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This article examines the impact of within-class age differences on educational outcomes, using students' birth months in Madrid's primary schools as a natural experiment. Employing a regression discontinuity design, we analyze third-grade students to investigate these age-related effects. Additionally, we explore whether early childhood education attendance works as a mitigating factor. Results indicate that relatively older students achieve higher scores in both Language and Mathematics and have lower grade retention rates. However, this gap is attenuated among students who attended childhood education for two years or more. These novel results highlight the importance of early childhood education in reducing natural inequalities that may persist over time.

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Does Early Childhood Education mitigate the birthdate effect? A regression discontinuity analysis of administrative data.

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Highlights

- Using standardized test scores from Madrid's primary schools, we examine the effects of relative age differences within 3rd grade cohort.
- Students who are the oldest at 3rd grade outperform their youngest peers by 0.16 standard deviations in Language and 0.13 in Mathematics and have a 2-percentage point lower probability of grade retention.
- Early childhood education (0-2 years) reduces the relative age achievement gap by 0.05 standard deviation in Mathematics, while in Language only by 0.02 standard deviation.
- Parental support at home for relatively younger students does not mitigate the relative age gap.

Abstract

This article examines the impact of within-class age differences on educational outcomes, using students' birth months in Madrid's primary schools as a natural experiment. Employing a regression discontinuity design, we analyze third-grade students to investigate these age-related effects. Additionally, we explore whether early childhood education attendance works as a mitigating factor. Results indicate that relatively older students achieve higher scores in both Language and Mathematics and have lower grade retention rates. However, this gap is attenuated among students who attended childhood education for two years or more. These novel results highlight the importance of early childhood education in reducing natural inequalities that may persist over time.

Keywords: birthdate effect, student test scores, relative age, childhood education, school, repetition
JEL classification: I20, I21

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1. Introduction

The timing of a child's birthdate can have subtle but profound impacts on their educational journey, influencing their developmental readiness and academic outcomes. Children born at different times of the year face inherent disparities in cognitive, emotional, and physical maturity when they start school. This raises critical questions about how such differences might translate into measurable gaps in performance, particularly in subjects like Language and Mathematics, by the time they reach third grade. The literature suggests that older children within the same cohort—those born earlier in the year in the case of Spain—tend to perform better academically than their younger peers. This phenomenon, known as the relative age effect, can also lead to higher rates of grade retention and long-term disparities in educational attainment and socioeconomic outcomes (Bedard & Dhuey, 2006; Cook & Kang, 2016; Dhuey et al., 2019; Dhuey & Lipscomb, 2010; Elder & Lubotsky, 2009; P. A. Peña, 2017).

While evidence indicates that relative age influences both short-term and long-term outcomes for individuals, yet research on effective policy interventions to close this natural gap remains limited. Dhuey et al., (2019) suggest that smaller class sizes may benefit these younger students as well as early retention policies because these have been shown to improve short-term outcomes – particularly for those from disadvantaged families who do not engage in redshirting practices. Another approach involves using age-adjusted national achievement tests to account for maturity differences (Crawford et al., 2014; P. Peña, 2022), although the feasibility of implementing such policies in education settings is not widely accepted. Conversely, as most countries do, deferring decisions on tracking ability at the group or institutional level has also been shown to reduce the relative advantage of older students due to the catch-up effect (Oosterbeek et al., 2021)

However, the extent to which early childhood education and care (ECEC) might mitigate these disadvantages remains underexplored. Specifically, it is crucial to understand whether attending structured learning environments at a younger age can help bridge the performance gap that younger students face. If so, how effective are these interventions in levelling the playing field for students born later in the year considering that these early advantages compound over time, creating a cumulative gap in skill acquisition (Cunha et al., 2006). So, while ECEC interventions have shown significant benefits for students from lower socioeconomic backgrounds (Duncan et al., 2023), their potential role in addressing age-related educational disparities warrants further research.

This study investigates the relative age effect in the Region's educational system in Madrid, where school enrollment is based strictly on birth year. By analyzing a comprehensive dataset from the Madrid Skills Assessment, encompassing census-level information on third-grade students from the 2016-2017 and 2018-2019 academic years, we estimate the performance gap in Language and Mathematics associated with relative age. Then, we aim to determine whether participation in early childhood programs before primary school reduces the performance disparity between older and younger students in the same cohort by exploring how varying durations of ECEC attendance influence the outcomes, providing insights into the critical role of early interventions in mitigating long-term educational inequalities.

To address these questions, we employ a regression discontinuity design (RDD) that takes advantage of the natural cut-off in school entry dates, enabling us to estimate the causal effect of relative age on academic performance. This approach provides a robust framework for isolating the influence of birthdate on educational outcomes. Furthermore, we examine the role of ECEC by comparing students who participated in early childhood programs at different ages, allowing us to explore how early interventions might help narrow the relative age gap.

Our results indicate a modest yet statistically significant relative age effect, with January-born students outperforming their December-born peers by 0.16 standard deviations (SD) in Language and 0.13 SD in Mathematics. Although the difference between the subjects is modest, it points to a plausible age-related impact on academic performance. Notably, the gap narrows for students who attended ECEC. For example, those who participated in early education programs from 0-2 years old show a reduced gap in Mathematics (0.13 SD) compared to students who started later. These findings underscore the potential of ECEC to mitigate age-based disadvantages and suggest that early interventions may play a crucial role in reducing educational inequality.

This study makes several significant contributions to the literature. First, it provides new evidence on the role of ECEC in addressing the relative age effect. While previous studies have documented its benefits to disadvantaged children (Duncan et al., 2023; van Huizen & Plantenga, 2018), few have explored how these programs specifically reduce the performance gap between younger and older students within a cohort; thus, it allows us to provide a novel measure of ECEC effectiveness. Second, our study uses a population-level dataset from Madrid, offering insights that can be generalized to other contexts with similar educational systems. Combining census-level data and a robust empirical design provides high internal and external validity. Third, by focusing on a specific policy question—whether early childhood education can offset natural birthdate disparities—we contribute to the ongoing policy debate on how to allocate resources for early education best.

Regarding internal validity, our study benefits from an intense identification strategy. Regression discontinuity, combined with a large sample size and population-level data, ensures our findings are robust and generalizable. Unlike previous studies that rely on small or regional samples, our dataset includes about 70,000 observations, providing a comprehensive view of the educational landscape in Madrid. Additionally, our focus on a well-defined policy shock—school enrollment cut-off dates—allows us to estimate the causal impact of relative age with precision.

Externally, this research has broader implications for educational policy. By demonstrating the effectiveness of ECEC in reducing the relative age gap, our findings support the expansion of early childhood programs, particularly for younger and disadvantaged students. Moreover, our results align with international evidence on the importance of early interventions in reducing long-term educational inequalities, making this study relevant for policymakers in other countries facing similar challenges. The generalizability of our findings is further supported by the fact that Madrid's educational system shares many characteristics with other regions in Spain and beyond.

The remainder of this paper is structured as follows. The next section provides a detailed overview of the contextual framework, focusing on the Spanish education system and the Madrid Skills Assessment dataset. The third section outlines our empirical strategy, describing the regression discontinuity design used to estimate the causal impact of birthdate on educational outcomes and the moderating role of early childhood education. In the fourth section, we present the main results, including the effect of relative age on academic performance and the heterogeneity of outcomes based on early childhood education attendance. The fifth section includes robustness checks to validate our findings and a discussion of policy implications. Finally, we summarize the key takeaways and suggest avenues for future research.

2. Contextual framework and database

Spain's education system is characterized by a high degree of decentralization, with regional governments (Comunidades Autónomas) managing their education policies within a national framework established by the country's Education Laws. This framework sets the foundation for compulsory primary education, starting when children turn six years old. School admission is based on birth year, and students are placed into an academic year accordingly. Enrollment typically occurs in September, strictly adhering to the calendar year of birth, resulting in age gaps of up to one year between classmates. For instance, students born in January are considered relatively older, while those born in December are the youngest in their cohort (P. A. Peña, 2017). The specific cut-off system generates nearly a year of age difference between the youngest and oldest students in a cohort, which can have significant implications for their educational performance (Cook & Kang, 2020). These age differences can also be exacerbated by factors like grade retention or being identified as gifted, which further alters the composition of age groups within classrooms (Urruticoechea et al., 2021)

In many countries, parents can delay their child's school entry—"redshirting"—especially if the child is born just before the cut-off date. This practice is common in countries like the United States (Deming & Dynarski, 2008), but is not allowed under Spanish law. In Spain, all children must start school at the designated age regardless of their birth date, ensuring uniformity in school entry across the country.

Between 2013 and 2020, the Spanish education system was shaped by the LOMCE law, which mandates regional governments to evaluate student competencies. However, the design and implementation of these assessments are left to the regional authorities. Consequently, these evaluations vary across regions, making it difficult to compare educational outcomes directly. However, some regions, like Madrid, have implemented their large-scale evaluations. Unlike most other regions in Spain, the Community of Madrid conducts census-based student assessments, allowing for more comprehensive data collection from 2016 until the onset of the COVID-19 pandemic.

2.1 Database

In this study, we rely on the census-based Skills Assessment conducted in the Region of Madrid, which provides a rich dataset comprising two critical types of information: evaluation results and contextual questionnaires. These assessments are modelled after major international proficiency tests such as PISA, PIRLS, and TIMSS. The results are grounded in Item Response Theory (IRT), explicitly using the Rasch model, which estimates students' abilities based on their responses and the difficulty of test items. To standardize the results, the tests use a similar methodology to that employed in PISA, normalizing scores to an average of 500 with a standard deviation of 100.

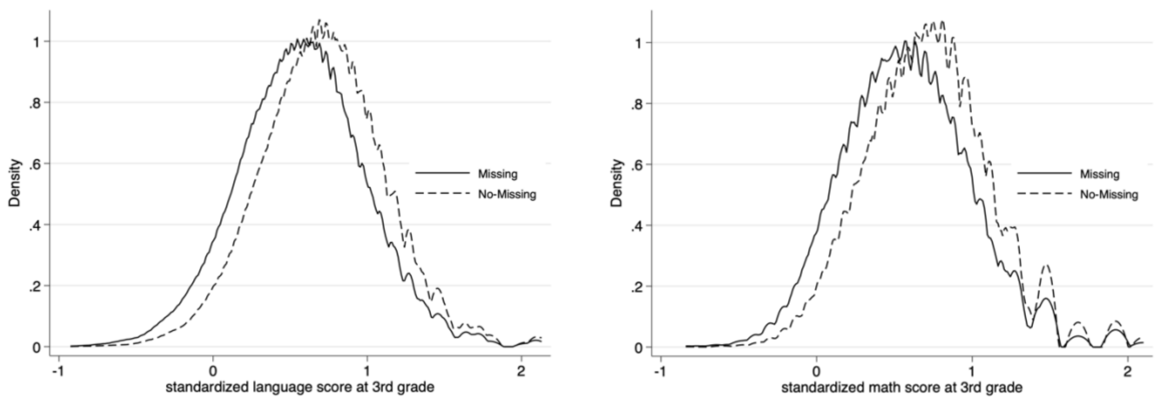
In addition to the test results, the dataset includes a wealth of contextual information from multiple sources. These consist of family context questionnaires completed by parents, school context questionnaires completed by school principals, and teacher questionnaires from those teaching the evaluated subjects. This multi-faceted data allows for an in-depth analysis of how social, family, and school environments influence student performance. The dataset also records information on ECEC attendance, enabling a comprehensive analysis of how early interventions impact academic outcomes.

Our analysis focuses on two academic cohorts, 2016-2017 and 2018-2019[1]. After addressing missing data about ECEC attendance and birth month, we work with a final sample of 67,387 students. To ensure that the missing data does not introduce bias into our results, we conduct kernel density analyses of Language and Mathematics scores, comparing students with and without missing data. As seen in Figure 1, both distributions show similar shapes, with the missing data group slightly shifted to the left, suggesting lower average performance. However, the overall similarity in the curves indicates that the missing data is random and not systematically related to the outcome variables. This suggests that the results are not likely to be biased due to missing data. Moreover, the data shows ECEC attendance rates consistent with national figures: 56% of children attended from 0-2 years old, 20% from age 2, and 21% from age 3, indicating that nearly all children in Madrid are enrolled in preschool by age four (Zhang, 2023).

Figure 1. Kernel test scores distributions before and after excluding missing values.

Figure 1a. Language

Figure 1b. Mathematics



3. Empirical Strategy

Our empirical strategy leverages the natural variation in birth dates within a single cohort, resulting in an almost one-year age gap between students born in January and those born in December. This distinct cutoff allows us to use a regression discontinuity design (RDD), a method widely used in quasi-experimental settings to identify causal effects when the treatment assignment is determined by an arbitrary threshold (Cattaneo et al., 2019). By capitalizing on this cutoff, we aim to estimate the causal impact of relative age on key

[1] The 2017-2018 academic year presents a challenge as the available data is limited to information provided solely by the students. This restriction stems from a discrepancy in the coding system used across different databases (school-level, family-level, and student-level). As Sanz and Tena (2023) note, students might not have accurate information on certain aspects, such as their parent's level of education or whether they started early childhood education before age two.

academic outcomes, including test scores in Language and Mathematics as well as the likelihood of grade repetition.

We model the relative age effect using the following specification:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \varepsilon_i$$

Where Y_i represents the outcome of interest for student i, either test scores or grade repetition. The variable D_i is a binary variable which takes value 1 if the student was born in January, making him/her relatively older, and takes value 0 otherwise. The coefficient β captures the causal effect of being older within the cohort, with a set of covariates X_i that control for student and family characteristics. ε_i is the error term.

The cutoff date for school entry (January 1st) is an exogenous threshold under the assumption that the birth month is quasi-random concerning unobservable characteristics. With this assumption, students born in January should be comparable to those born later in the year, except for their relative age within the cohort. This assumption is backed by Spain's strict school entry policy, which leaves little room for redshirting—a practice where parents delay a child's school start to make them older than their peers (Deming & Dynarski, 2008)

To validate the quasi-random assignment of birth month, Table 1 presents key characteristics of students born in the first half of the year (January to June) and those born in the second half (July to December). The table shows the distribution of female students is identical (50%) in both semesters, and parental education shows no significant differences across all categories. While we observe statistically significant differences in immigration-related covariates, these differences are very small in magnitude (1 percentage point) and likely only detectable due to our large sample size of 67,253 students.

Table 1: Balance of Covariates Across Birth Semesters

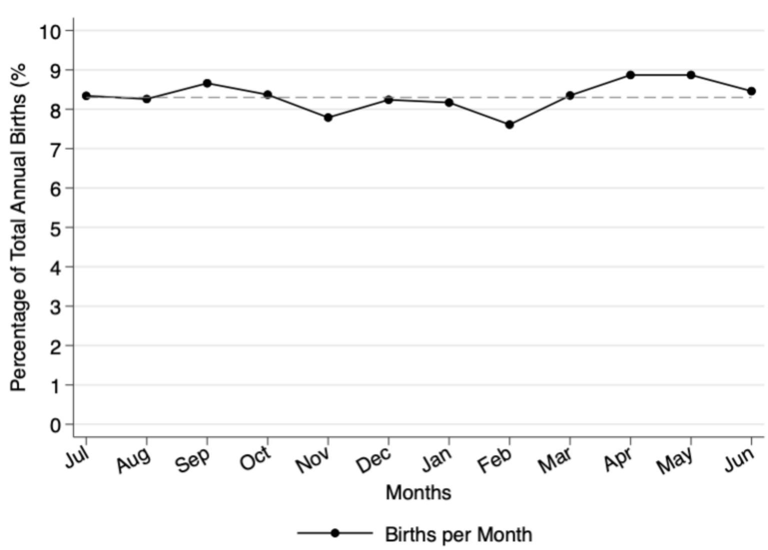
	1st semester		2nd semester		1st v/s 2nd semester	
	Mean	SD	Mean	SD	Mean Difference	p-value
female	0.50	0.50	0.50	0.50	0.00	0.556
1st gen immigrant student	0.02	0.14	0.02	0.15	0.00	0.170
2nd gen immigrant student	0.14	0.35	0.15	0.36	0.01***	0.001
immigrant father	0.16	0.37	0.17	0.37	0.01***	0.009
immigrant mother	0.16	0.37	0.18	0.38	0.01***	0.000
Mother education level: high	0.54	0.50	0.55	0.50	0.00	0.412
Father education level: high	0.46	0.50	0.46	0.50	0.00	0.590

	1st semester		2nd semester		1st v/s 2nd semester	
	Mean	SD	Mean	SD	Mean Difference	p-value
Mother education level: medium	0.31	0.46	0.31	0.46	-0.00	0.171
Father education level: medium	0.34	0.47	0.34	0.47	0.00	0.746
Mother education level: low	0.14	0.34	0.14	0.35	0.00	0.416
Father education level: low	0.20	0.40	0.20	0.40	-0.00	0.430
Mother education level: No education	0.00	0.06	0.00	0.06	-0.00	0.375
Father education level: No education	0.01	0.08	0.01	0.07	-0.00	0.161
Observations	33850		33403		67253	

Last columns show mean differences with t-test significance and its respective p-value.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2 illustrates the monthly distribution of births, supporting the assumption of randomness in birth timing. If parents were strategically timing births to gain advantages (e.g., to ensure their child is relatively older), we would expect visible deviations in birth rates around critical months like January. However, the figure shows that birth rates are consistently distributed across the months, with each month close to the expected 8.3% of total births (dashed line).

Figure 2: Monthly Distribution of Births as a Percentage of Annual Births



While some months, such as February and November, fall slightly below the expected level, these deviations are likely due to the shorter number of days in these months rather than any strategic timing. For example, the dip in February's birth rate is consistent with its being the shortest month of the year. Conversely, the modest increase in births during April and May could be attributed to seasonality, but the magnitude of these deviations is negligible. This even distribution across all months, especially around the critical cutoff of January, provides further evidence that parents are not engaging in behaviors like redshirting.

The consistent birth distribution supports our regression discontinuity design (RDD) because it confirms that birth month can be treated as quasi-random. There is no clustering of births near the cutoff, which would suggest manipulation. This lack of bunching supports the exogeneity of the cutoff, giving us confidence that we are identifying the actual causal effect of relative age on educational outcomes.

To estimate the impact of relative age on academic outcomes, we first implement an Ordinary Least Squares (OLS) regression as a baseline. We then apply inverse distance weighting (IDW) to account for proximity to the cutoff. This method assigns a weight of 1/d, where d represents the distance from the cutoff. This technique allows us to give more importance to students close to the cutoff, thus improving the precision of our estimates for marginal cases (Cook & Kang, 2016; Dicks & Lancee, 2018)

In addition, we apply a local randomization approach to account for the discrete nature of our running variable. Following (Dhuey et al., 2019) and (Cattaneo et al., 2023), we restrict our analysis to a one-month window around the cutoff. This approach allows us to treat the January-December birth interval as a random assignment, mitigating concerns of bias due to the discrete nature of birth months. By focusing on students born in January and December, we improve the internal validity of our estimates, isolating the effect of relative age more effectively.

Following the same approach, we conduct a heterogeneity analysis to explore whether early childhood education and care (ECEC) can mitigate the relative age effect. Specifically, we compare students who attended ECEC for two or more years with those who did not. This allows us to assess whether early educational interventions can narrow the performance gap between older and younger students. The analysis includes interaction terms between birth month and the duration of ECEC attendance, offering insights into the long-term effects of early educational programs on academic performance.

Finally, to ensure the robustness of our findings, we conduct several validity checks. First, we address potential selection concerns related to birth timing. Given that more educated parents might strategically plan childbirth to ensure their children are among the oldest in their cohort, we examine the relationship between birth dates and parental education levels. Second, we analyze if parents of relatively younger students provide extra support to compensate for potential age-related disadvantages. It is important because this additional support could confound the relationship between relative age and academic performance. Third, we implement a falsification test around the school entry cutoff by comparing the characteristics of students born in December versus January. This test helps validate the assumption that there is no systematic sorting of students around the cutoff date. Finally, to explore potential heterogeneous effects, we conduct subgroup analyses stratifying our sample by parental education, gender, and immigration status. These analyses allow us to investigate whether the age-at-school-entry effects vary systematically across different demographic groups.

In conclusion, our combination of a sharp RDD, inverse distance weighting, and local randomization provides a strong empirical framework for identifying the causal effect of relative age on academic outcomes.

4. Main Results

4.1 Graphical Analysis.

The graphical representations in Figures 3 and 4 reveal clear patterns in the relationship between birth month and academic outcomes. Specifically, Figure 3 displays the conditional means of standardized test scores in Language and Mathematics by birth month. Each graph fits a quadratic line, with confidence intervals providing additional context for variability. As the data shows, students born in January consistently perform better in both subjects, with average scores gradually decreasing for those born in subsequent months. This pattern holds across Language and Mathematics assessments, confirming the well-documented relative age effect in education.

Figure 3. Test scores mean by month of birth

Figure 3a: Language

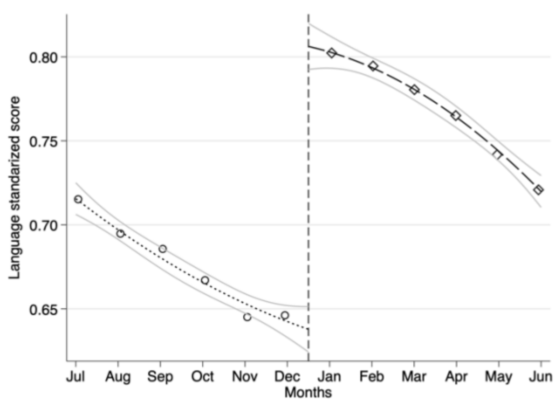
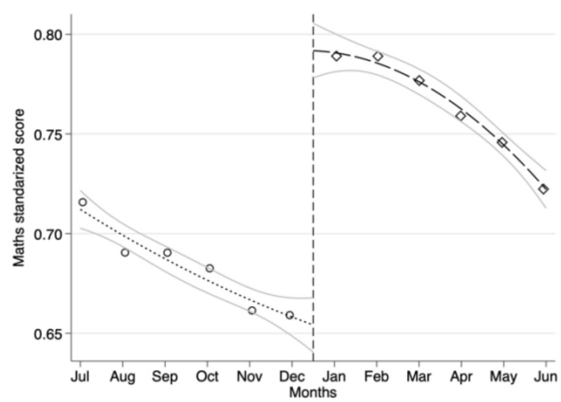


Figure 3b: Mathematics

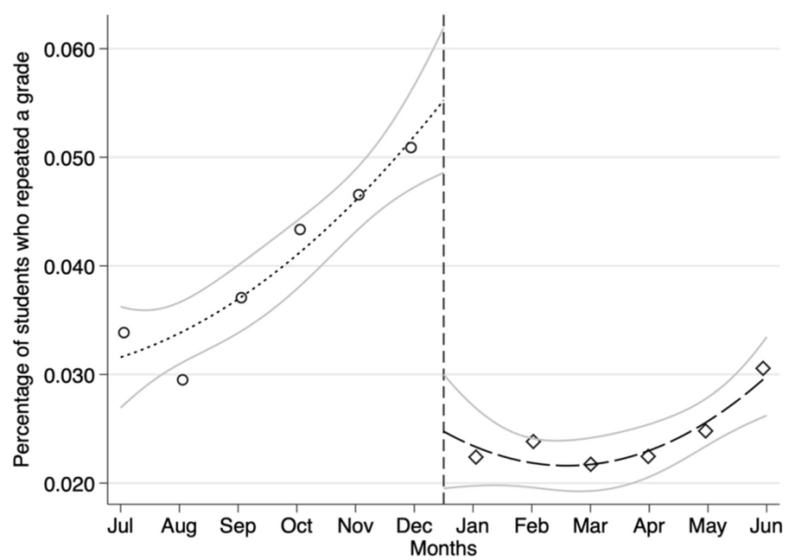


The relationship between birth month and test scores is monotonic and decreasing across the two competencies analyzed. This suggests that older students (those born earlier in the year) tend to score higher on average than their younger peers, reinforcing findings from previous studies for Spain (Gutiérrez-Domènech & Adserà, 2012). Notably, the steepest declines occur from January to June, indicating that students born closer to the cutoff benefit significantly from being relatively older, while the gap narrows as we approach the year's midpoint.

A key observation from Figure 3 is that while the score decline is consistent, the rate of decline is slightly steeper for Language than for Mathematics. This difference may reflect that Language development is more sensitive to age differences during early schooling, though both competencies exhibit similar trends overall.

Figure 4 plots the relationship between the rate of grade repetition and birth month. Once again, a distinct pattern emerges; students born in December have a markedly higher likelihood of repeating a grade than those born in January. The difference is substantial, at approximately 3.5 percentage points. More importantly, there is an apparent threshold effect. For students born between January and May, the repetition rate remains relatively stable. However, it begins to rise sharply for students born after May, reaching its peak for December-born students.

Figure 4. Rate of repetition by month of birth.



The graph illustrates that birth month not only affects standardized test scores but also strongly impacts the likelihood of repeating a grade. This observation aligns with the broader literature on relative age effects, which has consistently found that younger cohort students face higher risk of grade retention (Dhuey et al., 2019). Students born in the earlier part of the year (January through April) experience a particularly low likelihood of repeating a grade.

The insights from Figures 3 and 4 highlight the importance of relative age in shaping both academic performance and educational progression. The fact that the trends are so consistent across two different competencies (Language and Mathematics) and across grade repetition emphasizes the robustness of the relative age effect. Importantly, these findings underscore the need for early interventions aimed at supporting younger students within a cohort, as they clearly face disadvantages compared to their older peers.

4.2 OLS and IDW estimates.

Table 2 presents the regression results for Language and Mathematics scores and the probability of grade repetition, comparing students born in January (the oldest in the cohort) to those born later in the year. We apply ordinary least squares (OLS) and inverse distance weighting (IDW). Both approaches yield positive and statistically significant results, indicating that being born in January positively affects academic outcomes while reducing the likelihood of grade repetition.

The OLS estimates, displayed in columns 1 to 6, remain stable even after including control variables. This consistency suggests that birth month is not systematically correlated with other student or family characteristics, reducing the risk of bias from omitted variables. The IDW method, applied in columns 7 to 9, assigns higher weights to students born closer to the January cutoff (e.g., those born in December or earlier). Although the IDW estimates produce slightly larger coefficients, the differences are modest, reinforcing the exogeneity assumption for a birth month in this context.

For Language scores, students born in January score approximately 9% SD higher than their peers born later in the same cohort. For Mathematics, the effect is slightly smaller, at around 7% of a standard deviation. When applying the IDW method, the effects increase slightly to 11% for Language and 9% for Mathematics, indicating a more pronounced advantage for those born earlier in the year. These findings align with the broader literature, which consistently finds positive effects of relative age on academic performance.

Columns 3, 6, and 9 of Table 2 show the results from a logit model that estimates the probability of grade repetition. The data confirms that younger students are more likely to repeat a grade. The coefficient for being born in January is roughly -0.4, corresponding to a 33% reduction in the odds of repetition compared to students born later in the year. Using the IDW method, this effect becomes slightly more pronounced, with a coefficient of -0.56, indicating a 43% reduction in the odds of repetition.

Table 2. OLS and IDW estimates

	OLS			OLS + covariates			IDW + covariates		
	(1) Language	(2) Maths	(3) Logit Repetition	(4) Language	(5) Maths	(6) Logit Repetition	(7) Language	(8) Maths	(9) Logit Repetition
D = being born in January	0.0879***	0.0713***	-0.399***	0.0905***	0.0742***	-0.440***	0.112***	0.0930***	-0.569***
	(0.00573)	(0.00569)	(0.0931)	(0.00556)	(0.00543)	(0.0951)	(0.00559)	(0.00547)	(0.0959)
female				0.0270***	-0.00628	-0.00697	0.0262***	-0.00712	-0.00947
				(0.00474)	(0.00397)	(0.0468)	(0.00497)	(0.00434)	(0.0514)
1st gen immigrant student				-0.140***	-0.115***	2.131***	-0.132***	-0.111***	2.187***
				(0.0119)	(0.0121)	(0.0847)	(0.0131)	(0.0131)	(0.0930)
2nd gen immigrant student				-0.0374***	-0.0446***	0.421***	-0.0380***	-0.0461***	0.415***
				(0.00530)	(0.00575)	(0.0577)	(0.00568)	(0.00616)	(0.0643)
Mother education level: high				0.101***	0.155***	-0.605	0.0911**	0.144***	-0.738
				(0.0284)	(0.0295)	(0.337)	(0.0309)	(0.0311)	(0.384)
Father education level: high				0.154***	0.102***	-1.155***	0.146***	0.0956***	-1.039***
				(0.0243)	(0.0261)	(0.262)	(0.0273)	(0.0281)	(0.298)
Mother education level: medium				0.0130	0.0573	-0.128	0.00205	0.0482	-0.246
				(0.0284)	(0.0296)	(0.335)	(0.0307)	(0.0311)	(0.384)
Father education level: medium				0.0783**	0.0197	-0.759**	0.0710**	0.0113	-0.672*
				(0.0241)	(0.0258)	(0.259)	(0.0273)	(0.0280)	(0.294)
Mother education level: low				-0.0518	-0.00596	0.607	-0.0607*	-0.0134	0.471
				(0.0284)	(0.0297)	(0.334)	(0.0308)	(0.0312)	(0.381)
Father education level: low				0.0142	-0.0393	-0.311	0.00969	-0.0451	-0.218
				(0.0238)	(0.0255)	(0.257)	(0.0271)	(0.0278)	(0.293)
Constant	0.714***	0.718***	-3.377***	0.557***	0.582***	-2.681***	0.553***	0.581***	-2.523***
	(0.00474)	(0.00551)	(0.0292)	(0.0251)	(0.0271)	(0.240)	(0.0277)	(0.0273)	(0.263)
Observations	67051	66779	67253	67051	66779	67253	67051	66779	67253

The covariate results offer additional insights. Interestingly, we observe no significant gender differences in Mathematics scores, contrary to some previous research suggesting boys outperform girls in this subject (Nollenberger et al., 2016). However, in Language, girls perform slightly better than boys, scoring about 0.02 SD higher, though the effect size remains small. Surprisingly, gender does not significantly influence grade repetition in our sample, which could be attributed to the early stage of schooling (third grade), where gender-based academic divergence has not yet emerged as strongly as it may in later years. Additionally, the third-grade repetition rates are still relatively low, which may further explain the lack of significant gender effects.

Our study also introduces the analysis of immigration status as a risk factor for relative age effects, which is consistent with previous literature. (Thoren et al., 2016). Both first-generation and second-generation immigrant students perform worse in Language and Mathematics than non-immigrant students. First-generation immigrant students show much lower academic outcomes, with a significantly higher probability of grade repetition. The odds of grade repetition for first-generation immigrant students are 8.91 times higher than for non-immigrant students, while for second-generation immigrants, the odds are 1.51 times higher. This reinforces the "double disadvantage" faced by immigrant students born in the second half of the year, who experience both the challenges associated with being younger within the cohort and the additional difficulties related to their immigration status. (Dicks & Lancee, 2018).

Regarding parental education, children whose mothers have higher levels of education (university or vocational training) perform significantly better in both Language and Mathematics. The effect of having a mother with higher education is more pronounced for Mathematics while having a father with higher education has a more substantial effect on Language scores. Conversely, students whose parents have low levels of education (completed only compulsory education) perform the worst, reflecting the well-documented intergenerational transmission of educational disadvantage. (Crede et al., 2015).

4.3 RDD Local Randomization Approach

We apply the local randomization approach within the RDD framework. This method is particularly suitable for our context because our running variable, the student's birth month, is discrete and can take only a finite number of values. As a result, the distribution of the running variable creates "mass points," where multiple observations share the same value. This feature makes it unrealistic to assume a continuous conditional expectation function, which is often required in continuity-based RDD approaches. In contrast, the local randomization method does not require such strict assumptions, making it better suited for handling the discrete nature of our variable.

We compare students born in January (the treatment group) and December (the control group), defining an ad-hoc window W around these months, as suggested in the literature (Cattaneo et al., 2023). Since birth month is exogenous to student characteristics, this design mimics a local experiment around the cutoff, where we consider the treatment effect as the mean difference in outcomes between students born in January and those born in December. It is important to note that this treatment effect applies to the comparison within the defined window W rather than at the exact cutoff.

Our estimates are statistically significant at conventional levels, providing strong evidence against the null hypothesis of no effect. The p-values from the randomization test confirm that the observed differences are statistically significant. As the narrow confidence intervals indicate, the large sample size contributes to more precise estimates. In addition, when viewed as a randomized experiment, our results exhibit high power to detect meaningful effects, particularly when compared to a medium effect size (0.5 SD as the benchmark for the control group.

The estimates in Table 3 show that being born in January positively and significantly impacts academic outcomes. Specifically, students born in January perform better in Language and Mathematics, with effect sizes of 0.156 and 0.130 SD, respectively. Additionally, January-born students are 2.9 percentage points less likely to repeat a grade than their December-born peers. The magnitude of this effect is slightly smaller than what previous studies have found. (Bedard & Dhuey, 2006; Givord, 2020), but it still underscores the importance of birth month in shaping educational outcomes.

Table 3. Local randomization approach

	RDD local randomization		
	Language	Mathematics	Repetition
Diff. in means	**0.156**	**0.130**	**-0.029**
Confidence intervals	[0.140 - 0.172]	[0.114- 0.145]	[-0.036 - -0.022]
P >|T|	0.000	0.000	0.000
N	11,003	10,964	11,032

5. Childhood Education Attendance

While the evidence regarding the impact of relative age on educational outcomes is compelling, there remains debate over which policies can effectively mitigate this gap. Although research indicates that preschool education can positively influence children's developmental outcomes, limited evidence exists on whether early childhood education explicitly reduces the performance gap between students born at different times of the year. (Duncan et al., 2023).

To address this question, we use our dataset to assess whether extended exposure to early childhood education diminishes the relative age gap. We conducted a heterogeneity analysis by dividing students into three groups based on the age at which they began attending early childhood education: before age 2, from age 2, and at age 3. Using our RDD local randomization approach within the January-December window W, as employed by Dhuey et al. (2019), we analyze the effect of early education attendance on academic performance.

Our analysis provides evidence that early childhood education is critical in mitigating the inherent disparities between students born in January and those born in December. Figure 5 shows a distinct pattern in how ECEC attendance relates to Language and Mathematics performance. In Language, a subtle linear trend indicates that students who attended childhood education before age two experience slightly smaller performance relative to age gaps than those who started later. Although the differences are not highly pronounced, the confidence intervals suggest some advantages for earlier attendance. For Mathematics, the impact is more apparent: students who started attending early childhood education before age 2 show a 0.05 standard deviation smaller performance gap than those who began at age 2, diminishing this advantage for age three entrants.

Figure 5: Coefficients for Student Performance by Early Childhood Education Attendance

Figure 5a: Language

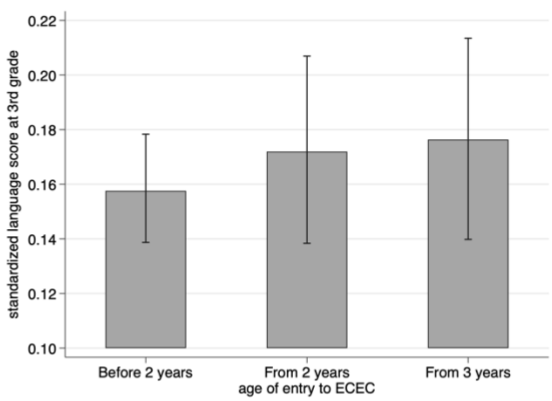
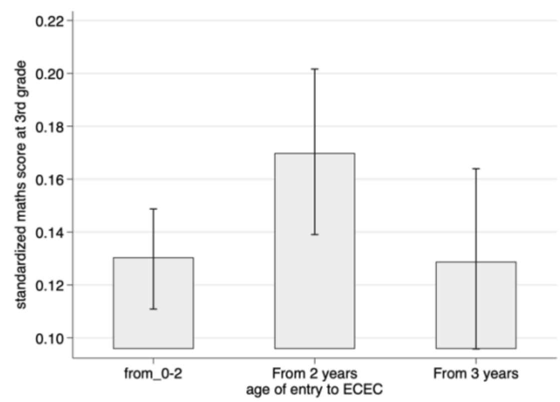


Figure 5b: Mathematics



Group sizes: 0-2 years (6,475); 2 years (2,319); 3 years (1,970)

These findings provide compelling evidence for ECE's role in mitigating birth-date-related academic disparities, particularly in Mathematics. The more pronounced effect on mathematical skills suggests that structured early learning environments may be precious for developing quantitative abilities. The wider error bars in Mathematics scores reflect more significant individual variability in mathematical skill development and increased statistical uncertainty due to a smaller sample size in the three-year entry group.

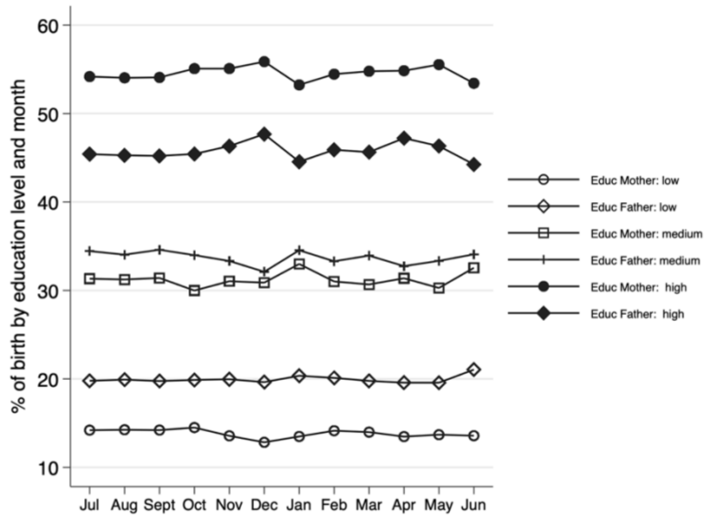
Early childhood education can serve as a critical intervention to mitigate the adverse effects of birth month on academic outcomes. High-quality early education equips children with essential cognitive and social skills, enabling them to overcome any developmental disadvantages stemming from their birthdate. (Odd et al., 2013)Research shows that early childhood programs can align developmental trajectories within peer groups, addressing disparities caused by relative age. Furthermore, we consider the impact of prenatal and early life factors—particularly during the first three years—on long-term development. This critical period of rapid brain growth lays the foundation for cognitive, emotional, social, and linguistic development. (Balbernie, 2017; Lubotsky & Kaestner, 2016; Young, 2019), underscoring the importance of early interventions.

6. Robustness check

Given that our study examines the impact of birth month on educational outcomes, it is essential to ensure that the month of birth is not influenced by external factors, such as parents intentionally planning births. Specifically, we need to verify whether the distribution of birth months among students is random or affected by factors such as parental education. Some may argue that parents with higher educational attainment may deliberately time births to increase the chances of their children being among the oldest in their cohort, potentially gaining an academic advantage. This phenomenon, often linked to "redshirting," could challenge the assumption of randomness in our analysis.

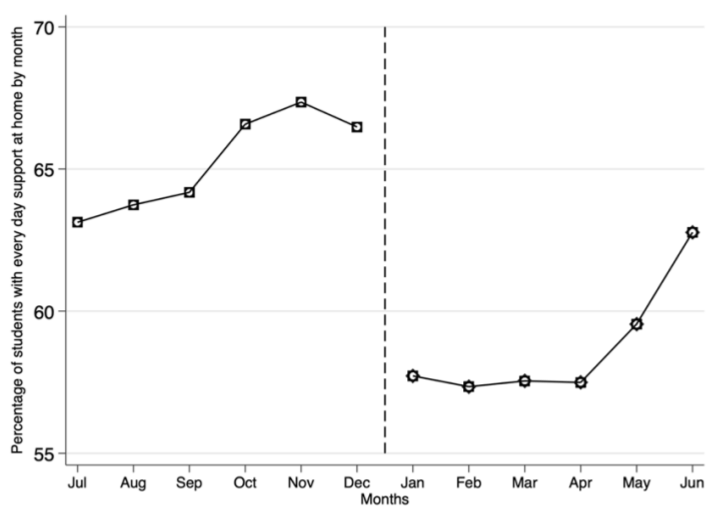
To verify whether the birth month is truly randomly distributed across families with varying parental education levels, we present the birth distribution by parental education level in Figure 6. Interestingly, the distribution is consistent across the months, with no evidence suggesting that families with higher education levels time births to specific months. This finding contrasts with observations from some U.S. states, where redshirting is more common. (Cook & Kang, 2020). In this context, the birth month appears to be randomly assigned, supporting the critical assumption of our regression discontinuity design (RDD).

Figure 6: Distribution of Births by Parents' Education Level



On the other hand, parental involvement may also influence students' academic performance by supporting children at home. However, the nature and intensity of this support varies with children's birth months, creating a potential confounding factor that links relative age to academic performance through parental involvement. Figure 7 illustrates the variation in family homework support across birth months, providing empirical evidence of this relationship.

Figure 7: Percentage of students with everyday family support by birth month



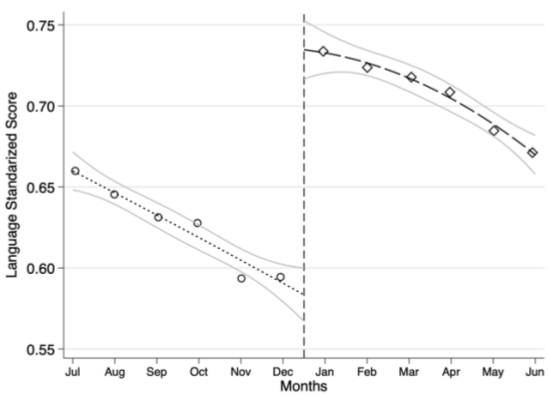
The data reveals a notable increase in support for children born later in the year, particularly during the last quarter (September to December), where the percentage of students receiving full family support peaks at around 68% in December. This trend may reflect parents' increased engagement as they try to help their younger children, who may face more academic challenges than their older peers.

Conversely, children born earlier in the year (from January to April) tend to receive comparatively less family support, as evidenced by the lower percentage of full support, dropping to around 58% during the first months of the year. This difference in parental involvement likely reflects the perception that children born earlier in the year are more mature and academically capable. This might make parents feel these children require less intervention or additional support. Therefore, the variation in parental support based on birth month highlights how parents compensate for the relative age effect. While parents may not be explicitly aware of the "relative age effect," their actions suggest that they recognize the need for more excellent assistance for younger children to help them overcome developmental differences compared to their older peers.

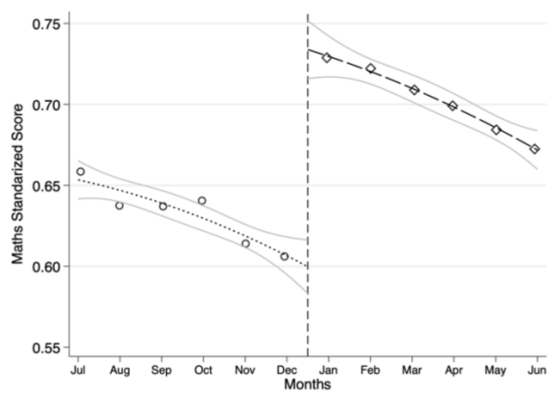
Nevertheless, as shown in Figure 8, this compensatory parental behavior does not fully mitigate the achievement gap associated with relative age. Even with higher levels of parental involvement, the performance gap between younger and older students remains. Thus, the relative age effect remains robust even in compensatory parental behavior, which seems insufficient to fully mitigate the advantages of being relatively older. These findings strengthen our RDD results by showing that the relative age effect remains evident even with endogenous responses from parents.

Figure 7: Mean Test Scores of students with everyday family support by birth month

7a. Language



7b. Mathematics.



To further strengthen the robustness of our methodology, we conducted a falsification test to examine whether any significant differences exist between students born just before and after the cutoff date. If our RDD approach is valid, we expect that covariates will be balanced on both sides of the cutoff, meaning that students born in January and December should exhibit similar characteristics aside from their birth month. Table 4 presents the results of this falsification test, utilizing the local randomization approach.

Table 4: Falsification test

Covariates	Mean of December (1)	Mean of January (2)	Diff. in means (3)	P>|T| (4)	N (5)
Female	0.500	0.496	-0.005	0.654	11032
1st gen immigrant student	0.021	0.024	0.003	0.296	11032
2nd gen immigrant student	0.153	0.146	-0.007	0.286	11032
Mother: High education level	0.559	0.532	-0.026	0.004	11032
Father: High education level	0.477	0.446	-0.031	0.000	11032
Mother: Medium education level	0.309	0.330	0.021	0.018	11032
Father: Medium education level	0.321	0.345	0.024	0.008	11032
Mother: Low education level	0.128	0.135	0.007	0.298	11032
Father: Low education level	0.196	0.204	0.007	0.334	11032

In Column 1, we report the mean values of key covariates for students born in December, while Column 2 provides the mean values for students born in January. Column 3 highlights the differences in means between these two groups. As the results indicate, most covariates—such as gender and immigration status—are well-balanced across the threshold, lending further support to the validity of our RDD framework. This balance suggests that, in most respects, the students born just before and after the cutoff are comparable, reinforcing our confidence in the estimates of educational outcomes derived from the RDD analysis.

However, one notable exception in the balance of covariates pertains to parental education levels. As seen in Column 4, statistically significant differences emerge regarding the educational attainment of both mothers and fathers. Specifically, the data reveals that a higher percentage of more educated parents had children born in December compared to January. For example, 55.9% of December-born students have mothers with higher education, compared to 53.2% of January-born students (a statistically significant difference of 2.6 percentage points, p=0.004). Similarly, 47.7% of December-born students have fathers with higher education, compared to 44.6% of January-born students, yielding a 3.1 percentage point difference (p=0.000). This pattern also holds for parents with medium education levels, where a higher proportion of students born in January are associated with this category.

These differences suggest that a slight imbalance in parental education could work against our estimates, as more highly educated parents—who might provide more robust academic support—are more likely to have children born in December. In this case, the effect would potentially bias our results downward, underestimating the advantage of being born earlier in the year, as students born in December may benefit from more favorable family backgrounds despite their relative age disadvantage.

While these differences are statistically significant, their practical significance is likely minimal, especially considering the relatively small magnitude (around 2–3 percentage points). Additionally, the large sample size likely amplifies the statistical significance of these differences. Therefore, while it is essential to acknowledge this slight deviation from the assumption of random assignment, it does not substantially undermine the validity of our overall findings.

Finally, we perform subgroup analyses to confirm our findings' robustness further. By running separate RDD models for relevant subgroups (e.g., by parental education, gender, and immigration status), we assess whether the effects vary across different population segments. Table 5 shows that the overall results remain consistent across all subgroups. The only notable exception is among first-generation immigrant students, whose relative age effect appears smaller for Language scores. However, these differences are not statistically significant, likely due to Language barriers that hinder performance, as Spanish is not their first Language.

Table 5: Subgroup Analysis for Language and Mathematics

	Mother educational level			Gender		Student: immigration status.	
	High	Medium	Low	Girls	Boys	1st gen	2nd Gen
Language	0.161	0.163	0.150	0.163	0.150	0.066	0.150
P >|T| Language	0.000	0.000	0.000	0.000	0.000	0.246	0.000
Maths	0.137	0.132	0.133	0.139	0.121	0.091	0.132
P >|T| Maths	0.0000	0.0000	0.0000	0.0000	0.0000	0.0320	0.0000

The consistency of the relative age effect across various subgroups supports the robustness of our analysis. Our results indicate that the relative age effect does not depend on parental education, gender, or immigration status. Overall, the relative age effect seems to be a pervasive factor affecting students from diverse backgrounds, reinforcing the stability of our findings.

7. Conclusions and policy implications

This study highlights the significant impact of relative age on educational outcomes among third-grade students in Madrid, demonstrating that students born earlier in the year perform better in both Language and Mathematics than their younger peers. While the magnitude of this gap is smaller than international benchmarks, it remains a cause for concern, as it underscores the persistence of educational inequalities based on the birth month. Moreover, the relative age effect is further compounded by factors such as immigration status and parental education levels, with first-generation immigrant students and those from less educated families facing the highest risks of grade repetition. Given the potential long-term consequences of the relative age effect, targeted policy interventions are necessary to address these disparities. First, ECEC programs have been shown to mitigate some of the disadvantages younger students face, particularly in Mathematics. However, while early education narrows the gap, it does not eliminate it, suggesting more comprehensive, long-term strategies are needed. Policymakers should prioritize expanding access to high-quality early education, especially for immigrant and disadvantaged students, to reduce the structural inequalities that arise from the birth month differences.

One policy option could involve adjusting the timing of school entry for younger students, allowing for greater flexibility in enrollment dates. Alternatively, schools could implement interventions that support younger students early in their academic careers, such as targeted tutoring or ability grouping within classrooms. These strategies can help younger students catch up with their older peers, particularly in subjects like Mathematics, which may require more structured learning environments. Another vital aspect is parental involvement. Although families tend to increase support for younger students born later in the year, this alone is insufficient to close the performance gap. Schools could complement parental efforts by offering workshops or resources that equip parents with strategies to support their children's learning effectively. In addition, teacher training programs could focus on raising awareness about the relative age effect and provide strategies for addressing classroom developmental differences.

Finally, the interaction between relative age and other factors, such as immigration status and parental education, highlights the need for a multi-faceted approach to reducing educational inequality. Immigrant students may benefit from specialized support services, including Language assistance and programs that foster integration into the school system.

In conclusion, while the relative age effect is mainly unintended, its consequences are far-reaching and persistent. By implementing early interventions, enhancing ECEC access, and supporting teachers and families, policymakers can help mitigate the educational disadvantages younger students face. Future research should explore the long-term effects of these policies and their potential to reduce broader educational inequalities across different contexts and regions.

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