Month of Birth and Cognitive Effort:

A Laboratory Study of the Relative Age Effect among Fifth Graders

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Abstract: All around the world school entry cohorts are organized on an annual calendar, so that the age of students in the same cohort differs up to one year. It is a well-established finding that this age gap entails a consequential (dis)advantage for academic performance referred to as the relative age effect (RAE). This study contributes to a recent strand of research that has turned to investigate the RAE on non-academic outcomes such as personality traits. An experimental setup is used to assess the willingness to exert cognitive effort in a sample of 798 fifth grade students enrolled in the Spanish educational system, characterized by strict enrolment rules. After controlling for cognitive ability, we observe that older students outwork their youngest peers by two-fifths of a standard deviation, but only when rewards for performance are in place. Implications for sociological research on educational inequality and policy are discussed.

Keywords: Relative age effect; month of birth; cognitive effort; experimental design; Spain.

1 Introduction

Student's month of birth is a relevant factor for academic performance at least in the initial stages of the educational career. Most educational systems organize school cohorts so that children born before a cutoff date enter school in a certain academic year and children born after that date wait for another year to start primary education. As a result, those students born early in their school cohort (in the first months after the cutoff date) are up to one year older at school entry than their peers born late in their cohort (in the months before the next cutoff date). As students typically start school around age six, that one-year gap represents between 15-20% of the time lived by the youngest students in the cohort, which entails a consequential academic disadvantage. They will be less intellectually, psychologically, and physically mature, and this developmental lag compared with their older peers will be noticeable in learning. The subsequent difference in academic performance between the oldest and youngest students in a cohort is normally referred to as the relative age effect (RAE).

While most previous studies on the RAE have focused on students' cognitive skills and academic achievement, the current study contributes to an emerging thread of research addressing socio-behavioral traits and non-cognitive skills. Arguably, these characteristics play an increasingly important role in the labor market over and above educational attainment (Heckman, Stixrud, and Urzua 2006), and the factors determining their development have become a hotly debated research topic (Kröger, Palacios-Abad, and Radl forthcoming). Thus, we examine the relationship between the relative age at school entry and real effort provision elicited in an experimental setting with fifth grade students enrolled in the Spanish educational system. Spain constitutes an insightful case of study as previous works have identified a comparatively large and enduring relative age effect over the educational career of Spanish students (Beneito and Soria-Espín 2020; González-Betancor and López-Puig 2015; Gutiérrez-Domènech and Adserà 2012; Jerrim, Lopez-Agudo, and Marcenaro-Gutierrez 2021). Furthermore, the school-entry rule is strictly enforced in Spain (all students are to begin primary education in September of the calendar year in which they turn 6 years old), which solves several methodological issues associated with the possibility to delay or anticipate school-entry.

As for the outcome of interest, we assess real effort exerted in three tasks designed to capture cognitive effort in multiple domains. A limitation of previous research is the dubious validity of effort proxies based on individual self-reports, which can be subject to different biases, including reference bias (West et al. 2016) and social desirability bias (Apascaritei, Demel, and Radl 2021). Crucially, mental labor goes along with cognitive costs and fatigue, which invites distraction and procrastination (Kool et al. 2010; Vohs et al. 2021). Thus, task engagement is arguably a more valid effort measure than self-declarations. At the same time, single-task designs can be distorted by specific cognitive abilities. The design employed in the present study avoids these threats to validity by observing actual effortful behavior under controlled conditions, and by employing multiple tasks with varying mental demands. Furthermore, those tasks were performed under different conditions, so we can assess how the relative age effect varies if students are not rewarded at all (intrinsic condition), if material incentives are included (extrinsic condition), and if they compete for peer recognition (tournament condition). To the best of our knowledge, only two studies have previously analyzed the RAE in an experimental setting, but instead of effort their focus lied on the preference for competition, self-confidence, and risk attitudes (Page, Sarkar, and Silva-Goncalves 2017, 2019).

Curiously, and although sociologists have paid much attention to miscellaneous characteristics that influence educational attainment, they have widely overlooked the effects associated to the student's month of birth. Only a handful of sociological studies have been interested in the month of birth as a source of educational inequality (Bernardi 2014; Bernardi and Grätz 2015; Dicks and

Lancee 2018). We argue that the RAE deserves greater attention, not only because it impacts the acquisition of skills but also because it affects students' quality of life, their bullying victimization, and their self-esteem (Fumarco, Baert, and Sarracino 2020; Mühlenweg 2010; Thompson, Barnsley, and Battle 2004). In our work, we observe that older students in the school cohort are substantially more willing to exert cognitive effort, but only after material incentives are included and not more so if students compete for peer recognition. Moreover, well-known differences in attainment between boys and girls or students with high and low socioeconomic status (SES) can be better understood by exploiting the exogeneous variation of the month of birth that might affect students differently depending on their ascriptive attributes (Bernardi 2014). Thus, we interact the effect identified on cognitive effort with the student's gender and SES, and, despite the uncertainty of the estimates, we observe that the RAE is larger among boys and low-SES students. We discuss the implications of our findings for research on educational inequality in the last section.

2 Theoretical framework

2.1 The Relative Age Effect

During the last two decades, numerous studies have reported disadvantages among the youngest students in a school cohort. They perform worse at school, repeat course more often, are diagnosed with a learning disorder more frequently, obtain lower test scores in external assessments, and are more likely placed in lower educational tracks (Arrhenius et al. 2021; Bedard and Dhuey 2006; González-Betancor and López-Puig 2016; Oosterbeek, ter Meulen, and van der Klaauw 2021; Peña 2017; Schneeweis and Zweimüller 2014). This relative age effect (RAE) normally peaks at the initial stages of the educational career and wanes as students grow older (Bedard and Dhuey 2006; Cáceres-Delpiano and Giolito 2018; Elder and Lubotsky 2009; Oosterbeek, ter Meulen, and van der Klaauw 2021). However, the effect sometimes persists and the age at school entry finally impacts educational attainment (Fredriksson and Öckert 2013; Skirbekk, Kohler, and Prskawetz 2004; Zhang and Xie 2018). Thus, although several questions remain about the mechanisms causing this disadvantage (Buckles and Hungerman 2013; Crawford, Dearden, and Greaves 2014; Elder and Lubotsky 2009), the RAE on academic outcomes is a well-established empirical finding.

Recent research has now turned to investigate the RAE on non-academic outcomes such as non-cognitive skills (Datar and Gottfried 2015; Dhuey and Lipscomb 2008; Mühlenweg et al. 2012; Peña and Duckworth 2018), personality traits (Page, Sarkar, and Silva-Goncalves 2017, 2019; Peña and Duckworth 2018), emotional well-being (Ando et al. 2019; Mühlenweg 2010), popularity at school (van Aalst and van Tubergen 2021; Fumarco and Baert 2019), leisure time use (Fumarco and Schultze 2020), or health (Fumarco, Baert, and Sarracino 2020; Matsubayashi and Ueda 2015; Patalay et al. 2015). Thus, even if the effect of the age at school entry on academic outcomes worn off before affecting final educational attainment, it might leave a permanent imprint on other individual traits such as leadership skills (Dhuey and Lipscomb 2008), taste for competition (Page, Sarkar, and Silva-Goncalves 2017), risk-taking (Page, Sarkar, and Silva-Goncalves 2019), social skills (van Aalst and van Tubergen 2021), or grit and perseverance (Peña and Duckworth 2018). The present study contributes to this growing body of research by analyzing the RAE on the willingness to exert cognitive effort, that is, the mobilization of mental resources to fulfill a task (Radl and Miller 2021).

2.2 The dimensions of the Relative Age Effect

Although the association between the month of birth and achievement is commonly referred to as the relative age effect, this label is somewhat ill-fitting as this effect itself has an absolute and a relative dimension. On the one hand, early-born students are older at school entry than students born late in the cohort, which entails a higher level of maturity and, consequently, a higher school readiness. As school readiness impacts performance on the initial stages of the educational career (Haskins 2014), the age at school entry will be highly consequential (age-at-school-entry effect). Furthermore, since all students are assessed at the same moment in time, older students at school entry are also older the day of the test, which entails an additional advantage (age-at-test effect). These two components form the absolute dimension of the RAE. On the other hand, the month of birth determines students' position within the age distribution of their classroom. This relational component is relevant because students inevitably compare with each other, and young pupils might arrive at the conclusion that they are low performers when maybe they are simply younger than their peers at each given moment in time. Such uneven comparisons might shape the student' self-image and other individual traits such as the willingness to exert effort. Alternatively, young students might benefit from sharing the classroom with older students in the same way that low-achieving students benefit from being grouped with high-achieving students.

Due to data limitations, only a few works have been able to decompose the RAE into its different components (Black, Devereux, and Salvanes 2011; Cascio and Schanzenbach 2016; Crawford, Dearden, and Greaves 2014; Crawford, Dearden, and Meghir 2010; Peña 2017). In this work, we will not be able to properly distinguish the absolute and relative dimensions of the RAE[1]. However, all participants in the experiment perform a fluid intelligence test, which is indicative of cognitive development. Thus, we can adjust for IQ to assess whether the development associated to the student's absolute age controls out the identified RAE on cognitive effort. If the RAE remains large after accounting for ability, we will be more confident that the relative dimension (derivative from peers' effects) plays a non-trivial role in the effort (dis)advantage of older (younger) students within a cohort.

2.3 Competitiveness and the Relative Age Effect

It is generally accepted in the month-of-birth literature that the size of the RAE peaks in highly competitive environments such as elite sports (Wendling and Mills 2018), politics (Muller and Page 2016), or big companies (Du, Gao, and Levi 2012). Apart from the physical advantage in the case of sports, the strong RAE in competitive settings has been associated to the effect of the month of birth on students' leadership skills (Dhuey and Lipscomb 2008) and taste for competition (Page, Sarkar, and Silva-Goncalves 2017).

The study of Page et al. (2017) is of particular interest here as they measured student's preferences about competition in an experimental setup. Participants completed a first task under a non-competitive retribution scheme (piece-rate compensation) and a second task under a competitive setting (tournament compensation). For the third task, students were allowed to choose which setting they preferred, and the authors observed that older males in their cohort preferred the competitive setting more often. As a follow-up, Page et al. (2019) conducted an experimental survey with Australian adults, where participants again completed a real-effort task and then chose the retribution scheme they preferred. In this case, results regarding taste for competition were less clear, but the authors observed that adults that were older at school entry exhibited higher self-confidence, were more tolerant to risk in real life situations, and trusted other people more in social interactions.

In our study, cognitive effort was elicited under three different experimental conditions and one of them included competition among students (tournament condition). Given the hypothesized higher taste for competition of students born early in their school cohort, we expect them to have an additional advantage in the real-effort tasks when assessed in the tournament condition.

[1] We intend to leverage the fact that students born in the same months were assessed in different months because the fieldwork extended for six months. However, the largest part of the fieldwork concentrated in three months, and we did not count with enough variation to perform the test.

2.4 Heterogeneity in the advantage of relatively old students

Finally, not many works have assessed the heterogeneity in the relative age effect. Scant sociological research on the matter points towards a larger negative RAE on academic outcomes among low-SES students. High-SES families would be able to compensate for the disadvantage of being young at school entry and experience a lower or no penalization regarding, for instance, the probability to retake a grade (Bernardi 2014; Bernardi and Grätz 2015; Dicks and Lancee 2018).

Similarly, different studies have shown that girls experience a lower RAE than boys, meaning that girls born late in the school cohort are better able to catch up with older girls than boys (Datar 2006; McEwan and Shapiro 2008; Mühlenweg 2010; Page, Sarkar, and Silva-Goncalves 2017). For instance, in the formerly described paper of Page et al. (2017), the reported effect was only observed among boys.

In this vein, we expect the RAE on cognitive effort to peak among low-SES students and boys. Such effect heterogeneity would be relevant for research on educational inequality as it might account for part of the overall advantage of girls over boys and high-SES students over their low-SES peers.

3 Measuring cognitive effort

Most social science research addressing effort relies on self-assessed psychological characteristics such as self-esteem or locus of control (Breen and Goldthorpe 2001; Hall and Farkas 2011). However, skewed responses may arise in surveys due to social desirability or memory bias (Apascaritei, Demel, and Radl 2021). In addition, sustained mental effort taxes the brain, leads to fatigue, and imposes the unpleasant opportunity cost of not being able to flexibly shift attention elsewhere at any given moment (Westbrook and Braver 2015). Hence, our minds are prone to take shortcuts in ways that may escape self-assessments, making it important for measurement designs to require actual cognitive effort. Therefore, in laboratory psychology subjects perform actual tasks. In behavioral economics, similarly, so-called real-effort tasks have been purposefully designed to be ability-neutral, but still demand constant attention and focus (Gill and Prowse 2019). This approach attempts to mimic real-life situations where effort cannot merely be declared but must be actively exerted.

Furthermore, in most designs subjects only perform one single task, which may be unproblematic when the focus is on an experimental manipulation. However, when the focus lies on describing and explaining individual differences in effort, reliance on a single task potentially biases the results to the specific abilities required for the task. In neuroscience, similarly, experimental tasks have been used pervasively to measure executive control. However, most conventional tasks have not primarily been developed to measure between-subject differences, raising methodological concerns regarding their reliability to estimate individual and group-level characteristics (Snijder et al. 2022).

The measurement strategy pursued in the present study exploits the performance exhibited in three different tasks demanding effort in varying domains. Since any task-based measurement will still be unavoidably influenced by high-order cognitive functions, it is important to control for cognitive ability. Thus, to cleanse our effort measure of any residual confounding role of ability, our analyses take account of fluid intelligence. Moreover, our research design systematically addresses the role of incentives to assess the relative age effect on cognitive effort under various relevant conditions. Effort-related research in economics places a key emphasis on incentives (e.g. Levitt et al. 2016). In contrast, performance-based payoffs used to be rather rare in psychological and neuroscience studies. Recently, there is an increased interest in the role of incentives in motivating cognitive effort under experimental conditions (for an overview, see

Kool et al. 2010). Nevertheless, the populations typically analyzed in psychological studies are based on small convenience samples.

4 Data and methods

4.1 Data

The data for this study comprises 798 students attending the fifth grade at 18 primary schools located in the urban area of Madrid, Spain. Data were collected between 2019 and 2022 during 35 visits – one per school class – to the campus of a public university in the urban area of Madrid, which were organized as daily field trips to the university. Participating schools were selected as a stratified random sample of all schools in the Community of Madrid.[2] Thanks to a stratified random sample of primary schools and high participation rates, the laboratory data analyzed in the present study are representative of the population of fifth grade students in the urban area of Madrid.

4.2 Experimental setup

Table 1 illustrates the structure of the experimental sessions. Each participant carried out three real-effort tasks. The first task was performed without performance incentives (intrinsic condition), and then again under a piece-rate scheme, where points could be gained for each correct response (extrinsic condition). Those points were later converted into toys from a menu with selective options. Subsequently, the second and third tasks were performed under the piece-rate condition. Finally, the third task was performed again with a competitive scheme on top of the piece-rate payoff. Specifically, the three top performers in each session were additionally awarded a diploma and a public round of applause (tournament condition). Thus, we can assess the relative age effect on cognitive effort elicited under three different conditions.

In all rounds, students were offered the possibility to play one of two games instead of performing the corresponding task. In many real-life situations people eschew effortful tasks by opting for an alternative activity that is more immediately rewarding. Therefore, this so-called leisure task adds an opportunity cost to the decision to exert effort, making the laboratory setting more closely resembling reality.

Table 1. Session setup

Task	Duration
Instructions + Leisure task practice	1 round each game of 1.5 min
Task 1	
Practice	2 rounds of 2 min
Intrinsic condition	2 rounds of 2 min
Extrinsic condition	2 rounds of 2 min
Task 2	
Practice	2 rounds of 2 min
Extrinsic condition	2 rounds of 2 min
Task 3	
Practice	2 rounds of 2 min
Extrinsic condition	2 rounds of 2 min
Tournament condition	2 rounds of 2 min

[2] The sample was stratified by school type (public; public-private mixed; fully private) and neighborhood income (average household income in quartiles). The school-level participation rate for was about 24%.

The specific tasks performed by participants were the Slider task, the Simon task, and the AX task.[3] The three tasks tap into different domains in which cognitive effort can be exerted. The Slider task consists in a large set of sliders that appear on the screen, with a range between 0 and 100. Each slider is initially placed at the very left, at position 0. Students need to use the mouse to center as many sliders as possible at exactly position 50 within the allotted time. In terms of basic executive functions, the slider task especially taps into cognitive effort invested in processing speed and goal maintenance.

The Simon task consists in responding to a series of arrows prompted on the screen, each time pushing one of two keys to indicate their direction (left or right). Arrows might point towards a different direction from the position of the screen where they appear (left, right or center). Since it demands more attention to press the correct button when the position and direction are incongruent, this task especially measures cognitive effort in inhibition.

The AX Continuous Performance task consists in a sequence of pairs of letters that appear on the screen. Anytime the subject is presented with the letter A, followed by the letter X, one key must be pressed. When any other sequence is presented (e.g., A-Z or B-X), a different key must be pressed. This task requires switching back and forth between proactive to reactive control, thus especially capturing cognitive effort exerted in attentional control.

4.3 Identification strategy

The relative age effect is commonly expressed as the change caused by a one-year age gap due to students' month of birth. Provided that the month of birth is random, it constitutes an exogeneous source of variation in the outcome of interest and the RAE admits a causal interpretation. However, the identification of the effect is often hindered by data limitations and the possibility of delaying ("redshirting") or anticipating ("greenshirting") school entry by one year. As a result, different identification strategies have been followed depending on the study environment.

In countries that allow parents to delay or anticipate school entry, most works rely on the Instrumental Variable (IV) design first introduced by Bedard and Dhuey (2006). They proposed to examine the effect of the student's age at the beginning of the academic year in which they were observed. As there are three sources of variation in the observed age (the month of birth, compliance with the school-entry rule, and the possibility of repeating/skipping a grade), they used the student's assigned age (the age of students had they entered and progressed through school on time) as an instrument to isolate the variation stemming from the month of birth:

$$\text{IV:} \begin{cases} OA_i = \beta_0 + \beta_1 AA_i + \beta_2 \boldsymbol{Z_i} + \upsilon_i \\ y_i = \alpha_0 + \alpha_1 \widehat{OA}_i + \alpha_2 \boldsymbol{Z_i} + \varepsilon_i \end{cases} \tag{1}$$

Where y is the outcome of interest (in our case, cognitive effort under three different conditions), OA and AA are the student's observed and assigned age, Z is a vector of controls, and the coefficient α_1 yields the effect of a one-year difference in instrumented observed age.

This solution is quite popular (Fumarco and Schultze 2020; Mühlenweg and Puhani 2010; Peña and Duckworth 2018; Schneeweis and Zweimüller 2014; Zweimüller 2013). However, the IV estimate pertains to the population of students who entered and progressed through school on time. In turn, the reduced-form model that regresses the outcome of interest on the assigned age of the student provides an estimate that applies to the whole sample.

[3] To avoid that the order of the tasks affects the results, which specific task was performed as task 1, 2, or 3 varied across sessions.

$$\text{RF: } y_i = \beta_0 + \beta_1 AA_i + \beta_2 \boldsymbol{Z_i} + \omega_i \tag{2}$$

This model allows the student's month of birth to affect the outcome of interest through a number of channels, including the decision to delay or anticipate school entry, and it has also been applied frequently (Ando et al., 2019; Datar & Gottfried, 2015; Dhuey & Lipscomb, 2008; Peña & Duckworth, 2018). To properly interpret these results, it is important to keep in mind that the assigned age of the student is just a transformation of the month of birth relative to the school-entry cutoff.

For both the IV and RF models, a common threat for identification is seasonality in births and, more particularly, that parents of certain characteristics target specific seasons to deliver (Buckles and Hungerman 2013). Previous work on Spain has provided empirical evidence of such socially stratified timing of fertility (Ramirez and Caceres-Delpiano 2014). Therefore, our models control for different socioeconomic characteristics about the student and the school.

Finally, a third common identification strategy employs a Regression Discontinuity Design (RDD). The core idea of the RDD is that, when participation in the treatment (being old in a school cohort versus being young) depends on crossing a threshold (the school-entry cutoff date) in a running variable (the date of birth), comparing units around the threshold mimics a local randomized experiment (Cattaneo et al., 2020). Therefore, comparing students born in a narrow enough window of observation around the school-entry cutoff also provides an estimate for the RAE (Bernardi, 2014; Bernardi & Grätz, 2015; Dicks & Lancee, 2018; Matsubayashi & Ueda, 2015):

$$\text{RD: } y_i = \beta_0 + \beta_1 After_i + \beta_2 \boldsymbol{Z_i} + \omega_i \tag{3}$$

Where $After$ is a dummy variable that takes value 1 for students born in January or February, and value 0 for students born in November or December.

The RDD is also interesting because it allows testing whether seasonality is a threat for identification. If focusing on a particular season (the months before and after the cutoff) the effect resembles the one identified in the IV and RF models, this means that those estimations were not affected by seasonality (Bernardi, 2014). However, the identification threat in this case is that parents due to deliver around the school-entry cutoff systematically shift births to one or the other side of the cutoff (Huang, Zhang, and Zhao 2020; Kim 2021; Shigeoka 2015). Reassuringly, Valdés and Requena (forthcoming) have provided evidence exploiting birth registers that Spanish parents do not incur in this kind of strategic behavior.

As the school-entry rule is strictly applied in Spain, most methodological challenges for the estimation of the causal effect of the month of birth disappear, and the three described approaches should provide similar results. To offer estimates comparable with existing research on the RAE and assess the robustness of our results, we will compute all three models. However, our preferred specification will be the reduced-form model depicted in eq (2), because the RDD model restricts the sample to the months around the cutoff (leaving us with too few observations to perform the heterogeneity analysis) and the IV estimate pertains to the population that never repeated a grade (a common phenomenon in Spain) and is computed with larger standard errors.

For our preferred specification, we perform two additional analyses. First, we progressively include different variables to assess how the coefficient of the student's assigned age changes. Second, we assess whether the effect of the assigned age varies with the student's gender and socioeconomic status.

4.4 Variables in the study

4.4.1 Dependent variable: cognitive effort

As we elicit cognitive effort under three different conditions, we work with three different dependent variables. First, we compute cognitive effort under the intrinsic condition as the z-standardized number of correct answers in the first task performed without incentives. If students decided to play a game instead of performing the effort task at hand, they were assigned a score of zero in that round.

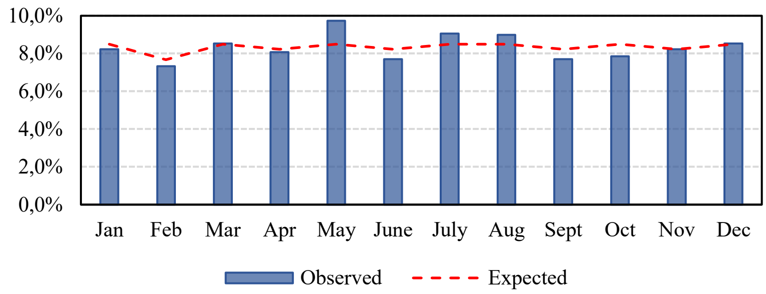
Second, we assess how a piece-rewarding system affects the relative age effect on the exertion of cognitive effort by including material incentives in the extrinsic condition. As all students performed the three tasks under this condition, we z-standardized the number of correctly answered trials in each task, add up the results, and re-standardized the variable. Since students could only gain points through task engagement, again non-participants in the task were assigned a score of zero in that round.

Finally, we examine whether any advantage of older students increases after the setting of the experiment becomes competitive. Thus, we compute the difference in performance between the tournament and extrinsic conditions for each individual. As students only participated in one task under the tournament condition, we calculate the (symmetric) difference between the z-standardized number of correct answers under the tournament condition and the z-standardized number of correct answers in the same task under the extrinsic condition.

4.4.2 Independent variable: the month of birth

In Spain, where the school-entry rule is strictly enforced, the age at school entry is perfectly determined by the student's month of birth. As observed in Figure 1, despite the limited sample size, the observed distribution of the month of birth highly resembles the expected distribution[4], with a slight surplus of students born in May, July, and August, and a minor deficit in June, September, and October. This evidence suggests that seasonality might not be an issue here.

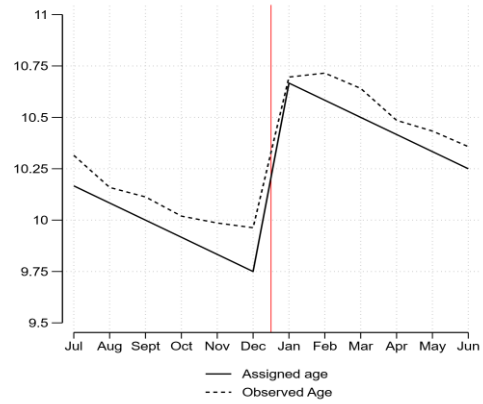
Figure 1. Distribution of the month of birth



Furthermore, Figure 2 depicts the average observed and assigned age of students by month of birth. Remember that the assigned age captures the age of fifth graders had they entered and progressed through school on time, so the only source of variation is the student's month of birth. In turn, the observed age is the actual age at which we observe fifth graders. Since the school-entry is strictly applied in Spain, the only source of variation in observed age other than the month of birth is the possibility to repeat a grade. As repeating increases the age at which we observe students, the observed age curve is displaced vertically upwards compared with the assigned age curve.

[4] Assuming that births are equally likely to occur in each day of the year, the expected proportion of births per month is computed as the proportion of days per month.

Figure 2. Observed and assigned age of the student by month of birth



4.4.3 Controls

It can be argued that certain students might perform better in the experimental tasks because they are more familiar with computers and, in particular, more used to handling a mouse, or because they play videogames more often and, thus, have more practice in completing computerized tasks. Therefore, all models control for how often students use a computer with a separate mouse and how much time they spend each day playing videogames.

Furthermore, there could be doubts about the exogeneity of the month of birth and even if it was truly random, our medium-sized sample might randomly present an unbalanced distribution by month of birth of certain characteristics later related to task performance such as gender or SES. To account for it, we control for the students' gender (boys/girls), their parents' educational attainment (the highest level of education completed by either parent and recodified as: low, lower secondary education or less; intermediate, high-school/vocational training; and high, university education), the type of school (public/private schools, either fully private or public-private mixed schools), and the income of the school neighborhood (low-income/high-income depending on whether the average household income at the zip code level of the school was above or below median household income).

Additionally, teachers were questioned about whether students have any diagnosed language issues (e.g. dyslexia), attention-deficit/hyperactivity-disorder (ADHD) or any other special needs. We created a dummy variable that takes value one if any of those issues were present and zero otherwise. As younger children in a school cohort have a higher probability to be diagnosed with a learning disorder (Arrhenius et al. 2021), which should be detrimental for performance in the effort tasks, the indicator might account for part of the advantage of the oldest students in the school cohort.

Alongside the experimental tasks, students also performed a 5-minute version of the Raven Progressive Matrices Test. We control for this measure of fluid intelligence to neutralize any confounding influence of cognitive ability and, at the same time, control out part of the advantage of older students because, as explained above, the IQ measure captures the development linked to the absolute age of the student.

Finally, we also collected information on an adapted questionnaire to assess personality traits among fifth graders. Thus, we have information on the BIG 5 personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) and the locus of control. We also include this set of z-standardized controls to assess whether there was a personality-driven edge behind the advantage of older students in the school cohort.

5 Results

5.1 The Relative Age Effect on cognitive effort

5.1.1 RAE on cognitive effect under the intrinsic condition

Table 2 displays the results for the Relative Age Effect on cognitive effort under the intrinsic condition (no rewards) following the three identification strategies described above. We find no RAE on cognitive effort elicited under the intrinsic condition. Older students seem to display slightly more effort, but the difference is not statistically significant. In our preferred specification, the reduced-form model, a one-year difference in assigned age (the maximum gap between students born in January and December) increases cognitive effort by 0.13σ (p-value = 0.311). Similarly, the IV model indicates that a one-year difference in instrumented observed age increases cognitive effort by 0.12σ (p-value = 0.295) and the RD model estimates a RAE of 0.17σ (p-value = 0.098).

As explained, students were offered the possibility to play one of two games instead of doing the task in each round. As the task was not rewarded under the intrinsic condition, only 70% of participants performed at least one of the two rounds of the task instead of playing a game. Thus, we also assess whether the decision to participate in the effort task was affected by the student's month of birth. While the task scores reflect the *intensity* dimension of effort, the choice to engage reflects the *identity* dimension of effort (Shenhav et al. 2017). Again, we find no effect of the month of birth on the probability to perform the task instead of playing in the intrinsic condition (β = 0.00; p-value = 0.980).

Finally, as we assigned an effort score of 0 to students that decided to play a game instead of participating in the effort task, we also check whether the conclusions hold if we restrict the analysis to students that performed at least one round of the task. As displayed in the third column, coefficients in IV and RF models are now negative, but remain small and non-statistically significant. For the RD model the estimated effect is virtually zero (β = 0.02; p-value = 0.629).

Overall, we conclude that, in the absence of a reward, being old or young within a school cohort is mostly irrelevant for the willingness to exert cognitive effort.

Table 2. Relative Age Effect on the effort scores under the intrinsic condition

	Scores	Participation in the task	Scores (only participants)
IV model: First stage[a]	0.91 (0.06)† [257.0]	0.91 (0.06)† [257.0]	0.94 (0.06)† [243.6]
IV model: Second stage	0.13 (0.13)	0.00 (0.07)	-0.15 (0.106)
RF: Reduced-form model	0.12 (0.12)	0.00 (0.07)	-0.15 (0.104)
RD model	0.17 (0.10)	-0.01 (0.07)	0.02 (0.137)
Observations[b]	797	797	560

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.
[a] F-statistics on the excluded instrument are reported between brackets.
[b] The number of observations is reduced to 254 in the RD model.

5.1.2 RAE on cognitive effort under the extrinsic condition

In a second stage, participants were awarded points for their performance in the three effort tasks that were later interchanged for toys. Under this extrinsic condition, there is clear evidence of an emerging RAE (Table 3): a one-year difference in assigned age increases cognitive effort by 0.43σ, a remarkable and highly statistically significant effect (p-value = 0.000). As before, the results from the IV and RD models highly resemble those from the RF model, which reinforces the robustness of the finding.

As all participants performed the three tasks under the extrinsic condition (and virtually all subjects chose the rewarded tasks over playing a game), we can compute the RAE separately for the scores obtained in each task. The RAE peaks for the Slider task, rising above half a standard deviation ($\beta = 0.51$; p-value = 0.000), and falls to one-fifth of a standard deviation in the AX task ($\beta = 0.19$; p-value = 0.137) and the Simon task (0.22; p-value = 0.021). Thus, although the RAE is remarkable when including performance rewards, and positive throughout, it is much more evident for effort directed toward cognitive processing or inhibition than towards switching.

Table 3. Relative Age Effect on effort elicited the extrinsic condition

	All tasks	Slider	AX	Simon
IV model: First-stage[a]	0.91 (0.06)† [255.1]	0.91 (0.06)† [257.0]	0.91 (0.06)† [257.0]	0.91 (0.06)† [255.1]
IV model: Second stage	0.48 (0.13)†	0.56 (0.13)†	0.21 (0.13)	0.24 (0.10)*
RF: Reduced-form model	0.43 (0.11)†	0.51 (0.11)†	0.19 (0.12)	0.22 (0.09)*
RD model	0.43 (0.08)†	0.49 (0.10)†	0.17 (0.09)	0.19 (0.10)
Observations[b]	797	798	798	797

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.
[a] F-statistics on the excluded instrument are reported between brackets.
[b] The number of observations is reduced to 254 in the RD model.

5.1.3 RAE on the change in performance under the tournament condition

In the third stage, we induce direct competition among students by awarding a certificate and a public round of applause to the three top performers in each class. Material performance awards are kept in place, so the one distinguishing feature of this tournament condition vis-à-vis the extrinsic condition is peer recognition.

Table 4 shows the RAE on the (symmetric) difference between the task performed under the tournament condition and the same task under the extrinsic condition. Within an overall uptick in average performance, we expect older students to increase their performance to a greater degree under the tournament condition given their hypothesized taste for competition. However, a one-year difference in assigned age increases performance under the tournament condition by 0.051σ (p-value = 0.257), a trivial and statistically insignificant change.

For the sake of completeness, we also show in Table 4 the RAE on the (asymmetric) difference between the performance in all three tasks under the extrinsic condition and the performance in the task assessed under the tournament condition. This method rests on more data points but sacrifices some internal validity. Although the coefficient now becomes negative, it is again trivial and not statistically different from zero. Thus, we conclude that introducing competition in the experimental setting does not further increase the effort advantage of early-born students within their cohort.

Table 4. Relative Age Effect on the difference in performance between the tournament and extrinsic conditions.

	Tournament - Extrinsic (within task)	Tournament - Extrinsic (across tasks)
IV model: First-stage [a]	0.89 (0.06)† [237.8]	0.89 (0.06)† [237.8]
IV model: Second-stage [b]	0.06 (0.09)	-0.03 (0.12)
Reduced-form model [c]	0.05 (0.08)	-0.03 (0.11)
RD model [d]	0.05 (0.08)	-0.05 (0.08)
Observations [e]	746	746

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.
[a] F-statistics on the excluded instrument are reported between brackets.
[b] The number of observations is reduced to 238 in the two months before and after the school-entry cutoff.

5.2 Controlling for student and school characteristics

Results in the previous section made clear that, under a piece-rate reward system, students born early in the year greatly outwork their peers born at the end of the year. However, no effect was observed in the absence of a reward, nor any change was found after including competition. To better understand the RAE on effort, we proceed now to progressively incorporate different controls into the reduced-form model.

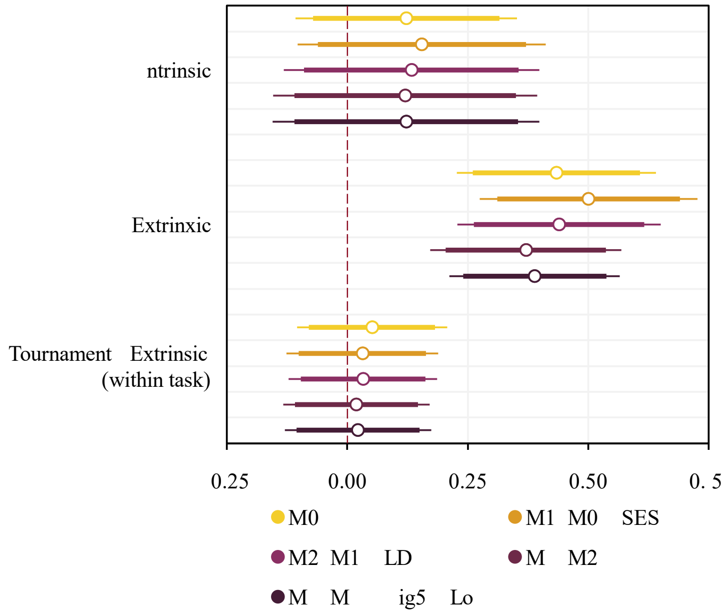
Figure 3 graphically depicts the results (full results in Tables A1 – A3 in the Appendix). The baseline model (model M0) only controls for frequency of videogaming and computer use familiarity. In the next step, we include the student's gender and educational background, the school's type, and the neighborhood's income (model M1). The effect of the students' assigned age increases after controlling for these covariates, particularly for the extrinsic condition. Now, students born early in their cohort outperform their peers born late by 0.50σ (p-value = 0.000), a 15% increase with respect to the baseline model.

Subsequently, we include the indicator for the teacher's assessment of learning disorders (model M2). The coefficient of the effect of the student's assigned age under the extrinsic condition slightly reduces to 0.44σ (p-value = 0.000), which indicates not only that learning disorders affects performance in the effort tasks, but also that the month of birth conditions the probability of being assessed by teachers as having difficulties for learning (Arrhenius et al. 2021).

In the third step, we add the fluid intelligence measure (model M3). This control is relevant not only because it purges our measure of effort of any differences in cognitive ability, but also because it controls out part of the absolute advantage of students born early in the year. After considering IQ, the coefficient for assigned age under the extrinsic component reduces further to 0.37σ (p-value = 0.000). Nonetheless, the effect is still economically and statistically significant. Thus, we are more confident that the relational dimension of the RAE plays a non-trivial role.

Finally, model M4 includes the Big 5 personality traits and the locus of control of the student. We reasoned that older students in their school cohort might have a personality-driven advantage when performing the effort tasks compared with younger pupils. However, ancillary analysis showed that the month of birth barely affected any of the Big 5 personality traits and exert only a minor effect on the locus of control. Correspondingly, we do not find that controlling for personality traits would meaningfully change the RAE estimates. If anything, there is an indication of a slight suppressor effect under the extrinsic condition, with the coefficient increasing minimally to 0.39σ (p-value = 0.000).

Figure 3. Relative age effect in the reduced-form model after controlling for different variables.



Note: 95% (thin) and 90% (thick) confidence intervals. All models include controls for frequency of videogaming and computer mouse familiarity. M0, no further controls; SES, socioeconomic characteristics of the student and the school; LD, teacher's assessment of any learning disorder; IQ, fluid intelligence; Big5, Big 5 personality traits; LoC, locus of control.

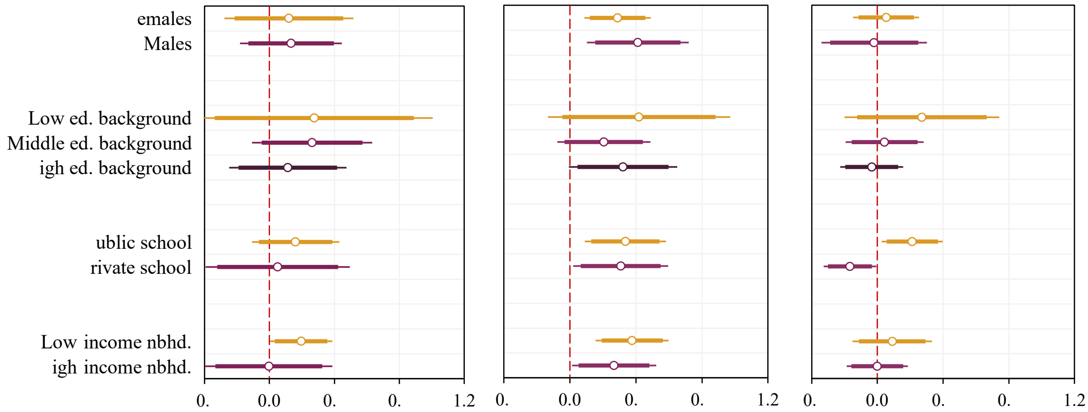
5.3 Heterogeneity analysis

Figure 4 displays the RAE for boys and girls, and high and low-SES students (full results in Table A4 in the Appendix). We employ three different indicators of socioeconomic status (parents' education, type of school and neighborhood income) and add the corresponding interaction terms to the specification of M3. However, to avoid overcontrol bias (Grätz 2022), when computing the interaction between birth month and each of those variables, we do not include the other two.

On the one hand, the RAE seems to be larger among boys. Under the extrinsic condition, a one-year difference in assigned age entails an advantage of 0.41σ among boys, while the effect drops to 0.29σ among girls. Although we lack statistical power to affirm the statistical significance of that difference (β = 0.12; p-value = 0.507), it represents one-quarter of the effect identified for the whole sample.

On the other hand, low-SES children (from low-educated families, attending public schools, and living in low-income neighborhoods) exhibit overall larger RAEs on cognitive effort than their high-SES counterparts. Under the intrinsic condition, the small and statistically insignificant effect found for the whole sample masked a substantial effect for students from low educational backgrounds, enrolled in public schools, and schooled in low-income neighborhoods. In this latter case, the interaction effect even reaches statistical significance (β = 0.19σ; p-value = 0.065). The interaction with SES is less intense for the effect of assigned age on effort elicited under the extrinsic condition. It is again in the distinction between students schooled in low and high-income neighborhoods where we observe a larger difference in the RAE (0.11σ), but not statistically significant (p-value = 0.534). Finally, for the change in performance due to status competition, we observe a substantial interaction between the RAE and the student' SES for all indicators. For instance, while the effect among students with university-educated parents did not change at all in the competitive setting, for students with low-educated parents it increased by 0.27σ. Apparently, the competitive setting particularly steered low-SES students born early in their cohort. Note, however, that these estimates are computed with high uncertainty.

Figure 4. Heterogeneity analysis



Note: 95% (thin) and 90% (thick) confidence intervals. All models include controls for frequency of videogaming, computer mouse familiarity, the gender, SES and fluid intelligence of the student, and the teacher's assessment about learning disorders.

6 Discussion and Conclusions

A fast-growing body of research has investigated the effect of the month of birth within a school cohort on academic outcomes. There is wide agreement on the relevance of the so-called relative age effect on academic performance in the early stages of the educational career. However, the results for final educational attainment are more ambiguous. In some contexts, the month of birth conditions final attainment and even later-life outcomes such as the occupational career (Crawford, Dearden, and Greaves 2013; Røed Larsen and Solli 2017), the access to the positions of power in the society (Du, Gao, and Levi 2012; Muller and Page 2016), or the dynamics of family formation (Peña 2017; Skirbekk, Kohler, and Prskawetz 2004). In other cases, the RAE has been observed to wear off before affecting final educational attainment (Bedard and Dhuey 2006; Cáceres-Delpiano and Giolito 2018; Elder and Lubotsky 2009; Oosterbeek, ter Meulen, and van der Klaauw 2021), possibly alleviating concerns about this social problem. Nonetheless, we argue that, even in contexts where this was the case, the effect of the month of birth deserves attention as it affects the quality of life during compulsory education of students born late within the cohort and might leave a permanent imprint in non-academic outcomes such as personality traits or socio-behavioral skills. As these characteristics play an increasingly important role in the labor market over and above educational attainment (Heckman, Stixrud, and Urzua 2006), the month of birth effect might have long-term implications even if it does not affect educational attainment. We contribute to this thread of research by assessing the relative age effect on the willingness to exert cognitive effort elicited in an experimental setting.

For starters, we observed that the student's month of birth did not affect cognitive effort in the absence of a reward, nor did it affect task choice. The fact that no RAE was found under the intrinsic condition is reassuring because it suggests that there are no underlying ability differences affecting performance in the tasks. In other words, if older students were simply better equipped to perform the tasks than younger classmates, they should have performed at higher levels already in the intrinsic condition.

In a second step, students were awarded points for their performance in the effort tasks that were later cashed in for toys. We expected the RAE to emerge under this extrinsic condition because all students had now a powerful incentive to give it their best. Consistently with that expectation, students born at the beginning of the year outworked their peers born at the end of the year by two-fifths of a standard deviation. To benchmark this result, boys outperform girls in the effort tasks under the extrinsic condition by 0.39σ and students with university-educated parents outperform their peers with low-educated parents by 0.33σ (Table A2 in the Appendix). Therefore, a one-year difference in age within a cohort has a larger effect on the willingness to exert cognitive effort than the student's gender or social origin. This result adds to previous evidence of older students showing higher persistence and grit (Peña and Duckworth 2018), a higher taste for competition and self-confidence (Page, Sarkar, and Silva-Goncalves 2017), or higher leadership skills (Dhuey and Lipscomb 2008). With age-related developmental gaps waning naturally over time, the boost in "soft skills" that older children receive may be the key to understanding the persistence of the RAE on academic outcomes over time. A higher willingness to exert effort should account for part of the well-documented academic advantage of older students in a school cohort.

However, we cannot provide evidence on *why* fifth graders born early in the cohort came to be more willing to exert effort than their fifth-grade peers born late in the cohort. A plausible explanation is that older students obtained higher returns to their efforts in the initial years of their educational careers, which in turn justified the realization of new efforts to attain subsequent academic goals. In turn, the lower returns to effort among late-born students will disincentivize new efforts in the future, leading to the observed pattern. This kind of Bayesian learning process is common in sociological explanations of educational inequalities drawing on rational choice models (Breen 1999).

Finally, we anticipated that the effort advantage of older students might be strengthened after inducing competition for peer recognition on top of material incentives. Our expectation was based on previous research observing that early-born students in the school cohort have a stronger preference for competition (Page, Sarkar, and Silva-Goncalves 2017). However, we do not observe any within-cohort age effect on the change in effort between the extrinsic and the tournament condition. While average effort increased with the added inclusion of status incentives, this uptick was not age-graded. Despite of that, the fact that older students in a cohort are more willing to exert effort might help explain the strong age effects observed in highly competitive settings (Du, Gao, and Levi 2012; Muller and Page 2016; Wendling and Mills 2018).

It is important to acknowledge further limitations of our work. Although the experimental tasks demand the exertion of fundamental cognitive functions that are also required in countless everyday interactions, the external validity can be questioned. The laboratory design is arguably better equipped to capture differences in intensive, short-term effort than longer-term persistence or grit. Moreover, our measure of cognitive effort might still be influenced by unobserved ability. Controlling for fluid intelligence and special needs contributes to purging the estimation of differences in cognitive ability. Also, we cannot neatly differentiate the absolute component of the RAE from its truly relational component. Nonetheless, since a notable age effect remains after controlling for fluid intelligence and learning disabilities, our results suggest that part of the effort (dis)advantage of older (younger) students derives from the relational component. Finally, when we disaggregate the results under the extrinsic condition by task, we observe a particularly strong RAE on the slider task. As hand-eye coordination is still developing at these ages and especially salient in the slider task, it may affect our RAE estimate.

Despite these limitations, we consider these results to have important consequences for research on educational inequality. Indeed, it is surprising that sociological research has largely overlooked the academic inequalities induced by the month of birth relative to the school entry cutoff. To contribute to filling that gap, we interact the relative age effect with the student's gender and various indicators of SES. Although we lack statistical power to affirm the statistical significance of most of the interactions analyzed, those interactions are consistent in sign and size with most literature that has investigated the RAE on academic outcomes as well as its heterogeneity by gender (Datar 2006; McEwan and Shapiro 2008; Mühlenweg 2010) and SES (Bernardi 2014;

Bernardi and Grätz 2015; Dicks and Lancee 2018). Our results suggest that the relative age effect on cognitive effort might be larger among boys and low-SES students. Thus, one reason why boys and low-SES students lag behind at school might be that boys and low-SES students born late into the year are highly unwilling to exert effort.

In terms of policy implications, we make two suggestions to ameliorate the consequences of the month of birth on academic and non-academic outcomes. First, it is crucial that teachers keep in mind the relevance of the student's age within the cohort when assessing their performance, particularly during the initial stages of schooling. Therefore, it might be advisable that the IT applications where teachers register students' grades display the student's exact age and the average age of the classroom. Through such a nudge, teachers would be reminded of the position of the student in the age distribution of the class when making their academic assessments. Second, this work joins a large body of research concluding that, even though the intention behind calendars organizing school entry-cohorts is to homogenize groups in terms of school readiness, substantial developmental heterogeneity remains when grouping students born up to one year apart. Two entry cohorts per year (with one cutoff per semester) would largely solve the problem, but probably cause excessive administrative costs. Therefore, even if school cohorts continue to be organized on a yearly rhythm, classes or learning-groups within a cohort could be organized considering the month of birth. In this way, students will compare themselves and be compared by teachers with peers who are more similar in terms of maturity and readiness to learn.

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9 Appendix

Table A1. Full results for the stepwise model for the intrinsic condition

	Model 0	Model 1	Model 2	Model 3	Model 4
Assigned age	0.12 (0.12)	0.15 (0.13)	0.13 (0.14)	0.12 (0.14)	0.12 (0.14)
Ed. background (Middle vs Low)		-0.06 (0.11)	-0.07 (0.12)	-0.08 (0.12)	-0.08 (0.12)
Ed. background (High vs Low)		0.17 (0.13)	0.16 (0.13)	0.14 (0.13)	0.14 (0.13)
Gender (Male vs Female)		-0.01 (0.07)	0.00 (0.07)	0.00 (0.07)	0.03 (0.07)
Neighborhood income (High vs Low)		0.01 (0.16)	0.01 (0.16)	0.00 (0.16)	0.00 (0.16)
Type of school (Public vs Private)		0.14 (0.16)	0.14 (0.16)	0.14 (0.16)	0.13 (0.16)
Learning disorder			-0.22 (0.12)	-0.21 (0.12)	-0.21 (0.11)
IQ				0.05 (0.04)	0.05 (0.04)
Openness					-0.02 (0.03)
Conscientiousness					0.00 (0.05)
Extraversion					0.01 (0.03)
Agreeableness					0.05 (0.03)
Neuroticism					0.05 (0.03)
Locus of control					0.00 (0.03)

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.

Table A2. Stepwise model for the extrinsic scores

	Model 0	Model 1	Model 2	Model 3	Model 4
Assigned age	0.43 (0.11)†	0.50 (0.12)†	0.44 (0.11)†	0.37 (0.10)†	0.39 (0.09)†
Ed. background (Middle vs Low)		0.00 (0.13)	-0.03 (0.13)	-0.04 (0.12)	-0.05 (0.11)
Ed. background (High vs Low)		0.33 (0.11)†	0.29 (0.11)*	0.19 (0.10)	0.20 (0.09)*
Gender (Male vs Female)		0.39 (0.08)†	0.41 (0.07)†	0.42 (0.06)†	0.46 (0.05)†
Neighborhood income (High vs Low)		0.12 (0.09)	0.13 (0.08)	0.12 (0.06)	0.12 (0.05)*
Type of school (Public vs Private)		0.12 (0.09)	0.11 (0.09)	0.11 (0.06)	0.13 (0.06)*
Learning disorder			-0.64 (0.14)†	-0.50 (0.13)†	0.26 (0.03)†
IQ				0.26 (0.03)†	-0.47 (0.12)†
Openness					-0.03 (0.04)
Conscientiousness					0.01 (0.04)
Extraversion					0.03 (0.03)
Agreeableness					0.11 (0.03)†
Neuroticism					0.01 (0.05)
Locus of control					0.01 (0.03)

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.

Table A3. Stepwise model for the difference between the tournament and extrinsic scores (within task)

	Model 0	Model 1	Model 2	Model 3	Model 4
Assigned age	0.05 (0.08)	0.03 (0.08)	0.03 (0.08)	0.02 (0.08)	0.02 (0.08)
Ed. background (Middle vs Low)		0.16 (0.09)	0.16 (0.09)	0.15 (0.08)	0.15 (0.09)
Ed. background (High vs Low)		0.10 (0.07)	0.10 (0.07)	0.08 (0.07)	0.07 (0.07)
Gender (Male vs Female)		0.07 (0.04)	0.07 (0.04)	0.07 (0.04)	0.07 (0.04)
Neighborhood income (High vs Low)		0.09 (0.08)	0.09 (0.08)	0.09 (0.08)	0.09 (0.08)
Type of school (Public vs Private)		-0.18 (0.07)*	-0.18 (0.07)*	-0.18 (0.07)*	-0.18 (0.07)*
Learning disorder			0.01 (0.09)	0.04 (0.09)	0.03 (0.09)
IQ				0.05 (0.03)	0.05 (0.03)
Openness					0.02 (0.04)
Conscientiousness					0.03 (0.04)
Extraversion					-0.02 (0.03)
Agreeableness					0.00 (0.03)
Neuroticism					0.00 (0.02)
Locus of control					0.01 (0.02)

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.

Table A4. Heterogeneity analysis.

	Intrinsic	Extrinsic	Tournament – Extrinsic (within task)
Interaction with gender			
Coefficients (reduced-form model)			
Assigned age	0.12 (0.20)	0.29 (0.10)*	0.05 (0.10)
Assigned age * Male	0.01 (0.22)	0.12 (0.18)	-0.07 (0.22)
Marginal effect of assigned age			
Female	0.12 (0.20)	0.29 (0.10)*	0.05 (0.10)
Male	0.13 (0.16)	0.41 (0.16)*	-0.02 (0.16)
Interaction with educational background			
Coefficients (reduced-form model)			
Assigned age	0.27 (0.37)	0.42 (0.28)	0.27 (0.24)
Assigned age * Middle ed. background	-0.01 (0.51)	-0.21 (0.36)	-0.23 (0.27)
Assigned age * High ed. background	-0.16 (0.42)	-0.10 (0.32)	-0.31 (0.25)
Marginal effect of assigned age			
Low ed. background	0.27 (0.37)	0.42 (0.28)	0.27 (0.24)
Middle ed. background	0.26 (0.19)	0.21 (0.14)	0.04 (0.12)
High ed. background	0.11 (0.18)	0.32 (0.17)	-0.03 (0.10)
Interaction with type of school			
Coefficients (reduced-form model)			
Assigned age	0.05 (0.23)	0.31 (0.15)	-0.17 (0.08)
Assigned age * Public	0.11 (0.25)	0.03 (0.20)	0.38 (0.13)†
Marginal effect of assigned age			
Public	0.16 (0.14)	0.34 (0.13)*	0.21 (0.10)*
Private	0.05 (0.23)	0.31 (0.15)	-0.17 (0.08)
Interaction with income of neighborhood			
Coefficients (reduced-form model)			
Observed age	0.19 (0.10)	0.38 (0.11)†	0.09 (0.12)
Observed age * High-income nbhd.	-0.20 (0.21)	-0.11 (0.17)	-0.09 (0.16)
Marginal effect of assigned age			
Low-income nbhd.	0.19 (0.10)	0.38 (0.11)†	0.09 (0.12)
High-income nbhd.	0.00 (0.20)	0.27 (0.13)	0.00 (0.10)

Note: † p-value ≤ 0.01; * p-value ≤ 0.05. All models include controls for frequency of videogaming and computer mouse familiarity. Standard errors, in parentheses, are clustered at the classroom level.