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Long-lasting effects of relative age at school

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Abstract

We investigate the long-lasting effects on behaviour of relative age at school. We conduct an online incentivised survey with a sample of 1007 adults, who were born at most two months before or after the school entry cut-off date in four Australian states. We find those who were among the oldest in the classroom throughout their school years display higher self-confidence, are more willing to enter in some form of competition and declare taking more risk in a range of domains in their life, compared to those who were among the youngest.

1 Introduction

Having been among the oldest or the youngest in the class throughout the educational trajectory has been found to have significant effects on a range of outcomes measured later in life. Those who happened to be among the oldest in their cohort tend to have higher educational attainment (Crawford et al., 2014).[1] They also tend to be more successful in competitive environments such as sports (Allen and Barnsley, 1993), managerial positions (Du et al., 2012) and politics (Muller and Page, 2016).[2] Smaller and short-lived effects have also been found on earnings (Fredriksson and Öckert, 2014).[3] However, the mechanisms underlying these differences in long term outcomes are not well known.

In this study we investigate if the experience of being among the oldest or youngest in the classroom throughout the school trajectory can have a sustained effect on behavioural traits deemed important for success later in life. We conduct an online incentivised survey with a large sample of 1007 Australian adults aged 24 to 60 years old who were either among the oldest or the youngest in the classroom (also referred to as *relatively old / young*) and elicit their self-confidence, competitiveness, risk tolerance, trusting attitude and patience. We find that having been among the oldest in one's peer group in school is positively associated with self-confidence in adulthood. We also find a positive effect of relative age in school on the propensity to declare higher risk tolerance in real life situations. Finally, we find suggestive evidence of a positive long-lasting effect on trusting attitude.

The potential advantage in children's psychological development stemming from being among the oldest in the classroom has been a subject of interest in psychology, and more recently, in economic research. Studies with children and adolescents have shown that being relatively old in the school cohort influences self-confidence and social interactions in school.

[1] See also Bedard and Dhuey (2006); Datar (2006); Puhani and Weber (2007); McEwan and Shapiro (2008); Smith (2009); Elder and Lubotsky (2009); Grenet (2009); Fredriksson and Öckert (2014). Using German data, Mühlenweg and Puhani (2010) also find that relative age positively influences the chances of self-selecting into an academic versus vocational school stream at age 10.

[2] See also Musch and Grondin (2001).

[3] See also Grenet (2009); Black et al. (2011).

For instance, Crawford et al. (2014) show that relative age influences children's belief about potential achievement in school. They explore the variation in school entry cut-off dates in England and apply a regression discontinuity design on a sample of children born around the school entry cut-off date. They find evidence of an advantage for relatively old children on self-confidence which is three times as large as the gap between children with high and low socio-economic advantage.

There is also evidence that relatively old children have higher self-esteem (Fenzel, 1992; Thompson et al., 1999, 2004), are less likely to suffer from psychological and behaviour problems (Goodman et al., 2003; Mühlenweg et al., 2012; Chen et al., 2015), and school victimisation (Mühlenweg, 2010). Dhuey and Lipscomb (2008) find that relatively old high school students are more likely to be involved in leadership activities at school and in a previous study we find that relatively old boys are more competitive (Page et al., 2017).

Fewer studies have looked at the persistent effects of relative age, when small age differences become less consequential in terms of cognitive and physical development or when individuals cease to be in an environment where they systematically are among the youngest or the oldest, typically encountered after leaving school. For instance, using data from the US and Canada, Bedard and Dhuey (2006) find a positive effect of the relative age on the likelihood to attend university, even though the advantage in tests scores for relatively old students vanishes in the adolescent years. Using Swedish data, Fredriksson and Öckert (2014) find that people who were relatively old in their school cohort are likely to have completed more years of education than those who were relatively young. Moreover, they report a stronger effect of relative age for women and individuals from socio-economically disadvantaged backgrounds. In contrast, using Norwegian data, Black et al. (2011) find no impact of relative age on educational attainment. Both Fredriksson and Öckert (2014) and Black et al. (2011) find little evidence for an effect of relative age on life cycle earnings. Other studies document an over-representation of individuals who were relatively old in their school cohort in jobs where high interpersonal skills and self-confidence are likely to be important, like politicians (see Muller and Page, 2016, for evidence from the US) and CEOs of very large companies (Du et al., 2012). Bai et al. (2018) also document that mutual fund managers who were relatively old at school outperform those who were relatively young and that this is linked to differences in the adoption of confident financial behaviour.[4]

Our study contributes to several areas of research. First, by providing empirical support for long-lasting consequences of relative age in school on behavioural traits, our study adds to the investigation of the behavioural explanations for the relative age effect. Participants who were relatively old in school and those who were relatively young behaved differently in our experiment. The former were substantially more self-confident about performance in an effort task and more willing to take part in some form of competition than relatively young participants. They also declared taking more risk in life. Our findings suggest that part of the long-lasting effect of relative age on career choices may be attributable to the difference in self-confidence and risk attitude created by the experience of being relatively old or young in the classroom.

Second, our study relates to the literature investigating the role of self-confidence in career success. Several studies have demonstrated both theoretically and empirically the importance of self-confidence for achievement. For instance, Bénabou and Tirole (2002) show in a theoretical framework that holding positively biased beliefs about oneself can increase motivation to undertake challenging projects, and Bénabou (2012) show that it can enhance performance (see also Compte and Postlewaite, 2004; Hong et al., 2018). These predictions are supported by empirical findings showing that self-confidence leads to higher provision of effort and performance (Galasso and Simcoe, 2011; Hirshleifer et al., 2012; Puri and Robinson, 2007). Considering this literature, the positive effect on self-confidence created by the experience of being among the oldest in the classroom may contribute to the long-lasting

[4] Focussing on long lasting effects also has the major advantage of providing 'clean' evidence of the relative age effect as it is not affected by the classical problem of the relative age being confounded with absolute age (and time spent in school) as found in studies with children and adolescents. Some studies focussing on educational achievement try to eliminate or weaken this problem by exploiting regional variation in the school entry cut-off dates (Crawford et al., 2010; Smith, 2009). Crawford et al. (2014) find that absolute age is likely to be the main explanatory factor for a relative age advantage on academic achievement.

effect of relative age on success for specific professions evidenced in previous studies.

Finally, our study extends the literature on children's behavioural traits. Many large studies have investigated behavioural differences among children by eliciting economic preferences such as risk aversion or time preference (Bettinger and Slonim, 2007; Sutter et al., 2013; Castillo et al., 2018). Our study relates to the research on the role of education in the formation of these behavioural traits (e.g Borghans et al., 2008; Cunha and Heckman, 2009). Specifically, our findings indicate that school entry rules influence the formation of behavioural traits, creating long-lasting disparities between individuals born on different sides of the cut-off date. Our findings highlight the importance of recognising the potential adverse effect of school entry rules when designing educational policies.

The paper proceeds as follows: In Section 2 we describe our study design, including the empirical strategy, participant pool, experimental procedure and hypotheses. In Section 3 we present our results and in Section 4 we provide a general discussion of the study.

2 Study design

2.1 Empirical strategy

We use the exogenous variation in relative age at school to investigate its long-lasting effect on behavioural traits. Our empirical strategy relies on the fact that relative age in Australia is highly influenced by an exogenous rule, the school entry cut-off date. School entry rules create a discontinuity in the probability to be relatively old at school around the cut-off date. Children born *before* the cut-off date reach the required age for school entry before that date and are expected to be among the youngest in their school cohort. Children born *after* the cut-off date do not reach the required age in time and have to wait until the following year, ending up among the oldest in their cohort. In Australian public schools most students live within the school catchment area. Therefore, children have the same school peer group throughout primary school. When they move on to high school, the cohort typically moves together owing to enrolment within catchment restrictions. There may be new peers as a catchment area that is designated for high school enrolment comprises of several smaller primary school catchments. Importantly, children who were among the oldest (or the youngest) in their cohort in primary school, continue being among the oldest (or the youngest), even though they might have new peers.

School entry cut-off dates in Australia are not binding, and therefore compliance is imperfect. For instance, some children born before the cut-off dates are sometimes held back one more year and end up among the oldest in their school cohort, even though they were expected to be among the youngest. Therefore, parental preferences will play a role in determining their child's relative age, in particular for children born in the vicinity of the cut-off date.

Our identification assumption is that being born shortly before or after the cut-off date can be considered an accidental event, independent of family characteristics. Specifically, the timing of birth around the cut-off date is uncorrelated with family characteristics which can influence the child's behavioural traits. Previous studies using data from different countries including Australia have shown that this assumption is generally reasonable.[5] Therefore, individuals born only a few weeks apart in the vicinity of the cut-off date are likely to be very similar, yet those born after the cut-off date had a very high chance of being relatively old among their peers while those born before had a high chance of being relatively young. In practice, we chose the smallest window around the cut-off date that allowed us to reach a suitable sample size. Participants in our study were selected so that they were born *at most* two months before or after the school entry cut-off date applied to the state in which they attended school. To ensure that our results are not dependent on the size of this window, we reproduce in Appendix C.3 our data analysis on the subsample of participants born only 1

[5] See for example Dickert-Conlin and Elder (2010) for evidence from the US, Black et al. (2011) for evidence from Norway and Ryan and Zhu (2015) for evidence from Australia. For Australia in particular, using data from the Longitudinal Survey of Australian Children, Ryan and Zhu (2015) show no evidence of a discontinuity around the school entry cut-off date in several relevant characteristics including mother's education, ethnic background, number of siblings, mother's age, child's gender, the incidence of the child having a medical condition, Indigenous status, birth weight and current height.

month before or after the cut-off date. Generally the results are very consistent, and we will refer to the analysis on this subsample when describing our results. We recruited participants across four Australian states with cut-off dates placed either in the middle of the Australian Summer or in the middle of the Australian Winter to reduce the risk of unobserved family differences associated with seasonal variations in the timing of birth described by Buckles and Hungerman (2013) for the US.

To measure the *actual* relative age, we use the participant's declaration of whether she[6] was among the oldest or the youngest in the classroom, and whether she has repeated or skipped primary school grades. A participant complied with the school entry cut-off date if her actual relative age corresponds to the relative age predicted by the cut-off date. We call this predicted relative age her *assigned relative age*.[7] Table 1 presents the breakdown of our sample in terms of relative age. Among the 530 participants who were born after the cut-off date in their state, 385 (73%) were among the oldest in their cohort. Similarly, among the 477 participants assigned as the youngest in their cohort, 358 (75%) were in fact among the youngest. Among the compliers, 52% were born after the cut-off date. Among the non-compliers, 55% were born after the cut-off date.[8]

[6]For simplicity, we use the female pronoun throughout to denote a generic participant in the study.

[7]A participant complied with the cut-off date if she was either born before the school entry cut-off date in her state and declares having been among the youngest in her classroom, or if she was born after the school entry cut-off date and declares having been among the oldest in her classroom.

[8]The subsample of compliers does not differ from the whole sample in sociodemographic characteristics including age, occupation and the likelihood of having university education. We note a slightly smaller proportion of men among the complier subsample than the whole sample (33% versus 36%, respectively).

Table 1: Actual and assigned relative age

	Assigned relative age				
Actual relative age	Oldest	%	Youngest	%	Total
Oldest	385	73	119	25	504
Youngest	145	27	358	75	503
Total	530	100	477	100	1007

Note: Count and (column) percentages of participants whose assigned relative age, determined by whether they were born before or after the school entry cut-off date in their state, corresponds to their actual (self-declared) relative age in school.

The imperfect correspondence between the assigned and the actual relative age is partly due to the fact that some participants assigned as relatively young have repeated grades and others, assigned as relatively old, have skipped grades in primary school. This is only the case for 3% and 4% of our sample, respectively. Therefore, the main factor is the non-observance of the school entry cut-off date due to early school entry (before becoming eligible according to the cut-off date) (23%) or delayed entry (22%).

The decision by the child's caregivers to opt for an early or delayed entry is likely to be influenced by several factors which may also be correlated with the child's characteristics. To correct for a potential selection bias, we follow the standard practice in the relative age literature and use the assigned relative age as an instrumental variable for the actual relative age (Bedard and Dhuey, 2006; Dhuey and Lipscomb, 2008; Crawford et al., 2014). In our data, the assigned relative age is a strong predictor and hence a good instrument for the actual relative age (p<0.01, see Appendix A).

2.2 Participants

We recruited our participants in September and October 2017 through a market and social research company (Online Research Unit [ORU]) with one of the largest online panels in

Australia.[9] Online panels are now widely used in economics, in particular Amazon Mechanical Turk has become a standard tool to run online experiments (Weinzierl, 2017; Robbett and Matthews, 2018).[10] Our participants attended school in Australia, either in one state only or in more than one state having the same cut-off date.[11] To be eligible, participants had to be born within a two-month window on each side of the cut-off date defined in the state in which they went to school.

We recruited participants across four Australian states: Queensland, Tasmania, Victoria and Western Australia.[12] The age range of participants was adjusted based on changes over time in the school entry cut-off date policy implemented in each state. Thus, eligible participants are 24 to 36 years old in Queensland, 24 to 42 in Tasmania, 28 to 60 in Victoria and 24 to 60 in Western Australia.[13] The school entry cut-off dates which apply to our participants is the 31st of December for Queensland, Tasmania and Western Australia, and the 30th of June for Victoria.

Based on the eligibility criteria, a total of 1083 individuals took part in the study. We excluded 76 participants who declared being highly uncertain of whether they were among the youngest or the oldest in the classroom during primary school in the pre-experimental survey. On a scale from 0 to 10, a response value lower than 5 to the question on whether they had been among the oldest or the youngest students in the classroom was used to exclude participants.[14] They account for 7% of the sample only and although we opted to exclude these participants, all our results are robust to including them in the sample.[15] Overall, our

[9] ORU has the most accredited panel in Australia currently holding ISO 26362 (Global Access Panels), ISO 20252 (Market Research Standard) and the AMSRO QSOAP 'Gold Standard' (Quality standard for Access Panels).

[10] A recent comparison of an online sample (MTurk), a US representative sample and students from a US university found that correlations between behaviour are similar across samples (Snowberg and Yariv, 2018).

[11] A person who went to school in more than one state was eligible to participate if the states had the same school entry cut-off date in place throughout her 12 years of school.

[12] These are the states where cut-off dates have been used as a rule to determine school entry eligibility over a sustained period of time and that remained unchanged for a time span of at least 10 years.

[13] The age limit of eligible participants is substantially smaller in Queensland and Tasmania compared to Victoria and Western Australia since it was much later that the school entry cut-off dates became a strong norm in the former two states to determine school entry eligibility.

[14] See the full distribution of answers in Figure D.1 in the appendix.

[15] Results including these participants are provided in Appendix C.4.

participants were quite confident about their relative age in school with three-quarters of them having chosen a value of at least 8 on the response scale.

In Table 2 we present sociodemographic characteristics of our participant pool. A majority, 64%, are women, which is typical of participant pools recruited online (Paolacci et al., 2015).[16] However, we observe no significant difference in the gender ratio between participants born on each side of the cut-off date (p=0.48). Forty-seven percent of our participants declared to be employed full time, 24% are employed part time, 6% are retired, 5% are undertaking education or training and 18% are unemployed.[17] With respect to marital status, 10% of our participants are divorced, 55% are married and 35% are single. With regard to education, the highest attainment for 25% of our participants is high school. Thirty-nine percent have an intermediate professional degree (Certificate, Diploma) and 36% have at least a bachelor degree.[18] In terms of geographic distribution, 16% of our participants went to school in Queensland, 3% in Tasmania, 55% in Victoria and 26% in Western Australia. For all variables we observe no differences at conventional levels between participants born before and after the cut-off date (p>0.05 in all cases). Finally, the average age of our participants is 29 in Queensland, 32 in Tasmania, 44 in Victoria and 40 in Western Australia.[19]

[16]For instance, on Amazon Mechanical Turk, 65% of US participants are women (Paolacci et al., 2015).

[17]While the percentage of unemployed largely exceeds the unemployment rate in Australia (around 5.5%), this statistic is likely to be overstated as many participants answering 'unemployed' may be out of the labour force, meaning that they should not be considered unemployed according to the official unemployment statistics.

[18]Our participants have higher education than the general Australian population, a common characteristic of participants recruited online (Paolacci et al., 2015).

[19]In order to test the sensitivity of our results to differences in the age span of our participants across the different states, we reproduce the regression analysis on the subsample of participants (N=364) for which the age range overlap across the different states (28 to 36 years old) (see Appendix C.2). We find that overall our conclusions are unaffected by this restriction.

Table 2: Descriptive statistics of the participant pool

	All		Born before/after the cut-off date				
			Before		After		Difference
	N	%	N	%	N	%	p-value
Gender							
Female	643	64	310	65	333	63	0.48
Male	364	36	167	35	197	37	
Job status							
Full-time job	476	47	223	47	253	48	0.76
Part-time job	239	24	112	23	127	24	0.86
Retired	57	6	34	7	23	4	0.06
In education or training	51	5	28	6	23	4	0.27
Unemployed	184	18	80	17	104	20	0.24
Marital status							
Divorced	96	10	47	10	49	9	0.74
Married	557	55	266	56	291	55	0.78
Single	349	35	161	34	188	35	0.57
Widowed	5	0	3	1	2	0	0.57
Education							
High school	252	25	131	27	121	23	0.09
Certificate I/II	43	4	15	3	28	5	0.09
Certificate III/IV	202	20	103	22	99	19	0.25
Advanced diploma/Diploma	150	15	66	14	84	16	0.37
Bachelor degree or above	360	36	162	34	198	37	0.26
State							
Queensland	165	16	69	14	96	18	0.12
Tasmania	30	3	11	2	19	4	0.23
Victoria	555	55	268	56	287	54	0.52
Western Australia	257	26	129	27	128	24	0.29
N	1007	100	477	100	530	100	

Note: Sociodemographic statistics of our participant pool. We report the data for the whole sample, and separately for participants born before and after the school entry cut-off date in their state. We also report the p-value of a test of equality of proportions between the subsample of participants born before and those born after the school entry cut-off date.

2.3 Procedures

Participants performed a series of tasks online on a website specifically programmed for this study.[20] They accessed the website through a personalised link sent by ORU. They were first invited to answer a sociodemographic survey including questions on their date of

[20]We follow the literature on the elicitation of individual economic preferences in laboratory experiments (see Bardsley et al. (2010) for a discussion).

birth and the state(s) in which they attended school. Their answers were used to identify individuals' assigned relative age and eligibility to take part in the study.[21] Participants were also asked whether they were among the oldest or the youngest in the classroom during primary school, which was used to define their actual relative age, and how sure they were about their answer. In addition, their responses on having repeated or skipped any grade were used to infer about the reasons for potential discrepancies between the assigned relative age and the actual relative age.

After these initial questions, participants proceeded with the online tasks. Overall the tasks took approximately 30 minutes to complete. Prior to each task, participants went through an instruction video using pictures and voice recording to explain the task.[22] Participants could go through the video as many times as they wanted until they decided to proceed and start the task. Most tasks were incentivised with monetary payments. After completing all tasks, participants were informed about their final payment, consisting of a 3 dollar fixed participation fee plus their earnings in one randomly chosen incentivised task. They received their payment (average earnings were 14 dollars) in the form of a voucher which can be used in major supermarket chains or department stores in Australia.

2.4 Behavioural measures

Self-confidence and competitiveness

We implement the widely used experiment by Niederle and Vesterlund (2007) to study confidence and competitiveness. Participants are presented with a series of real effort tasks: finding numbers adding to 10 in a matrix containing 12 numbers with two decimal digits (Faravelli et al., 2015). Self-confidence and competitiveness are measured as follows. **Self-confidence**: difference between the participants' actual rank (among other participants) and their guess of their rank. This method gives us a measure of over-placement of one's

[21] Participants eligible to take part in the study proceeded to the tasks, while the others were informed that they were not eligible to take part in the study.

[22] Full instructions are provided in the supplementary material.

performance relative to others.[23] **Competitiveness with submitting past performance to a tournament**: participants choose for their *past* performance to be rewarded in a piece rate or in a competitive manner (top performers get a higher reward while others get nothing). **Competitiveness with performing in a tournament**: participants choose for their *next* performance to be rewarded in a piece rate or in a competitive scheme.[24] By giving participants the option to enter a tournament in these two different situations, we are able to assess whether participants have a pure preference for competition. In that case, they would choose to perform in a tournament more often than to submit the past performance to a tournament.

Risk attitude

We use two standard incentive compatible methods to elicit risk attitude. First, we use a choice list task where participants opt between safe versus risky lotteries (Holt and Laury, 2002). In the first list, participants face a risk prospect, whereas in the second list they face an ambiguity prospect (the difference being that in the latter the exact degree of risk faced is unknown).[25] Second, we elicit risk attitude with the Balloon Analogue Risk Task (BART), where participants can pump a balloon which may blow up at any moment in time. The rewards increase with the size of the balloon and vanish if the balloon blows up. The BART has the advantage of being very easy to understand relative to the lottery choice list task (Lejuez et al., 2002, 2007).[26]

In addition, we use self-assessed risk attitude measures through standard survey questions as in Dohmen et al. (2011).[27] Survey questions have both the advantage of being very easy

[23] Moore and Healy (See 2008, for a discussion on different measures of overconfidence).

[24] A detailed description of the task is provided in Appendix F.

[25] Our experimental software allowed one single switch, i.e. it did not allow inconsistent choices (Andersen et al., 2006). At the end of the experiment, the computer randomly draws one out of the 20 rows in each list and the participant's choice in the selected row is considered to determine her earnings in the task.

[26] We describe the risk elicitation procedures in detail in Appendix F.

[27] The questions are formulated as follows: 'People can behave differently in different situations. Please rate your willingness to take risk in the following areas' *(driving, financial matters, leisure and sport, in your occupation, with your health)*. The answer scale ranges from 0 to 10.

to understand and allowing to assess risk attitude in a range of daily life domains.

Trusting attitude

We measure trusting attitude with the standard trust question from the World Values Surveys (Knack and Keefer, 1997). It is formulated as follows *'Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?'*. Participants are asked to indicate the extent to which they agree with the statement on a scale from 0 (strongly disagree) to 6 (strongly agree).[28]

Time preference

We measure time preference with ordered choice lists (Sutter et al., 2013). Participants are presented lists with twenty rows and need to decide in each row whether they prefer a smaller amount of money paid at an earlier date or a larger amount paid at a later date. The amount paid at the earlier date is fixed whereas the amount paid at a later date increases by 50 cents in every row. Participants see two lists in successive order. In the first list, in each row they opt between 10.50 dollars now and an amount paid in five months, ranging from 10.50 to 20 dollars. The only difference in the second list is that both possible payment dates are delayed by one month.[29] For each list we construct a measure of future equivalent (negatively associated with patience) based on the first row in which the participant opts for the later payment over the earlier payment.[30] One of the participant's choices, selected randomly, was paid on the chosen date.

[28]The seven answer options were 'Strongly disagree', 'Mostly disagree', 'Somewhat disagree', 'Neither agree nor disagree', 'Somewhat agree', 'Mostly agree', 'Strongly agree'.

[29]Footnote 24 also applies in this task.

[30]The future equivalent measure is given by the mid-point between the later payment in the row where the participant first prefers the later payment to the earlier payment and the later payment offered in the previous row.

2.5 Hypotheses

Among children, being relatively old at school has been found to positively influence important behavioural traits, in particular self-confidence (e.g Crawford et al., 2014; Thompson et al., 2004; Page et al., 2017) and competitiveness (Page et al., 2017). In light of existing research findings, we make the following hypotheses about adults who were relatively old at school:

Hypothesis 1 (Confidence)**.** *Participants who were relatively old are more self-confident than those relatively young.*

Hypothesis 2 (Competitiveness)**.** *Participants who were relatively old are more competitive than those relatively young.*

Hypotheses 1 and 2 are motivated by past research on this possibility, including our previous research on school aged children finding that relatively old children, in particular boys, are more willing to compete and overestimate their ability relative to their peers. Our conjecture is that this effect observed at school could be long lasting.

Hypothesis 3 (Risk)**.** *Participants who were relatively old are more risk seeking than those relatively young.*

Hypothesis 4 (Trust)**.** *Participants who were relatively old are more trusting than those relatively young.*

Hypothesis 5 (Patience)**.** *Participants who were relatively old are more patient than those relatively young.*

Hypotheses 3, 5 and 4 are exploratory. Our choice of investigating risk attitude and trust is motivated by the element of confidence as more confident people are possibly more willing to take risk, including the risk of trusting others. We also included patience as it is considered a critical trait for economic success (Castillo et al., 2011).

Hypothesis 6 (Gender)**.** *On the different behavioural traits we elicit, the effect of relative age is greater for men than for women.*

Hypothesis 6 is motivated by our past research which found a larger effect of relative age on competitiveness for boys than girls at school (Page et al., 2017). Moreover, relative age will lead to differences in height during school age which may matter more for boys than girls due to the more physical nature of intra-gender competition for school age boys (Persico et al., 2004). For that reason, we present all our results for women and men separately and test for gender differences.

3 Results

We present the estimation results for the effect of relative age on behavioural traits. We follow Bedard and Dhuey (2006) and use an IV regression where the participants' assigned relative age is used as an instrument to predict the actual relative age in school. The assigned relative age is a binary variable, which takes on the value 1 if the participant was born after the cut-off date and 0 if she was born before the cut-off date.[31] The actual relative age is also a binary variable, equal to 1 if the participant was among the oldest in her school cohort and 0 and she was among the youngest.[32] This IV regression gives an estimation of the local average treatment effect of having been relatively old in school on the sample of individuals who complied with the cut-off date, under the condition that the monotonicity assumption is satisfied. This condition assumes having no defiers (Fiorini and Stevens, 2014). In our case, the defiers would be individuals whose school entry would have been delayed if they were born before the cut-off date, but who would have been early entrants if they were born after the cut-off date. While parents who opt for delaying entry typically want to ensure the child is mature enough to start school, those who enrol their child in school before eligibility

[31]In Appendix D we consider a continuous measure of assigned relative age (given by the exact date of birth) and show graphically the relation between each of our outcome variables and this continuous measure of assigned relative age.

[32]We report the first stage of the IV regression in Appendix A.

may deem the child sufficiently mature or be motivated by other factors, such as wanting a formal school environment or exposure to interaction with teachers and other children as early as possible, or saving on childcare costs. It is very unlikely that the same parents would delay the school entry of their child if the child becomes eligible to start school before the cut-off date, and would enrol their child in school early, if the child becomes eligible after the cut-off date. For this reason, we can reasonably assume absence of defiers and, therefore, that monotonicity violation is unlikely to occur.[33]

The second stage equation of the IV estimation is as follows:

$$(1) \quad y_{ij} = \alpha_0 + \alpha_1 Rel\,Old_i + \alpha_2 X_i + \upsilon_{ij}$$

y_{ij} is the measure for individual i of each behavioural trait j: self-confidence, competitiveness, lab elicited risk attitude, self-reported risk attitude in real life domains, trust and time preference. $Rel\,Old$ is our main explanatory variable of interest, which takes on the value 1 if the participant was relatively old in her school cohort and 0 otherwise, and is instrumented by the assigned relative age. X is a vector of control variables (age, gender and state in which she went to school).[34]

In order to investigate potential gender differences in the effect of relative age on behavioural traits (Hypothesis 6), we consider a second model obtained by adding to equation

[33]Our sample includes compliers, that is, individuals whose actual relative age is determined by their date of birth. It also includes non-compliers, who can either be always takers or never takers. The always (never) takers are individuals who would always have been relatively old (young) irrespective of whether they were born before or after the cut-off date. However, these non-compliers are not taken into account in the estimation of the local average treatment effect, since their actual relative age is not affected by the instrument. We thank Katrien Stevens for her insightful comments on this aspect of our identification strategy.

[34]Our results are robust to using a specification with additional control variables, including employment and marriage status, education and BMI. Controlling for these factors may increase the precision of the coefficient estimate of our main variable of interest. At the same time there is a risk of endogeneity with these additional control variables being influenced by the participant's behavioural traits (reverse causality). For that reason, we only use them as robustness checks (results are available from the authors upon request).

(1) an interaction between the relative age and gender. The model is as follows:

$$(2) \quad y_{ij} = \beta_0 + \beta_1 Rel\,Old_i + \beta_2 Rel\,Old_i \cdot Male + \beta_3 X_i + \varepsilon_{ij}$$

When presenting our results we report the estimates of $\boldsymbol{Rel\,Old}$ from equation (1) (α_1), the estimates of $\boldsymbol{Rel\,Old}$ for women and men (β_1 and $\beta_1 + \beta_2$, respectively), as well as the difference between the two (β_2) from equation (2). The standard errors of $\boldsymbol{Rel\,Old}$ for women and the interaction term are obtained directly from the estimation of equation (2); the standard errors of $\boldsymbol{Rel\,Old}$ for men are obtained by estimating a modified version of equation (2), where the gender dummy is *Female*. For simplicity the estimates for age and gender are omitted from the results tables and we briefly describe their statistical significance and magnitude when discussing our results.

We conduct more than one test for the effect of relative age on some behavioural traits increasing the chances of a type I error, that is, concluding in favour of a statistically significant effect of relative age in the absence of a true effect. This is the case for self-confidence in one's rank, risk attitude elicited with lab methods, self-reported risk attitude in life domains and time preference, since for each of these behavioural traits we have at least two outcome measures. We use two standard methods allowing us to correct for the potential multiple inference problem. First, for each behavioural trait we pool the multiple measures into a standardized summary index and estimate the effect of relative age on this index.[35] Second, we calculate the family-wise error rate (FWER) p-values which are adjusted upwards to reduce the probability of a false rejection (reported in Appendix C.1).[36] Our results

[35]The summary index is a weighted mean of all standardized measures for the same behavioural trait and is obtained following Anderson (2008). It has the advantage of being robust to overtesting because each index represents a single test. Moreover, it may be more powerful than individual outcome tests, since multiple outcomes that approach marginal significance may aggregate into a single index that attains statistical significance (Anderson, 2008). The procedure used to calculate the standardized summary index is described in Appendix E.

[36]The family-wise error rate (FWER) p-values are obtained based on 10,000 iterations of the free step-down resampling method of Westfall and Young (1993). See Anderson (2008), Finkelstein et al. (2012) and Jones et al. (2018) for more detailed descriptions and applications of this method.

are generally consistent across the different methods (standard p-value approach, summary standardized index test and FWER p-value approach.)

Throughout the presentation of our results, we also discuss their stability in two robustness checks, reported in Appendix C.2 and C.3. In our first check, we restrict the sample to participants in an age range which overlaps across the four states (28 to 36 years old) (N=364). These participants are young adults, allowing us to gain insights on whether the long-lasting effect of relative age is larger among younger than older adults. In our second robustness check, we restrict the sample to participants born at most one month before or one month after the cut-off date (N=527). This allows us to gain insights on whether our results are sensitive to the choice of date of birth window around the cut-off date.

3.1 Self-confidence and competitiveness

Our measure of self-confidence, given by the difference between a participant's actual rank (in percentile) and her guessed rank, indicates overconfidence for positive values and underconfidence for negative values.[37]

We show in Figure 1 the average level of self-confidence of our participants by splitting the sample in two groups - those born before and those born after the school entry cut-off date. When looking at self-confidence in the piece rate stage of the effort task (top half of Figure 1), it appears that participants born before the cut-off date are on average underconfident, whereas those born after the cut-off date are on average overconfident. Being born after the cut-off date is associated with greater self-confidence for both men and women. With respect to the tournament stage (bottom half of Figure 1), we find a similar pattern, which is more pronounced for women than for men.

[37]The average value of self-confidence in the piece rate stage is -1 (1 for men and -2 for women). In the competitive stage, the average value is 1 (2 for men and 1 for women). We did not observe differences in task performance according to relative age (see Appendix B).

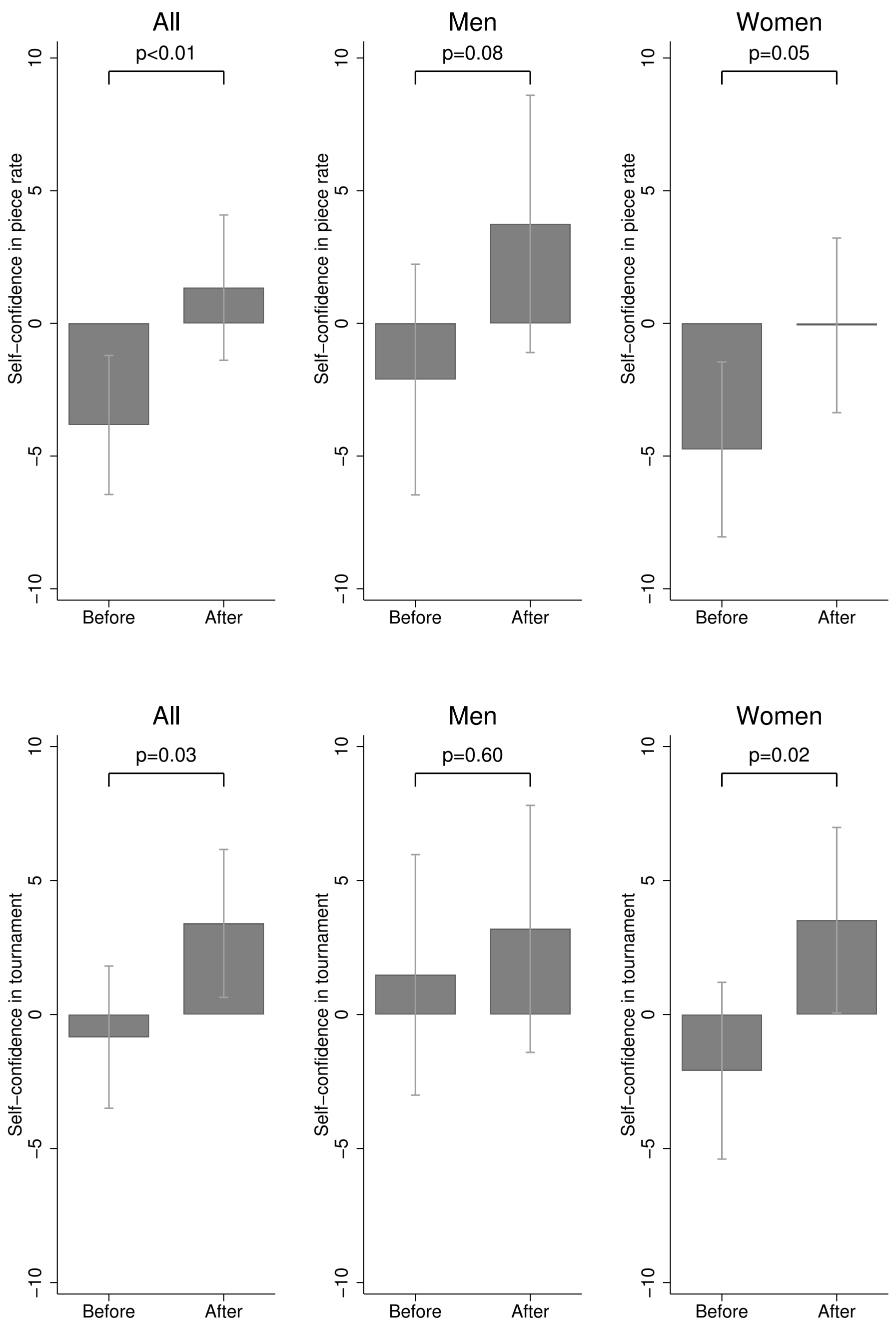

Figure 1: Self-confidence: in piece rate (top), in tournament (bottom). *Note:* On the *x*-axis, 'Before' refers to being born before the cut-off date (assigned to be relatively young) and 'After' refers to being born after the cut-off date (assigned to be relatively old).

We report in Table 3 the IV estimates for the effect of relative age on self-confidence. We find that having been relatively old in school increases confidence with respect to one's rank by about 11 percentile points in the piece rate stage (column 1) and 9 percentile points in the tournament stage (column 2). These results are statistically significant at 1 and 5 percent level respectively. Looking at the results by gender, we observe that the effect is larger for men in the piece rate stage and smaller in the tournament stage but the gender differences are not statistically significant ($p \approx 0.5$). Since we consider two measures of self-confidence, we also estimate the effect of relative age on a standardized index, indicating that having been relatively old is associated with a 0.32 standard deviation increase in self-confidence (significant at the 1 percent level). The family-wise error rate p-values also support a positive effect of relative age on self-confidence (FWER $p<0.05$) and no gender difference in the effect of relative age on self-confidence (see Appendix C.1). Moreover, when considering the subsample of of younger participants with overlapping age range across the four states and the subsample of participants born within a one-month window around the cut-off date, we also find that relative age positively influences self-confidence (see Appendix C.2 and C.3). In both cases, the effects are larger in magnitude and statistical significance than the ones reported in Table 3.

Our measure of self-confidence has potentially some boundary limitation: top performers cannot be identified as overconfident while the weakest performers are more likely to be identified as overconfident. In order to check the extent to which this influences our results, we compare the performance of participants born after and before the cut-off date (see Appendix B). Overall, we observe no statistical differences, even when comparing their performance distributions (see Table B.1 and Figure B.1). We also ran our analysis excluding the participants with a score of zero in the task (9% of the sample in the piece rate stage, and 5% of the sample in the tournament stage) as well as the participants at the top of the performance distribution (with a score larger than 15, accounting for 3% of the sample in both the piece rate and tournament stage). In both cases, we find that excluding these participants does not affect our conclusion on the effect of relative age on self-confidence.

With regards to the effect of our other independent variables on self-confidence, gender and age (not reported in the table), there is weak evidence that men are more self-confident than women and no evidence of age effects.

In summary, our results indicate that having been relatively old in school has a long-term effect on self-confidence, in line with Hypothesis 1. This effect seems larger on a subsample of younger participants compared to the whole sample, indicating that it may fade among older adults. In contrast with Hypothesis 6, the effect of relative age on self-confidence does not differ between men and women.

Result 1 (Confidence)**.** *Having been relatively old in school is associated with higher confidence in one's performance.*

Table 3: Effect of relative age on self-confidence

	Self-confidence		
	Piece rate (1)	Tournament (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	10.908***	8.924**	0.320***
	(4.094)	(4.132)	(0.120)
Equation (2)			
Rel Old			
Women $[\beta_1]$	8.886**	10.555**	0.314**
	(4.474)	(4.613)	(0.132)
Men $[\beta_1+\beta_2]$	16.124*	4.720	0.338
	(9.094)	(8.735)	(0.260)
Difference $[\beta_2]$	7.238	-5.835	0.024
	(10.128)	(9.871)	(0.292)
N	1007	1007	1007
Mean	-1.105	1.390	0.000
Std. Dev.	30.807	31.073	0.902

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state. We report the mean and standard deviation of the dependent variables at the bottom of the table.

We now discuss the results on the effect of relative age on competitiveness, reported in Table 4.[38] Participants had two opportunities to opt for competition. First they could opt for the tournament payment scheme and then perform the effort task; second, they could opt for the tournament payment scheme for their past performance (in the first [piece rate] stage of the task).[39] Following Niederle and Vesterlund (2007) we interpret submitting the past

[38]Note that we do not report the FWER p-values for the estimations in Table 4 in the appendix. The reason is that in each column, we are estimating models which have a different set of independent variables (as indicated at the bottom of the table). The calculation of FWER *p*-values requires the same set of independent variables in all regression models.

[39]The proportion of participants choosing the competitive payment scheme for their next performance is 25% (19% and 36% for women and men respectively). Twenty-four percent of the participants submitted their past performance to the competitive payment scheme. The numbers were 20% among women and 31% among men.

performance to a tournament payment scheme as potentially influenced by confidence and risk attitude and the choice of performing under a tournament payment scheme as potentially influenced by the same variables plus a pure preference for competition itself.

We find that participants who were relatively old in school are more likely to submit their past performance to the tournament payment scheme by 12 percentage points ($p<0.05$, column 1).[40] The point estimates are very similar in magnitude for men and women and they are not statistically different ($p>0.1$). When controlling for participants' self-confidence (rank guessed for the piece rate stage), the effect of relative age is halved and becomes statistically non-significant ($p>0.1$, column 2). We show the results of robustness checks in Appendix, looking at these effects on the subsample of participants with an overlapping age range in all states (Table C.6) and on the subsample of participants born within one month of the cut-off date (Table C.11). The results of these analyses are directionally similar, but we note that the coefficients estimated for the effect of relative age on the submission to the tournament tend to be larger and more significant in the former subsample, and smaller and not significant in the latter. Overall these results are suggestive of self-confidence at least partly accounting for the decision by the relatively old to submit the past performance to a tournament, but further research is needed to confirm an important role of confidence in explaining competitiveness among the relatively old.

In columns 3 and 4 we present the estimation results for the choice to perform in a tournament. We do not observe any significant effect of relative age. It is true overall and also when considering the effect for men and women (column 3). Controlling for self-confidence and the choice to submit the past performance to a tournament gives similar

[40] We report the estimates obtained with a linear model instead of a probit model even though our dependent variable is binary, since the probit model does not allow for an interpretation of the estimates for interaction terms (in our case, the interaction between relative age and gender). Neither the magnitude nor the statistical significance of the marginal effects obtained with the IV probit model differ from the coefficient estimates obtained with the IV linear model reported in Table 4.

results (column 4).[41] Overall, our robustness checks reported in Appendix C also support the absence of a systematic long-lasting effect of relative age on the preference to perform in a competitive environment (Hypothesis 2).

Finally, in both choice situations men are significantly more likely to enter a tournament than women (by 0.07 and 0.13 percentage points, respectively). There is also weak evidence that age negatively affects the decision to perform in a tournament.

Result 2 (Competitiveness)**.** *Having been relatively old in school is associated with higher competitiveness when offered the possibility to enter the past performance into a tournament. Nonetheless, it is not associated with being more competitive when having to choose whether to perform in a tournament.*

[41] The smaller effect size of relative age on opting for performing in a tournament compared to submission of past performance to a tournament payment scheme could suggest that having been among the oldest in one's peers group has a negative effect on the pure preference for competition which is assumed to only play a role when one opts for performing in a tournament. However, the difference between the coefficients for the relative age in column 1 and column 3 is not statistically significant (a test of equality of the coefficients for the relative age in column 1 and column 3 in Table 4 obtained by bootstrapping the sample – 500 replications – yields a p-value of 0.15). It is therefore impossible to make inferences based on this difference.

Table 4: Effect of relative age on competitiveness

	Submit to tournament		Perform in tournament	
	(1)	(2)	(3)	(4)
Equation (1)				
Rel Old $[\alpha_1]$	0.122**	0.070	0.036	-0.028
	(0.055)	(0.051)	(0.055)	(0.049)
Equation (2)				
Rel Old				
Women $[\beta_1]$	0.129**	0.083	0.092	0.018
	(0.059)	(0.055)	(0.057)	(0.051)
Men $[\beta_1 + \beta_2]$	0.104	0.036	-0.111	-0.149
	(0.125)	(0.118)	(0.133)	(0.116)
Difference $[\beta_2]$	-0.025	-0.047	-0.203	-0.167
	(0.138)	(0.131)	(0.144)	(0.128)
Controls				
Piece rate performance	✓	✓		
Guessed piece rate rank		✓		
Tournament performance			✓	✓
Piece rate - tournament performance			✓	✓
Guessed tournament rank				✓
Piece rate submitted to tournament				✓
N	1007	1007	1007	1007
Mean	0.238		0.254	
Std. Dev.	0.426		0.436	

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state. We report the mean and standard deviation of the dependent variables at the bottom of the table.

3.2 Risk attitude

We present in Table 5 the IV estimation results obtained with our lab elicited measures of risk attitude: choice lists (lottery) and BART. The results obtained using the risk measure from the lottery task suggest that overall, relative age does not impact risk attitude (p>0.1, column 1).[42] When looking at the results for men and women separately, the coefficient for the relative age effect is larger for women than for men. This difference is significant at the 5% level when using unadjusted p-values and at the 10% when using the FWER p-values (see Appendix C.1). In regard to the preference over ambiguity, we find no effect of relative age overall (p>0.1, column 2), and no difference between men and women (p>0.1, column 2).[43] These results are generally consistent across our different robustness checks reported in the Appendix.

Looking at the BART, we follow Lejuez et al. (2002) and use the total number of pumps in the balloon as our primary measure of propensity to take risk task.[44] We observe that the total number of pumps by participants who were relatively old in school is lower by about 15 units compared to the relatively young (column 3). The effect is statistically significant at the 10 percent threshold and not statistically significant when using the FWER p-value (see Table C.2 in Appendix). The point estimate of the effect is larger for men (28 versus 9 for women) but the difference, despite its magnitude, is not statistically different. Our ex-post power analysis indicates that, with our sample size, the minimal detectable effect on this measure is -21. Our sample size is not large enough to detect effects smaller than a third of a standard deviation (s.d. 57). The absence of significance in the effect is therefore not an indication that relative age has necessarily no or a negligible effect on risk taking in the BART. To further explore the possibility of a negative effect of the relative age on risk taking in the BART, we analyse the results on the subsample of participants with overlapping age range across all states (see Table C.7 in Appendix) and on the subsample of participants born within a one-month window of the cut-off date (see Table C.12 in Appendix). In the former subsample, the results are very similar the ones described above. When restricting

[42] The risk seeking measure from the lottery task takes values between 0 and 1, with 0 indicating extreme risk aversion and 1 extreme risk love. The average value of the risk seeking variable is 0.5 for the whole sample, 0.49 and 0.52 for female and male participants respectively.

[43] The ambiguity seeking variable takes values between -1 (extreme ambiguity aversion) and 1 (extreme ambiguity love). The average ambiguity aversion value is -0.06 for both male and female participants.

[44] The sample average is 103 pumps; 104 for women and 101 for men. The BART risk seeking variable is the total number of clicks over the balloon numbers 2 to 5 (the first balloon is excluded as learning is likely to take place).

the sample to participants born within one month just before or after the cut-off date, we find that the effect of relative age on the total number of pumps is much larger and statistically significant at conventional levels. These results suggest that, even though we cannot draw a firm conclusion given our results, relative age may have a negative effect on risk taking as measured by the BART.

When considering a standardized summary index of lab elicited risk attitude based on all three tasks, we find no effect of relative age on risk attitude (column 4). We also find no evidence of gender differences in risk attitude. Age does not affect risk taking in the lottery, but negatively affects risk taking in the BART and positively affects ambiguity seeking (both significant at the 5% level).

In summary, our results on the effect of relative age on lab elicited risk preference measures provide no support for Hypothesis 3 on the effect of relative age at school on risk attitude. On the contrary, we find suggestive evidence of a potential negative effect of relative age on risk taking measured with the BART.

Table 5: Effect of relative age on risk and ambiguity seeking, and trust

	Lottery		BART	Std Index	Trust
	Risk	Ambiguity			
	(1)	(2)	(3)	(4)	(5)
Equation (1)					
Rel Old [α_1]	0.022	0.046	-14.543*	0.034	0.355**
	(0.037)	(0.045)	(7.649)	(0.071)	(0.171)
Equation (2)					
Rel Old					
Women [β_1]	0.073*	0.020	-9.464	0.087	0.406**
	(0.042)	(0.049)	(8.480)	(0.079)	(0.192)
Men [$\beta_1 + \beta_2$]	-0.109	0.114	-27.639*	-0.103	0.223
	(0.077)	(0.094)	(16.458)	(0.148)	(0.352)
Difference [β_2]	-0.183**	0.095	-18.174	-0.191	-0.183
	(0.088)	(0.105)	(18.474)	(0.166)	(0.398)
N	1007	1007	1007	1007	1007
Mean	0.478	-0.061	102.852	0.000	3.396
Std. Dev.	0.281	0.326	57.361	0.529	1.268

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state. We report the mean and standard deviation of the dependent variables at the bottom of the table.

In addition to elicitation of risk attitude through choices in a controlled setting, participants indicated their tendency to take risk in general and in specific domains - car driving, financial matters, health, leisure and occupation - on a 11-point Likert scale. A larger value indicates higher tolerance to risk. We show in Figure 2 the average level of self-assessed risk taking for participants born before and those born after the cut-off date. There is a general pattern of higher tolerance to risk for participants born after the cut-off date (assigned to be relatively old) compared to those born before the cut-off date (assigned to be relatively young). This difference is statistically significant at conventional levels in all five specific domains, but not in general risk taking.

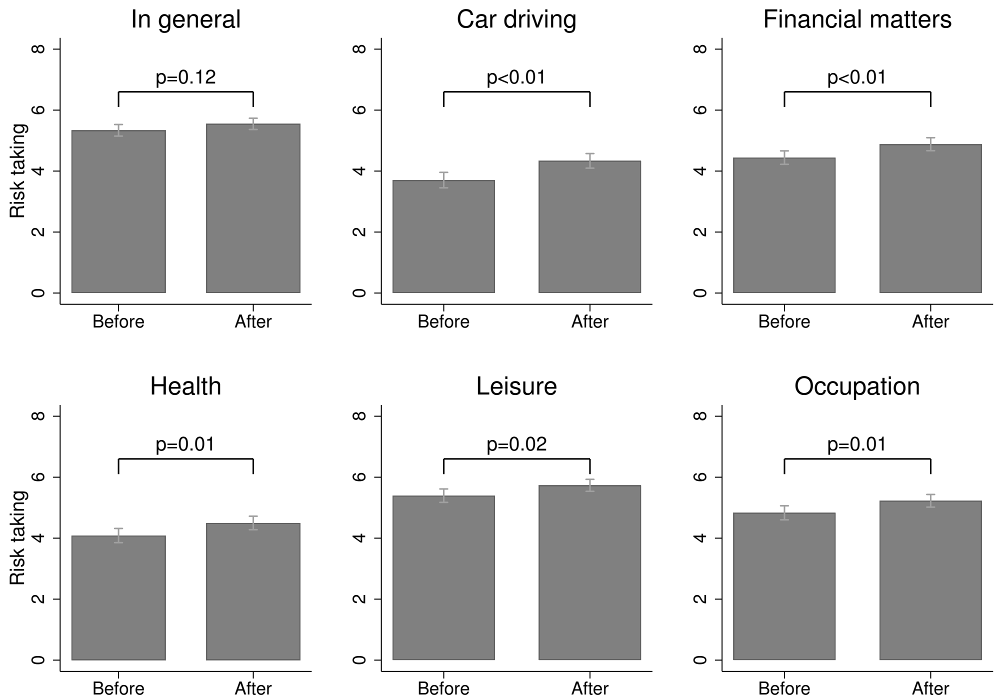

Figure 2: Self-assessed risk tolerance in real life situations. *Note:* On the *x*-axis, 'Before' refers to being born before the cut-off date (assigned to be relatively young) and 'After' refers to being born after the cut-off date (assigned to be relatively old).

In Table C.3 we present the IV estimation results for the effect of relative age on risk taking in the different domains. The results are in line with the descriptive observation and provide support for Hypothesis 3. Relative age has a positive and statistically significant effect on the self-assessed likelihood to take risk in car driving (at the 1% level), financial matters and health (at the 5% level). Overall, we find no indication of gender difference in the effect of relative age on these domains (p>0.1 in all cases), providing no support for Hypothesis 6. The FWER p-values reported in Appendix C.1 are smaller than 5 percent for risk taking in car driving only. The effect of relative age on the standardized index indicates that being relatively old leads to a 0.24 standard deviation increase in risk taking in real life situations, statistically significant at the 5 percent level. Our results are generally supported by our robustness checks on the two subsamples reported in the Appendix.

Our results also indicate that age negatively affects risk taking in self-declared measures. The effect sizes of age across the different domains are in the range of [-0.06, -0.04] and always significant at the 1% level. Moreover, men declare being more risk taking than women in all domains. The effects are sizeable and statistically significant at conventional levels.

Table 6: Effect of relative age on risk seeking behaviour in real life situations

	In general (1)	Driving (2)	Finance (3)	Health (4)	Leisure (5)	Occupation (6)	Std Index (7)
Equation (1)							
Rel Old $[\alpha_1]$	0.256	1.049^{***}	0.705^{**}	0.693^{**}	0.456	0.618^{*}	0.241^{**}
	(0.279)	(0.368)	(0.323)	(0.341)	(0.307)	(0.328)	(0.100)
Equation (2)							
Rel Old							
Women $[\beta_1]$	0.325	1.039^{**}	0.793^{**}	0.845^{**}	0.499	0.610^{*}	0.266^{**}
	(0.304)	(0.409)	(0.363)	(0.385)	(0.348)	(0.367)	(0.113)
Men $[\beta_1 + \beta_2]$	0.078	1.073	0.478	0.300	0.345	0.638	0.177
	(0.604)	(0.775)	(0.662)	(0.703)	(0.620)	(0.689)	(0.204)
Difference $[\beta_2]$	-0.247	0.033	-0.314	-0.544	-0.154	0.028	-0.089
	(0.672)	(0.872)	(0.750)	(0.800)	(0.706)	(0.778)	(0.232)
N	1007	1007	1007	1007	1007	1007	1007
Mean	5.449	4.037	4.673	4.304	5.573	5.040	0.000
Std. Dev.	2.143	2.829	2.485	2.597	2.374	2.497	0.780

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state. We report the mean and standard deviation of the dependent variables at the bottom of the table.

Our results suggest that relative age is a relevant factor in shaping risk attitude in real life situations, with participants who were relatively old in school declaring higher tolerance to risk. A possible reason for the difference in results obtained across different measures of risk attitude is that risk aversion in small experimental tasks may imperfectly predict real life behaviour (Verschoor et al., 2016). Another possible reason for this difference could be that the relative age differences in real life risk taking are not driven by pure risk preferences (measured in our experimental tasks). Rather, differences in risk taking in real life could be driven by self-confidence. Self-confidence cannot play a role in our experimental tasks as participants have no control over the outcome. The probability of an adverse event is determined by the experiment and a random draw from the computer determines the outcome. In contrast, in real life situations, skill is likely to influence both the probability of an adverse event and the outcome. It is possible that the higher self-confidence exhibited by participants who were relatively old can lead to greater risk taking in real life situations where skill influences outcomes. They may overestimate their chance of success when taking risk since they are more confident about their skills (Krueger and Dickson, 1994).

Result 3 (Risk attitude)**.** *Having been relatively old in school is associated with higher propensity to take risk in real life situations, but not in lab-elicited measures of risk preferences.*

3.3 Trusting attitude

Participants were asked to indicate on a 7-point scale the extent to which they think other people can be trusted. We present the IV estimation results of the effect of relative age on this measure of trust in column 5 of Table 5. We find that relative age has a positive impact on trust. Participants who were relatively old on average trust other people more than participants who were relatively young (by approximately 0.4 units significant at the 5 percent level). In our first robustness check, using a subsample of participants with overlapping age across the four states, the effect of relative age on trust is larger compared to the effect on the full sample and remains statistically significant (see Table C.7 in Appendix). In contrast, in our second robustness check, using a smaller window around the cut-off, the effect is smaller than the effect on the full sample and loses significance (see Table C.12 in Appendix). Finally, we find no evidence that age or gender influence trusting attitude.

Overall, our results tend to support Hypothesis 4, but it should be noted that the relative age effect is not significant in one of our two robustness checks. We find no support for Hypothesis 6 as the gender difference in the effect of relative age on trusting attitude is not statistically significant (p>0.1).

Result 4 (Trust)**.** *Having been relatively old in school is likely to lead to higher trusting attitude, but our results do not allow for a firm conclusion.*

3.4 Time preference

Our measure of time preference is obtained with two choice lists. In the first list, participants choose between \$10.50 now and an equal or higher amount with a delayed payment time of five months. The amount to be paid in five months starts at \$10.50 in the first row, increasing by 50 cents in each row. In the second list both payments are delayed. The earlier payment is in one month and the later payment in six months. We calculate *future equivalents* (FE), as in Sutter et al. (2013), based on the row in which the participant switches from preferring the earlier payment to preferring the later payment.[45] The later a participant opts for the (larger) later payment instead of the earlier payment, the larger is the FE, indicating lower patience. We present the IV estimation results for the effect of relative age on the FE for each list and the standardized index in Table C.9. In all our main specifications and robustness checks the estimates for relative age are consistently negative which would suggest that having been relatively old increases patience. However, they are never statistically different from zero (p>0.1; FWER p>0.1) providing no support for Hypothesis 5. Finally, we find that age positively affects patience while gender has no significant effect.

Result 5 (Patience)**.** *Having been relatively old in school does not influence patience.*

[45] The FE measure takes values between 10.25 and 20.25.

Table 7: Effect of relative age on time preference (future equivalents)

	Now *vs* 5 months (1)	1 *vs* 6 months (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	-0.033	-0.322	-0.048
	(0.493)	(0.486)	(0.125)
Equation (2)			
Rel Old			
Women $[\beta_1]$	-0.190	-0.389	-0.079
	(0.550)	(0.543)	(0.140)
Men $[\beta_1+\beta_2]$	0.372	-0.149	0.030
	(1.036)	(1.011)	(0.263)
Difference $[\beta_2]$	0.562	0.240	0.109
	(1.168)	(1.143)	(0.296)
N	1007	1007	1007
Mean	16.025	15.631	0.000
Std. Dev.	3.710	3.661	0.944

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state. We report the mean and standard deviation of the dependent variables at the bottom of the table.

4 Discussion

We investigated if being among the oldest versus the youngest at school has long lasting consequences on behavioural traits: self-confidence, competitiveness, tolerance to risk, trusting attitude and patience. We conducted an online experimental survey covering a large sample of Australian adults who were either among the oldest or the youngest in their school cohort. We find that participants who were relatively old in school exhibit higher self-confidence about their performance at an effort task compared to those who were relatively young. They are also more likely to choose to submit their past performance to a tournament instead of being paid in a piece rate. Moreover, they declare being more tolerant to risk in a range of real life situations. Finally, they are likely to be more trusting of other people in social interactions.

Taken together this set of results offers important insights on the long term effects of relative age at school on behavioural traits. While the effect of relative age on a range of educational and professional outcomes is well documented, little is known about the underlying mechanisms driving these differences. Our findings suggest potential psychological pathways for relative age at school to impact people's success in adulthood. We find that people who were relatively old exhibit greater self-confidence, risk tolerance and competitiveness, which tend to be associated with economic success (see, for example, Filippin and Paccagnella, 2012; Buser et al., 2014).

Our results do not point to a positive effect of relative age on risk preferences and preference for competition as such. When looking at laboratory measures, participants who were relatively old at school do not appear to be more risk taking. On one measure (BART), relative age seems to even possibly have a negative effect on the propensity to take risks. A possible explanation for the positive effect of relative age in risk taking in real life situations is that participants who were relatively old at school may take more risk because of greater self-confidence (associated with more optimistic beliefs in chances of success), not because of higher tolerance to risk. Similarly, the choice of submitting one's past performance to a tournament could reflect greater self-confidence (higher expectations in terms of rank).

We conjecture that greater self-confidence is acquired throughout the many years of school where people who were relatively old enjoyed greater success than their peers due to their additional maturity. Being relatively old may confer greater maturity helping students to perform well at school and be confident in their ability to do so when comparing themselves to their peers or through feedback from teachers. It can also help students gain confidence in physical competition in sports.

Interestingly, we did not find noticeable evidence of gender differences in relative age effect. We hypothesised that it would be the case due to the possible role of height and differences in body size in competitions between boys at school. The evidence we find does not provide support for this phenomenon.

Finally, our findings suggest a connection between behavioural traits and professional success. Relative age at school has been found to have a substantial effect on later professional outcomes. Studying the effect of relative age on behavioural traits can help cast a light on the role of these traits in professional success. More generally, the understanding gained from our study can inform policy, for example, related to work environments, in alleviating the disadvantage faced by people who were relatively young at school. It can in particular help inform the design of curriculum and assessment programs to avoid the unintended penalty imposed upon relatively young students who were born before the cut-off date rather than after it.

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Appendix

A IV first stage regression

Table A.1: First stage of IV regression

	Relatively old
Equation (1)	
Predicted Rel Old	0.476***
	(0.028)
F-stat	62.75
Equation (2)	
Predicted Rel Old	
Women	0.534***
	(0.033)
Men	0.373***
	(0.048)
F-stat	57.37
N	1007

Note: *** $p < 0.01$. Robust standard errors in parentheses. Controls for gender, age and state.

B Effect of relative age on performance

Table B.1: Effect of relative age on performance

	Piece rate (1)	Tournament (2)
Equation (1)		
Rel Old $[\alpha_1]$	-0.361	-0.830
	(0.501)	(0.550)
Equation (2)		
Rel Old		
Women $[\beta_1]$	-0.292	-0.457
	(0.510)	(0.579)
Men $[\beta_1 + \beta_2]$	-0.540	-1.791
	(1.202)	(1.257)
Difference $[\beta_2]$	-0.248	-1.335
	(1.300)	(1.377)
N	1007	1007
Mean	5.417	7.078
Std. Dev.	3.864	4.190

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state. We report the mean and standard deviation of the dependent variables at the bottom of the table.

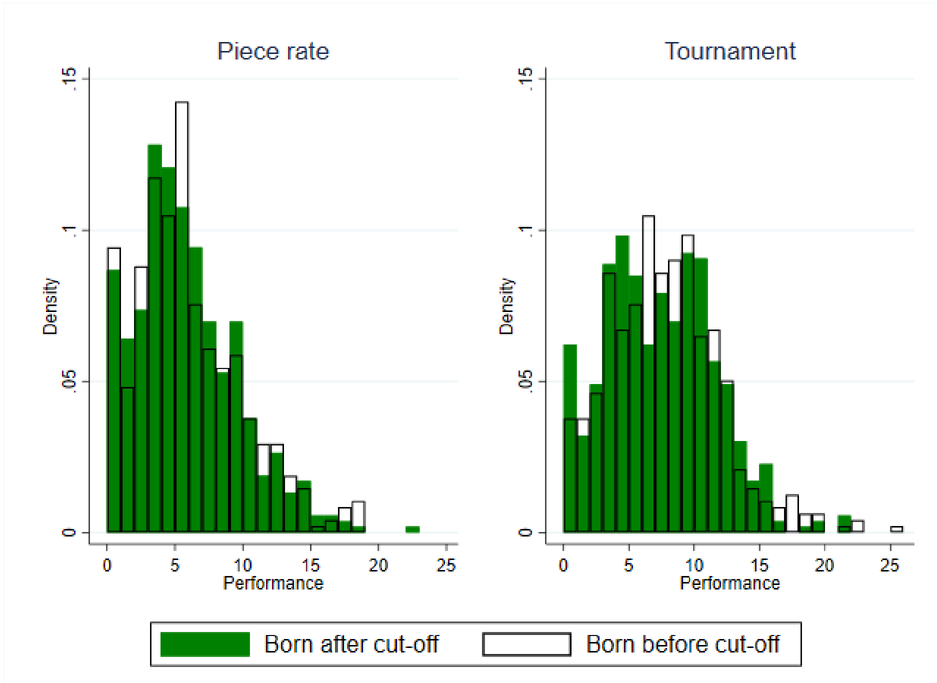

Figure B.1: Performance distribution in piece rate and tournament. A test of distributional differences of performance in each task between participants born before and after the cut-off date shows no evidence of statistical differences (p-values of a Kolmogorov-Smirnov test are 0.999 and 0.239 in piece rate and tournament, respectively).

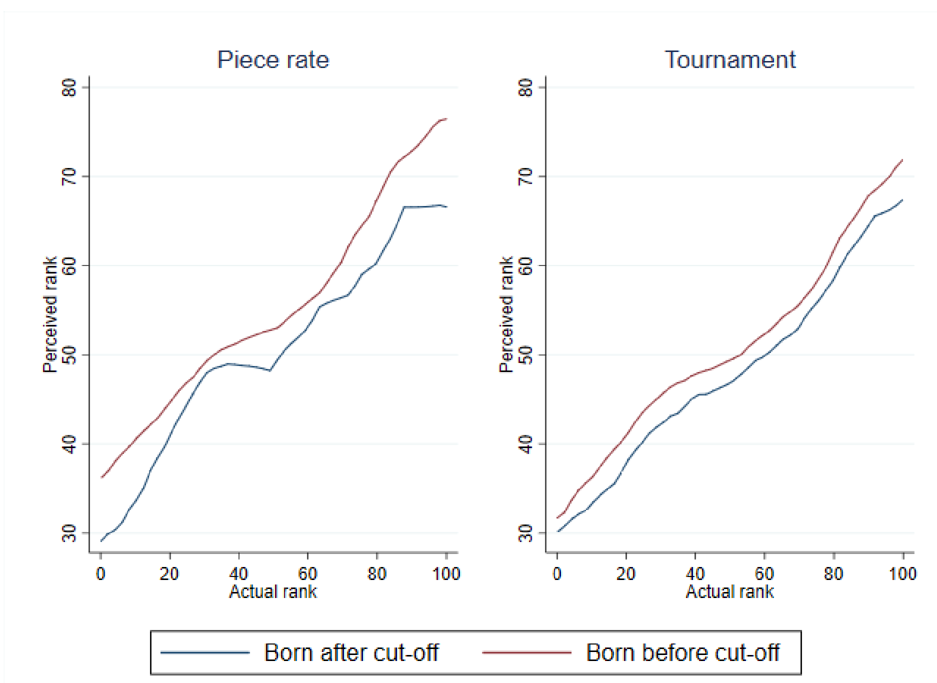

Figure B.2: Average perceived rank for each possible actual rank in the piece rate and tournament tasks.

C Robustness checks

C.1 FWER adjusted p-values

In this section we report the regression results presented in the paper including the FWER p-values adjusted for multiple hypothesis testing controlling for family-wise error rate.

Table C.1: Effect of relative age on self-confidence

	Self-confidence	
	Piece rate	Tournament
	(1)	(2)
Equation (1)		
Rel Old $[\alpha_1]$	10.908**	8.924**
	(4.094)	(4.132)
Equation (2)		
Rel Old		
Women $[\beta_1]$	8.886**	10.555**
	(4.474)	(4.613)
Men $[\beta_1 + \beta_2]$	16.124	4.720
	(9.094)	(8.735)
Difference $[\beta_2]$	7.238	-5.835
	(10.128)	(9.871)
N	1007	1007

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values obtained with FWER method. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.2: Effect of relative age on risk and ambiguity seeking, and trust

	Lottery		BART
	Risk	Ambiguity	
	(1)	(2)	(3)
Equation (1)			
Rel Old $[\alpha_1]$	0.022	0.046	-14.543
	(0.037)	(0.045)	(7.649)
Equation (2)			
Rel Old			
Women $[\beta_1]$	0.073	0.020	-9.464
	(0.042)	(0.049)	(8.480)
Men $[\beta_1 + \beta_2]$	-0.109	0.114	-27.639
	(0.077)	(0.094)	(16.458)
Difference $[\beta_2]$	-0.183*	0.095	-18.174
	(0.088)	(0.105)	(18.474)
N	1007	1007	1007

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values obtained with FWER method. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.3: Effect of relative age on risk seeking behaviour in real life situations

	In general (1)	Driving (2)	Finance (3)	Health (4)	Leisure (5)	Occupation (6)
Equation (1)						
Rel Old $[\alpha_1]$	0.256	1.049**	0.705	0.693	0.456	0.618
	(0.279)	(0.368)	(0.323)	(0.341)	(0.307)	(0.328)
Equation (2)						
Rel Old						
Women $[\beta_1]$	0.325	1.039**	0.793	0.845	0.499	0.610
	(0.304)	(0.409)	(0.363)	(0.385)	(0.348)	(0.367)
Men $[\beta_1 + \beta_2]$	0.078	1.073	0.478	0.300	0.345	0.638
	(0.604)	(0.775)	(0.662)	(0.703)	(0.620)	(0.689)
Difference $[\beta_2]$	-0.247	0.033	-0.314	-0.544	-0.154	0.028
	(0.672)	(0.872)	(0.750)	(0.800)	(0.706)	(0.778)
N	1007	1007	1007	1007	1007	1007

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values obtained with FWER method. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.4: Effect of relative age on time preference (future equivalents)

	Now *vs* 5 months (1)	1 *vs* 6 months (2)
Equation (1)		
Rel Old $[\alpha_1]$	-0.033	-0.322
	(0.493)	(0.486)
Equation (2)		
Rel Old		
Women $[\beta_1]$	-0.190	-0.389
	(0.550)	(0.543)
Men $[\beta_1+\beta_2]$	0.372	-0.149
	(1.036)	(1.011)
Difference $[\beta_2]$	0.562	0.240
	(1.168)	(1.143)
N	1007	1007

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *p*-values obtained with FWER method. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

C.2 Using an age range for participants identical across states

In this section we report the results considering only participants in the overlapping age range of 28 to 36 years old across the four Australian states (N=364). The conclusions discussed in the paper about the positive effect of relative age on self-confidence, trust and risk taking in real life domains remain valid in this subsample. Moreover, we observe that the effect of relative age on self-confidence, the decision to submit one's past performance to a tournament and trust become much larger (double in size) in this subsample compared to the results obtained for the full sample. The effects of relative age on self-declared risk taking become larger in some cases, but some lose statistical significance. All other results are not affected. These results support the idea that the effect of relative age might be stronger among younger adults and fade over time.

Table C.5: Effect of relative age on self-confidence

	Self-confidence		
	Piece rate	Tournament	Std Index
	(1)	(2)	(3)
Equation (1)			
Rel Old $[\alpha_1]$	19.816***	23.790***	0.675***
	(7.477)	(7.829)	(0.215)
Equation (2)			
Rel Old			
Women $[\beta_1]$	13.721	25.586***	0.608**
	(8.385)	(8.835)	(0.241)
Men $[\beta_1 + \beta_2]$	34.017**	19.607	0.832*
	(16.405)	(15.760)	(0.452)
Difference $[\beta_2]$	20.297	-5.979	0.223
	(18.549)	(17.991)	(0.514)
N	364	364	364

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.6: Effect of relative age on competitiveness

	Submit to tournament		Perform in tournament	
	(1)	(2)	(3)	(4)
Equation (1)				
Rel Old $[\alpha_1]$	0.321***	0.281***	0.158	-0.025
	(0.104)	(0.098)	(0.104)	(0.084)
Equation (2)				
Rel Old				
Women $[\beta_1]$	0.394***	0.361***	0.250**	0.015
	(0.124)	(0.119)	(0.116)	(0.097)
Men $[\beta_1 + \beta_2]$	0.144	0.093	-0.066	-0.119
	(0.195)	(0.185)	(0.218)	(0.177)
Difference $[\beta_2]$	-0.251	-0.268	-0.316	-0.134
	(0.232)	(0.221)	(0.244)	(0.204)
N	364	364	364	364
Controls				
Piece rate performance	✓	✓		
Guessed piece rate rank		✓		
Tournament performance			✓	✓
Piece rate - tournament performance			✓	✓
Guessed tournament rank				✓
Piece rate submitted to tournament				✓

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.7: Effect of relative age on risk and ambiguity seeking, and trust

	Lottery		BART	Std Index	Trust
	Risk	Ambiguity			
	(1)	(2)	(3)	(4)	(5)
Equation (1)					
Rel Old $[\alpha_1]$	-0.014	0.084	-16.527	0.029	0.756**
	(0.056)	(0.076)	(13.872)	(0.128)	(0.299)
Equation (2)					
Rel Old					
Women $[\beta_1]$	-0.000	0.038	-9.471	0.015	0.972***
	(0.068)	(0.085)	(16.639)	(0.148)	(0.354)
Men $[\beta_1 + \beta_2]$	-0.047	0.194	-32.965	0.063	0.255
	(0.092)	(0.148)	(24.873)	(0.242)	(0.562)
Difference $[\beta_2]$	-0.046	0.156	-23.494	0.048	-0.717
	(0.114)	(0.168)	(29.778)	(0.282)	(0.663)
N	364	364	364	364	364

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.8: Effect of relative age on risk seeking behaviour in real life situations

	In general	Driving	Finance	Health	Leisure	Occupation	Std Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Equation (1)							
Rel Old $[\alpha_1]$	0.058	1.515**	1.387**	0.596	0.614	0.268	0.282
	(0.449)	(0.702)	(0.608)	(0.608)	(0.539)	(0.576)	(0.180)
Equation (2)							
Rel Old							
Women $[\beta_1]$	0.446	0.994	1.140	0.679	0.349	0.066	0.256
	(0.506)	(0.812)	(0.697)	(0.713)	(0.619)	(0.647)	(0.209)
Men $[\beta_1 + \beta_2]$	-0.848	2.730**	1.962*	0.401	1.232	0.738	0.342
	(0.952)	(1.359)	(1.175)	(1.141)	(1.030)	(1.149)	(0.341)
Difference $[\beta_2]$	-1.294	1.736	0.822	-0.277	0.883	0.672	0.086
	(1.076)	(1.563)	(1.349)	(1.338)	(1.190)	(1.305)	(0.396)
N	364	364	364	364	364	364	364

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.9: Effect of relative age on time preference (future equivalents)

	Now *vs* 5 months (1)	1 *vs* 6 months (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	-0.805	-1.031	-0.255
	(0.861)	(0.843)	(0.220)
Equation (2)			
Rel Old			
Women $[\beta_1]$	-0.076	-0.330	-0.057
	(0.986)	(0.979)	(0.250)
Men $[\beta_1 + \beta_2]$	-2.503	-2.666	-0.717
	(1.761)	(1.749)	(0.465)
Difference $[\beta_2]$	-2.427	-2.337	-0.661
	(2.001)	(1.998)	(0.524)
N	364	364	364

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

C.3 Restricting the sample to participants born within a one-month window of the cutoff date

In this section we report all regression results restricting the sample to participants who were born either one month prior or after the school entry cut-off date (N=527). Our conclusions on the positive effect of relative age on self-confidence reported with the full sample remain valid in this subsample. Moreover, we observe that the estimates for the relative age increase in magnitude and statistical significance. The results on the effect of relative age on the decision to submit one's part performance to a tournament become smaller and loose statistical significance. With regards to risk taking elicited with lab methods, we find that the negative effect of relative age on risk taking in the BART becomes larger and gains statistical significance, further supporting that relative age might negatively affect risk taking in the BART. With regards to risk taking in real life domains, the positive estimate for relative age generally increases in size but looses statistical significance, potentially due to a loss of power. The magnitude of the effect of relative age on the standardized index for risk taking in real life domains remains unaffected and stays marginally significant at 10%. With respect to trust, the effect of relative age slightly decreases and becomes non-significant.

Table C.10: Effect of relative age on self-confidence

	Self-confidence		
	Piece-rate (1)	Tournament (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	18.158***	17.852***	1.229***
	(6.719)	(6.604)	(0.391)
Equation (2)			
Rel Old			
Women $[\beta_1]$	18.541**	17.967**	1.139***
	(7.408)	(7.151)	(0.457)
Men $[\beta_1+\beta_2]$	17.097	17.533	1.419**
	(14.225)	(14.502)	(0.718)
Difference $[\beta_2]$	-1.444	-0.435	0.279
	(15.844)	(15.983)	(0.838)
N	527	527	527

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.11: Effect of relative age on competitiveness

	Submit to tournament		Perform in tournament	
	(1)	(2)	(3)	(4)
Equation (1)				
Rel Old $[\alpha_1]$	0.074	0.020	-0.019	-0.071
	(0.086)	(0.080)	(0.085)	(0.075)
Equation (2)				
Rel Old				
Women $[\beta_1]$	0.135	0.080	0.103	0.023
	(0.088)	(0.082)	(0.085)	(0.076)
Men $[\beta_1+\beta_2]$	-0.102	-0.145	-0.370*	-0.331*
	(0.202)	(0.195)	(0.218)	(0.197)
Difference $[\beta_2]$	-0.237	-0.225	-0.473**	-0.354*
	(0.217)	(0.210)	(0.229)	(0.210)
N	527	527	527	527
Controls				
Piece rate performance	✓	✓		
Guessed piece rate rank		✓		
Tournament performance			✓	✓
Piece rate - tournament performance			✓	✓
Guessed tournament rank				✓
Piece rate submitted to tournament				✓

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.12: Effect of relative age on risk and ambiguity seeking, and trust

	Lottery		BART	Std Index	Trust
	Risk	Ambiguity			
	(1)	(2)	(3)	(4)	(5)
Equation (1)					
Rel Old $[\alpha_1]$	-0.056	0.115*	-26.940**	-0.030	0.247
	(0.059)	(0.066)	(11.836)	(0.109)	(0.252)
Equation (2)					
Rel Old					
Women $[\beta_1]$	0.000	0.083	-21.741*	0.021	0.380
	(0.065)	(0.068)	(12.263)	(0.118)	(0.288)
Men $[\beta_1 + \beta_2]$	-0.212*	0.203	-41.307	-0.171	-0.123
	(0.129)	(0.155)	(28.672)	(0.241)	(0.508)
Difference $[\beta_2]$	-0.212	0.120	-19.567	-0.191	-0.503
	(0.142)	(0.166)	(30.988)	(0.266)	(0.581)
N	527	527	527	527	527

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.13: Effect of relative age on risk seeking behaviour in real life situations

	In general	Driving	Finance	Health	Leisure	Occupation	Std Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Equation (1)							
Rel Old $[\alpha_1]$	0.334	1.442**	0.870*	0.686	0.273	0.839*	0.268*
	(0.418)	(0.569)	(0.489)	(0.523)	(0.473)	(0.508)	(0.153)
Equation (2)							
Rel Old							
Women $[\beta_1]$	0.509	1.006	0.712	0.212	0.445	0.718	0.223
	(0.440)	(0.614)	(0.537)	(0.566)	(0.529)	(0.559)	(0.168)
Men $[\beta_1 + \beta_2]$	-0.147	2.648**	1.307	1.998*	-0.200	1.171	0.392
	(0.956)	(1.326)	(1.059)	(1.198)	(0.973)	(1.078)	(0.332)
Difference $[\beta_2]$	-0.656	1.642	0.595	1.786	-0.645	0.453	0.169
	(1.042)	(1.446)	(1.168)	(1.306)	(1.094)	(1.197)	(0.368)
N	527	527	527	527	527	527	527

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.14: Effect of relative age on time preference (future equivalents)

	Now *vs* 5 months (1)	1 *vs* 6 months (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	-0.425	-0.341	-0.102
	(0.751)	(0.748)	(0.189)
Equation (2)			
Rel Old			
Women $[\beta_1]$	-0.521	-0.190	-0.095
	(0.815)	(0.807)	(0.203)
Men $[\beta_1+\beta_2]$	-0.160	-0.758	-0.123
	(1.656)	(1.677)	(0.428)
Difference $[\beta_2]$	0.361	-0.567	-0.028
	(1.829)	(1.844)	(0.469)
N	527	527	527

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

C.4 Results including participants unconfident about their relative age in school

In this section we report the results obtained when considering all participants in our study, that is, including those who declared being very unconfident about their relative age in school. They account for 7% of our sample (76 observations). Overall, the results remain very stable and the conclusions unchanged. The estimates of relative age on self-confidence and the decision to submit the past performance to a tournament payment scheme become slightly attenuated, but remain statistically significant at conventional levels for the whole sample. The results for risk taking elicited with lab measures, self-declared risk taking in life domains, trust and time preference remain practically unchanged.

Table C.15: Effect of relative age on self-confidence

	Self-confidence		
	Piece rate (1)	Tournament (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	8.967**	7.076*	0.259**
	(4.136)	(4.142)	(0.120)
Equation (2)			
Rel Old			
Women $[\beta_1]$	7.436*	9.009**	0.266**
	(4.520)	(4.596)	(0.132)
Men $[\beta_1 + \beta_2]$	12.772	2.270	0.243
	(9.047)	(8.784)	(0.261)
Difference $[\beta_2]$	5.336	-6.738	-0.022
	(10.000)	(9.902)	(0.292)
N	1083	1083	1083

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.16: Effect of relative age on competitiveness

	Submit to tournament		Perform in tournament	
	(1)	(2)	(3)	(4)
Equation (1)				
Rel Old $[\alpha_1]$	0.096*	0.050	0.019	-0.034
	(0.055)	(0.052)	(0.056)	(0.050)
Equation (2)				
Rel Old				
Women $[\beta_1]$	0.116**	0.078	0.080	0.013
	(0.059)	(0.056)	(0.058)	(0.053)
Men $[\beta_1 + \beta_2]$	0.046	-0.016	-0.134	-0.152
	(0.124)	(0.119)	(0.134)	(0.117)
Difference $[\beta_2]$	-0.070	-0.093	-0.214	-0.165
	(0.137)	(0.131)	(0.146)	(0.129)
Controls				
Piece rate performance	✓	✓		
Guessed piece rate rank		✓		
Tournament performance			✓	✓
Piece rate - tournament performance			✓	✓
Guessed tournament rank				✓
Piece rate submitted to tournament				✓
N	1083	1083	1083	1083

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.17: Effect of relative age on risk and ambiguity seeking, and trust

	Lottery		BART	Std Index	Trust
	Risk	Ambiguity			
	(1)	(2)	(3)	(4)	(5)
Equation (1)					
Rel Old $[\alpha_1]$	0.024	0.052	-13.523*	0.048	0.347**
	(0.038)	(0.045)	(7.759)	(0.072)	(0.174)
Equation (2)					
Rel Old					
Women $[\beta_1]$	0.072*	0.028	-8.178	0.099	0.406**
	(0.043)	(0.049)	(8.617)	(0.079)	(0.195)
Men $[\beta_1 + \beta_2]$	-0.093	0.111	-26.814	-0.080	0.201
	(0.079)	(0.095)	(16.428)	(0.149)	(0.359)
Difference $[\beta_2]$	-0.164*	0.084	-18.636	-0.179	-0.205
	(0.089)	(0.105)	(18.477)	(0.168)	(0.406)
N	1083	1083	1083	1083	1083

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.18: Effect of relative age on risk seeking behaviour in real life situations

	In general (1)	Driving (2)	Finance (3)	Health (4)	Leisure (5)	Occupation (6)	Std Index (7)
Equation (1)							
Rel Old $[\alpha_1]$	0.161	1.110***	0.729**	0.643*	0.539*	0.615*	0.238**
	(0.287)	(0.376)	(0.332)	(0.346)	(0.315)	(0.339)	(0.102)
Equation (2)							
Rel Old							
Women $[\beta_1]$	0.168	1.105***	0.791**	0.719*	0.549	0.521	0.244**
	(0.313)	(0.419)	(0.373)	(0.389)	(0.358)	(0.378)	(0.115)
Men $[\beta_1+\beta_2]$	0.143	1.123	0.574	0.453	0.513	0.850	0.224
	(0.622)	(0.786)	(0.676)	(0.711)	(0.627)	(0.708)	(0.208)
Difference $[\beta_2]$	-0.025	0.018	-0.218	-0.266	-0.037	0.329	-0.019
	(0.693)	(0.886)	(0.767)	(0.808)	(0.718)	(0.799)	(0.237)
N	1083	1083	1083	1083	1083	1083	1083

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

Table C.19: Effect of relative age on time preference (future equivalents)

	Now *vs* 5 months (1)	1 *vs* 6 months (2)	Std Index (3)
Equation (1)			
Rel Old $[\alpha_1]$	-0.025	-0.232	-0.035
	(0.499)	(0.491)	(0.127)
Equation (2)			
Rel Old			
Women $[\beta_1]$	-0.070	-0.312	-0.052
	(0.557)	(0.551)	(0.142)
Men $[\beta_1+\beta_2]$	0.089	-0.034	0.007
	(1.039)	(1.012)	(0.263)
Difference $[\beta_2]$	0.159	0.279	0.059
	(1.173)	(1.147)	(0.297)
N	1083	1083	1083

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Estimates obtained with IV linear regression models. Robust standard errors in parentheses. All regression models control for gender, age and state.

D Additional graphs

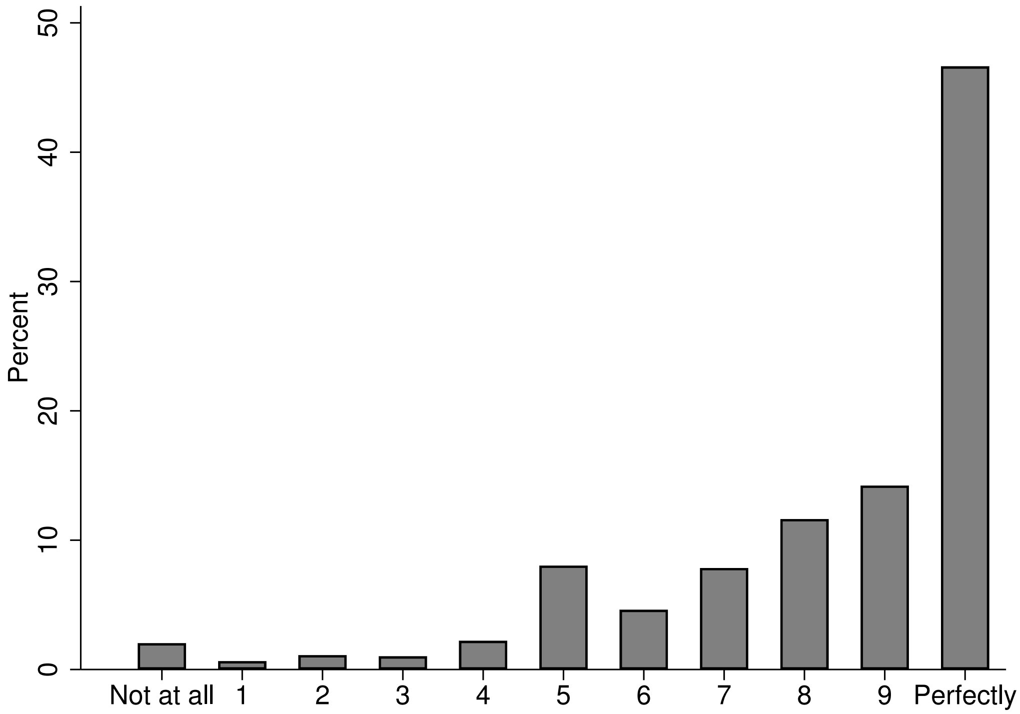

Figure D.1: Participants' rating on how sure they were about their declaration on being among the oldest / youngest in the classroom

Figures D2-D6 are obtained by running a kernel-weighted local polynomial regression with bandwidth 200.

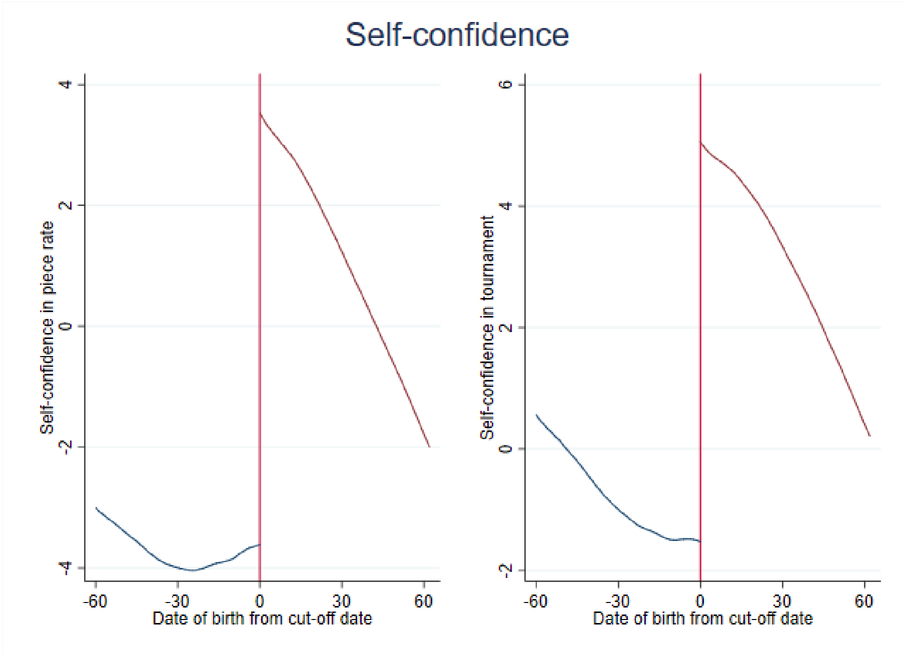

Figure D.2: Self-confidence by continuous relative age (number of days born from the cut-off date)

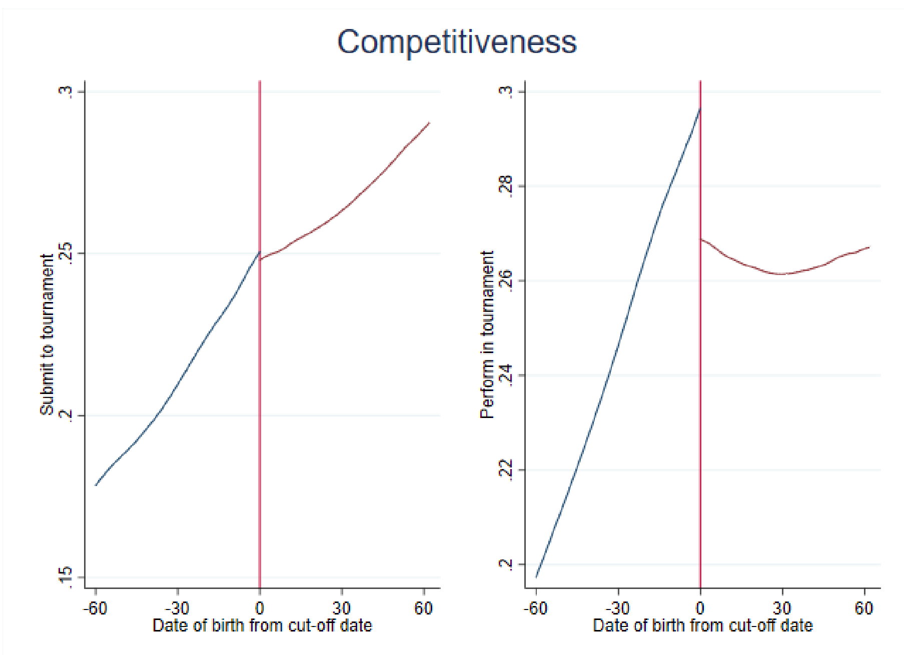

Figure D.3: Competitiveness by continuous relative age (number of days born from the cut-off date)

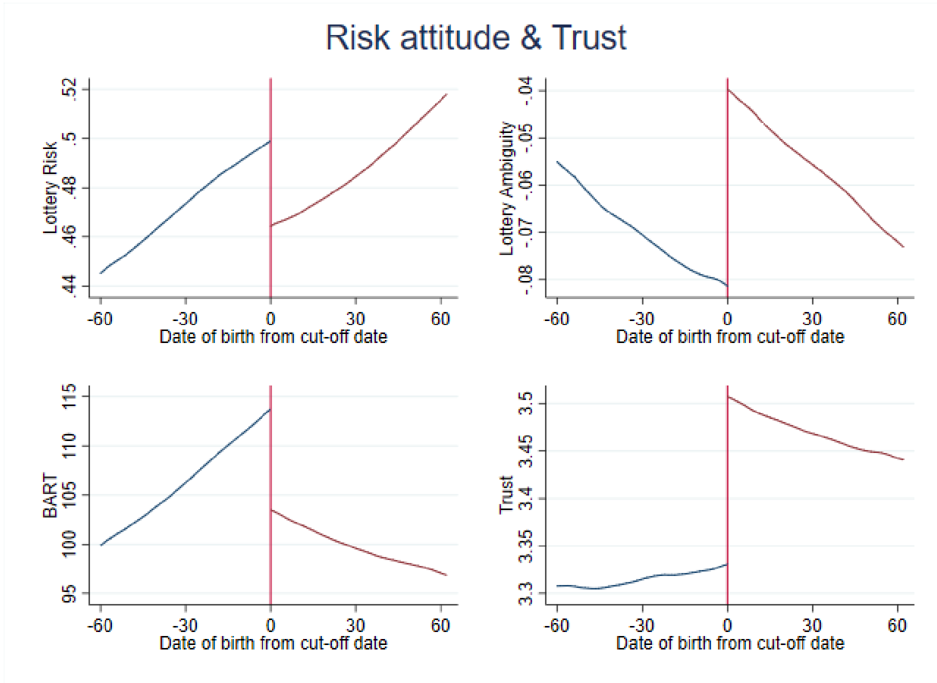

Figure D.4: Risk and trusting attitude by continuous relative age (number of days born from the cut-off date)

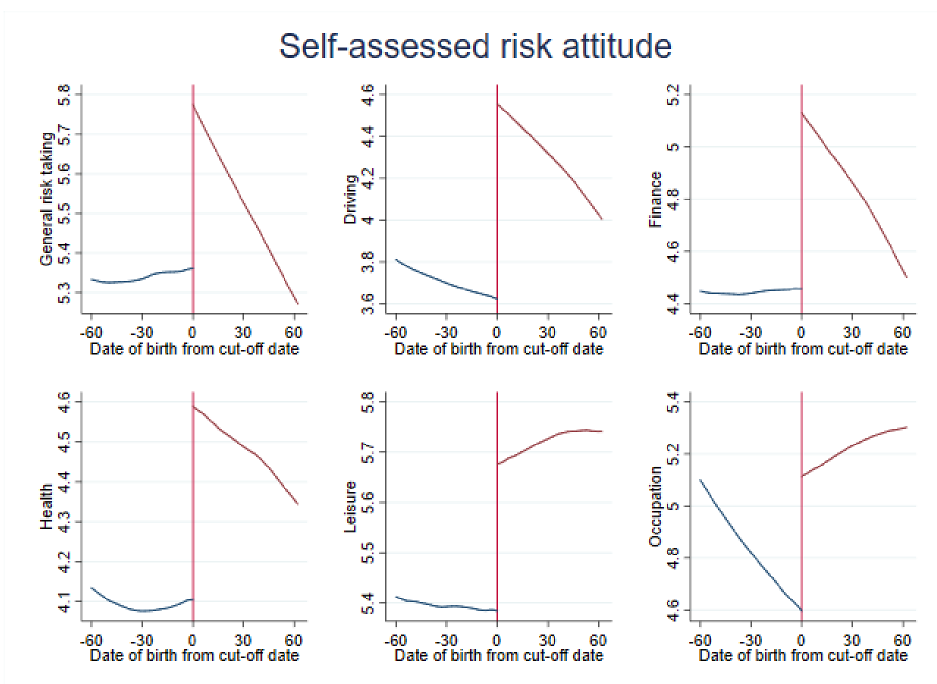

Figure D.5: Self-assessed risk attitude by continuous relative age (number of days born from the cut-off date)

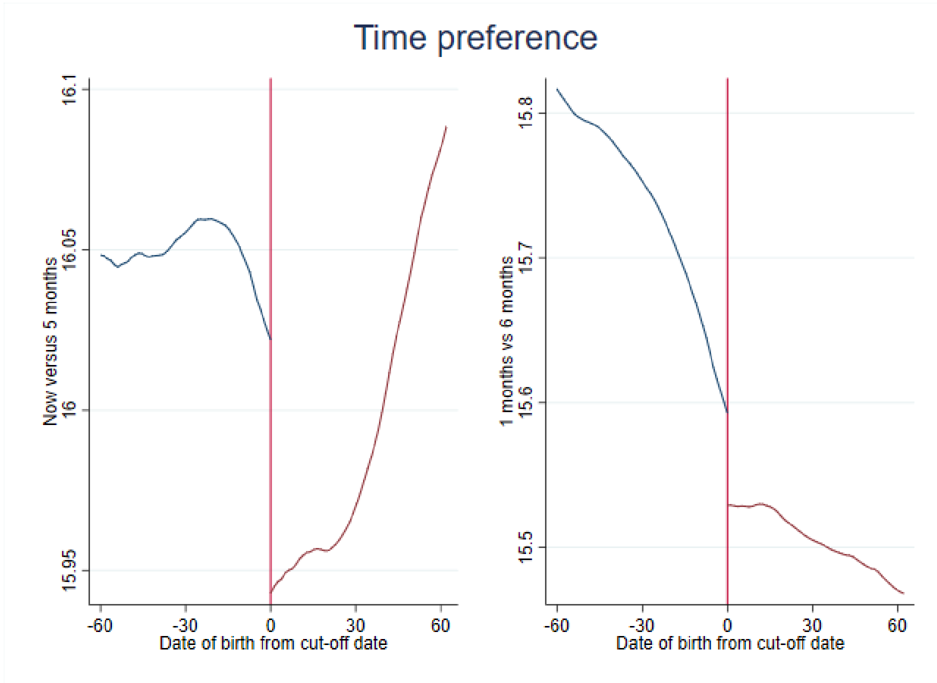

Figure D.6: Time preference by continuous relative age (number of days born from the cut-off date)

E Standardized summary index

Following Anderson (2008) we calculate summary indices using the formula below:

$$\bar{s}_{ij} = \frac{1}{W_{ij}} \sum_{k \in \mathbb{K}_{ij}} w_{jk} \frac{y_{ijk} - \bar{y}_{jk}}{\sigma^{y}_{jk}}$$

where k indexes the outcome measures within each behavioural trait j, $\mathbb{K}_{ij}$ is the set of nonmissing measures for individual i in the behavioural trait j, σ^{y}_{jk} is the control group standard deviation for measure k in the behavioural trait j, w_{jk} is the measure weight from the inverted covariance matrix $\hat{\Sigma}_j^{-1}$, and $W_{ij} = \sum_{k \in \mathbb{K}_{ij}} w_{jk}$.

F Description of the tasks

Confidence and competitiveness

In the first stage of the task participants are shown grids containing 12 numbers and need to find the two numbers in the grid which add up to exactly 10. There is only one possible solution in each grid. Participants work on the task for 3 minutes and earn 1 dollar per correct answer. In the second stage participants work on the same task for 3 minutes and the payment is now defined in a competitive setting. Participants earn 3 dollars per correct answer but only if they are ranked in the top third among a random sample of 100 participants in the experiment. In the third stage participants work once again on the same task for 3 minutes, however, prior to performing the task they need to decide whether they want to be paid according to a piece rate scheme (as in stage 1) or according to a competitive scheme (as in stage 2), in which case their score in stage 3 is compared to the score in stage 2 of a random sample of 99 other participants in the experiment. This stage is designed to measure preference for competition. In the fourth stage participants simply decide if they want to submit their score in stage 1 to a competitive payment scheme or to a piece rate scheme. This stage provides a measure of self-confidence and risk attitude. In the fifth stage participants are asked to guess their rank in stage 1 and stage 2 among a random sample of 100 participants. This stage aims to measure participants' confidence in their ability to perform in the task relative to others.

Lottery-based task

We use the ordered choice list to measure risk aversion as in **?**. Participants see a list with twenty rows and decide in each row whether they prefer a lottery or a certain amount of money. The lottery is identical in each row whereas the certain amount of money offered always increases by 1 dollar. Participants are presented with two lists successively. The first list corresponds to the risk prospect. In each row, participants opt between a lottery in which they have a 50% chance of earning 20 dollars and a 50% chance of earning nothing, and a certain amount of money ranging from 1 dollar in row 1 to 20 dollars in row 20. The second list corresponds to the ambiguity prospect and differs from the risk prospect only in the fact that participants are not aware of the probability of earning the 20 dollars in the lottery. The lottery is explained to participants referring to a bag with 10 balls, of which at the end of the experiment one is randomly picked by the computer. If the ball picked is white they earn 20 dollars, whereas they earn nothing if the ball picked is black. In the risk prospect, participants are informed that there are five white and five black balls in the bag. In the ambiguity prospect, participants are not informed about the number of black and white balls in the bag. Therefore, they are unaware of the probability that a black or white ball is randomly picked by the computer.

We construct measures of risk and ambiguity aversion following **?**, using the certainty equivalence method. We calculate the certainty equivalent as the mid-point between the amount of money offered in the row in which the participant first prefers the certain amount of money over the lottery and the certain amount of money offered in the previous row. The risk aversion measure is calculated as $1-(CE_{risk}/20)$. The ambiguity aversion measure is calculated as $(CE_{risk}-CE_{amb})/(CE_{risk}+CE_{amb})$.

BART

A second method that we use to measure risk attitude is the BART (Lejuez et al., 2002). Participants see a balloon and a pump on the computer screen. Each time the participant pumps the balloon, earnings increase by 50 cents and the size of the balloon increases. The balloon may explode at any random pump and the participant needs to decide when to stop pumping the balloon. If the balloon explodes, the accumulated earnings in the balloon are lost. After a balloon has either exploded or the participant has decided to stop pumping the balloon, a new balloon appears. There are five balloons in total. At the end of the experiment, if one of the balloons is selected for payment, the participant earns the money accumulated in the balloon if the balloon has not exploded. If the selected balloon has exploded, the participant earns nothing. We measure the propensity to take risk by the total number of pumps in the balloons.

Survey questions

Finally, we use a self-assessment measure of risk attitude. We use the standard general risk question and questions on risk attitude in different relevant domains of life as in Dohmen et al. (2011). The exact wording of the general risk question is 'How do you see yourself: are you generally a person who is fully prepared to take risks or do you generally avoid taking risks? *Please tick a box on a scale where the value 0 means 'not at all willing to take risks' and the value 10 means 'very willing to take risks'*. Each domain specific risk question was worded as follows: 'People can behave differently in different situations. How would you rate your willingness to take risks in the following areas? a) Driving, b) Financial matters, c) During leisure and sport, d) In your occupation, e) With your health'.