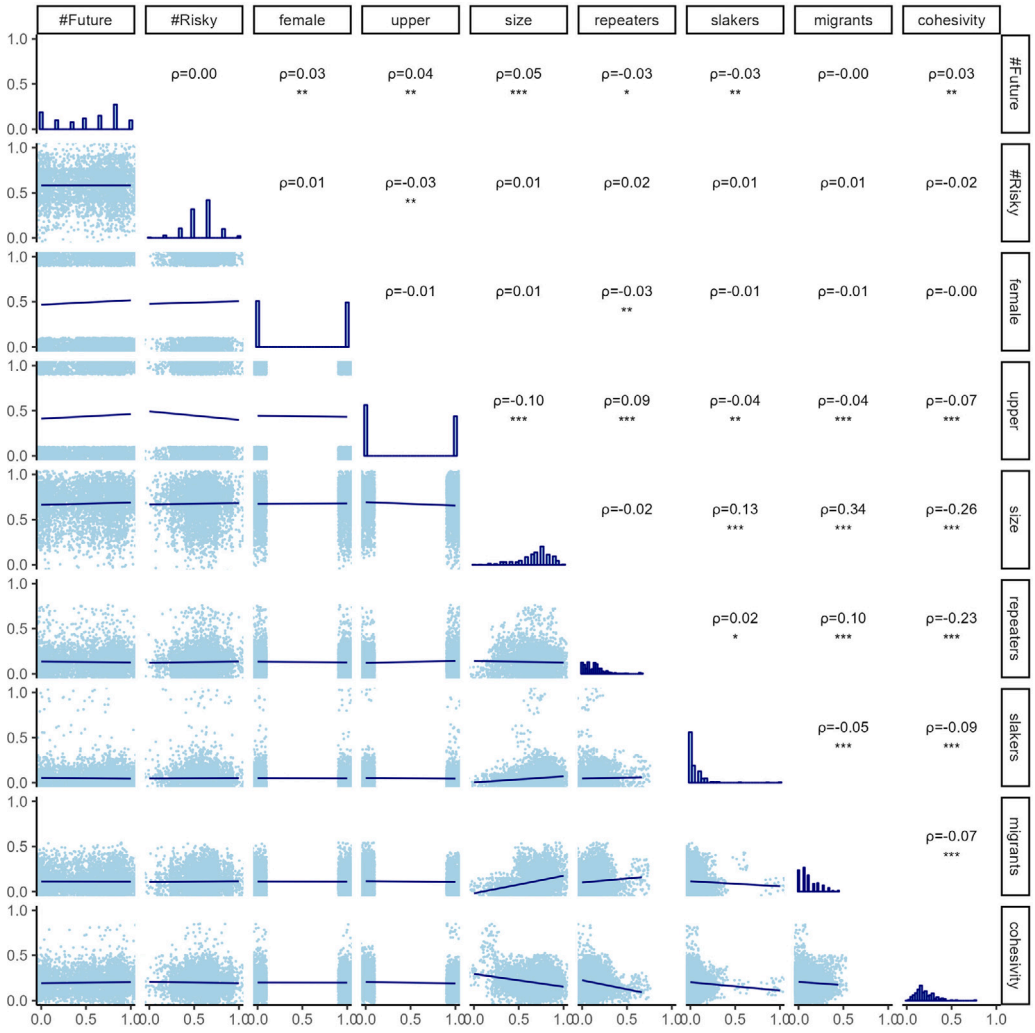


Fig. 2. Class heterogeneity: Correlations (ρ). Asterisks denote significance levels:*** p<0.01, **p<0.05 and *p<0.10.

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, respectively.[20] 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 $friendsAR$).[21] Table C.1.1 provides some summary statistics for these variables.

Fig. 3 shows the distribution and pairwise correlations between each relevant variable and the social network measures. Several patterns emerge. First, we observe that *popularity.f* (in friends) is positively correlated with $\#Future$ allocations ($p < 0.05$) and with *centrality* in the class network ($p < 0.01$), but negatively correlated with $female$ ($p < 0.01$), being in an *upper* grade ($p < 0.01$), *popularity.e* ($p < 0.01$), and $friendsAR$ ($p < 0.05$). This suggests that adolescents with more risk-loving friends tend to be less popular. Regarding popularity in enemy networks, we also find negative correlations with being in an *upper* grade ($p < 0.01$), *centrality* in the class network ($p < 0.01$), and $friendsAP$ ($p < 0.01$), indicating that individuals who are more popular among enemies tend to 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

[20] 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.

[21] These 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). See also footnote 4.

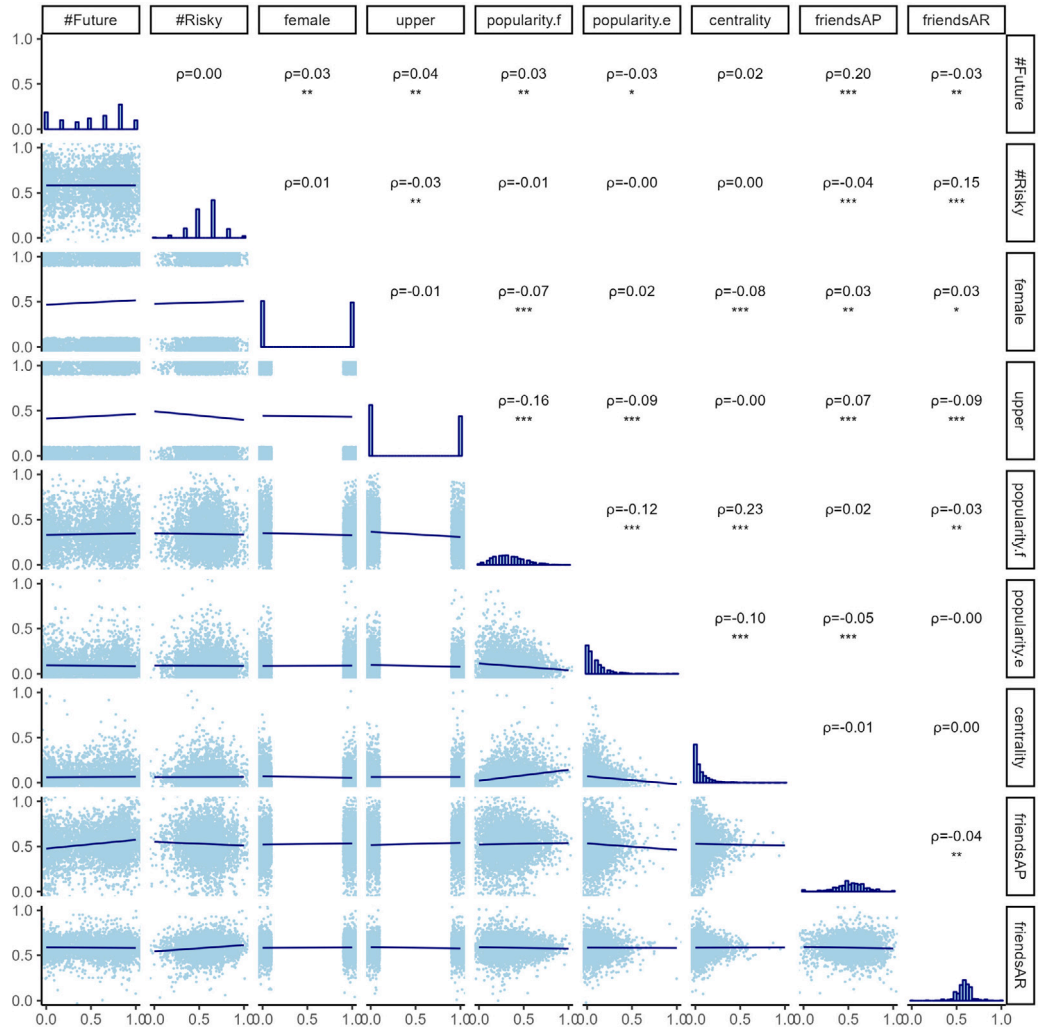


Fig. 3. Network characteristics: Correlations (ρ). Asterisks denote significance levels:*** p<0.01, **p<0.05 and *p<0.10.

negatively correlated with *upper* grade, meaning that teenagers tend to be 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 $\#Future$ allocations are strongly and positively correlated with $friendsAP$ ($p < 0.01$), and a similar pattern is found between $\#Risky$ choices and $friendsAR$ ($p < 0.01$). These results indicate that individuals who allocate more to the future tend to have more patient friends, and those who make more risky choices tend to have more risk-loving friends. Overall, individuals appear to be embedded in peer networks characterized by similar economic preferences. We also note that the variable $\#Future$ is negatively correlated with $friendsAR$ ($p < 0.05$), and that $\#Risky$ is negatively correlated with $friendsAP$ ($p < 0.01$). This pattern is consistent with the idea that individuals surrounded by more risk-loving friends tend to be less future-oriented, and those with more impatient friends tend to take more risks. Finally, we find a positive correlation between $female$ and $friendsAP$ ($p < 0.05$), suggesting that girls are more likely to be connected to patient peers.

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).[22] 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 English[23] during the last academic year. We obtained three dummy variables with a value of 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 to 10 income stair to have a proxy of the family SES. However, several schools did not approve the inclusion of this question. Therefore, 18.07% of the sample did not provide this information and consequently, we decided to not use this variable in our analysis.

[22] For more details on the CRT and the probability understanding task, see sections 3 and 4 of Appendix B.

[23] *Spanish* as a native language in Spain and *English* as a foreign language in Spain (EFL).

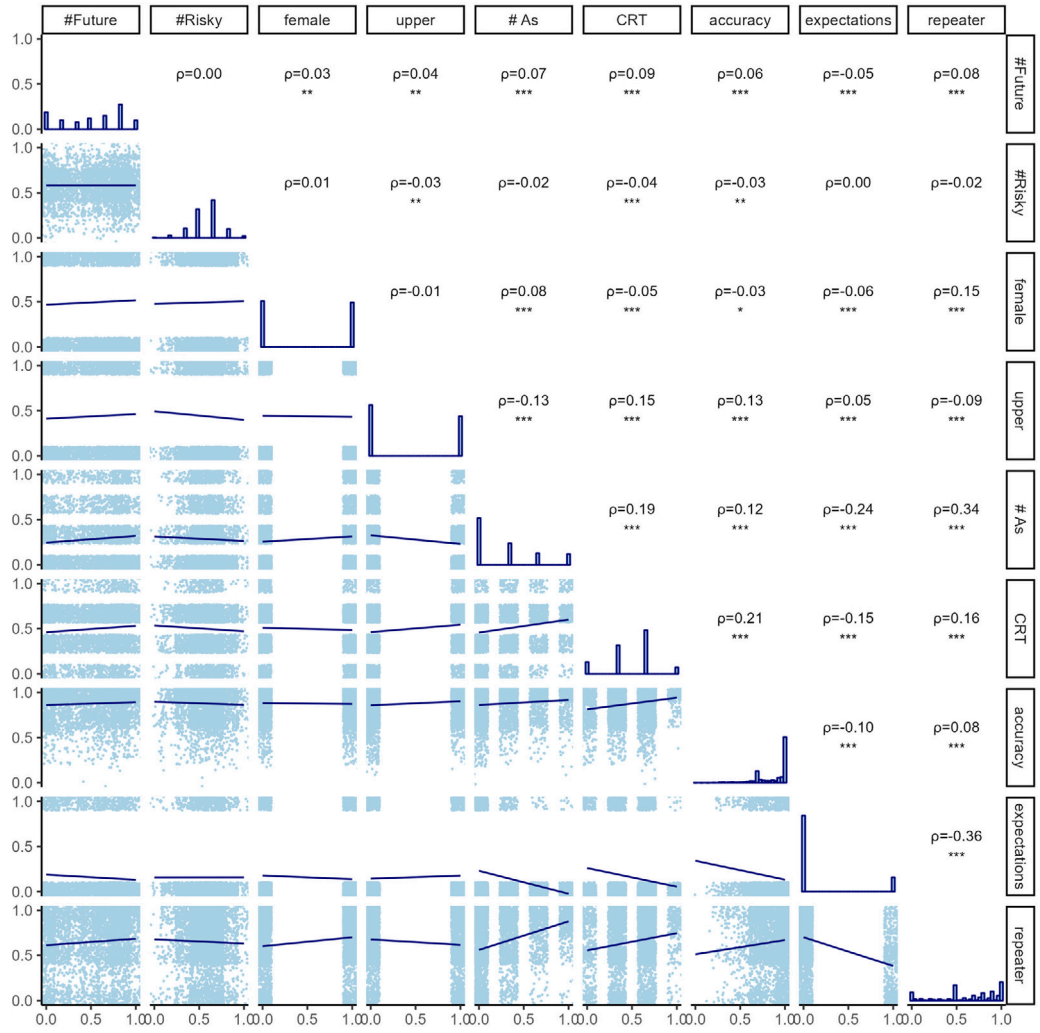


Fig. 4. Individual characteristics: Correlations (ρ). Asterisks denote significance levels:*** p<0.01, **p<0.05 and *p<0.10.

Fig. 4 shows the distribution and the correlations between these variables and Appendix C.1 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 $female$ are more likely to 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 are more likely to obtain lower CRT score ($p < 0.01$). Third, we focus on grade differences. Subjects in $upper$ grades tend to have higher CRT scores and greater $accuracy$ in the probabilities test. However, 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). This pattern suggests a potential disconnect between measured cognitive skills and academic outcomes across grades. 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 $repeaters$ ($p < 0.01$ in all cases).[24]

2.4. Important remarks

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

Power: our sample consists of a large number of adolescents in grades 7 to 10: we account for 2751 students (56.96%) in grades 7–8 (49.4% females), and 2079 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 4830) of subjects refused to participate in the experiment. These students did not sign the

[24] And they are also positively correlated between themselves ($p < 0.01$).

consent form and were automatically expelled from the platform. Additionally, 5.57% (269 out of 4830) 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 distinguish our dataset from other experimental studies of adolescents in at least two ways: (i) we did not use monetary incentives; therefore, our dataset is considerably larger and the schools are more diverse in background; and (ii) our participants were not self-selected 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[25]:

$$y_i^j = \beta_0 + \beta_1 \times female_i + \beta_2 \times upper_i + \beta_3 \times female_i \times upper_i + \epsilon_i \quad (1)$$

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.

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 Eq. (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 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, CRT score, *accuracy* in probabilities, *expectations* to go to the university, and whether the subject is a *repeater*.

It is important to note that our analysis focuses on subjects who completed each task and exhibited consistent preferences. As a result, our initial sample of 4830 subjects is reduced to 3923 (81.2%) observations for the analysis of time preferences and 3727 (77.2%) for the analysis of risk preferences. In addition, 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 (4,7%) and 137 (3.7%) observations in the *time* and *risk* outcome variables regressions, respectively.

[25] We do not study the same individual across adolescence (like in a panel), but different teens in different cohorts.

4. Results

4.1. Time preferences

Fig. 5 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 $female \times upper$ is never significant.

Although the interaction term between $female$ and *upper* is not statistically significant, we follow the recommendations of Brambor et al. (2006) and Hainmueller et al. (2019) and present the marginal effects of these variables. As they emphasize, a non-significant interaction coefficient does not necessarily imply the absence of conditional relationships. The interpretation of interaction effects should rely not solely on the statistical significance of the coefficient, but also on the magnitude and substantive relevance of the marginal effects. Our intention is not to emphasize a null result, but to provide transparency regarding a pattern that may be of interest for future research.

Fig. 6 summarizes the marginal effects of $female$ and $male$ on each outcome variable for $lower$ and *upper* grades and their 95% confidence intervals. For this analysis, we use 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 exhibit more nuanced preferences than younger ones. In addition, that older teens are less present oriented and exhibit more nuanced preferences than younger ones. Among upper-grade students, females show a higher probability of selecting interior options than males. While the marginal difference is statistically significant ($p = 0.05$), we note that the corresponding gender-by-grade interaction term is not. Therefore, we present this pattern descriptively rather than as a statistically confirmed moderation effect. The estimated difference corresponds to a 4.6 percentage point (7.4%) increase in the probability of choosing interior solutions for females compared to males in upper grades. This evidence means that girls and boys exhibit more nuanced behavior with age and that this effect is higher for girls than for boys.

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

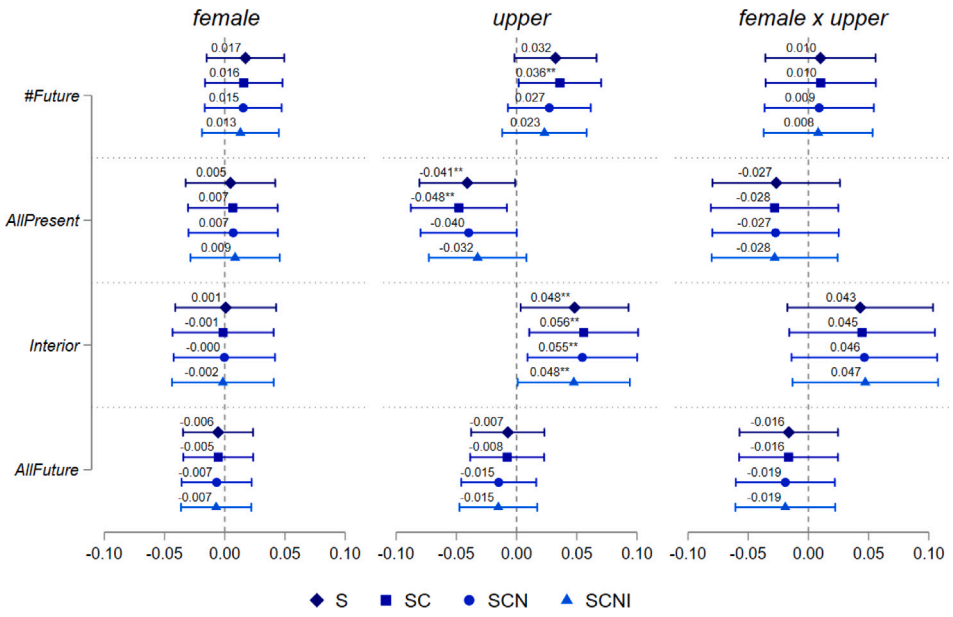


Fig. 5. OLS estimations for time preferences outcomes. Coefficient point estimates are shown in numbers and lines represent their 95% confidence interval. Asterisks denote significance levels:*** p<0.01, **p<0.05 and *p<0.10.

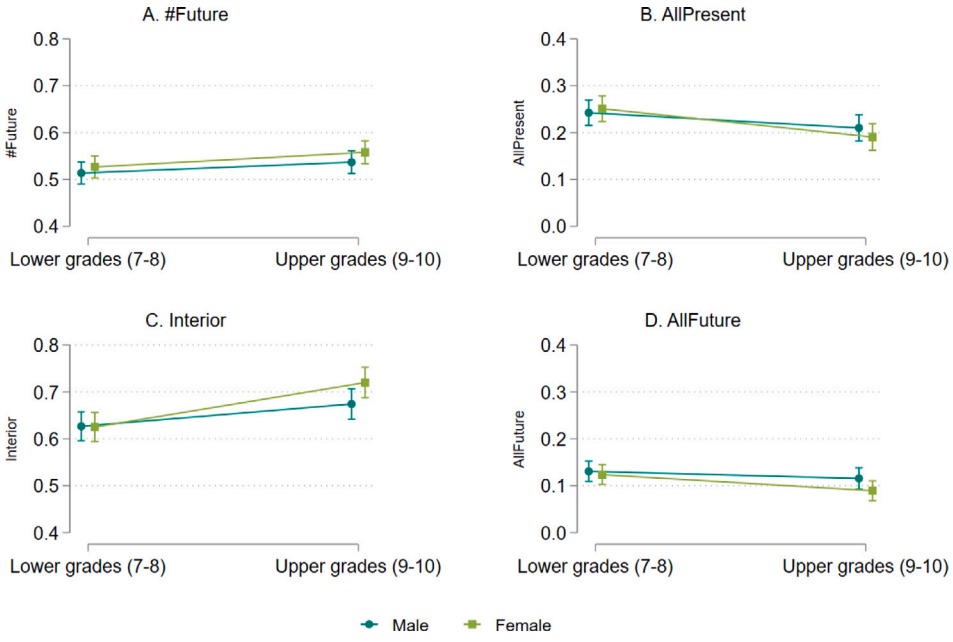


Fig. 6. Linear prediction of female and male on time preferences by lower and upper grades.

Result 1a: Older adolescents display greater patience than younger ones, primarily because they adopt more nuanced, internal choices.

Result 1b: Among younger adolescents, there are no gender differences, but these differences emerge among older adolescents because girls are more likely to use interior (or nuanced) solutions.

Table C.2.1 (Appendix C.2) shows all the regressions with the estimated coefficients of all the control variables. The most salient result is the effect of the average level of patience of individuals' friends and the role of cognitive abilities. Regarding the former, we find that patient subjects used to be friends of patient individuals (or vice-versa). About the latter, we observe that those subjects endowed with higher cognitive abilities are more likely to be patient.

4.2. Risk preferences

Fig. 7 focuses on risk attitudes and displays the same regression analysis across various control specifications as Fig. 5. We observe no significant associations between being $female$ and the number of $\#Risky$ choices ($p > 0.50$), being risk $Averse$ ($p > 0.30$), or risk $Neutral$ ($p > 0.70$). However, in the SCNI specification, we find that younger females are more likely to display risk $Lover$ preferences compared to males ($p = 0.04$). It should be noted that this result emerges only under one specification and applies to a relatively small subgroup, as only 11.7% of the subjects are classified as risk-lovers. Results, therefore, indicate that there is no gender differences on risk preferences for young subjects. Additionally, we observe a negative and statistically significant association between $upper$ and the number of $\#Risky$ choices ($p < 0.05$ across all specifications), suggesting that older males tend to

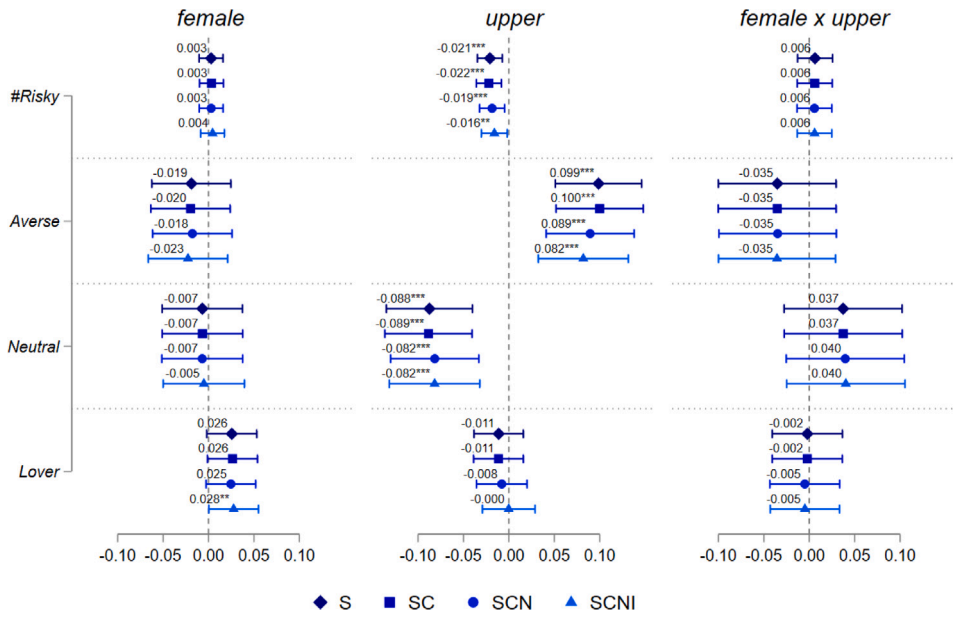


Fig. 7. OLS estimations for risk preferences. Coefficient point estimates are shown in numbers and lines represent their 95% confidence interval. Asterisks denote significance levels:*** p<0.01, **p<0.05 and *p<0.10.

take fewer risks than younger ones. When we focus on the different types of risk preferences, we find a consistent positive association between *upper* and the likelihood of being classified as risk *Averse* ($p < 0.01$), and a negative association with being risk *Neutral* ($p < 0.01$). These patterns indicate that older males are more likely to be risk-averse and less likely to be risk-neutral compared to younger males. Finally, we find that the interaction term is never significant ($p \geq 0.2$), 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. Fig. 8 provides these results for the specification with all the control variables (SCNI).[26] Panel A shows that girls and boys choose fewer #*Risky* choices at upper grades compared to lower grades, and that this pattern does not significantly differ across genders. This is consistent with the 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 suggests some gender-specific differences in upper grades: while the probability of being risk *Averse* does not differ significantly between girls and boys at lower grades ($p > 0.20$), in upper grades it is 0.06 percentage points (13.2%) higher for boys compared to girls ($p = 0.02$).

Therefore, we conclude that teens in upper grades are more likely to be risk *Averse* and less likely to be risk *Neutral* compared to those in lower grades. There is also evidence that the increase in the proportion of risk *Averse* individuals is more pronounced among boys than among girls. Finally, Panel D shows a small gender difference in the probability of being risk *Lover* at lower grades, a difference that is not present in 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 association is explained by an increase in the fraction of risk-averse and a reduction of risk-neutral subjects. We also find that this relation is different between girls and boys: the increase in risk aversion is higher for males than for females. Therefore, our result 2 is:

Result 2a: Older adolescents are more risk-averse than younger ones, and this is because they make fewer neutral decisions.

Result 2b: Among younger adolescents, gender differences in risk preferences are not observed. However, among older adolescents, girls tend to be less risk-averse and more inclined to select neutral options.

While the first part of Result 2 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.

In addition, Table C.2.2 of Appendix C.2 displays the estimated coefficients of the variables of interest along with all the controls. Some results are quite revealing: the subject's cognitive abilities and the risk preferences of their friends predict their risk preferences. Regarding the former, we find that more risky subjects are friends of risky subjects as well (or vice-versa). Additionally, we find that individuals with higher cognitive abilities are more risk averse.

4.3. Robustness checks

To assess the robustness of our results, Appendices C.3 and C.4 extend the analysis by using the original variable *grade* instead of the discrete variable *upper* grade. Table C.4.1 in Appendix C.3 replicates the results presented in Table C.2.1 for time preferences. Similarly, Table C.4.2 in Appendix C.4 reproduces the findings of Table C.2.2 for risk preferences. We find that results are robust to an alternative specification of the grade variable. Additionally, Section OA.2 of the Online Appendix 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 of the Online Appendix, we analyze whether inconsistency depends on gender and upper 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 are more likely to exhibit consistent choices in

[26] Again, this specification has the lowest AIC statistic and the highest adjusted R-squared.

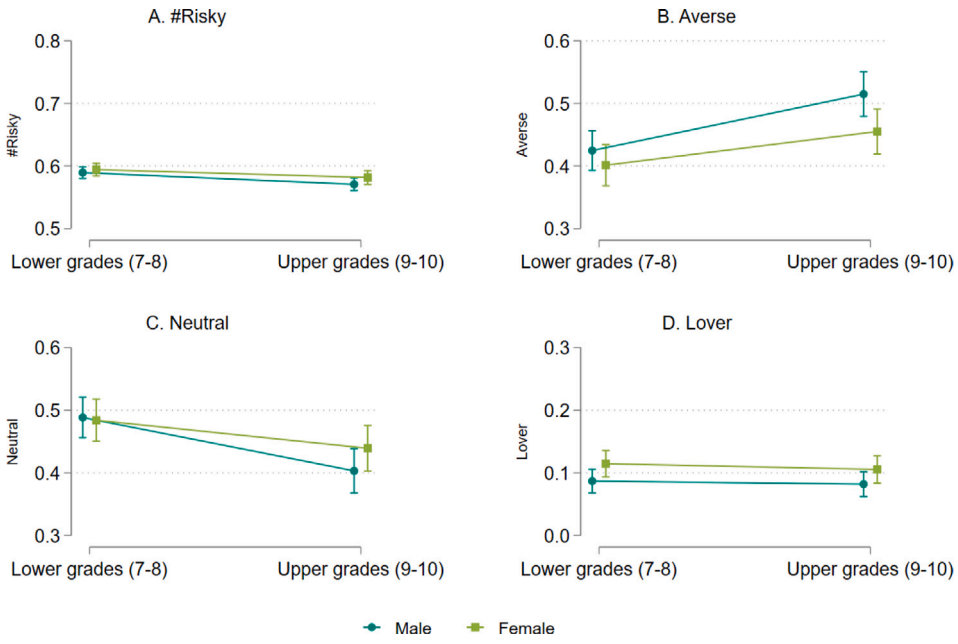


Fig. 8. Linear prediction of female and male on risk preferences by lower and upper grades.

the task ($p < 0.01$ in all specifications), while older females are less likely to be consistent ($p = 0.02$ in all specifications). These results suggest a trend toward greater consistency among boys in upper grades, while no such pattern appears for girls. For risk preferences, we find 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 is not statistically significant in any specification ($p > 0.10$), which suggests that the difference between younger and older subjects may not vary substantially by gender.

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 for time preferences. However, for risk preferences, we found that cognitive abilities do not influence the $\#Risky$ choices anymore. Moreover, there is evidence that subjects make errors (e.g. switching options multiple times) in standard multiple-price list elicitation tasks, which can lead to either overestimation or underestimation of risk aversion (see Amador-Hidalgo et al., 2021; Andersson et al., 2016 for more details). To control for this selection problem and analyze whether cognitive abilities are relevant, we estimate the risk aversion coefficient assuming a CRRA utility function (constant relative risk aversion). To account for these 'mistakes' we estimate a maximum likelihood (ML) structural estimation with the Luce error specification (Harrison et al., 2008). Table OA.3.2 displays these results and confirms Result 2. Additionally, it shows that cognitive abilities are positively related to risk aversion, a result also found in Table C.2.2 with consistent subjects. Overall, we conclude that our results are robust to alternative specifications and to whether consistent or inconsistent subjects are considered in these estimations.

5. 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:

$$y_i^j = \beta_0 + \beta_1 \times female_i + \beta_2 \times upper_i + \beta_3 \times female_i \times upper_i + \beta_4 \times V_i^j + \beta_5 \times V_i^j \times female_i + \beta_6 \times V_i^j \times upper_i + \beta_7 \times V_i^j \times female_i \times upper_i + \epsilon_i \quad (2)$$

Eq. (2) is similar than Eq. (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 C.2.1 and C.2.2, that is j={CRT, $accuracy$, $\#As$, $friendsAP$ or $friendsAR$}. The error term is denoted by ϵ_i. We estimate Eq. (2) using OLS for the specification with full controls (SCNI).

Appendices C.5 and C.6 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. It should be noted that we performed this analysis using only consistent subjects, as in the previous sections.

5.1. Heterogeneity in time preferences

Panels A to D from Fig. 9 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. At lower grades, we observe no significant gender differences at any level of CRT ($p > 0.07$). Among boys, higher levels of reflection are associated with more future-oriented choices ($p = 0.03$), while no such association is observed among girls ($p > 0.40$). In upper

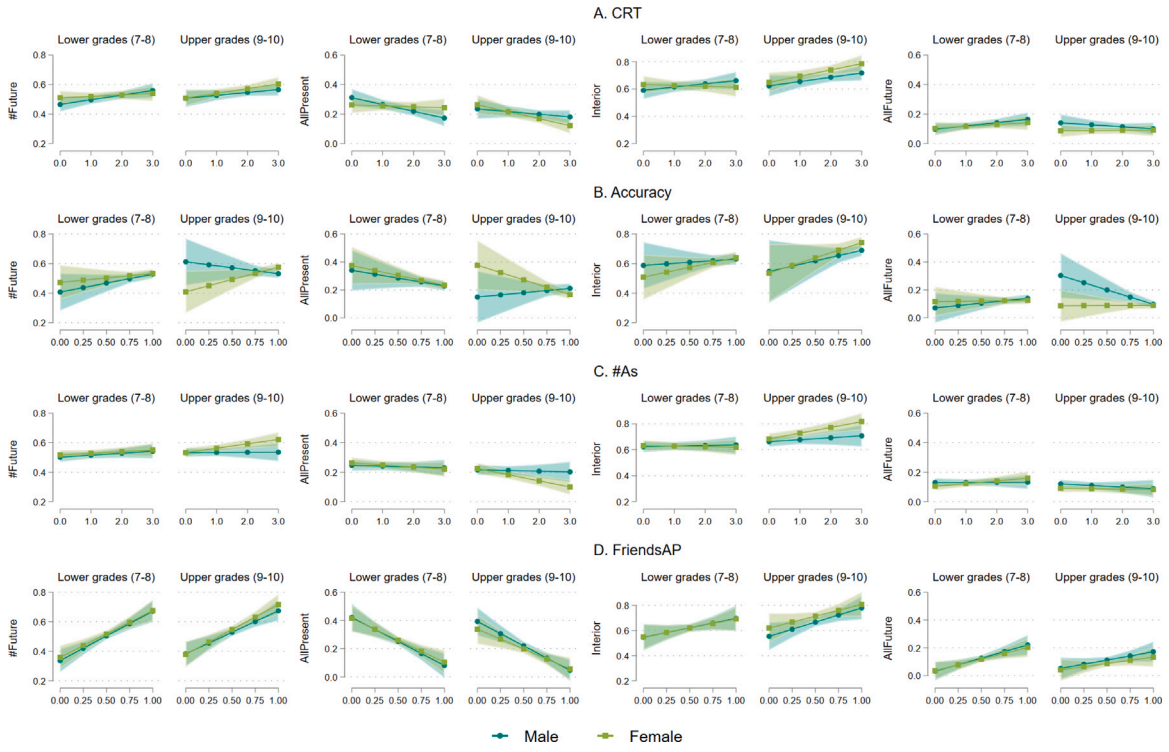


Fig. 9. Linear prediction of time preferences according to the values of V_i^j for males and females by lower and upper grades. The shaded area represents the 95% confidence interval.

grades, there are also no significant gender differences ($p > 0.40$), but now CRT is positively associated with the number of future allocations among girls ($p = 0.03$), but not among boys ($p > 0.10$). These results suggest that reflective abilities are positively related to the patience levels of young boys and older girls, but do not account for gender differences.[27]

We now examine the association between CRT and the three types of time allocations. The second graph from the left in Panel A refers to $AllPresent$ allocations and reveals some notable patterns. Among boys in lower grades, higher levels of reflection are associated with a lower likelihood of allocating everything to the present ($p < 0.01$). In contrast, among girls, the probability of choosing $AllPresent$ does not vary significantly with reflection levels ($p > 0.10$). In upper grades, this pattern appears reversed: higher reflection is associated with a lower likelihood of $AllPresent$ allocations for girls ($p = 0.03$), while no significant association is observed among boys ($p > 0.07$). The third graph from the left in Panel A shows the results for $Interior$ allocations, where no significant associations are found between CRT and this outcome for either girls or boys in lower grades ($p > 0.20$). However, at upper grades, higher levels of reflection are associated with more nuanced preferences among girls ($p = 0.02$), while no such association is observed among boys ($p > 0.10$). Finally, the fourth graph from the left of Panel A focuses on $AllFuture$ allocations. It shows that reflection levels are not significantly associated with this outcome variable at any grade for either boys or girls ($p > 0.06$).

Panel B of Fig. 9 shows the same analysis using $accuracy$ as the interacting variable. The first graph on the left shows that, in lower grades, this variable is not significantly associated with $\#Future$ 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 tend to allocate more to the future ($p = 0.03$), while no significant association is observed for boys ($p > 0.30$). From the second graph, we observe that $accuracy$ is not significantly associated with $AllPresent$ allocations for either gender in lower grades ($p > 0.06$). In upper grades, however, higher $accuracy$ levels are associated with fewer $AllPresent$ choices among girls ($p = 0.03$), with no corresponding association for boys ($p > 0.50$). The third graph shows that $accuracy$ is not significantly associated with $Interior$ allocations for either boys or girls at any grade level ($p > 0.06$). Finally, the fourth graph suggests no significant association between $accuracy$ and $AllFuture$ allocations in lower grades ($p > 0.26$). In contrast, for upper grades, we find interesting results across genders. Boys with lower $accuracy$ scores tend to be more future-oriented than girls with similar scores ($p = 0.04$), but as $accuracy$ increases, the likelihood of future-oriented choices among boys decreases ($p = 0.01$), while it remains unchanged among girls ($p > 0.90$).

Panel C of Fig. 9 uses $\#As$ as the interacting variable and shows no significant associations with any of the outcome variables in lower grades ($p > 0.10$). In upper grades, however, different patterns emerge. First, among girls, a higher number of $\#As$ is associated with more future-oriented choices ($p = 0.05$), while no such association is observed for boys ($p > 0.20$). Second, among girls, this pattern appears to be driven by a lower probability of allocating everything to the present ($AllPresent$, $p < 0.01$) and a greater tendency to choose interior allocations ($Interior$, $p < 0.01$). For boys, $\#As$ is not significantly associated with these outcomes ($p > 0.20$). Finally, we find no significant association between $\#As$ and $AllFuture$ allocations for either gender at any grade level ($p > 0.06$).

Finally, Panel D presents the results using $friendsAP$ as the interacting variable. We observe that, across all subjects – regardless of age and gender – higher values of $friendsAP$ are associated with more $\#Future$, $Interior$, and $AllFuture$ allocations, and with fewer $AllPresent$ allocations ($p < 0.01$ for all the mentioned outcome variables).

Overall, our results indicate that higher cognitive abilities – measured by CRT, $accuracy$, or $\#As$ – are positively associated with greater patience among boys at lower grades, while at upper grades this association appears primarily among girls. This pattern is driven by the

[27] All these results and those described below for the other outcome variables, come from the estimation using OLS of Eq. (2). The regression results are shown in Figs. C.5.1 and C.5.2 of Appendix C.5.

fact that girls with higher cognitive ability are less present-oriented and exhibit more nuanced preferences compared to boys. Finally, we also find that having more patient friends is associated with being more future-oriented, for both boys and girls. Therefore, we can summarize this evidence in the following result:

Result 3a: Cognitive abilities are positively correlated with patience. However, this association varies according to age and gender: in lower grades, boys with higher cognitive ability tend to be less present-oriented than girls, while in upper grades, girls with higher cognitive ability are more likely to display both less present-oriented and more nuanced time preferences than boys.

Result 3b: A higher average level of patience among friends is associated with more future-oriented choices across all groups.

5.2. Heterogeneity in risk preferences

Similar to the previous subsection, we now study risk preferences. Fig. 10 replicates the same analysis as Fig. 9 for the different outcome variables. Panel A of Fig. 10 uses the CRT as the interacting variable. The first graph on the left shows the results for the number of risky options ($\#Risky$). In lower grades, higher levels of reflectiveness are associated with fewer risky choices among boys ($p = 0.04$), while no significant association is observed for girls ($p > 0.90$). In upper grades, the pattern differs: girls with lower reflective ability tend to choose more risky options than boys ($p = 0.04$), but this gender difference diminishes at higher levels of reflection, where girls choose fewer risky options than boys ($p < 0.01$ and $p > 0.08$, respectively). The second graph from the left shows the results for the $Averse$ variable. In lower grades, higher levels of cognitive ability are associated with a greater likelihood of being classified as risk averse among boys ($p = 0.04$), while no such association is observed for girls ($p > 0.90$). In upper grades, the pattern differs: boys with low reflection levels show a higher probability of being risk averse than girls ($p = 0.01$), but as reflection increases, girls are more likely than boys to be risk averse ($p < 0.01$ and $p > 0.50$, respectively), suggesting a convergence in the levels of risk aversion across genders at higher levels of cognitive ability. 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 ($p > 0.10$).

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 ($p > 0.10$). In upper grades, however, higher CRT scores are associated with a lower likelihood of being risk $Lover$ among girls ($p = 0.03$), while no such association is observed among boys ($p > 0.10$).[28]

We now look at Panel B of Fig. 10, where $accuracy$ in probability is used as the interacting variable. As before, the first graph shows the results for $\#Risky$. We observe that, at lower grades, higher levels of $accuracy$ are associated with fewer risky choices among boys ($p = 0.04$), but no significant association is found for girls ($p > 0.60$). At upper grades, this negative association between $accuracy$ and $\#Risky$ is no longer significant for either gender ($p > 0.10$). The second graph presents the analysis for risk $Averse$. At lower grades, higher levels of $accuracy$ in probability is associated with a greater likelihood of being risk $Averse$ among boys ($p < 0.01$), but this association is not significant for girls ($p > 0.08$). In upper grades, this association remains for boys ($p < 0.01$), and a positive association emerges for girls as well ($p = 0.04$). The third graph examines risk $Neutral$ choices. At lower grades, girls with low $accuracy$ levels are less likely to be risk $Neutral$ than boys ($p = 0.02$); however, as $accuracy$ increases, girls show a higher probability of being risk $Neutral$ ($p = 0.02$), while there is no significant association for boys ($p > 0.09$). In upper grades, $accuracy$ is not significantly associated with risk neutrality for either gender ($p > 0.20$). Finally, the fourth graph shows that, among girls in lower grades, higher $accuracy$ scores are associated with a lower probability of being risk $Lover$ ($p < 0.01$). No significant association is observed for boys ($p > 0.17$). In upper grades, $accuracy$ is not significantly related to risk $Lover$ preferences for either girls or boys ($p > 0.07$).

Panel C of Fig. 10 shows the same analysis using the $\#As$ variable as the interaction term. The first graph displays the results for the number of risky options ($\#Risky$). For lower grades, $\#As$ is not significantly associated with $\#Risky$ choices for either girls or boys ($p > 0.08$). At upper grades, some differences emerge: boys with fewer $\#As$ grades select fewer risky options than girls with similar academic records ($p = 0.02$). However, as $\#As$ increases, girls show a lower likelihood of choosing risky options ($p < 0.01$), while no significant association is found for boys ($p > 0.60$). The second graph presents results for risk $Averse$. At lower grades, $\#As$ is not significantly associated with this outcome for either gender ($p > 0.30$). At upper grades, however, boys without any A grades are more likely to be risk averse than girls in the same situation ($p = 0.02$). As $\#As$ increases, girls show a higher likelihood of being risk averse ($p = 0.02$), while this pattern is not observed among boys ($p > 0.70$). In the third graph, we observe that $\#As$ is not significantly associated with risk $Neutral$ for either gender at lower grades ($p > 0.13$). Among upper-grade students, girls without any A grades are more likely to be risk neutral than boys ($p = 0.03$), but this probability decreases for girls as $\#As$ increases ($p = 0.02$). Again, no significant association is found for boys ($p > 0.70$). Finally, the fourth graph shows that, at lower grades, a higher number of $\#As$ is associated with a lower probability of being risk $Lover$ among boys ($p < 0.01$), but not among girls ($p > 0.50$). At upper grades, the pattern reverses: girls with more $\#As$ have a lower likelihood of being risk lovers ($p < 0.01$), while no significant relationship is found for boys ($p > 0.13$).

Finally, Panel D of Fig. 10 shows the results when $friendsAR$ is used as the interacting variable. Across all subgroups, regardless of age or gender, higher values of $friendsAR$ are significantly associated with a greater number of risky options chosen by participants ($\#Risky$). In addition, $friendsAR$ is negatively associated with the probability of being risk $Averse$, and positively associated with the probability of being risk $Lover$ ($p < 0.01$ for all mentioned outcomes).

Overall, our results suggest that cognitive abilities are associated with different patterns in the development of risk preferences: higher cognitive abilities are linked to fewer risky choices for boys at lower grades, while girls with higher cognitive abilities tend to choose fewer risky options at upper grades. We, therefore, conclude:

Result 4a: Cognitive abilities are inversely associated with risk taking, but this association varies by age and gender: it emerges at lower grades for boys but not for girls, and at upper grades for girls but not for boys.

Result 4b: Having friends who tend to choose more risky options is associated with a higher likelihood of taking risks for all subjects.

6. Conclusion

We use a large and powered sample of almost $n = 4000$ 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

[28] As before, all these results and those presented below, come from the different estimated coefficients using Eq. (2). Figs. C.6.1 and C.6.2 of Appendix C.6 display the results for $\#Risky$ and the different risk types respectively, using each of the interacting variables separately (rows).

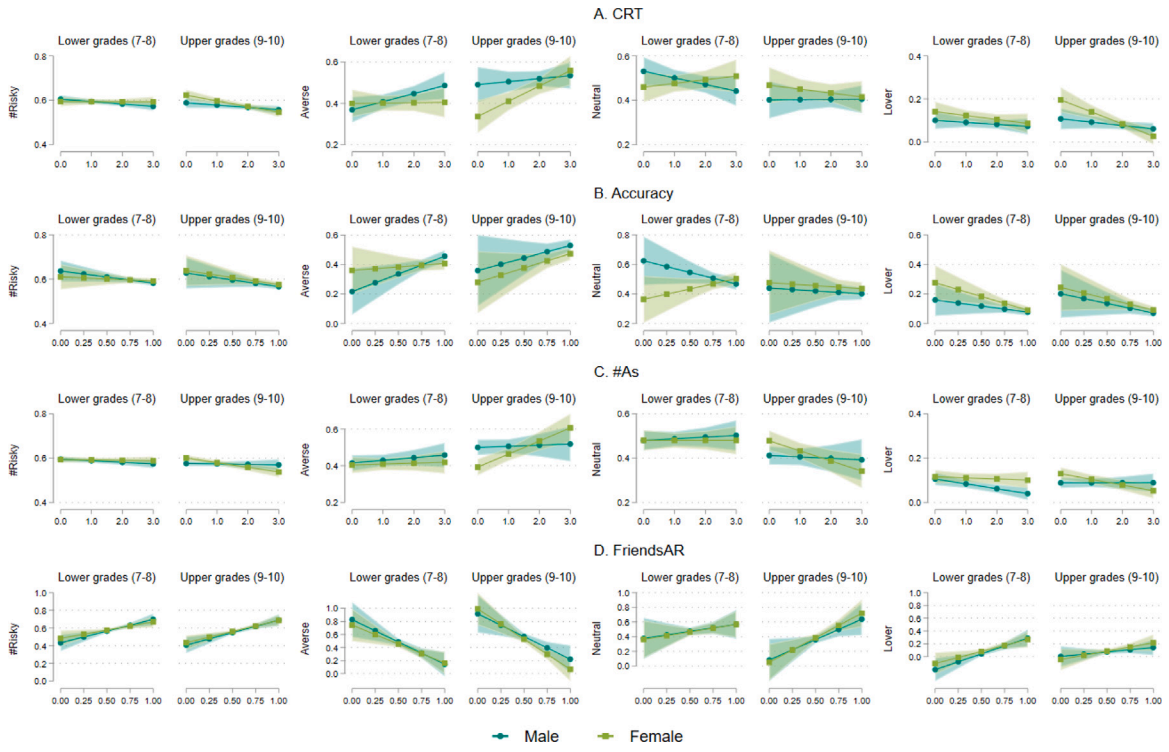


Fig. 10. Linear prediction of risk preferences according to the values of V_i^j for males and females by lower and upper grades. The shaded area represents the 95% confidence interval.

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. Regarding students' characteristics, we also collected 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).

By taking all these factors as exogenous, we observe no gender differences in patience at younger ages. Older adolescents tend to be less present-oriented and exhibit more nuanced time preferences, as reflected in a higher likelihood of selecting interior solutions and a lower tendency to allocate everything to the present. This pattern appears more pronounced among girls. Regarding risk preferences, we find no significant gender differences in the number of risky choices among younger adolescents. However, older adolescents tend to choose fewer risky options. Within this older group, we also observe some gender differences across risk preference types: girls are less likely to be classified as risk averse and more likely to be risk neutral compared to boys.

One of our results deserves particular attention, as it differs from the common finding that girls are more risk averse than boys. Our study relies on a large Spanish sample, uses hypothetical incentives, and employs tasks specifically adapted for adolescents. In addition, we include detailed controls for individual, classroom, and network heterogeneity. These features clearly distinguish our design from previous studies, making it difficult to determine whether the observed pattern is driven by cultural context, task structure, incentive type, or the inclusion of rich covariates. Further research is needed to clarify under what conditions these patterns emerge.

To better understand the results in time and risk preferences across grades, we conduct an exploratory heterogeneity analysis. This analysis yields two novel insights relative to the existing literature. First, cognitive abilities appear to be closely associated with the development of time and risk preferences. Specifically, cognitive abilities are positively associated with patience, although this relationship varies by age and gender: in lower grades, boys with higher cognitive abilities tend to be less present-oriented than girls, whereas in upper grades, girls with higher cognitive abilities are less present-oriented and exhibit more nuanced preferences compared to boys. In the case of risk preferences, cognitive abilities are also linked to age and gender differences: higher levels of cognitive abilities are associated with lower risk-taking among boys in lower grades, and with lower risk-taking among girls in upper grades.

Second, classroom social networks also appear to be associated with adolescents' preferences. We find that the average level of patience (or risk preference) among peers correlates with individual patterns: higher average patience (or risk) among friends is associated with a lower probability of being present-oriented (or risk averse), and a higher likelihood of choosing all future (or all risky) options. However, we do not detect significant interactions with gender or age (grade), suggesting that these associations hold similarly across demographic groups.

However, our main 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 – also has 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 & 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. Our findings highlight the significance of including probability calculus in efforts to reduce gender differences in patience. This suggests the need to incorporate probability education into such financial literacy interventions and even into standard school curricula.

Before closing the paper it is necessary to acknowledge its limitations. The first limitation is that 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 is 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 Francisco (2025) respectively. While these tasks provide very good results in terms of consistency (higher than 78% in both cases), it still is true that our results are valid for these tasks only and therefore we cannot extrapolate them to other experimental settings. Third, 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. Lastly, while our findings generally indicate a positive relationship between risk aversion and cognitive abilities, it is important to note that this relationship could be partially driven by self-selection. The critical issue is whether choices made by subjects with lower cognitive abilities are more likely influenced by errors or lack of understanding rather than true preferences for risk. However, when we employ structural estimation to account for potential mistakes, the results hold, reinforcing the validity of our conclusions but further research with large samples and different tasks is needed to validate this result.

CRediT authorship contribution statement

Antonio Alfonso: Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Pablo Brañas-Garza:** Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Diego Jorrat:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Methodology, Data curation, Conceptualization. **Benjamin Prissé:** Software, Methodology, Formal analysis. **María José Vázquez-De Francisco:** Writing – review & editing, Project administration, Funding acquisition, Data curation, Conceptualization.

Appendix A. Abbreviations

See Table A.0.1.



Fig. B.1.1. Example of decision screen for the time preferences task.

Appendix B. Experimental tasks

B.1. Time preferences

We measured time preferences with a modified version of the Multiple Price Lists task. Subjects were asked to make 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 €10, and the amount of money at the later date increases from decision to decision: €10, €12, €14, €16, €18 and €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. Fig. B.1.1 provides an example of a decision screen for the second decision.

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. Fig. B.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.

B.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. Fig. B.2.1 displays an example of a decision screen for the second decision.

We used the visual representation of a gumball machine to help teenagers understand the concept of risk since the function 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

Table A.0.1
Description of all variables used in the analysis.

Variable	Description
Outcome variables	
#Future	Number of future allocations (ranging 0–6)
AllPresent	Dummy = 1 if subject selected the present option in all 6 decisions
Interior	Dummy = 1 if subject selected both present and future options across the 6 decisions
AllFuture	Dummy = 1 if subject selected the future option in all 6 decisions
#Risky	Number of risky choices (ranging 0–6)
Averse	Dummy = 1 if subject showed risk-averse behavior
Neutral	Dummy = 1 if subject showed risk-neutral behavior
Lover	Dummy = 1 if subject showed risk-loving behavior
Individual-level variables	
CRT	Number of correct answers in the Cognitive Reflection Test (0–3)
#As	Number of A grades in core subjects
Accuracy	Accuracy in probabilities understanding, see section B.4.
Female	Dummy = 1 if subject is female
Upper	Dummy = 1 for grades 3–4 of ESO, 0 for grades 1–2
Repeater	Dummy = 1 if the subject has repeated a grade
Expectations	Likelihood of enrolling in university (0–100)
Social network variables	
FriendsAP	Average number of future allocations among subject's nominated friends
FriendsAR	Average number of risky options chosen by subject's nominated friends
Popularity.f	Number of classmates who named subject *i* as a friend
Popularity.e	Number of classmates who named subject *i* as an enemy
Centrality	Betweenness centrality of the student in the class network
Class-level variables	
Class size	Total number of students in the class
Repeaters	Number of students in the class who repeated a grade
Slackers	Number of students in the class who did not complete the experiment
Migrants	Number of migrant students in the class
Cohesivity	Difference in the density of friendship and enemy links in the class

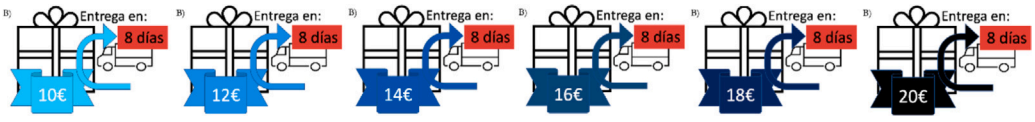


Fig. B.1.2. Monetary values in late period used in the experiment.

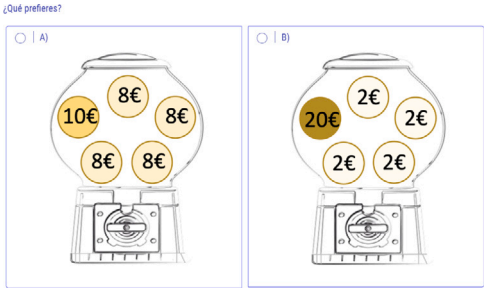


Fig. B.2.1. Example of decision screen for the risk preferences task.

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. Fig. B.2.2 shows how the number of higher values balls increases from trial to trial for lottery B. Fig. B.2.3 does the same for lottery A.

B.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.

B.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?

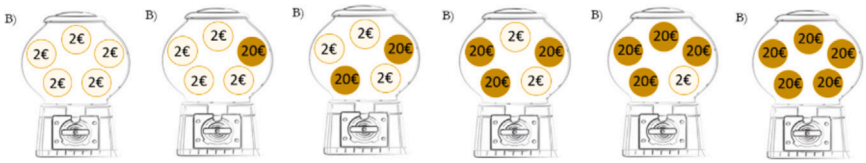


Fig. B.2.2. Lottery B used in the experiment.

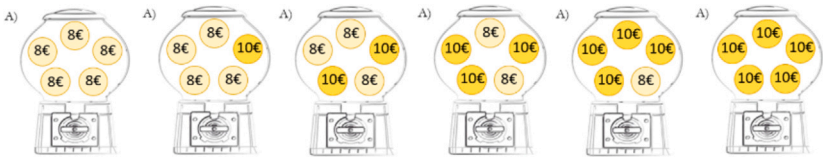


Fig. B.2.3. Lottery A used in the experiment.

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*.

Appendix C. Additional analysis

C.1. Summary statistics

See Table C.1.1.

C.2. Regression tables

See Tables C.2.1 and C.2.2.

Table C.1.1
Summary statistics of the variables without standardizing.

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

C.3. Time preferences and grade variable

In this section, we analyze the robustness of results shown in Table C.2.1, considering all the values of the variable grade (1, 2, 3, and 4). Table C.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

Table C.2.1
OLS estimations on time preferences.

	(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	0.017	0.016	0.015	0.013	0.005	0.007	0.007	0.009	0.001	−0.001	−0.000	−0.002	−0.006	−0.005	−0.007	−0.007
	(0.016)	(0.016)	(0.016)	(0.016)	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.022)	(0.022)	(0.015)	(0.015)	(0.015)	(0.015)
upper	0.032*	0.036**	0.027	0.023	−0.041**	−0.048**	−0.040*	−0.032	0.048**	0.056**	0.055**	0.048**	−0.007	−0.008	−0.015	−0.015
	(0.017)	(0.018)	(0.018)	(0.018)	(0.020)	(0.020)	(0.020)	(0.021)	(0.023)	(0.023)	(0.023)	(0.024)	(0.016)	(0.016)	(0.016)	(0.017)
female × upper	0.010	0.010	0.009	0.008	−0.027	−0.028	−0.027	−0.028	0.043	0.045	0.047	0.047	−0.016	−0.017	−0.019	−0.019
	(0.023)	(0.023)	(0.023)	(0.023)	(0.027)	(0.027)	(0.027)	(0.027)	(0.031)	(0.031)	(0.031)	(0.031)	(0.021)	(0.021)	(0.021)	(0.021)
size		0.125**	0.095*	0.087*		−0.148**	−0.111*	−0.102*		0.097	0.047	0.038		0.051	0.064	0.064
		(0.051)	(0.052)	(0.052)		(0.059)	(0.061)	(0.060)		(0.067)	(0.069)	(0.069)		(0.044)	(0.045)	(0.045)
repeaters		−0.112*	−0.092	−0.025		0.114	0.095	0.051		−0.139*	−0.130	−0.105		0.024	0.035	0.055
		(0.061)	(0.061)	(0.065)		(0.073)	(0.072)	(0.077)		(0.079)	(0.079)	(0.086)		(0.054)	(0.054)	(0.058)
slackers		−0.065	−0.064	−0.079		0.083	0.081	0.099		−0.055	−0.054	−0.068		−0.028	−0.027	−0.031
		(0.085)	(0.085)	(0.086)		(0.113)	(0.111)	(0.111)		(0.115)	(0.115)	(0.115)		(0.053)	(0.053)	(0.053)
migrants		−0.047	−0.035	−0.037		−0.059	−0.071	−0.071		0.118	0.131	0.131		−0.059	−0.059	−0.061
		(0.082)	(0.081)	(0.081)		(0.093)	(0.092)	(0.092)		(0.107)	(0.108)	(0.108)		(0.073)	(0.073)	(0.074)
cohesivity		0.149**	0.095	0.108		−0.201**	−0.120	−0.127		0.120	−0.049	−0.048		0.080	0.169**	0.174**
		(0.073)	(0.088)	(0.088)		(0.082)	(0.099)	(0.099)		(0.097)	(0.117)	(0.117)		(0.068)	(0.081)	(0.082)
popularity.f			0.032	−0.006			−0.058	−0.021			0.155**	0.128*			−0.098**	−0.107**
			(0.050)	(0.050)			(0.058)	(0.059)			(0.067)	(0.067)			(0.045)	(0.045)
popularity.e			0.067	0.089			−0.071	−0.094			0.068	0.086			0.002	0.008
			(0.062)	(0.062)			(0.071)	(0.071)			(0.083)	(0.084)			(0.058)	(0.058)
centrality			0.088	0.071			−0.076	−0.056			0.002	−0.016			0.074	0.072
			(0.069)	(0.069)			(0.080)	(0.080)			(0.090)	(0.090)			(0.060)	(0.060)
friendsAP			0.334***	0.319***			−0.335***	−0.319***			0.189***	0.176***			0.146***	0.144***
			(0.039)	(0.039)			(0.046)	(0.046)			(0.053)	(0.052)			(0.036)	(0.036)
#As				0.041**				−0.047**				0.036				0.012
				(0.018)				(0.020)				(0.024)				(0.017)
CRT				0.069***				−0.087***				0.067**				0.020
				(0.023)				(0.027)				(0.031)				(0.021)
accuracy				0.074*				−0.109**				0.121**				−0.013
				(0.038)				(0.045)				(0.051)				(0.035)
expectations				0.029				−0.030				0.032				−0.001
				(0.022)				(0.025)				(0.029)				(0.020)
repeater				−0.013				−0.011				0.022				−0.011
				(0.019)				(0.023)				(0.026)				(0.016)
constant	0.580***	0.478***	0.298***	0.183***	0.162***	0.302***	0.482***	0.635***	0.695***	0.608***	0.509***	0.354***	0.143***	0.090*	0.009	0.010
	(0.026)	(0.052)	(0.054)	(0.064)	(0.028)	(0.059)	(0.064)	(0.076)	(0.035)	(0.068)	(0.073)	(0.085)	(0.027)	(0.047)	(0.048)	(0.056)
N	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737
Adj. R^2	0.033	0.036	0.057	0.064	0.024	0.028	0.043	0.051	0.020	0.021	0.025	0.029	0.012	0.011	0.017	0.016
AIC	2926	2920	2844	2820	4023	4015	3960	3934	4984	4985	4972	4961	2088	2095	2078	2086
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

Robust standard errors in brackets. Asterisk denote significance levels.

*** p<0.01.

** p<0.05.

* p<0.1.

to the present ($p < 0.10$) while older teens are more likely to choose at least one interior allocation ($p < 0.05$).

C.4. Risk preferences and grade variable

We now proceed to assess the robustness of the results presented in Table C.2.2 by considering all possible values of the variable grade. Table C.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 ($p < 0.01$).

C.5. Heterogeneity in time preferences

Fig. C.5.1 presents the estimated coefficients of Eq. (2) and their 95% CI for the heterogeneity analysis on time preferences. The first row replicates model (4) from Table C.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

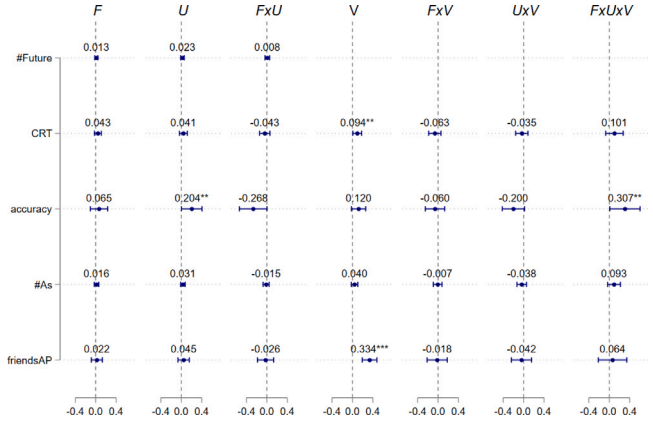


Fig. C.5.1. Estimated coefficients from the heterogeneity analysis in time preferences (where: $V = CRT$, $\#As$, $accuracy$, $friendsAP$). Dependent variable: $\#Future$.

$U{\times}V$ and the triple interaction between the interacting variable, $female$ and $upper$ is presented in column $F{\times}U{\times}V$.

Fig. C.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 C.2.1, and their results are plotted in the first row.

Table C.2.2
OLS estimations on risk 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	0.0033	0.0029	0.0045	−0.0188	−0.0198	−0.0178	−0.0226	−0.0068	−0.0067	−0.0069	−0.0051	0.0257*	0.0264*	0.0247*	0.0277**
	(0.0067)	(0.0067)	(0.0067)	(0.0067)	(0.0222)	(0.0223)	(0.0223)	(0.0223)	(0.0226)	(0.0226)	(0.0227)	(0.0228)	(0.0140)	(0.0140)	(0.0140)	(0.0139)
upper	−0.0209***	−0.0221***	−0.0185***	−0.0160**	0.0987***	0.0999***	0.0895***	0.0819***	−0.0875***	−0.0885***	−0.0816***	−0.0818***	−0.0112	−0.0114	−0.0078	−0.0002
	(0.0070)	(0.0071)	(0.0071)	(0.0073)	(0.0242)	(0.0245)	(0.0247)	(0.0253)	(0.0242)	(0.0245)	(0.0248)	(0.0254)	(0.0138)	(0.0140)	(0.0142)	(0.0148)
female × *upper*	0.0064	0.0061	0.0057	0.0059	−0.0352	−0.0353	−0.0348	−0.0355	0.0373	0.0374	0.0397	0.0402	−0.0021	−0.0021	−0.0049	−0.0048
	(0.0098)	(0.0098)	(0.0098)	(0.0097)	(0.0331)	(0.0331)	(0.0330)	(0.0328)	(0.0331)	(0.0332)	(0.0331)	(0.0332)	(0.0197)	(0.0197)	(0.0196)	(0.0194)
size		0.0120	0.0085	0.0128		0.0575	0.0650	0.0511		−0.132*	−0.152**	−0.149**		0.0745*	0.0871*	0.0976**
		(0.0216)	(0.0221)	(0.0220)		(0.0715)	(0.0733)	(0.0731)		(0.0714)	(0.0736)	(0.0737)		(0.0439)	(0.0455)	(0.0452)
repeaters		0.0419*	0.0376	0.0082		−0.1000	−0.0861	−0.0008		−0.0051	−0.0140	−0.0446		0.105**	0.100*	0.0454
		(0.0253)	(0.0247)	(0.0265)		(0.0858)	(0.0846)	(0.0904)		(0.0857)	(0.0852)	(0.0920)		(0.0515)	(0.0512)	(0.0558)
slackers		−0.0074	−0.0011	0.0032		−0.0064	−0.0248	−0.0360		−0.0304	−0.0183	−0.0123		0.0368	0.0431	0.0483
		(0.0405)	(0.0402)	(0.0414)		(0.114)	(0.112)	(0.114)		(0.113)	(0.113)	(0.114)		(0.0748)	(0.0739)	(0.0733)
migrants		−0.0157	−0.0244	−0.0247		−0.0906	−0.0668	−0.0647		0.106	0.0938	0.0916		−0.0158	−0.0270	−0.0269
		(0.0348)	(0.0347)	(0.0346)		(0.117)	(0.117)	(0.117)		(0.119)	(0.119)	(0.119)		(0.0674)	(0.0676)	(0.0668)
cohesivity		−0.0555*	−0.0525	−0.0557		0.148	0.147	0.154		−0.0467	−0.159	−0.165		−0.101	0.0121	0.0109
		(0.0315)	(0.0385)	(0.0383)		(0.106)	(0.128)	(0.127)		(0.105)	(0.128)	(0.128)		(0.0625)	(0.0788)	(0.0781)
popularity.f			0.0054	0.0214			−0.0202	−0.0670			0.110	0.125*			−0.0894**	−0.0581
			(0.0214)	(0.0214)			(0.0711)	(0.0715)			(0.0717)	(0.0726)			(0.0434)	(0.0432)
popularity.e			0.0122	−0.0001			−0.0264	0.0098			−0.0515	−0.0631			0.0780	0.0532
			(0.0284)	(0.0280)			(0.0916)	(0.0902)			(0.0915)	(0.0915)			(0.0573)	(0.0570)
centrality			−0.0232	−0.0161			0.122	0.0991			−0.0978	−0.0927			−0.0238	−0.0064
			(0.0274)	(0.0272)			(0.0954)	(0.0951)			(0.0948)	(0.0948)			(0.0529)	(0.0526)
friendsAR			0.250***	0.242***			−0.746***	−0.720***			0.406***	0.398***			0.340***	0.322***
			(0.0399)	(0.0396)			(0.118)	(0.117)			(0.120)	(0.120)			(0.0797)	(0.0784)
#As				−0.0227***				0.0667***				−0.0266				−0.0401***
				(0.0075)				(0.0256)				(0.0258)				(0.0140)
CRT				−0.0339***				0.0938***				−0.0243				−0.0695***
				(0.0097)				(0.0326)				(0.0331)				(0.0201)
accuracy				−0.0458***				0.157***				−0.0201				−0.137***
				(0.0171)				(0.0536)				(0.0542)				(0.0369)
expectations				−0.0175*				0.0604**				−0.0119				−0.0485**
				(0.0093)				(0.0300)				(0.0305)				(0.0200)
repeater				−0.0001				0.0066				0.0053				−0.0118
				(0.0081)				(0.0269)				(0.0274)				(0.0176)
constant	0.609***	0.609***	0.459***	0.535***	0.399***	0.347***	0.791***	0.543***	0.465***	0.560***	0.324***	0.373***	0.136***	0.0929**	−0.115*	0.0841
	(0.0108)	(0.0214)	(0.0319)	(0.0356)	(0.0373)	(0.0720)	(0.101)	(0.112)	(0.0381)	(0.0723)	(0.101)	(0.112)	(0.0260)	(0.0471)	(0.0653)	(0.0737)
N	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590
Adj. 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)	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

Robust standard errors in brackets. Asterisk denote significance levels.

*** p<0.01.

** p<0.05.

* p<0.1.

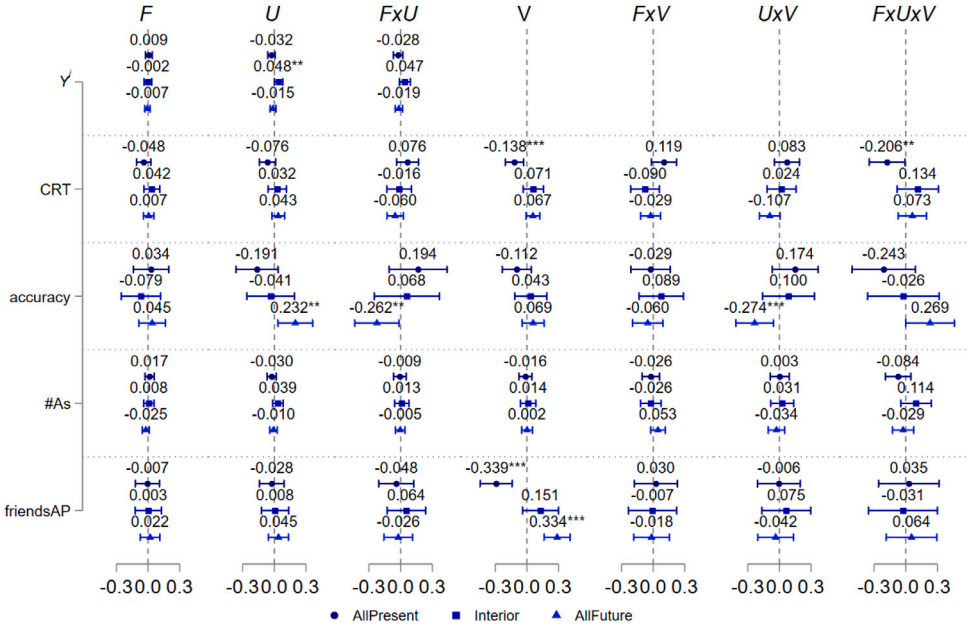


Fig. C.5.2. Estimated coefficients from the heterogeneity analysis in time preferences (where: $V = CRT$, $\#As$, $accuracy$, $friendsAP$). Dependent variables: $AllPresent$, $Interior$ and $AllFuture$.

Table C.4.1
OLS estimations on time preferences using grade variable.

	(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) AllLater	(14) AllLater	(15) AllLater	(16) AllLater
female	0.0398	0.0379	0.0383	0.0352	−0.00793	−0.00522	−0.00520	−0.00171	−0.0144	−0.0172	−0.0186	−0.0214	0.0223	0.0225	0.0238	0.0231
	(0.0291)	(0.0291)	(0.0288)	(0.0287)	(0.0334)	(0.0334)	(0.0331)	(0.0330)	(0.0382)	(0.0382)	(0.0382)	(0.0382)	(0.0272)	(0.0272)	(0.0271)	(0.0272)
grade	0.0111	0.0122	0.0115	0.00905	−0.0185**	−0.0208**	−0.0203**	−0.0166*	0.0250**	0.0275***	0.0285***	0.0254**	−0.00645	−0.00673	−0.00813	−0.00880
	(0.00791)	(0.00796)	(0.00790)	(0.00809)	(0.00924)	(0.00928)	(0.00922)	(0.00941)	(0.0104)	(0.0105)	(0.0105)	(0.0108)	(0.00716)	(0.00719)	(0.00726)	(0.00759)
female × grade	−0.00773	−0.00747	−0.00810	−0.00780	0.000456	−0.000107	0.000183	−0.000715	0.0143	0.0148	0.0161	0.0168	−0.0147	−0.0147	−0.0163*	−0.0160
	(0.0107)	(0.0106)	(0.0105)	(0.0105)	(0.0123)	(0.0122)	(0.0121)	(0.0121)	(0.0141)	(0.0141)	(0.0141)	(0.0141)	(0.00982)	(0.00983)	(0.00984)	(0.00990)
size		0.122**	0.0957*	0.0878*		−0.149**	−0.116*	−0.106*		0.105	0.0568	0.0470		0.0439	0.0592	0.0586
		(0.0510)	(0.0521)	(0.0518)		(0.0592)	(0.0607)	(0.0602)		(0.0669)	(0.0691)	(0.0688)		(0.0441)	(0.0451)	(0.0451)
repeaters		−0.103*	−0.0857	−0.0184		0.107	0.0894	0.0444		−0.134*	−0.126	−0.101		0.0276	0.0364	0.0565
		(0.0608)	(0.0606)	(0.0647)		(0.0729)	(0.0726)	(0.0771)		(0.0791)	(0.0792)	(0.0855)		(0.0536)	(0.0536)	(0.0579)
slackers		−0.0777	−0.0719	−0.0868		0.0959	0.0903	0.108		−0.0649	−0.0628	−0.0769		−0.0310	−0.0276	−0.0307
		(0.0854)	(0.0849)	(0.0855)		(0.113)	(0.112)	(0.111)		(0.115)	(0.115)	(0.114)		(0.0524)	(0.0520)	(0.0520)
migrants		−0.0800	−0.0592	−0.0600		−0.0216	−0.0438	−0.0452		0.0866	0.103	0.107		−0.0649	−0.0595	−0.0613
		(0.0811)	(0.0802)	(0.0800)		(0.0917)	(0.0909)	(0.0909)		(0.106)	(0.106)	(0.106)		(0.0721)	(0.0721)	(0.0722)
cohesivity		0.142*	0.100	0.114		−0.190**	−0.119	−0.127		0.107	−0.0617	−0.0586		0.0833	0.180**	0.185**
		(0.0729)	(0.0880)	(0.0879)		(0.0815)	(0.0991)	(0.0992)		(0.0963)	(0.117)	(0.117)		(0.0683)	(0.0814)	(0.0818)
popularity.f			0.0197	−0.0181			−0.0485	−0.0121			0.153**	0.126*			−0.105**	−0.114**
			(0.0500)	(0.0503)			(0.0579)	(0.0586)			(0.0663)	(0.0670)			(0.0451)	(0.0454)
popularity.e			0.0599	0.0821			−0.0678	−0.0911			0.0708	0.0890			−0.00298	0.00218
			(0.0620)	(0.0624)			(0.0710)	(0.0712)			(0.0829)	(0.0835)			(0.0576)	(0.0578)
centrality			0.0937	0.0764			−0.0791	−0.0589			−0.000836	−0.0187			0.0799	0.0776
			(0.0688)	(0.0688)			(0.0803)	(0.0804)			(0.0899)	(0.0902)			(0.0601)	(0.0601)
friendsAP			0.341***	0.326***			−0.346***	−0.329***			0.203***	0.189***			0.143***	0.140***
			(0.0384)	(0.0386)			(0.0461)	(0.0460)			(0.0521)	(0.0520)			(0.0357)	(0.0359)
#As				0.0397**				−0.0484**				0.0407*				0.00762
				(0.0178)				(0.0202)				(0.0239)				(0.0169)
CRT				0.0711***				−0.0867***				0.0630**				0.0237
				(0.0232)				(0.0267)				(0.0309)				(0.0211)
accuracy				0.0774**				−0.108**				0.115**				−0.00621
				(0.0385)				(0.0450)				(0.0509)				(0.0350)
expectations				0.0286				−0.0301				0.0316				−0.00151
				(0.0217)				(0.0254)				(0.0287)				(0.0200)
repeater				−0.0137				−0.0100				0.0214				−0.0114
				(0.0192)				(0.0231)				(0.0256)				(0.0161)
constant	0.557***	0.460***	0.274***	0.161**	0.197***	0.336***	0.523***	0.670***	0.653***	0.562***	0.453***	0.309***	0.150***	0.102**	0.0239	0.0207
	(0.0303)	(0.0544)	(0.0570)	(0.0654)	(0.0326)	(0.0623)	(0.0667)	(0.0775)	(0.0401)	(0.0712)	(0.0759)	(0.0870)	(0.0306)	(0.0489)	(0.0506)	(0.0570)
N	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737	3737
Adj. R^2	0.0317	0.0345	0.0557	0.0634	0.0224	0.0254	0.0416	0.0496	0.0197	0.0207	0.0256	0.0296	0.0135	0.0129	0.0184	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)	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

Robust standard errors in brackets. Asterisk denote significance levels.

*** p<0.01.

** p<0.05.

* p<0.1.

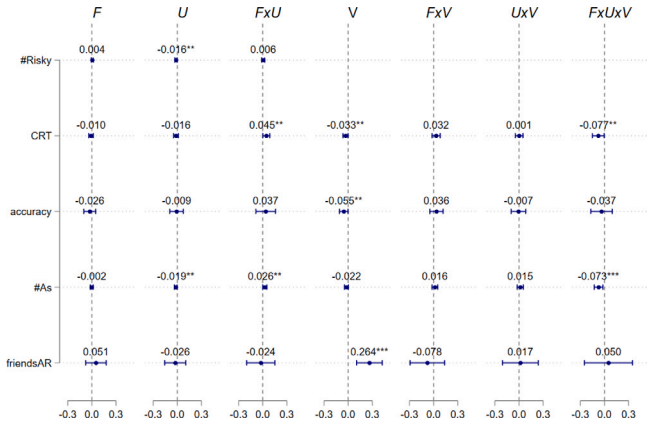


Fig. C.6.1. Estimated coefficients from the heterogeneity analysis in risk preferences (where: $V = CRT$, $\#As$, $accuracy$, $friendsAR$). Dependent variable: $\#Risky$.

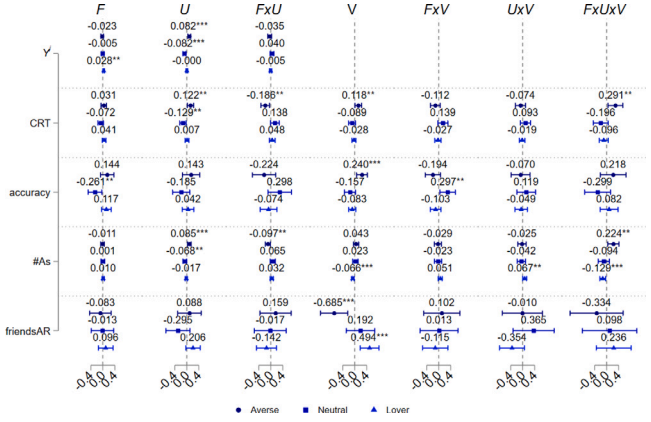


Fig. C.6.2. Estimated coefficients from the heterogeneity analysis in risk preferences (where: $V = CRT$, $\#As$, $accuracy$, $friendsAP$). Dependent variables: $Averse$, $Neutral$ and $Lover$.

C.6. Heterogeneity in risk preferences

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

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

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.socec.2025.102396.

Data availability

The data for replication is available at https://github.com/teenslab/datateenslab.

Table C.4.2
OLS estimations on risk preferences using grade variable.

	(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	0.00164	0.00219	0.000904	0.00271	−0.0124	−0.0136	−0.00858	−0.0141	−0.0311	−0.0309	−0.0355	−0.0338	0.0434*	0.0445*	0.0441*	0.0479*
	(0.0122)	(0.0122)	(0.0122)	(0.0121)	(0.0398)	(0.0399)	(0.0398)	(0.0396)	(0.0405)	(0.0406)	(0.0407)	(0.0407)	(0.0250)	(0.0250)	(0.0249)	(0.0246)
grade	−0.00875***	−0.00890***	−0.00793**	−0.00687**	0.0410***	0.0413***	0.0384***	0.0354***	−0.0327***	−0.0334***	−0.0315***	−0.0315***	−0.00829	−0.00791	−0.00691	−0.00392
	(0.00323)	(0.00324)	(0.00323)	(0.00334)	(0.0111)	(0.0111)	(0.0112)	(0.0115)	(0.0111)	(0.0112)	(0.0112)	(0.0116)	(0.00603)	(0.00606)	(0.00612)	(0.00644)
female × grade	0.00165	0.00157	0.00190	0.00183	−0.00915	−0.00901	−0.0102	−0.0102	0.0170	0.0170	0.0193	0.0194	−0.00785	−0.00795	−0.00909	−0.00916
	(0.00449)	(0.00449)	(0.00448)	(0.00445)	(0.0151)	(0.0151)	(0.0151)	(0.0150)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.00885)	(0.00885)	(0.00881)	(0.00875)
size		0.00985	0.00617	0.0108		0.0683	0.0763	0.0613		−0.136*	−0.158**	−0.155**		0.0672	0.0820*	0.0937**
		(0.0216)	(0.0220)	(0.0219)		(0.0716)	(0.0733)	(0.0731)		(0.0717)	(0.0737)	(0.0738)		(0.0440)	(0.0454)	(0.0451)
repeaters		0.0404	0.0365	0.00720		−0.0942	−0.0817	0.00326		−0.0143	−0.0223	−0.0526		0.109**	0.104**	0.0493
		(0.0253)	(0.0247)	(0.0265)		(0.0858)	(0.0845)	(0.0904)		(0.0855)	(0.0850)	(0.0920)		(0.0518)	(0.0514)	(0.0559)
slackers		−0.00444	0.00107	0.00510		−0.0177	−0.0337	−0.0446		−0.0167	−0.00652	−0.000813		0.0344	0.0402	0.0454
		(0.0405)	(0.0402)	(0.0413)		(0.114)	(0.112)	(0.114)		(0.113)	(0.113)	(0.113)		(0.0749)	(0.0740)	(0.0734)
migrants		−0.00754	−0.0183	−0.0200		−0.123	−0.0922	−0.0857		0.145	0.127	0.125		−0.0222	−0.0347	−0.0388
		(0.0341)	(0.0341)	(0.0340)		(0.116)	(0.116)	(0.115)		(0.118)	(0.118)	(0.118)		(0.0660)	(0.0663)	(0.0653)
cohesivity		−0.0523*	−0.0507	−0.0542		0.134	0.137	0.146		−0.0361	−0.161	−0.167		−0.0980	0.0234	0.0206
		(0.0315)	(0.0385)	(0.0383)		(0.107)	(0.128)	(0.128)		(0.106)	(0.128)	(0.128)		(0.0625)	(0.0788)	(0.0781)
popularity.f			0.00634	0.0222			−0.0234	−0.0700			0.122*	0.137*			−0.0983**	−0.0671
			(0.0214)	(0.0214)			(0.0711)	(0.0714)			(0.0717)	(0.0725)			(0.0432)	(0.0429)
popularity.e			0.0126	0.000203			−0.0278	0.00924			−0.0431	−0.0550			0.0709	0.0458
			(0.0283)	(0.0279)			(0.0913)	(0.0899)			(0.0914)	(0.0914)			(0.0572)	(0.0570)
centrality			−0.0234	−0.0163			0.122	0.0994			−0.103	−0.0974			−0.0191	−0.00192
			(0.0274)	(0.0272)			(0.0956)	(0.0952)			(0.0950)	(0.0951)			(0.0528)	(0.0525)
friendsAR			0.253***	0.244***			−0.757***	−0.730***			0.421***	0.413***			0.336***	0.317***
			(0.0399)	(0.0396)			(0.118)	(0.117)			(0.120)	(0.120)			(0.0794)	(0.0782)
#As				−0.0234***				0.0704***				−0.0263				−0.0442***
				(0.00752)				(0.0257)				(0.0260)				(0.0141)
CRT				−0.0336***				0.0922***				−0.0269				−0.0653***
				(0.00973)				(0.0327)				(0.0332)				(0.0201)
accuracy				−0.0447***				0.151***				−0.0212				−0.130***
				(0.0171)				(0.0539)				(0.0545)				(0.0370)
expectations				−0.0175*				0.0604**				−0.0112				−0.0492**
				(0.00929)				(0.0300)				(0.0305)				(0.0200)
repeater				−0.000191				0.00687				0.00527				−0.0121
				(0.00813)				(0.0269)				(0.0274)				(0.0176)
constant	0.622***	0.622***	0.469***	0.544***	0.341***	0.286***	0.740***	0.501***	0.514***	0.608***	0.361***	0.411***	0.145***	0.106**	−0.101	0.0881
	(0.0126)	(0.0223)	(0.0324)	(0.0360)	(0.0431)	(0.0757)	(0.104)	(0.113)	(0.0437)	(0.0761)	(0.104)	(0.114)	(0.0283)	(0.0485)	(0.0660)	(0.0739)
N	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590	3590
Adj. R^2	0.0161	0.0166	0.0297	0.0430	0.0241	0.0242	0.0345	0.0452	0.0183	0.0182	0.0217	0.0213	0.0112	0.0129	0.0209	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

Robust standard errors in brackets. Asterisk denote significance levels.

*** p<0.01.

** p<0.05.

* p<0.1.

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