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NO EARLY ADVANTAGE? THE EFFECTS OF PRESCHOOL ENTRY-AGE POLICIES ON CHILD DEVELOPMENT IN PERU

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Motherly Care: The impacts of exiting a childcare program on child and maternal health
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No Early Advantage? The Effects of Preschool Entry-Age Policies on Child Development in Peru

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Abstract

School entry cutoff policies establish the minimum age required to start school at a given date, determining whether a child is in a classroom with younger or older peers, which can affect their development. Existing research, particularly from high-income countries, shows that younger students face disadvantages in several areas, but little is known about the effects in low- and middle-income countries and for preschool children. We leverage the discontinuity created by government-imposed school entry cutoffs to measure the impact of late enrollment on child nutrition and early childhood development outcomes. Using data from Peru's Demographic and Health Surveys and a fuzzy regression discontinuity design, we show that the laxly enforced preschool entry age policies significantly increase the probability of late enrollment, but on average they do not affect child health or early childhood development. Nonetheless, we find that these insignificant effects hide differential impacts for boys and girls, and poor children.

Keywords: School entry age, preschool education, early childhood development, child health.
JEL classification: I14, I21, J13

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Resumen

Las políticas de ingreso escolar establecen una edad mínima para iniciar la educación formal, lo que determina si un niño(a) comparte el aula con compañero(a)s relativamente mayores o menores, con posibles efectos sobre su desarrollo. La evidencia disponible, centrada sobre todo en países de altos ingresos, muestra que los estudiantes más jóvenes suelen enfrentar desventajas en distintas dimensiones. Sin embargo, se conoce poco acerca de estos efectos en educación inicial y en países de ingresos bajos y medios. Este estudio aprovecha la discontinuidad generada por las edades mínimas de matrícula establecidas por el Ministerio de Educación para estimar el impacto del ingreso tardío en la nutrición y el desarrollo infantil temprano. Utilizando datos de la Encuesta Demográfica y de Salud Familiar (ENDES) y un diseño de regresión discontinua difusa, encontramos que las reglas de edad mínima aumentan significativamente la probabilidad de ingreso tardío, pero en promedio no afectan la salud ni el desarrollo infantil. No obstante, los resultados agregados ocultan efectos heterogéneos según sexo y condición de pobreza.

Keywords: Edad de ingreso escolar, educación incial, desarrollo infantil temprano, salud infantil.
Clasificación J.E.L.: I14, I21, J13

1 Introduction

Educational systems worldwide face challenges to ensure inclusive and equitable quality education (UN, 2023). A particular concern arises with school starting age policies. In most countries, children are eligible to start formal education either by a single cut-off date (e.g., turning 6 years old by March 1) or at a specific age (which implies a January 1 cutoff). These policies create cohorts of students with significant differences in age (Dhuey & Koebel, 2022).

Early school entry allows younger children to access formal education and get exposure to school programs (e.g., school lunch) and other interventions at an earlier stage. However, the age gap also entails differences in maturity with respect to peers of the same class, which can affect their development and later outcomes in life (Oosterbeek, ter Meulen, & van der Klaauw, 2021; Page, Sarkar, & Silva-Goncalves, 2019).

While substantial evidence on school-entry age effects is available for high-income countries (HICs), recent reviews highlight the lack of research for developing countries, particularly regarding health outcomes (Liao et al., 2023). Given the distinct institutional settings and health challenges in these regions, previous findings from HICs may not be generalizable (Deen, Von Seidlein, & Clemens, 2014).[1].

We contribute to the literature by examining how late enrollment in preschool, due to entry age rules, affect children's health and early development in Peru. Unlike previous studies that primarily focus on academic performance and psychological or behavioral aspects, this research delves into the effects on nutritional and early childhood development (ECD) outcomes, offering a more comprehensive perspective on the unintended consequences of school starting-age legislation. Specifically, regarding the Peruvian case, this issue is of high relevance, as evidenced by the sub-

[1]Even among HICs, some findings on the influence of relative age differ, indicating that the institutional context may either amplify or reduce its effects. For instance, older children in the United States show a higher likelihood of committing crimes (Cook & Kang, 2016)

mission of at least ten parliamentary bills between 2016 and 2022 aiming to change the school starting age cutoff. Moreover, by focusing on a middle-income country facing public health challenges, different from those in HICs, such as the lack of quality infrastructure and the coexistence of child stunting and overweight, common in many developing contexts (Kelishadi, 2007), we can provide policy lessons relevant for other developing countries.

To the best of our knowledge, previous research on this issue for developing countries is limited to Brazil, Mexico, Turkey, and Vietnam. They suggest that young-for-class students face worse health outcomes, though Brazilian anthropometric evidence is mixed (Levasseur, 2022). In Peru, Morales (2020) and Armas, Campos, and Gutiérrez (2019) have examined the effects of the school entry-age policies on educational outcomes, but no study has addressed their impact on health outcomes or child development.

Studying the Peruvian case offers valuable insights into the effects of school entry-age policies in a middle-income country context, where education and health systems face significant resource constraints. In such settings, factors like larger class sizes, under-resourced schools, and varying teacher quality and training may amplify the impact of age differences on students' outcomes.

Because school entry-age policies have been laxly enforced, we use a fuzzy regression discontinuity design to address the endogeneity of school starting age. This variable is endogenous because parents can adjust enrollment based on unobserved factors such as health and perceived school-readiness. We use the requirement that children must be born before the (exogenous) government-established date to instrument late enrollment. Specifically, for 3-year-olds, late enrollment implies not attending preschool; the policy establishes that children must start preschool when they are at least 3 years old by the cutoff date. Thus, 3-year-old children born right after the cutoff cannot attend preschool and must wait almost a full year to attend. In the case of 4-year-olds, late enrollment implies not attending an age-appropriate section, i.e., being enrolled in a section with younger children on average.

The analysis exploits the Demographic and Health Survey (DHS) for the period 2018-2019, conducted by the Peruvian National Bureau of Statistics (INEI). The DHS is a nationally representative survey, with more than 30,000 households interviewed annually on average. Because the DHS does not collect anthopometrics for children above 5 years old, we only focus on children close to 3 and 4 years of age. These ages align with the typical entry points into the three-year pre-primary education cycle. We examine health outcomes, including height-for-age and anemia, as well as early child development outcomes, such as emotional regulation and behavioral control.

Our results suggest that although preschool entry-age policies are laxly enforced, 3-year-old children born after the cutoff date are around 50% more likely to not be attending preschool, than children born before the cutoff date; and 4-year-olds born after the cutoff are around 60% more likely to be attending a class with younger peers than those born before the cutoff. Moreover, late enrollment due to the policy shows no significant effects on child health across specifications and subgroups. However, we find negative effects on ECD among 3-year-olds and positive effects among certain subgroups of 4-year-olds.

The rest of the paper is organized as follows. Section 2 reviews the related literature and section 3 provides background. Sections 4 and 5 describe the data and the empirical strategy, respectively. Section 6 presents the results, robustness checks, and a heterogeneity analysis. Section 7 presents a discussion and section 8 concludes.

2 Literature review

The appropriate age for school entry has been widely debated in educational and policy circles (Dhuey & Koebel, 2022). A substantial body of research from HICs suggests that younger students may face disadvantages in academic performance and socio-emotional development, particularly in early childhood (Peña, 2017, pp.172–176).

Causal evidence consistently shows that older children outperform their younger peers in standardized tests and classroom assessments, at least in the short term (Datar, 2006). These advantages are attributed to greater maturity and better-developed cognitive and emotional skills at school entry. Some studies from the U.S. and Europe indicate that this early advantage persists into adolescence, influencing educational attainment and labor market outcomes such as college enrollment and earnings (Fredriksson & Öckert, 2014; Zweimüller, 2013). However, other research finds no lasting effects on these outcomes (Dobkin & Ferreira, 2010; Nam, 2014), leaving the mid- and long-term impact of school-entry age an open question.

In low- and middle-income countries (LMICs), similar patterns have been observed, though with some particularities. In Chile, Navarro, García-Rubio, and Olivares (2015) show that relatively younger students from lower socioeconomic backgrounds show the worst academic performance. In Brazil, Herdeiro, Oliveira, and Menezes-Filho (2024) find that delayed school entry increases the likelihood of college enrollment, with larger effects for children who attended preschool, suggesting interactions between maturity and early care quality.

School entry age has also been linked to health and behavioral outcomes. In HICs, younger students tend to experience slightly more negative psychosocial outcomes (Rose & Barlow, 2024). Younger students are more likely to be diagnosed with attention deficit hyperactivity disorder (ADHD) and exhibit behavioral challenges, potentially due to mismatches in developmental readiness (Caye et al., 2020). However, these studies do not assess causal effects, and their results can also reflect misdiagnosis (Schwandt & Wuppermann, 2016).

Evidence from LMICs, though more limited, suggests distinct health-related consequences. In Brazil, Levasseur (2022) finds a negative effect on body mass index (BMI) for children who start school at a younger age, due to school entry policies, but no consistent impacts on stunting. In Vietnam, earlier school entry increases the likelihood of female early marriage and adolescent pregnancy (Nguyen & Lewis, 2020), while in Mexico, it increases the probability of having had sex, been pregnant and cohabited, for girls between 15 and 17 years old (Caudillo, 2019). These studies point to broader social and health implications of school-entry policies, especially for girls in vulnerable contexts.

In sum, despite the extensive literature from HICs, significant gaps remain in LMICs, particularly regarding the intersection of school-entry age, child health, and development outcomes. Existing research in these contexts tends to focus on short-term academic effects and overlooks broader indicators such as nutrition and ECD (Ijarotimi, 2013; Kramer & Allen, 2015). These domains are highly relevant in developing countries (Bornstein et al., 2012; Grantham-McGregor et al., 2007). We address this gap in the literature by examining the effects of school-entry age policies on health and early childhood development outcomes in Peru, a country that shares many of the challenges common to other LMICs (Atun et al., 2015), including lack of adequate health and educational infrastructure, high levels of inequality, demographic and socioeconomic diversity, and persistent nutrition-related public health concerns.

3 Background

In Peru, children can only enroll in pre-school or primary school if they are, respectively, at least 3 or 6 years old by March 31 (with a maximum of two additional years allowed), and classes start around mid-March every year.[2] This cutoff date may directly affect equity in access to educational opportunities as those born after the deadline must either wait until the following year to enroll (if they are starting preschool) or enroll in a class with younger peers (at age 4 or older). This creates significant disparities within the same school cohort due to variations in children's cognitive, physical, and socioemotional maturity, and may impose additional financial burdens on families regarding childcare. The cutoff date for entering public pre-school education may also indirectly affect children's health, likely due to additional childcare costs and lack of adequate nutrition at home, which is provided almost universally in public schools.

Consequences also include a growing number of legal cases. As of 2018, over 2,700 families have initiated writ of protection proceedings (*acción de amparo*, in Spanish) to enroll children who do not meet the official age requirement (Avila Rojas, 2018, p.11). Many cases have received favorable rulings in lower courts, but the Ministry of Education has appealed several of them to the Constitutional Court. This has contributed to increased caseloads and legal expenses for both the judicial system and families.

To date, no published studies have examined the consequences of school entry age cutoffs in Peru. Nonetheless, this issue has not gone unnoticed by Congress, where various bills have been proposed to suggest alternative cutoff dates (May 31, June 30, July 31, etc.). Proponents of these bills argue that parents do not want their children to lose a year of schooling (Flores Ancachi, 2022, p.5); and that chronological age is not a sufficient indicator for accepting or rejecting a child's enrollment, and cognitive age is more important (Avila Rojas, 2016, p.4). Others highlight the negative reactions of parents grouped in movements such as "No to March 31" and that over half a million children are disadvantaged by being born between April

[2] The cutoff dates have varied over time, as depicted in table B.1. Nonetheless, the cutoff has been March 31 from 2013.

and June (Avila Rojas, 2018, p.11).

In this context, there is an urgent need for evidence on the collateral effects of Peru's current minimum enrollment age policy, to inform policymakers and contribute to the development of evidence-based public policies.

4 Data

We use data from the Demographic and Health Survey (DHS), an annual, nationally representative household survey conducted by the Peruvian National Bureau of Statistics (INEI). The DHS employs a stratified, multi-stage cluster sampling design and provides survey weights to ensure representativeness at the national, regional, and urban/rural levels. The survey includes detailed modules on fertility, maternal and child health, household characteristics, nutrition, and early childhood development.

The timing of the DHS fieldwork has varied over time. From its inception until 2017, data collection ran from March to December. In 2018, it began in February, and since 2019, it has covered the full calendar year. Nonetheless, because we focus on birth dates, which are evenly distributed along the year (cf. Figure A.1), our analysis is not affected by this sampling change.[3]

Our main analysis draws on repeated cross-sectional data from the 2018 and 2019 waves of the DHS, the only two years for which both anthropometrics data and early childhood development questions are available.[4] We focus on children right above and right below 3 and 4 years old because of data availability: child health

[3]Figure A.1 aligns with anecdotal data that suggests time of birth planning is uncommon among Peruvian parents, unlike in developed countries, such as the United States.

[4]The Early Childhood Development (ECD) module has been implemented since 2015, but the age-specific targeting of outcomes prevents comparisons around the key threshold. In particular, many indicators are only collected for children aged 30–36 months or 53–59 months (MIDIS, 2019), making it impossible to evaluate the same outcome for children just below and just above age 36 or 48 months.

is measured for children ages 6 to 59 months, and ECD is measured for children 30 to 59 months old. These ages also correspond to the typical entry points into the three-year cycle of pre-elementary education (kindergarten). At age 3, children are eligible to begin the first year of preschool, while at age 4 they may either be enrolled in their second year or, if they entered late, still be in their first year.[5] Thus, we define *late enrollment*, our treatment variable, as the absence of preschool attendance for children just above or below age 3, and as placement in a section with younger peers (rather than an age-appropriate class) for children just above or below age 4.

Child health outcomes include weight-for-age (WAZ) and weight-for-height (WHZ) z-scores (compared to WHO recommended levels), and hemoglobin, as well as their corresponding statuses of being underweight (WAZ ≤ -2), overweight (WHZ ≥ 2), or wasting (WHZ ≤ -2), and having anemia (hemoglobin < 11 g/dl, unadjusted for altitude).[6]

ECD outcomes capture domains such as emotional regulation, behavioral control, and social interaction. We construct five binary indicators as follows. (1) Tantrums—the child frequently cries, screams, or throws tantrums; (2) Aggressive Response to Denial (ARD)—when denied something, the child harms themself, others, or objects; (3) Positive Waiting Behavior (PWB)—when asked to wait, the child remains calm; (4) Imitation—the child pretends to be fictional characters or other people; and (5) Toy Interaction (TIN)—the child talks to toys, attributes emotions to them, or engages in imaginary play.

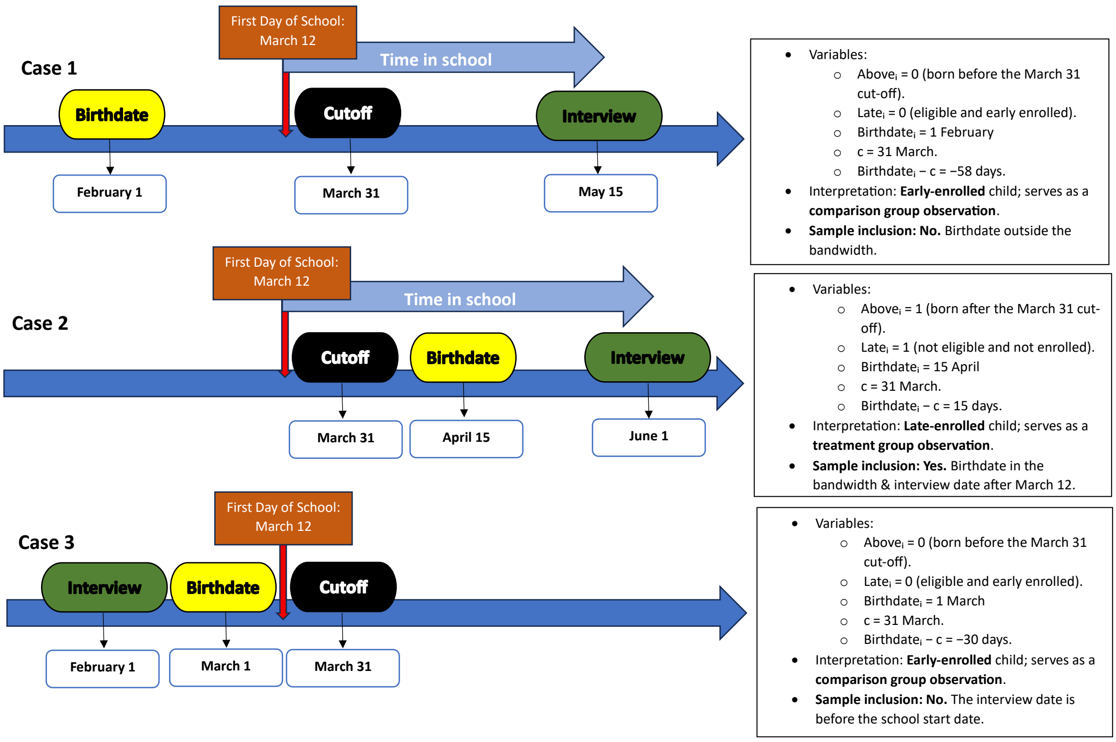
The Peruvian DHS also contains information about the child's exact birth date (reported by the respondent), school attendance, child's sex, maternal education level, household wealth index, area and region of residence, and altitude, which we use as

[5] Note that children are not required to be enrolled during all three years of preschool.

[6] Observations with implausible anthropometric values, as flagged by DHS protocols, are excluded.

covariates in the following analysis. We further use school attendance to define our final sample. To measure school attendance, the Peruvian DHS registers whether individuals aged 3 and older have ever attended school. If the response is affirmative, two follow-up questions inquire about current and previous year enrollment. For respondents interviewed before the school year begins, these responses may not reflect actual attendance. To address this, our sample includes only children surveyed after classes have started. We further assume that enrollment at the time of the survey reflects attendance throughout the academic year. Figure 1 shows different cases of inclusion or inclusion in our sample, based on a combination of birth dates, interview dates, and the date classes started, using a one-month bandwidth.

Figure 1: Example Timeline: Sample selection and variable definition



Note: Illustrative cases showing which children enter the sample and how treatment status is assigned.

Table 1 presents descriptive statistics for children aged 3 and 4, using a ±31-day bandwidth around the preschool entry cutoff date in 2018–2019. Specifically, for the school entry cutoff date of March 31, children below the cutoff are those born in March, and children above the cutoff are those born in April.

Among 3-year-olds, preschool attendance (i.e., our definition of late enrollment for this group age) is substantially more common for children born just before the cutoff, with ∼80% attending preschool at the time of the survey. In contrast, preschool participation among children born just after the cutoff date remains relatively low, at ∼25%. This difference underscores the strength of the cutoff rule as a source of variation in preschool exposure.

For 4-year-olds, the sample includes only those enrolled in preschool, i.e., only those self-selected into attending preschool, so we can compare children who are only different in terms of early enrollment. Among these children, about eight out of ten born before the cutoff date attend a class appropriate for their age (preschool level 2), while fewer than four in ten children born after the cutoff date attend the same class. This sizable gap suggests that differences in entry timing continue to shape class progression outcomes a year later, with many late enrollees placed below the expected level.

Moreover, we do not observe significant differences in child age, child sex, area of residence, altitude, or the wealth index.

5 Identification strategy

By allowing children to enroll in school only if they are 3 or 4 years old by March 31, the Ministry of Education creates natural variation in school exposure. Specifically a natural discontinuity in enrollment. At age 3, children are eligible to begin the first year of preschool, while at age 4 they may either be enrolled in their second

Table 1: Descriptive statistics by relative birthdate, using a 31-day bandwidth (2018-2019)

	3 years		4 years	
	Below Cutoff**	Above Cutoff	Below Cutoff**	Above Cutoff
Not Attending Preschool* (=1)	0.217	0.761	-	-
	(0.412)	(0.427)		
Not Attending Age-Appropriate Class (=1)	-	-	0.167	0.645
			(0.373)	(0.479)
Child's age in months	40.611	40.873	52.665	53.461
	(2.757)	(3.243)	(2.874)	(3.367)
Male (=1)	0.472	0.524	0.514	0.475
	(0.500)	(0.500)	(0.500)	(0.500)
Mother's age	30.728	30.856	32.066	31.366
	(7.017)	(6.791)	(6.837)	(6.704)
Poor (=1)	0.536	0.557	0.514	0.538
	(0.499)	(0.497)	(0.500)	(0.499)
Attends public school (=1)	0.752	0.601	0.799	0.779
	(0.432)	(0.491)	(0.401)	(0.415)
Urban (=1)	0.698	0.692	0.713	0.690
	(0.460)	(0.462)	(0.453)	(0.463)
Coast region (=1)	0.437	0.432	0.462	0.446
	(0.496)	(0.496)	(0.499)	(0.497)
Andes region (=1)	0.333	0.351	0.318	0.325
	(0.472)	(0.478)	(0.466)	(0.469)
Amazon region (=1)	0.231	0.218	0.220	0.229
	(0.421)	(0.413)	(0.415)	(0.421)
Altitude	1348.444	1313.070	1250.762	1272.764
	(1464.760)	(1439.101)	(1428.754)	(1445.517)
Weight-for-age Z-score	-0.057	-0.002	-0.012	0.004
	(1.008)	(1.034)	(1.051)	(1.118)
Height-for-age Z-score	-0.796	-0.811	-0.728	-0.715
	(0.968)	(0.989)	(0.985)	(0.994)
Weight-for-height Z-score	0.578	0.672	0.651	0.656
	(0.974)	(1.008)	(1.026)	(1.049)
Hemoglobin in g/dl	12.440	12.392	12.542	12.568
	(1.296)	(1.354)	(1.367)	(1.362)
Child is overweight (=1)	0.087	0.094	0.104	0.091
	(0.282)	(0.292)	(0.306)	(0.288)
Child is underweight (=1)	0.012	0.017	0.021	0.018
	(0.110)	(0.130)	(0.143)	(0.134)
Child suffers stunting (=1)	0.118	0.110	0.091	0.099
	(0.322)	(0.313)	(0.289)	(0.299)
Child suffers wasting (=1)	0.000	0.003	0.000	0.000
	(0.000)	(0.056)	(0.000)	(0.000)
Child has anemia (=1)	0.104	0.128	0.098	0.093
	(0.306)	(0.334)	(0.298)	(0.291)
Observations	655	639	623	606

Note: Standard errors in parentheses. We use a 31-day bandwidth around the cutoff.
*For 3-year-olds, the variable "Not Attending Preschool (=1)" includes children currently not attending preschool, while for 4-year-olds "Not Attending Age-Appropriate Class (=1)" includes those not attending the appropriate grade for their age. This adjustment accounts for surveys conducted in January and February, when current enrollment is not fully captured.
**Children born in the month immediately preceding the cutoff date are classified as "Below Cutoff," while those born immediately after are classified as "Above Cutoff." For 2018 and 2019, the cutoff date was March 31; therefore, children born in March are considered "below" and those born in April "above."

year or, if they entered late, still be in their first year. As shown in Table 1, being born after the school entry age cutoff does not fully determine late enrollment (not attending school for 3-year-olds, or not attending an age-appropriate class for 4-year-olds) but it increases the probability of late enrollment. We therefore exploit the discontinuity generated by the school entry age cutoff using a fuzzy regression discontinuity design.

Consider the following equation:

$$Y_i = \beta_0 + \beta_1 Late_i + \beta_2 f(Birthdate_i - c) + \beta_3 f(Birthdate_i - c)^{*} Late_i + X_i + \varepsilon_i \quad (1)$$

where Y_i is a health or ECD outcome for child i. The indicator $Late_i$ equals 1 if the child enrolled late (i.e., if they had to wait until the following year to begin preschool after turning 3, or if, at age 4, they were placed in a lower class with younger peers), and 0 otherwise. $Birthdate_i$ denotes the child's date of birth (month and day), so $(Birthdate_i - c)$ measures the distance between the birth date and the school entry cutoff date c (March 31), in the year she turned either 3 or 4. X_i is a vector of covariates at the child level, including child's sex, child's sex, maternal education level, household wealth index, area and region of residence, and altitude.

Because late enrollment is not fully determined by being above or below the school entry age cutoff, we estimate $Late_i$ using $Above_i$, being born after March 31, as an instrumental variable. Specifically, the first stage equation is:

$$Late_i = \alpha_0 + \alpha_1 Above_i + \epsilon_i \quad (2)$$

In sum, we compare children who enrolled late for their age, because they were born right after the school entry cutoff date, with children who enrolled early because they had just reached the eligibility threshold. Thus, β_1 captures the local average treatment effect (LATE) of delayed preschool entry induced by the cutoff rule.

The internal validity of the regression discontinuity approach rests on two main assumptions: (1) that there would be no discontinuity (smoothness) in the outcomes if the cutoff rule were not in place, and (2) that there is no manipulation of the running variable around the cutoff. Although the first assumption is untestable, Table 1 suggests there is no discontinuity at the school entry cutoff in other variables except for late enrollment, while Figure A.3 and Figure A.4 show that demographic characteristics (such as child sex, area of residence, poverty, or mother's age) do not *jump* at the cutoff. We test the second assumption using the McCrary test. Figure A.5 shows there is no manipulation of the birth date around the cutoff.

Additionally, for fuzzy regression discontinuity, internal validity requires that the discontinuity in enrollment is strongly related to the school entry date cutoff (relevance), that being above the cutoff increases or does not change the probability of late enrollment for all children (monotonicity), and that health and ECD outcomes for child i are related to the late enrollment of child i and not to the late or early enrollment of child j (Stable Unit Treatment Value Assumption or SUTVA).[7] Monotonicity is not testable, but based on anecdotal evidence, we can argue that, although there is no full compliance with the March 31 cutoff rule, being born after this date never decreases the probability of late enrollment.[8] Similarly, we cannot test SUTVA but, arguably the late enrollment of a child is unlikely to be related to the health and ECD outcomes of other late- or early-enrolled children. Among siblings, it is possible that having a child enrolled late might have changes on the enrollment of siblings, e.g., in a given school, but it is unlikely to increase or de-

[7]Instrumental variables designs also require the exclusion restriction assumption. This assumption is implicitly satisfied by the first assumption of smoothness of potential outcomes at the cutoff. Specifically, by assuming that only the probability of late enrollment changes at the cutoff, *Above* (determined by the running variable $(Birthdate - c)$) can only influence child health and ECD through its impact on late enrollment, *Late*.

[8]We also observe in Table 1 that children born before the cutoff are much less likely to be late enrolled. That is, there is little evidence of red-shirting. This is expected, because culturally, Peruvian parents send their children to school as early as possible.

crease the late enrollment of siblings, and thus health or ECD outcomes. Within the classroom, it is possible that having more late enrolled children affects ECD outcomes related to socialization. However, the sampling of the survey (DHS) we use does not compare children within the same classroom, so it is unlikely we violate SUTVA in our analysis of ECD outcomes. Moreover, child health outcomes are unlikely to be affected by other children's late or early enrollment. Finally, the relevance requirement holds, as we show in detail in the next section.

6 Results

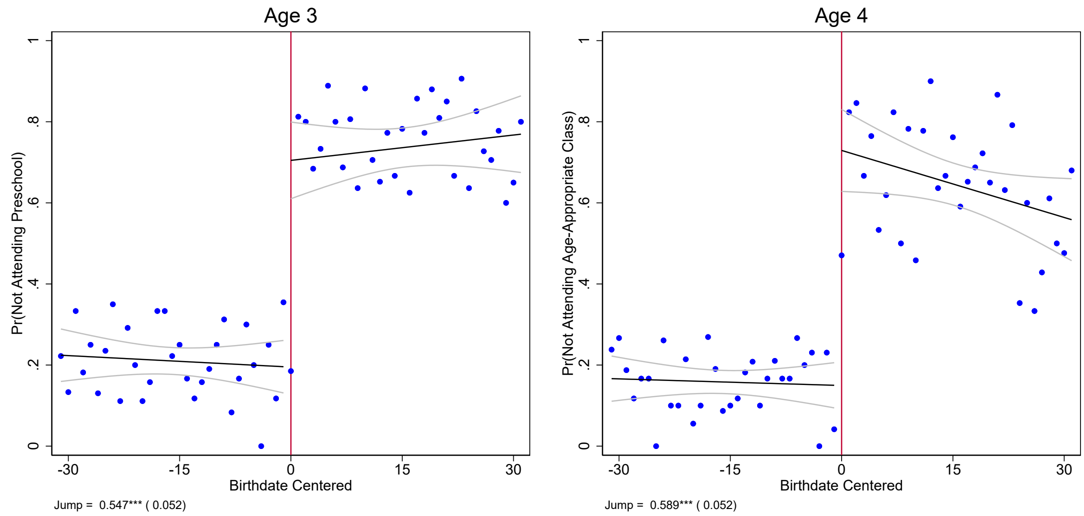
6.1 School entry cutoff enforcement

For our fuzzy regression discontinuity design to be valid, we require the first stage regression (Eq. 2), to show that the instrument (i.e., being above the school entry date cutoff) is strongly correlated to the treatment (being enrolled late). Figure 2 shows evidence of this relationship. The first panel shows that among 3-year-olds, there is a clear upward shift in no preschool enrollment at the cutoff, indicating a strong discontinuity: children born just after the cutoff date are 54.7% more likely not to attend preschool than those born just before. The second panel, for 4-year-olds, shows that, among enrolled children, the probability of not attending the age-appropriate class increases by 58.9% if they were born after the cutoff date, compared to children with birth dates before the cutoff. In sum, we show that the school entry date cutoff in 2018-2019 is relevant for identifying the late enrollment treatment effects.

Notably, Figure 2 also shows that the school entry cutoff date policy has only been laxly enforced. Moreover, because the Peruvian DHS has measured anthropometrics since 2009, we also check for each year to see whether there is a discontinuity in preschool late enrollment around the school entry date established by the Ministry of Education. Figure S5.1, for 3-year-olds, and Figure S5.2, for 4-year-olds, show that being above the cutoff was not significantly correlated to late enrollment in any year from 2009 to 2013. In other words, the school entry date cutoff policy did not significantly affect late enrollment until 2013, at least for children born ± 31 days from the cutoff. Thus, because of lack of instrument's relevance, we do not use data for the 2009-2013 period.

Anecdotal evidence suggests that the enforcement of the school entry date cutoff increased after full implementation of the SIAGIE (a platform for registering and managing information about students, including enrollment, attendance, evaluations, and grades) in public schools, introduced in 2011. Before then, it was easy to enroll children born right after the cutoff date as non-regular students even in classes with older peers, at the discretion of the teacher or principal.

Figure 2: First stage: Discontinuity in Preschool Late Enrollment (Age 3) and Age-Appropriate Class (Age 4) (2018-2019) - (bw: 31-days)



Note: This figure displays the regression discontinuity plot for children aged 3 and 4 on the left and right respectively. The dependent variable is "Not Attending Preschool" for 3-year-olds and "Not Attending Age-Appropriate Class" for 4-year-olds. Each dot represents the mean preschool enrollment rate for children at each value of the running variable (Age - c: days centered around the cutoff date). The dashed and dotted lines indicate fitted values on either side of the cutoff, estimated using linear regressions within a ±31-day bandwidth. The reported "Jump" corresponds to the estimated discontinuity at the cutoff, with standard error in parentheses. We include survey data from 2018 to 2019.

6.2 Impact of Late Enrollment on Health and Early Childhood Development

Our main specification accounts for the survey's complex sampling design using child-level weights, and uses a triangular kernel and a 31-day bandwidth around the cutoff date. Moreover, to ensure that we correctly measure the impact of late school enrollment on child health and ECD, we use only data for children who were surveyed after classes started each year (around March 15) and who were not attending a Cuna Más (public childcare program) center, and we control for child age and date of survey (thus, controlling for length of school exposure) in all regressions.

Despite the strong relationship between being above the cutoff and late enrollment, our results do not suggest any significant effects of late enrollment on child health for children whose enrollment was affected by the policy and with birth dates around the cutoff (i.e., the LATE), neither for the extensive or intensive margins, nor for 3- (i.e., impact of attending preschool up to a year later) or 4-year-olds (i.e., impact of being enrolled in a class with younger peers) (cf. Table C.1).

Figure 3 summarizes the LATE of late enrollment on child health for our main specification and shows that although the confidence intervals for the impacts in the intensive margin are somewhat large (i.e., for WAZ, WHZ, and hemoglobin), the impacts in the extensive margin are closer to true zero, especially for underweight.

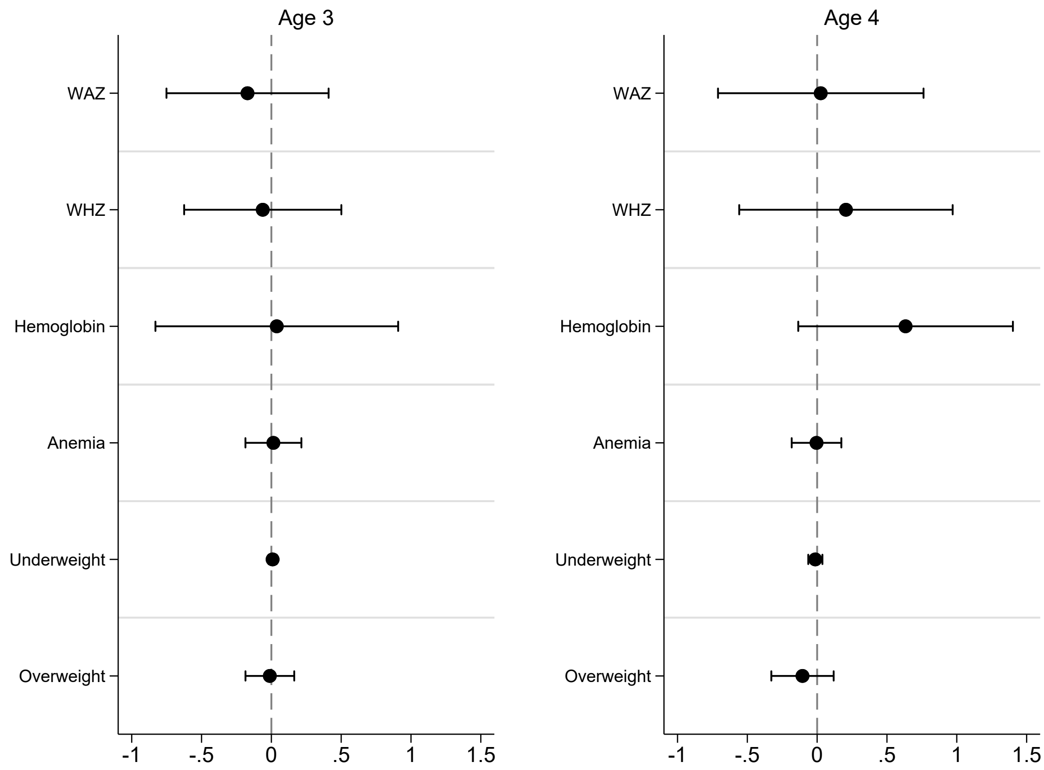
Similarly, we do not find significant impacts of late enrollment on the five measures of ECD (tantrums, aggressive response to denial, positive waiting behavior, imitation, or toy interaction), for 3- or 4-year-olds. Table C.2 shows that late enrollment only has an impact on toy interaction, significant at the 10% level. Figure 4 also shows that the confidence intervals are much larger for ECD outcomes than for child health binary outcomes.

6.3 Robustness checks

To check the robustness of our main results, presented in the previous section, we present the same results with a linear polynomial on each side of the school entry date cutoff, but instead of establishing a $\pm$31-day bandwidth, we use a data-driven approach to select the optimal bandwidth, specifically the bandwidth that minimizes the mean squared error (MSE) for each outcome, and a squared bias correction of the estimates.

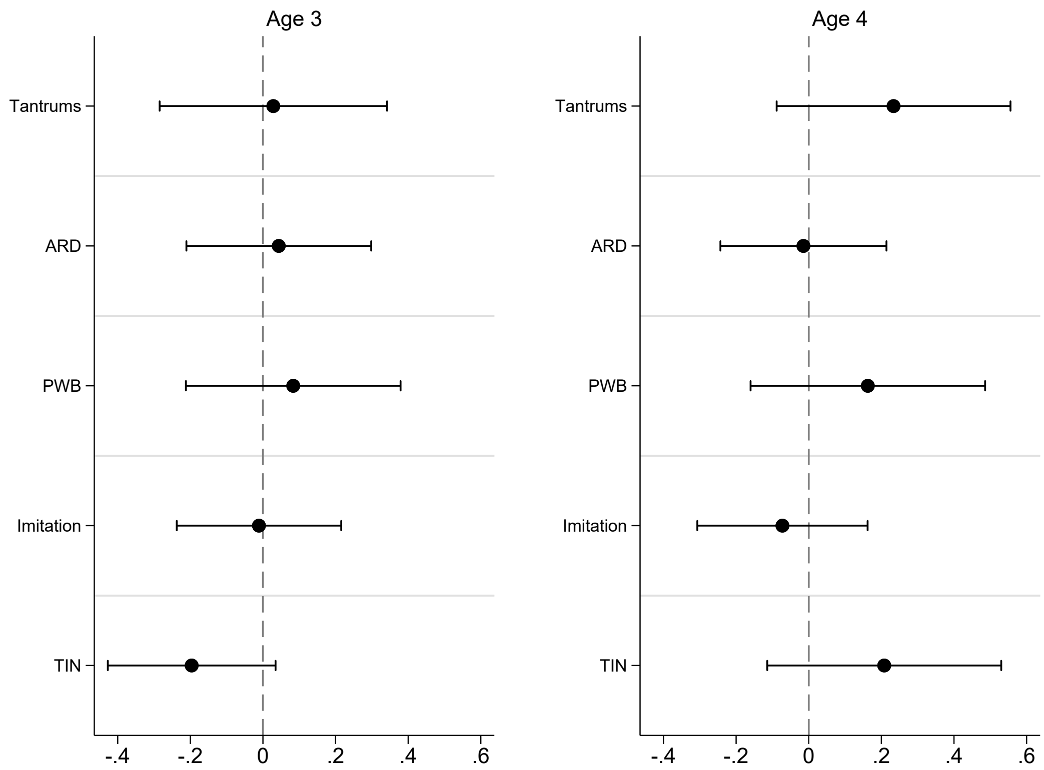
Table S1.1 shows that the optimal bandwidth for all child health variables is close to our *ad hoc* bandwidth of 31 days. This table also shows no significant impacts of late enrollment on any child health outcome for 3- or 4-year-olds due to being born

Figure 3: 2018-2019: LATE of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - Without Controls



Note: Note: Standard errors are clustered at the district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-olds, whereas Panel B presents the corresponding results for 4-year-olds. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Each dot represents the point estimate of the treatment effect from a fuzzy regression discontinuity design, with horizontal lines indicating 95% confidence intervals.

Figure 4: 2018-2019: LATE of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - Without Controls



Note: Standard errors are clustered at the district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-olds, whereas Panel B presents the corresponding results for 4-year-olds. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Each dot represents the point estimate of the treatment effect from a fuzzy regression discontinuity design, with horizontal lines indicating 95% confidence intervals.

after the school entry cutoff date. Similarly to our main results, we also observe close-to-zero effects with very small standard errors on the probability of children being underweight. Table S1.2 also shows that the optimal bandwidth for each of the ECD outcomes is close to the *ad hoc* bandwidth of 31 days. The estimated effects are not statistically significant, except for the increase in tantrums among 4-year-olds.

Using the $\pm$31-day bandwidth, but quadratic and cubic polynomials instead, we find no significant effects of late enrollment on child health outcomes, except for an increase in hemoglobin for 4-year-old late enrollees (cf. Table S1.3). Similarly, Table S1.4 contains analogous estimates of late enrollment effect on ECD. It shows no significant differences between late and early preschool enrollees, whether they are 3 or 4 years old.

Moreover, Table D.1 and Table D.2 in the Appendix present our main specification with demographic and geographic controls, and show no significant impact of late enrollment on child health or ECD.

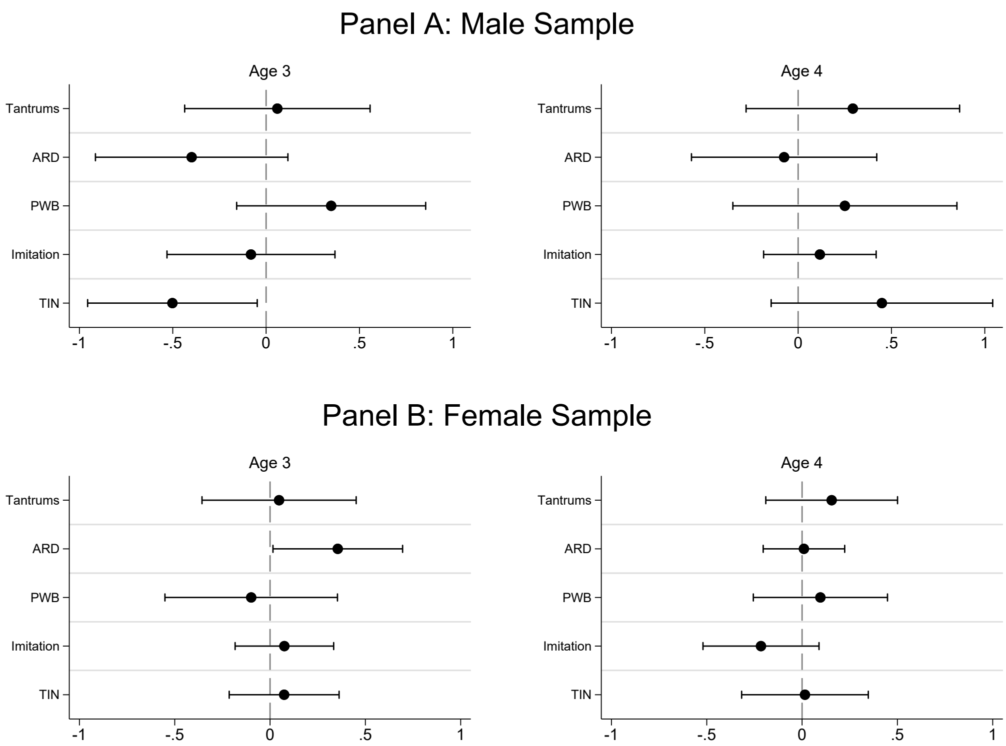
In sum, despite a couple of outcomes that become significant, when changing the bandwidth and polynomial of our main specification, or adding controls, we still find no consistent significant effects of late enrollment on child health or ECD for either 3- or 4-year-olds.

6.4 Heterogeneity analysis

Due to the lack of average effects around the cutoff of late preschool enrollment on child health and EDC, we turn to a heterogeneity analysis by child's sex, mother's age, public/private school, poverty, and area of residence.

Table S3.1 and Table S3.2 show no significant differences in health outcomes between boys and girls. However, Figure 5 shows a negative impact of late enrollment on toy interaction for 3-year-old boys, and a positive impact on aggressive response to

Figure 5: 2018-2019: LATE of Late School Enrollment on Early Childhood Development - (Male vs Female Sample, bw: 31-days) - Sample Weights and Triangular Kernel - Without Controls



Note: Standard errors are clustered at the district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3- and 4-year-old male children, whereas Panel B presents the corresponding results for female children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Each dot represents the point estimate of the treatment effect from a fuzzy regression discontinuity design, with horizontal lines indicating 95% confidence intervals.

denial for 3-year-old girls.

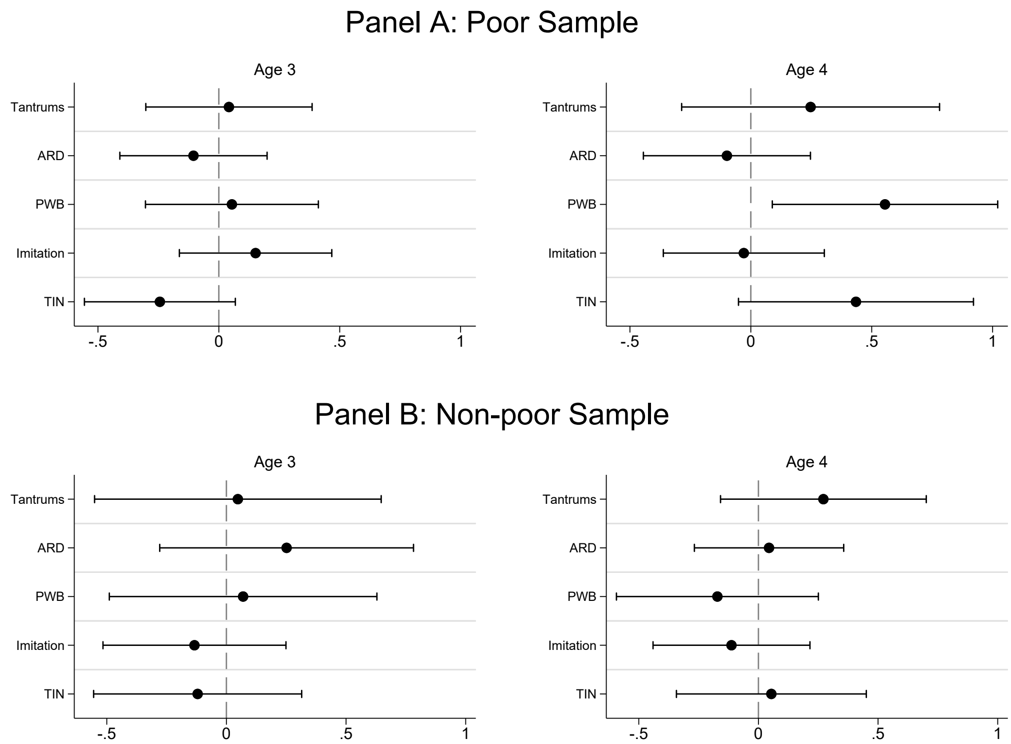
Table S3.3 and Table S3.4 show that there are no significant impacts of late enrollment on child health for either, 3- or 4-year-olds with younger (than the median) mothers, or for children with older mothers. Similarly, Table S3.14 and Table S3.15 show no significant impacts of late enrollment, due to being born after the school enrollment cutoff date, on any EDC outcomes among children with younger or older mothers.

For 3-year-olds born after the cutoff date, late enrollment implies not going to school, so we divide the sample into children attending public and private schools only for 4-year-olds, all of whom attend school. Exploring this difference is important because public schools provide school lunch almost universally, while private schools do not, and nearly one third of preschoolers attends a private school. We find no significant impacts of late enrollment on child health for children attending public schools (see Table S3.5) or private schools (see Table S3.6). This finding is also consistent with previous studies measuring the impact of school meals programs in Peru (Cueto & Chinen, 2000; Yamada & Pérez, 2005). Nor do we find significant impacts of late enrollment on ECD outcomes among children attending public schools (see Table S3.16) or private schools (see Table S3.17).

Using the DHS wealth index, we divide our sample between poor and non-poor. Table S3.7 and Table S3.8 show there are no significant impacts of late enrollment on child health among poor children, non-poor children, or 3- or 4-year-olds. Regarding impacts of late enrollment on ECD, we only find a significant increase of positive waiting behavior among poor 4-year-old children, and no significant impacts among non-poor children (see Figure 6).

Finally, given the well-known differences in school infrastructure investments across the Coast, Andes, and Amazon regions, we divide our sample among the three natural regions to explore differential impacts of late enrollment. Table S3.9, Table S3.10, and Table S3.11 show no significant effects of late enrollment on any child health indicators in the Coast, Andes, or Amazon regions of Peru, respectively. Nonetheless, we do find some differential ECD outcomes by natural region. Although there are no significant impacts of late enrollment on ECD in the Coast or Amazon regions (see Table S3.20 and Table S3.21), Table S3.22 shows that 3-year-olds in the Andes who enroll late, because of the school entry cutoff policy, significantly decrease toy interaction, while 4-year-olds decrease their aggressive

Figure 6: 2018-2019: LATE of Late School Enrollment on Early Childhood Development - (Poor vs Non-poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - Without Controls



Note: Standard errors are clustered at the district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old and 4-year-old children from poor households, whereas Panel B presents the corresponding results for children from non-poor households. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Each dot represents the point estimate of the treatment effect from a fuzzy regression discontinuity design, with horizontal lines indicating 95% confidence intervals.

response to denial, compared to early-enrolled children.

7 Discussion

Despite the strong relationship between the school entry date cutoff and preschool late enrollment, between 2018 and 2019 we find no significant effects of the school-entry cutoff policy on children's physical health (weight-for-age, weight-for-height, or hemoglobin) or early childhood development outcomes (throwing tantrums, aggressive response to denial, positive waiting behavior, imitation, or toy interaction) within the observed window (children born one month from the cutoff date).

Moreover, the heterogeneity analysis shows that the null effects on child health do not differ by child sex, mother's age, attending public or private schools, poverty, or area of residence. We only find significant differential effects of late enrollment among certain ECD outcomes by child's sex and by area of residence. Specifically, late enrollment decreases toy interaction among 3-year-old boys and increases aggressive response to denial among 3-year-old-girls; it increases positive waiting behavior among poor 4-year-olds; while it decreases toy interaction among 3-year-old children in the Andes; it also decreases aggressive response to denial among 4-year-olds in the Andes. Summarizing, all subgroup results for 3-year-olds imply negative impacts on ECD, which suggests that having to wait (many months to almost a year) to attend preschool prevents full ECD, especially for poor children and those in the Andes. At the same time, the results for 4-year-olds of different subgroups all indicate improvements in ECD, suggesting that being enrolled in a class with younger peers does not affect ECD or could improve it.

The null effects of late enrollment on child health and mostly null effects on ECD can be explained with several hypotheses. First, the exposure to preschool induced by the cutoff —although sizable in enrollment terms— may be too heterogeneous in quality to generate detectable changes in health or developmental outcomes.[9] Prior studies have emphasized that the intensity and quality of early education matter for producing long-term benefits, particularly in low-resource settings (Arteaga, Humpage, Reynolds, & Temple, 2014; Bustamante, Bermudez, Ochoa, Belgrave, & Vandell, 2023; Li et al., 2020; OECD, 2025; Wustmann Seiler, Sticca, Gasser-Haas, & Simoni, 2022; Zhang et al., 2021). If the additional year of preschool attendance consists largely of low-intensity activities, or if it varies substantially in teacher-child interactions and content, its average impact on outcomes may be diluted.

Second, early childhood developmental gains may take longer to emerge. Given that children in our sample had, on average, only 141 days of preschool exposure, our outcomes may not capture medium- or long-term effects. Studies from high-income countries suggest that relative age effects on academic performance and behavior become more pronounced over time.

Third, household compensatory behaviors might offset potential disadvantages of delayed school entry. Parents of children who must wait may invest more time or resources in early stimulation at home, mitigating short-term gaps.

Lastly, it is possible that early childhood health and development in Peru are more strongly shaped by persistent structural factors than by short-term variation in preschool exposure. If these broader constraints dominate, modest shifts in the timing of school enrollment may have limited marginal effects.

8 Conclusions

The literature on school entry age highlights consistent academic and behavioral advantages for older students, with emerging evidence on health impacts. However,

[9] Although we are comparing children born one month before or after the cutoff, these children are interviewed by the DHS during the year, so our results are not only for the very short run term (about two months).

LMIC contexts remain understudied, particularly regarding nutritional outcomes and long-term health impacts. By examining these issues in Peru, we contribute to a deeper understanding of how school entry policies impact preschoolers' health and development.

Despite a long political debate in Peru about how much school entry cutoff policies affect enrollment, and thus prevent children from accessing the benefits of being in school early on, our first finding is that between 2009 and 2013, there was no significant relationship between being born after the cutoff date and being late enrolled (not being enrolled in school, for 3-year-olds, or being enrolled with younger peers, for 4-year-olds). Moreover, since 2014, the school entry cutoff date established by the Ministry of Education has only been laxly enforced. Specifically, being born after the cutoff date increased the probability of being late enrolled by only about 50%. This lax enforcement can be explained, anecdotally, by widespread enrollment of children born right after the cutoff date as non-regular students, whether or not in age-appropriate sections of public and private schools.

For the years when the policy was at least laxly enforced and we had data available (2018-2019), our results show no significant impact of late enrollment on child health among children who enrolled late because they were born after the cutoff date. These null results persist across different specifications. Moreover, the null impacts of late enrollment on the probability of a child being underweight can be interpreted as true zeroes. Our heterogeneity analysis also shows that when we find significant effects for certain subgroups, there are still no significant effects on child health, and the impacts on ECD are negative for 3-year-olds, and positive for 4-year-olds. These results suggest that some children (poor and living in the Andes, especially) who did not access the first year of preschool because of the school entry cutoff date, saw their ECD diminished. Meanwhile, 4-year-old children who were enrolled in a class with younger peers because of the school entry policy saw their ECD improved or unchanged.

Summarizing, late enrollment, as long as children are attending school, does not affect their health or development negatively. Thus, the policy recommendation that follows is to keep the school entry policy cutoff date in place. Nonetheless, some children who do not access preschool due to the cutoff policy, although their health is not affected, could see their ECD diminished. For this group, the policy recommendation that follows is to expand early childhood development services such as Cuna Más and PRONOEI, which target poor children, and to implement a more adequate transition from these programs to preschool.

Data availability

The datasets used in this study are publicly available from the Peruvian National Bureau of Statistics at https://proyectos.inei.gob.pe/microdatos/.

Ethics statement

This study uses anonymized, publicly available secondary data from the *Encuesta Demográfica y de Salud Familiar* (DHS) conducted by the Instituto Nacional de Estadística e Informática (INEI) of Peru. In accordance with the ethics guidelines of the *Comité de Ética de la Investigación para Ciencias Sociales, Humanas y Artes* (CEI-CCSSHHyAA) –the institutional review board (IRB) for the social sciences at the Pontificia Universidad Católica del Perú (PUCP) –the research was determined to fall outside the scope of human subjects research, as the dataset contains no personally identifiable information. Therefore, formal ethics approval was not required. The committee issued an official waiver letter ("Constancia N° 005-2025-NR-OETIIC/PUCP") confirming that the project does not require evaluation. All procedures complied with applicable ethical standards for research using anonymized secondary data.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Armas, C., Campos, A., & Gutiérrez, J. (2019). *Can the school entrance age explain lower academic performance? Evidence from Peru* [mimeo]. Retrieved from https://sistemas.colmex.mx/Reportes/LACEALAMES/LACEA-LAMES2019_paper_669.pdf

Arteaga, I., Humpage, S., Reynolds, A. J., & Temple, J. A. (2014, May). One Year of Preschool or Two – Is It Important for Adult Outcomes? Results from the Chicago Longitudinal Study of the Child-Parent Centers. *Economics of education review*, *40*, 221–237. Retrieved 2025-08-13, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4727175/ doi: 10.1016/j.econedurev.2013.07.009

Atun, R., Andrade, L. O. M. d., Almeida, G., Cotlear, D., Dmytraczenko, T., Frenz, P., ... Wagstaff, A. (2015, March). Health-system reform and universal health coverage in Latin America. *The Lancet*, *385*(9974), 1230–1247. Retrieved 2024-10-02, from https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(14)61646-9/abstract?rss%253Dyes= (Publisher: Elsevier) doi: 10.1016/S0140-6736(14)61646-9

Avila Rojas, L. (2016). *Proyecto de Ley N° 709/2016-CR, Ley que modifica el artículo 36 de la ley N°28044, Ley general de educación.* Retrieved from https://www.leyes.congreso.gob.pe/Documentos/2016_2021/Proyectos_de_Ley_y_de_Resoluciones_Legislativas/PL0070920161128.pdf

Avila Rojas, L. (2018, August). *Proyecto de Ley N° 3188/2018-CR. Ley que modifica el artículo 36 de la Ley 28044, Ley General de Educación.*

Bornstein, M. H., Britto, P. R., Nonoyama-Tarumi, Y., Ota, Y., Petrovic, O., & Putnick, D. L. (2012). Child Development in Developing Countries: Introduction and Methods. *Child Development*, *83*(1), 16–31. Retrieved 2025-04-28, from https://onlinelibrary

.wiley.com/doi/abs/10.1111/j.1467-8624.2011.01671.x (_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-8624.2011.01671.x) doi: 10.1111/j.1467-8624.2011.01671.x

Bustamante, A. S., Bermudez, V. N., Ochoa, K. D., Belgrave, A. B., & Vandell, D. L. (2023, August). Quality of Early Childcare and Education Predicts High School STEM Achievement for Students from Low-income Backgrounds. *Developmental psychology*, *59*(8), 1440–1451. Retrieved 2025-08-13, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10524717/ doi: 10.1037/dev0001546

Caudillo, M. L. (2019, May). Advanced School Progression Relative to Age and Early Family Formation in Mexico. *Demography*, *56*(3), 863–890. Retrieved 2023-12-15, from https://doi.org/10.1007/s13524-019-00782-6 doi: 10.1007/s13524-019-00782-6

Caye, A., Petresco, S., de Barros, A. J. D., Bressan, R. A., Gadelha, A., Gonçalves, H., … Rohde, L. A. (2020, August). Relative Age and Attention-Deficit/Hyperactivity Disorder: Data From Three Epidemiological Cohorts and a Meta-analysis. *Journal of the American Academy of Child & Adolescent Psychiatry*, *59*(8), 990–997. Retrieved 2023-12-15, from https://www.sciencedirect.com/science/article/pii/S0890856719314327 doi: 10.1016/j.jaac.2019.07.939

Cook, P. J., & Kang, S. (2016, January). Birthdays, Schooling, and Crime: Regression-Discontinuity Analysis of School Performance, Delinquency, Dropout, and Crime Initiation. *American Economic Journal: Applied Economics*, *8*(1), 33–57. Retrieved 2024-09-29, from https://www.aeaweb.org/articles?id=10.1257/app.20140323 doi: 10.1257/app.20140323

Cueto, S., & Chinen, M. (2000). *Impacto educativo de un programa de desayunos escolares en escuelas rurales del Perú* (Working Paper). GRADE. Retrieved 2025-05-30, from https://repositorio.minedu.gob.pe/handle/

20.500.12799/164 (Accepted: 5/7/2013 15:25)

Datar, A. (2006, February). Does delaying kindergarten entrance give children a head start? *Economics of Education Review*, *25*(1), 43–62. Retrieved 2024-10-07, from https://linkinghub.elsevier.com/retrieve/pii/S0272775705000117 doi: 10.1016/j.econedurev.2004.10.004

Deen, J., Von Seidlein, L., & Clemens, J. (2014). Issues and Challenges of Public-Health Research in Developing Countries. In J. Farrar, P. Hotez, T. Junghanss, G. Kang, D. Lalloo, & N. White (Eds.), *Manson's Tropical Infectious Diseases* (23rd ed., pp. 40–48). Elsevier. Retrieved from https://doi.org/10.1016/B978-0-7020-5101-2.00006-6

Dhuey, E. K., & Koebel, K. (2022, April). Is there an optimal school starting age? *IZA World of Labor*. Retrieved 2024-09-29, from https://wol.iza.org/articles/age-at-school-entry-how-old-is-old-enough/long doi: 10.15185/izawol.247

Dobkin, C., & Ferreira, F. (2010, February). Do school entry laws affect educational attainment and labor market outcomes? *Economics of Education Review*, *29*(1), 40–54. Retrieved 2023-12-11, from https://www.sciencedirect.com/science/article/pii/S0272775709000685 doi: 10.1016/j.econedurev.2009.04.003

Flores Ancachi, J. L. (2022). *Proyecto de Ley N° 4884/2022-CR, Ley que propone modificar el artículo 36 de la Ley 28044, Ley General de Educación.* Retrieved from https://wb2server.congreso.gob.pe/spley-portal/#/expediente/2021/4884

Fredriksson, P., & Öckert, B. (2014). Life-cycle Effects of Age at School Start. *The Economic Journal*, *124*(579), 977–1004. Retrieved 2024-09-28, from https://onlinelibrary.wiley.com/doi/abs/10.1111/ecoj.12047 (_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecoj.12047) doi: 10.1111/ecoj.12047

Grantham-McGregor, S., Cheung, Y. B., Cueto, S., Glewwe, P., Richter, L., & Strupp, B. (2007, January). Developmental potential in the first 5 years for children in developing countries. *The Lancet*, *369*(9555), 60–70. Retrieved 2025-04-28, from https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(07)60032-4/fulltext (Publisher: Elsevier) doi: 10.1016/S0140-6736(07)60032-4

Herdeiro, R., Oliveira, A. P., & Menezes-Filho, N. (2024, February). The Effect of Age at School Entry on Educational and Labor Market Outcomes in Brazil: A Regression Discontinuity Analysis. *Economic Development and Cultural Change*, 000–000. Retrieved 2024-12-02, from https://www.journals.uchicago.edu/doi/epdf/10.1086/730190 (Publisher: The University of Chicago Press) doi: 10.1086/730190

Ijarotimi, O. S. (2013, September). Determinants of Childhood Malnutrition and Consequences in Developing Countries. *Current Nutrition Reports*, *2*(3), 129–133. Retrieved 2025-04-24, from https://doi.org/10.1007/s13668-013-0051-5 doi: 10.1007/s13668-013-0051-5

Kelishadi, R. (2007, January). Childhood Overweight, Obesity, and the Metabolic Syndrome in Developing Countries. *Epidemiologic Reviews*, *29*(1), 62–76. Retrieved 2024-10-02, from https://doi.org/10.1093/epirev/mxm003 doi: 10.1093/epirev/mxm003

Kramer, C. V., & Allen, S. (2015, September). Malnutrition in developing countries. *Paediatrics and Child Health*, *25*(9), 422–427. Retrieved 2025-04-24, from https://www.sciencedirect.com/science/article/pii/S1751722215000797 doi: 10.1016/j.paed.2015.04.002

Levasseur, P. (2022, April). School starting age and nutritional outcomes: Evidence from Brazil. *Economics & Human Biology*, *45*, 101104. Retrieved 2023-12-11, from https://www.sciencedirect.com/science/article/pii/S1570677X21001295 doi: 10.1016/j.ehb.2021.101104

Li, W., Duncan, G. J., Magnuson, K., Schindler, H. S., Yoshikawa, H., & Leak, J. (2020, February). *Timing in Early Childhood Education: How Cognitive and Achievement Program Impacts Vary by Starting Age, Program Duration, and Time since the End of the Program. EdWorkingPaper No. 20-201* (Tech. Rep.). Annenberg Institute for School Reform at Brown University. Retrieved 2025-08-13, from https://eric.ed.gov/?id=ED610271 (ERIC Number: ED610271)

Liao, J., Schröder, H., Chin, E. K., Bakare, M. O., Moshoeshoe, R., Caudillo, M. L., ... De Neve, J.-W. (2023, June). The effect of school-entry age on health is understudied in low- and middle-income countries: A scoping review and future directions for research. *SSM - Population Health*, *22*, 101423. Retrieved 2023-12-11, from https://www.sciencedirect.com/science/article/pii/S2352827323000885 doi: 10.1016/j.ssmph.2023.101423

MIDIS. (2019). *Análisis de Resultados del Módulo de Desarrollo Infantil Temprano Versión 1, ENDES – INEI.* Lima.

Morales, M. (2020). *School-entry Eligibility Effects in Developing Countries* (Doctoral dissertation, Columbia University). doi: 10.7916/d8-k2pa-fw63

Nam, K. (2014, June). Until when does the effect of age on academic achievement persist? Evidence from Korean data. *Economics of Education Review*, *40*, 106–122. Retrieved 2025-04-25, from https://www.sciencedirect.com/science/article/pii/S027277571400020X doi: 10.1016/j.econedurev.2014.02.002

Navarro, J.-J., García-Rubio, J., & Olivares, P. R. (2015, October). The Relative Age Effect and Its Influence on Academic Performance. *PLOS ONE*, *10*(10), e0141895. Retrieved 2025-01-22, from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0141895 (Publisher: Public Library of Science) doi: 10.1371/journal.pone.0141895

Nguyen, H., & Lewis, B. (2020). Teenage Marriage and Motherhood in Vietnam: The Negative Effects of Starting School Early. *Population Research and Policy Review*, *39*, 739–762. doi: https://doi.org/10.1007/s11113-019-09553-y

OECD. (2025). *Reducing Inequalities by Investing in Early Childhood Education and Care*. OECD Publishing. Retrieved 2025-08-13, from https://www.oecd.org/en/publications/reducing-inequalities-by-investing-in-early-childhood-education-and-care_b78f8b25-en.html doi: 10.1787/b78f8b25-en

Oosterbeek, H., ter Meulen, S., & van der Klaauw, B. (2021, October). Long-term effects of school-starting-age rules. *Economics of Education Review*, *84*, 102144. Retrieved 2024-09-28, from https://www.sciencedirect.com/science/article/pii/S0272775721000637 doi: 10.1016/j.econedurev.2021.102144

Page, L., Sarkar, D., & Silva-Goncalves, J. (2019, December). Long-lasting effects of relative age at school. *Journal of Economic Behavior & Organization*, *168*, 166–195. Retrieved 2024-09-28, from https://www.sciencedirect.com/science/article/pii/S0167268119303129 doi: 10.1016/j.jebo.2019.10.005

Peña, P. A. (2017, February). Creating winners and losers: Date of birth, relative age in school, and outcomes in childhood and adulthood. *Economics of Education Review*, *56*, 152–176. Retrieved 2024-09-28, from https://www.sciencedirect.com/science/article/pii/S0272775716306665 doi: 10.1016/j.econedurev.2016.12.001

Rose, S. E., & Barlow, C. M. (2024). The impact of relative age effects on psychosocial development: A systematic review. *British Journal of Educational Psychology*, *94*(1), 248–281. Retrieved 2024-09-28, from https://onlinelibrary.wiley.com/doi/abs/10.1111/bjep.12630 (_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/bjep.12630) doi: 10.1111/

bjep.12630

Schwandt, H., & Wuppermann, A. (2016, December). The youngest get the pill: ADHD misdiagnosis in Germany, its regional correlates and international comparison. *Labour Economics*, *43*, 72–86. Retrieved 2024-10-02, from https://www.sciencedirect.com/science/article/pii/S0927537116300410 doi: 10.1016/j.labeco.2016.05.018

UN. (2023). *The Sustainable Development Goals Report. Special Edition. Towards a Rescue Plan for People and Planet.* New York: United Nations. Retrieved from https://unstats.un.org/sdgs/report/2023/The-Sustainable-Development-Goals-Report-2023.pdf

Wustmann Seiler, C., Sticca, F., Gasser-Haas, O., & Simoni, H. (2022, May). Long-Term Promotive and Protective Effects of Early Childcare Quality on the Social–Emotional Development in Children. *Frontiers in Psychology*, *13*, 854756. Retrieved 2025-08-13, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9125337/ doi: 10.3389/fpsyg.2022.854756

Yamada, G., & Pérez, P. (2005). Programa del Vaso de Leche. In *Evaluación de impacto de proyectos de desarrollo en el Perú* (1st ed., Vol. 1, pp. 75–82). Fondo Editorial de la Universidad del Pacífico.

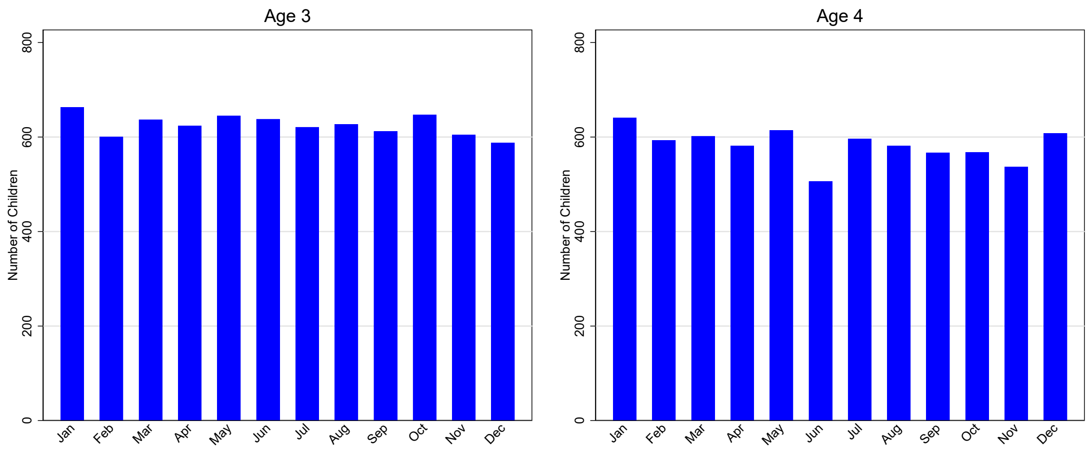
Zhang, L., Ssewanyana, D., Martin, M.-C., Lye, S., Moran, G., Abubakar, A., ... Malti, T. (2021). Supporting Child Development Through Parenting Interventions in Low- to Middle-Income Countries: An Updated Systematic Review. *Frontiers in Public Health*, *9*, 671988. doi: 10.3389/fpubh.2021.671988

Zweimüller, M. (2013). The Effects of School Entry Laws on Educational Attainment and Starting Wages in an Early Tracking System. *Annals of Economics and Statistics*(111/112), 141–169. Retrieved 2025-04-25, from https://www-jstor-org.ezproxybib.pucp.edu.pe/stable/23646329?seq=1 doi: https://doi.org/10.2307/23646329

Appendices

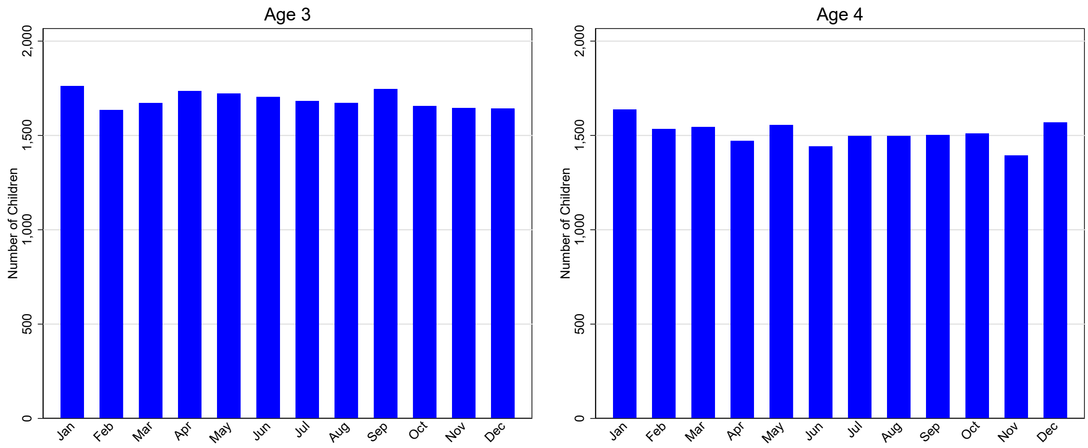
A Validity of the Regression Discontinuity Design

Figure A.1: Birth-date Distribution by Age (2018-2019)



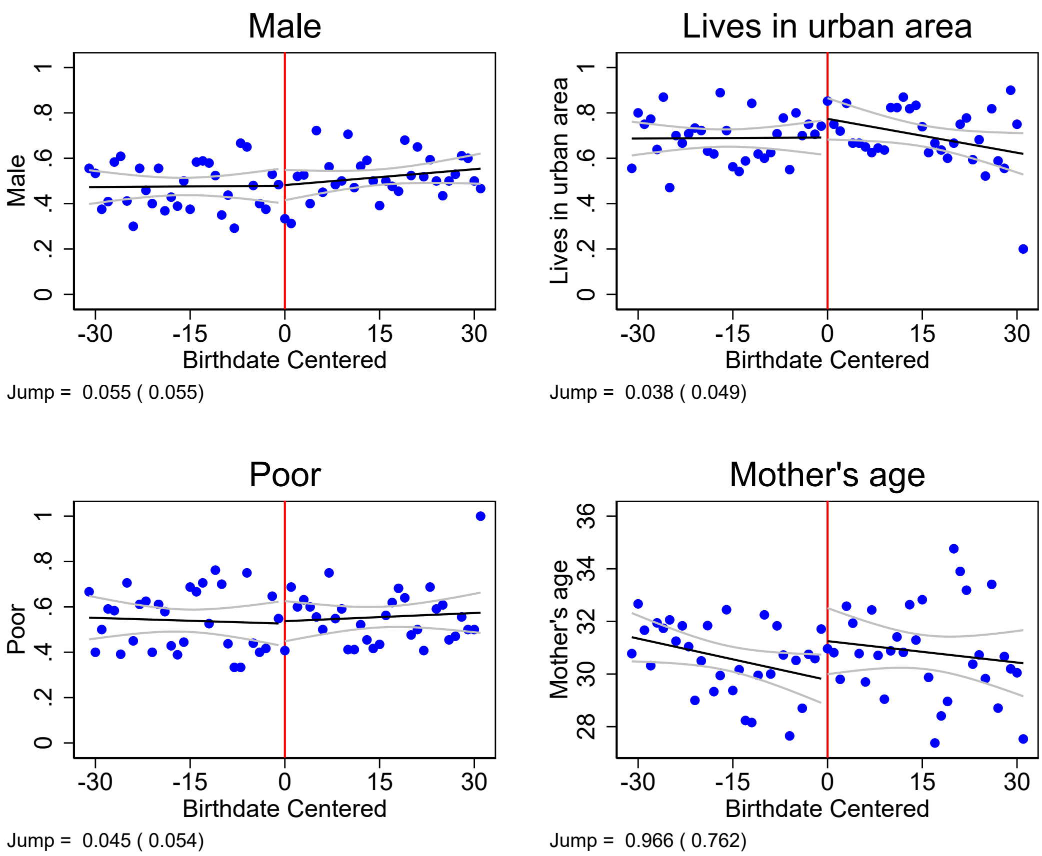
Note: This figure presents the distribution of birth dates across calendar months for children aged 3 and 4 in our sample. Each bar represents the number of children born in each month. We include survey data from 2018 to 2019.

Figure A.2: Birth-date Distribution by Age (2015-2019)



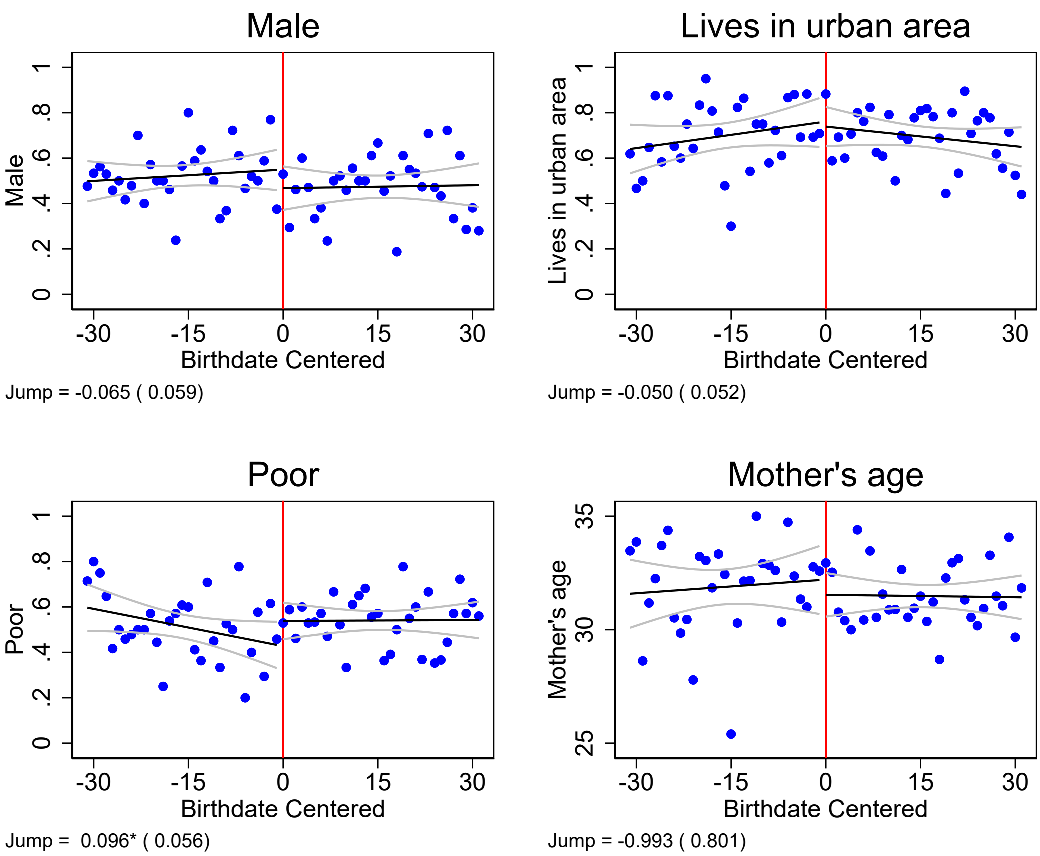
Note: This figure presents the distribution of birth dates across calendar months for children aged 3 and 4 in our sample. Each bar represents the number of children born in each month. We include survey data from 2015 to 2019.

Figure A.3: Discontinuity on Covariates, Age 3 - (bw: 31-days)



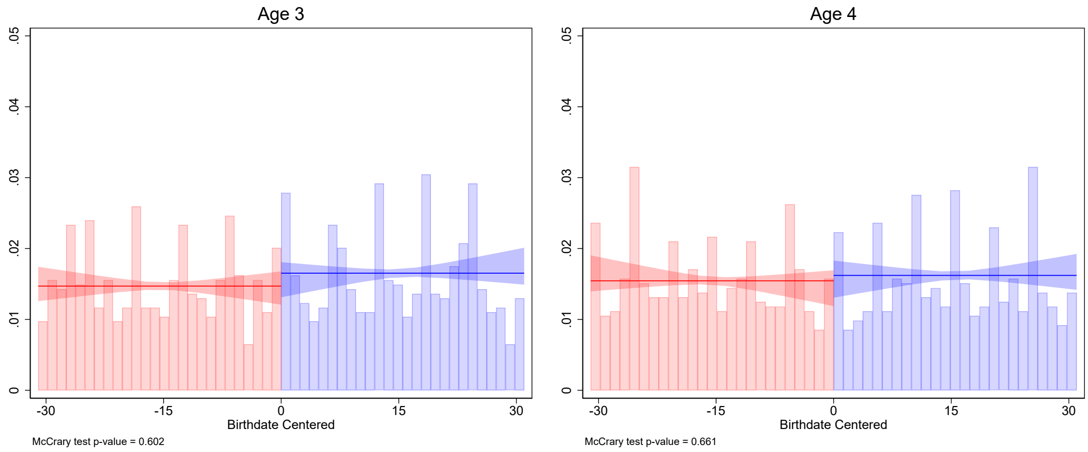
Note: This figure displays the regression discontinuity plot for children aged 3. We use the covariates as dependent variable to perform a covariate balance test. Each dot represents the covariate mean for children at each value of the running variable (Birthdate Centered). The dashed and dotted lines indicate fitted values on either side of the cutoff, estimated using linear regressions within a ±31-day bandwidth. The reported "Jump" corresponds to the estimated discontinuity at the cutoff, with standard error in parentheses. We include survey data from 2018 to 2019.

Figure A.4: Discontinuity on Covariates, Age 4 - (bw: 31-days)



Note: This figure displays the regression discontinuity plot for children aged 4. We use the covariates as dependent variable to perform a covariate balance test. Each dot represents the covariate mean for children at each value of the running variable (Birthdate Centered). The dashed and dotted lines indicate fitted values on either side of the cutoff, estimated using linear regressions within a ±31-day bandwidth. The reported "Jump" corresponds to the estimated discontinuity at the cutoff, with standard error in parentheses. We include survey data from 2018 to 2019.

Figure A.5: McCrary Density Test for Manipulation around the Running Variable (Birthdate - c) - (bw: 31-days)



Note: This figure presents the results of the McCrary density test applied to the running variable (Birthdate Centered). The test evaluates whether there is a discontinuity in the density of observations around the cutoff at zero, which would suggest manipulation in treatment assignment. At the bottom, we report the p-value of the test. We use a bandwidth of 31 days.

B Cutoff Dates

Table B.1: Cutoff dates for enrollment in early education in Peru, 2007–2020

Year	Cutoff date (age 3 by)	Ministerial Resolutions
2007	July 31	N°0712-2006-ED
2008	July 31	N°0494-2007-ED
2009	June 30	N°0441-2008-ED
2010	June 30	N°0341-2009-ED
2011	March 31	N°0348-2010-ED
2012	July 31*	N°0622-2011-ED, N°0044-2012-ED
2013	March 31	N°0431-2012-ED
2014	March 31	N°0622-2013-ED
2015	March 31	N°556-2014-MINEDU
2016	March 31	N°572-2015-MINEDU
2017	March 31	N°627-2016-MINEDU
2018	March 31	N°657-2017-MINEDU
2019	March 31	N°712-2018-MINEDU
2020	March 31	N°220-2019-MINEDU

*In 2012, exceptions were made allowing children who turned 3 by July 31 to enroll.

C Main specification without controls

C.1 Child Health

Table C.1: 2018-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.171	-0.062	0.039	0.015	0.009	-0.011
	(0.296)	(0.287)	(0.444)	(0.102)	(0.015)	(0.089)
Δ slope	-0.001	0.018	0.002	0.006	0.002**	0.004
	(0.019)	(0.019)	(0.019)	(0.005)	(0.001)	(0.005)
Observations:	1260	1260	1252	1252	1260	1260
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.026	0.206	0.633	-0.004	-0.013	-0.105
	(0.376)	(0.390)	(0.392)	(0.091)	(0.026)	(0.114)
Δ slope	0.019	0.022	-0.027	0.004	0.001	-0.003
	(0.027)	(0.026)	(0.028)	(0.007)	(0.002)	(0.008)
Observations:	1183	1183	1174	1174	1183	1183
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Early Child Development

Table C.2: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.029	0.044	0.083	-0.011	-0.196*
	(0.160)	(0.130)	(0.151)	(0.116)	(0.118)
Δ slope	-0.002	0.010	-0.007	-0.008	-0.005
	(0.009)	(0.007)	(0.009)	(0.006)	(0.006)
Observations:	1259	1258	1259	1258	1257
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.234	-0.015	0.163	-0.072	0.208
	(0.164)	(0.117)	(0.165)	(0.120)	(0.164)
Δ slope	0.029**	0.010	-0.018	-0.011	-0.006
	(0.012)	(0.009)	(0.012)	(0.008)	(0.011)
Observations:	1181	1180	1180	1181	1180
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Main specification with controls

D.1 Child Health

Table D.1: 2018-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.067	-0.014	-0.289	0.023	0.006	-0.004
	(0.280)	(0.278)	(0.331)	(0.096)	(0.014)	(0.090)
Δ slope	0.007	0.022	0.001	0.006	0.002*	0.005
	(0.018)	(0.018)	(0.015)	(0.005)	(0.001)	(0.005)
Observations:	1260	1260	1252	1252	1260	1260
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.297	0.373	-0.108	0.060	-0.021	-0.093
	(0.411)	(0.423)	(0.338)	(0.100)	(0.027)	(0.121)
Δ slope	0.016	0.020	-0.017	0.002	0.002	-0.002
	(0.023)	(0.023)	(0.021)	(0.007)	(0.001)	(0.007)
Observations:	1183	1183	1174	1174	1183	1183
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Early Child Development

Table D.2: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.053	0.022	0.063	0.008	-0.159
	(0.155)	(0.129)	(0.149)	(0.114)	(0.114)
Δ slope	-0.002	0.008	-0.008	-0.004	-0.003
	(0.008)	(0.007)	(0.009)	(0.006)	(0.006)
Observations:	1259	1258	1259	1258	1257
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.315*	0.008	0.121	-0.058	0.194
	(0.181)	(0.133)	(0.180)	(0.128)	(0.183)
Δ slope	0.026**	0.008	-0.018	-0.009	-0.005
	(0.011)	(0.009)	(0.011)	(0.007)	(0.010)
Observations:	1181	1180	1180	1181	1180
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.3 Other Child Health Outcomes

Table D.3: 2018-2019: Impact of Late School Enrollment on Other Child Health Outcomes - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	HAZ	Stunting	Adj. Anemia by altitude
Panel A: Age 3			
Jump	-0.221	0.072	0.195
	(0.278)	(0.079)	(0.122)
Δ slope	-0.025	0.009*	0.007
	(0.018)	(0.005)	(0.006)
Observations:	1260	1260	1252
Bandwidth:	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear
Panel B: Age 4			
Jump	-0.163	-0.041	0.046
	(0.275)	(0.067)	(0.109)
Δ slope	0.004	0.005	0.009
	(0.021)	(0.005)	(0.008)
Observations:	1183	1183	1174
Bandwidth:	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear
Controls	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: 2018-2019: Impact of Late School Enrollment on Other Child Health Outcomes - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	HAZ	Stunting	Adj. Anemia by altitude
Panel A: Age 3			
Jump	-0.099	0.045	0.132
	(0.260)	(0.079)	(0.114)
Δ slope	-0.015	0.006	0.006
	(0.016)	(0.005)	(0.006)
Observations:	1260	1260	1252
Bandwidth:	$\pm$31.00	$\pm$31.00	$\pm$31.00
Polynomial:	Linear	Linear	Linear
Panel B: Age 4			
Jump	0.080	-0.098	0.027
	(0.300)	(0.073)	(0.120)
Δ slope	0.002	0.005	0.008
	(0.018)	(0.004)	(0.008)
Observations:	1183	1183	1174
Bandwidth:	$\pm$31.00	$\pm$31.00	$\pm$31.00
Polynomial:	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Supplementary Material

S1 Robustness Checks without controls

Optimal bandwidth

Table S1.1: 2018-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: optimal, local polynomial RD) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.331	0.387	-0.197	0.139	-0.000	0.139
	(0.415)	(0.421)	(0.468)	(0.139)	(0.025)	(0.112)
Eff. Observations:	1151	1053	1252	915	1013	1013
Opt. Bandwidth:	±27.39	±25.10	±30.91	±22.63	±24.94	±24.12
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	-0.146	0.183	-0.057	0.155	-0.048	-0.043
	(0.417)	(0.417)	(0.448)	(0.112)	(0.035)	(0.133)
Eff. Observations:	1037	1082	1263	1220	1183	1117
Opt. Bandwidth:	±26.12	±27.33	±32.58	±31.15	±30.55	±28.61
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a local polynomial fuzzy regression discontinuity design are presented. We use the optimal MSE bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S1.2: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: optimal, local polynomial RD) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.066	0.215	0.131	0.181	0.048
	(0.183)	(0.162)	(0.195)	(0.178)	(0.182)
Eff. Observations:	1292	1051	1190	919	867
Opt. Bandwidth:	±31.05	±25.08	±28.04	±22.33	±21.64
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.560**	-0.016	-0.026	-0.079	0.098
	(0.225)	(0.138)	(0.205)	(0.127)	(0.173)
Eff. Observations:	901	1145	993	1181	1225
Opt. Bandwidth:	±23.02	±29.48	±25.06	±30.51	±31.30
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a local polynomial fuzzy regression discontinuity design are presented. We use the optimal MSE bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Different polynomials

Table S1.3: 2018-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls with different polynomials

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.340	-0.281	0.390	-0.182	0.026	-0.027
	(0.494)	(0.486)	(1.011)	(0.213)	(0.026)	(0.160)
Δ slope	-0.097	-0.069	0.047	0.009	0.005	-0.007
	(0.066)	(0.071)	(0.084)	(0.027)	(0.005)	(0.021)
Observations:	1260	1260	1252	1252	1260	1260
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	3.214	4.321	-17.427	8.130	-0.100	0.506
	(80.705)	(107.807)	(2850.777)	(1351.701)	(3.295)	(12.759)
Δ slope	-2.188	-2.904	9.990	-4.737	0.093	-0.344
	(58.163)	(77.715)	(1647.307)	(781.094)	(2.372)	(9.192)
Observations:	1260	1260	1252	1252	1260	1260
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Panel B: Age 4						
Jump	0.110	0.253	1.388**	-0.192	0.028	-0.183
	(0.516)	(0.536)	(0.610)	(0.119)	(0.031)	(0.156)
Δ slope	-0.009	0.014	-0.072	0.021	0.005	-0.013
	(0.067)	(0.071)	(0.107)	(0.022)	(0.008)	(0.025)
Observations:	1183	1183	1174	1174	1183	1183
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	-0.321	-0.028	-0.002	-0.051	-0.134	-0.110
	(4.010)	(2.697)	(9.963)	(1.140)	(1.386)	(0.243)
Δ slope	0.526	0.356	1.369	-0.149	0.193	-0.033
	(5.264)	(3.544)	(11.844)	(1.352)	(1.824)	(0.392)
Observations:	1183	1183	1174	1174	1183	1183
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S1.4: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls with different polynomials

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	-0.118	0.019	0.268	-0.016	-0.300
	(0.285)	(0.251)	(0.276)	(0.219)	(0.233)
Δ slope	-0.006	0.037	-0.044	-0.035	-0.040
	(0.032)	(0.033)	(0.034)	(0.022)	(0.028)
Observations:	1259	1258	1259	1258	1257
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	0.241	1.094	0.472	0.461	2.013
	(5.622)	(25.419)	(5.191)	(8.527)	(70.116)
Δ slope	-0.196	-0.766	-0.210	-0.329	-1.730
	(4.239)	(19.257)	(3.861)	(6.355)	(53.373)
Observations:	1259	1258	1259	1258	1257
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic
Panel B: Age 4					
Jump	0.181	-0.104	0.246	-0.206	0.172
	(0.228)	(0.170)	(0.236)	(0.187)	(0.237)
Δ slope	0.028	0.029	-0.040	0.025	-0.020
	(0.037)	(0.029)	(0.035)	(0.028)	(0.030)
Observations:	1181	1180	1180	1181	1180
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	0.331	-0.041	-0.581	-0.734	-0.021
	(3.322)	(1.142)	(12.930)	(7.028)	(2.683)
Δ slope	-0.329	-0.101	1.249	0.750	0.286
	(4.338)	(1.531)	(18.574)	(9.163)	(3.563)
Observations:	1181	1180	1180	1181	1180
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Main Specification (Sample, 2014-2019)

Table S1.5: 2014-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.150	0.022	0.195	-0.061	-0.013	-0.028
	(0.219)	(0.198)	(0.249)	(0.078)	(0.021)	(0.064)
Δ slope	-0.016	-0.025	0.013	-0.001	-0.001	-0.002
	(0.022)	(0.024)	(0.017)	(0.006)	(0.002)	(0.006)
Observations:	3717	3717	3698	3698	3717	3717
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	-0.094	0.030	0.597**	0.018	-0.018	-0.057
	(0.237)	(0.246)	(0.296)	(0.086)	(0.017)	(0.067)
Δ slope	0.033	0.027	0.017	0.001	0.002	0.007
	(0.021)	(0.022)	(0.023)	(0.007)	(0.002)	(0.006)
Observations:	3268	3268	3244	3244	3268	3268
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

S2 Robustness Checks with controls

Optimal Bandwidth

Table S2.1: 2018-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: optimal, local polynomial RD) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.376	0.338	-0.289	0.109	0.006	0.147
	(0.344)	(0.410)	(0.335)	(0.145)	(0.022)	(0.119)
Eff. Observations:	1225	971	1285	864	1225	971
Opt. Bandwidth:	±29.08	±23.88	±31.42	±21.59	±29.41	±23.52
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.189	0.316	-0.578	0.211*	-0.059	-0.038
	(0.420)	(0.425)	(0.366)	(0.121)	(0.037)	(0.134)
Eff. Observations:	1082	1037	1220	1138	1082	1147
Opt. Bandwidth:	±27.23	±26.29	±31.35	±29.64	±27.37	±29.92
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a local polynomial fuzzy regression discontinuity design are presented. We use the optimal MSE bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S2.2: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: optimal, local polynomial RD) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.113	0.231	0.123	0.150	0.093
	(0.177)	(0.158)	(0.189)	(0.169)	(0.182)
Eff. Observations:	1259	1011	1190	1011	794
Opt. Bandwidth:	±30.70	±24.61	±28.31	±24.95	±19.94
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.455**	-0.009	-0.003	-0.112	0.079
	(0.197)	(0.145)	(0.191)	(0.124)	(0.174)
Eff. Observations:	1036	1145	1145	1227	1180
Opt. Bandwidth:	±26.48	±29.34	±29.11	±31.33	±30.89
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a local polynomial fuzzy regression discontinuity design are presented. We use the optimal MSE bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Different polynomials

Table S2.3: 2018-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls with different polynomials

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.045	-0.120	-0.324	-0.146	0.017	-0.003
	(0.432)	(0.444)	(0.659)	(0.192)	(0.022)	(0.157)
Δ slope	-0.070	-0.054	0.036	0.008	0.004	-0.005
	(0.055)	(0.063)	(0.058)	(0.024)	(0.004)	(0.019)
Observations:	1260	1260	1252	1252	1260	1260
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	1.188	1.464	-1.689	0.409	-0.007	0.169
	(4.097)	(5.345)	(6.918)	(2.841)	(0.142)	(0.654)
Δ slope	-0.468	-0.605	0.433	-0.178	0.018	-0.072
	(2.251)	(2.949)	(2.625)	(1.077)	(0.074)	(0.358)
Observations:	1260	1260	1252	1252	1260	1260
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Panel B: Age 4						
Jump	0.535	0.512	0.489	-0.137	0.029	-0.172
	(0.615)	(0.619)	(0.501)	(0.134)	(0.034)	(0.169)
Δ slope	-0.024	0.005	-0.081	0.021	0.005	-0.013
	(0.067)	(0.069)	(0.072)	(0.020)	(0.008)	(0.022)
Observations:	1183	1183	1174	1174	1183	1183
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	0.153	0.263	-0.162	-0.068	-0.083	-0.084
	(4.149)	(2.633)	(5.302)	(0.958)	(1.160)	(0.133)
Δ slope	0.893	0.571	1.045	-0.183	0.257	-0.021
	(13.553)	(8.546)	(14.192)	(2.504)	(3.820)	(0.517)
Observations:	1183	1183	1174	1174	1183	1183
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S2.4: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls with different polynomials

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	-0.075	-0.020	0.226	0.049	-0.242
	(0.270)	(0.246)	(0.268)	(0.204)	(0.218)
Δ slope	-0.003	0.029	-0.045	-0.025	-0.031
	(0.029)	(0.030)	(0.030)	(0.021)	(0.025)
Observations:	1259	1258	1259	1258	1257
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	0.081	0.340	0.272	0.197	0.222
	(0.417)	(1.485)	(0.485)	(0.540)	(2.157)
Δ slope	-0.037	-0.158	-0.069	-0.077	-0.262
	(0.242)	(0.844)	(0.235)	(0.306)	(1.203)
Observations:	1259	1258	1259	1258	1257
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic
Panel B: Age 4					
Jump	0.284	-0.088	0.174	-0.146	0.162
	(0.261)	(0.199)	(0.260)	(0.207)	(0.275)
Δ slope	0.025	0.027	-0.037	0.021	-0.017
	(0.036)	(0.028)	(0.033)	(0.027)	(0.027)
Observations:	1181	1180	1180	1181	1180
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Jump	0.297	-0.052	-0.360	-0.526	0.041
	(4.546)	(1.881)	(15.714)	(8.579)	(3.431)
Δ slope	-0.597	-0.238	2.033	1.177	0.529
	(12.927)	(5.555)	(51.579)	(24.469)	(10.556)
Observations:	1181	1180	1180	1181	1180
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Cubic	Cubic	Cubic	Cubic	Cubic
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Main Specification (Sample, 2014-2019)

Table S2.5: 2014-2019: Impact of Late School Enrollment on Child Health - (Full Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.102	0.049	0.084	-0.053	-0.014	-0.022
	(0.216)	(0.198)	(0.173)	(0.075)	(0.021)	(0.065)
Δ slope	-0.014	-0.023	0.019	-0.002	-0.001	-0.001
	(0.021)	(0.023)	(0.012)	(0.005)	(0.002)	(0.006)
Observations:	3717	3717	3698	3698	3717	3717
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.124	0.158	0.065	0.055	-0.021	-0.030
	(0.234)	(0.243)	(0.237)	(0.086)	(0.016)	(0.068)
Δ slope	0.034*	0.028	-0.002	0.002	0.002	0.007
	(0.019)	(0.021)	(0.016)	(0.006)	(0.001)	(0.005)
Observations:	3268	3268	3244	3244	3268	3268
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

S3 Heterogeneity analysis without controls

Child Health

Table S3.1: 2018-2019: Impact of Late School Enrollment on Child Health - (Male Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.259	-0.416	-0.805	0.174	0.041	-0.090
	(0.404)	(0.452)	(0.710)	(0.162)	(0.025)	(0.157)
Δ slope	0.009	0.042	0.012	0.006	-0.001	0.004
	(0.031)	(0.033)	(0.043)	(0.009)	(0.001)	(0.010)
Observations:	626	626	622	622	626	626
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.254	0.349	1.300	-0.123	-0.027	-0.180
	(0.755)	(0.748)	(0.795)	(0.143)	(0.037)	(0.243)
Δ slope	0.003	0.012	-0.041	0.008	0.004*	-0.006
	(0.038)	(0.039)	(0.037)	(0.008)	(0.002)	(0.011)
Observations:	591	591	587	587	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.2: 2018-2019: Impact of Late School Enrollment on Child Health - (Female Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.087	0.211	0.681	-0.096	-0.014	0.042
	(0.412)	(0.369)	(0.500)	(0.117)	(0.018)	(0.104)
Δ slope	-0.009	-0.003	-0.018	0.010	0.004**	0.003
	(0.020)	(0.020)	(0.025)	(0.006)	(0.002)	(0.006)
Observations:	634	634	630	630	634	634
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.058	0.223	0.279	0.047	0.001	-0.050
	(0.359)	(0.366)	(0.431)	(0.099)	(0.033)	(0.098)
Δ slope	0.033	0.029	-0.022	0.002	-0.002	0.001
	(0.039)	(0.035)	(0.041)	(0.012)	(0.002)	(0.010)
Observations:	592	592	587	587	592	592
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table S3.3: 2018-2019: Impact of Late School Enrollment on Child Health - (More than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.689*	-0.587*	-0.362	0.053	-0.016	-0.066
	(0.417)	(0.348)	(0.644)	(0.191)	(0.022)	(0.141)
Δ slope	-0.033	0.003	0.093**	-0.003	0.004*	0.004
	(0.035)	(0.032)	(0.037)	(0.012)	(0.002)	(0.009)
Observations:	554	554	548	548	554	554
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	-0.350	-0.134	0.728	0.007	0.011	-0.107
	(0.472)	(0.474)	(0.546)	(0.121)	(0.043)	(0.148)
Δ slope	0.052	0.038	-0.049	0.005	0.001	-0.003
	(0.046)	(0.043)	(0.047)	(0.012)	(0.003)	(0.013)
Observations:	592	592	587	587	592	592
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.4: 2018-2019: Impact of Late School Enrollment on Child Health - (Less than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.218	0.305	0.343	-0.019	0.028	0.024
	(0.363)	(0.385)	(0.495)	(0.102)	(0.022)	(0.110)
Δ slope	0.012	0.023	-0.053**	0.012**	0.001	0.004
	(0.019)	(0.021)	(0.022)	(0.005)	(0.001)	(0.005)
Observations:	706	706	704	704	706	706
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.480	0.658	0.574	-0.017	-0.041	-0.083
	(0.640)	(0.641)	(0.598)	(0.156)	(0.033)	(0.157)
Δ slope	-0.004	0.015	-0.010	0.003	0.001	-0.003
	(0.030)	(0.030)	(0.036)	(0.011)	(0.002)	(0.009)
Observations:	591	591	587	587	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.5: 2018-2019: Impact of Late School Enrollment on Child Health - (Public School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 4						
Jump	-0.283	-0.113	0.363	0.074	-0.010	-0.103
	(0.298)	(0.290)	(0.404)	(0.094)	(0.031)	(0.080)
Δ slope	0.022	0.033	-0.020	0.008	0.001	-0.000
	(0.024)	(0.023)	(0.026)	(0.007)	(0.002)	(0.007)
Observations:	928	928	922	922	928	928
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.6: 2018-2019: Impact of Late School Enrollment on Child Health - (Private School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 4						
Jump	0.976	1.224	1.678	-0.337	-0.019	-0.152
	(1.170)	(1.312)	(1.157)	(0.210)	(0.020)	(0.426)
Δ slope	-0.087	-0.149	-0.175	0.007	0.000	-0.017
	(0.135)	(0.154)	(0.173)	(0.028)	(0.001)	(0.048)
Observations:	255	255	252	252	255	255
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.7: 2018-2019: Impact of Late School Enrollment on Child Health - (Poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.171	0.239	-0.259	-0.088	0.006	0.079
	(0.323)	(0.295)	(0.601)	(0.157)	(0.030)	(0.078)
Δ slope	-0.018	0.003	0.021	0.006	0.004**	-0.003
	(0.021)	(0.020)	(0.037)	(0.011)	(0.002)	(0.005)
Observations:	680	680	676	676	680	680
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	-0.002	0.031	0.889	-0.077	-0.071*	-0.123
	(0.432)	(0.407)	(0.601)	(0.088)	(0.043)	(0.092)
Δ slope	0.015	0.016	-0.002	0.011**	0.002	-0.002
	(0.024)	(0.024)	(0.038)	(0.005)	(0.002)	(0.007)
Observations:	617	617	614	614	617	617
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.8: 2018-2019: Impact of Late School Enrollment on Child Health - (Non-poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.177	-0.229	0.279	0.148	0.004	-0.085
	(0.543)	(0.582)	(0.765)	(0.161)	(0.004)	(0.185)
Δ slope	0.024	0.041	-0.023	0.004	0.000	0.013
	(0.027)	(0.029)	(0.025)	(0.007)	(0.000)	(0.009)
Observations:	580	580	576	576	580	580
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.193	0.452	0.283	0.071	0.019	-0.074
	(0.509)	(0.568)	(0.557)	(0.154)	(0.038)	(0.187)
Δ slope	0.006	0.008	-0.034	-0.009	-0.003	-0.008
	(0.049)	(0.050)	(0.049)	(0.014)	(0.003)	(0.016)
Observations:	566	566	560	560	566	566
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.9: 2018-2019: Impact of Late School Enrollment on Child Health - (Coast Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.334	0.261	-0.369	0.069	0.002	0.045
	(0.602)	(0.576)	(0.717)	(0.214)	(0.006)	(0.191)
Δ slope	0.019	0.046	0.012	0.003	0.001	0.006
	(0.032)	(0.031)	(0.023)	(0.008)	(0.000)	(0.009)
Observations:	553	553	548	548	553	553
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.392	0.292	-0.029	0.054	0.007	-0.142
	(0.739)	(0.749)	(0.549)	(0.179)	(0.016)	(0.218)
Δ slope	0.019	0.027	-0.020	0.001	-0.000	-0.001
	(0.044)	(0.042)	(0.037)	(0.013)	(0.001)	(0.013)
Observations:	540	540	538	538	540	540
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.10: 2018-2019: Impact of Late School Enrollment on Child Health - (Andes Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.144	-0.176	-0.197	-0.003	0.011	-0.024
	(0.323)	(0.333)	(0.297)	(0.014)	(0.044)	(0.076)
Δ slope	-0.007	0.006	0.027	0.001	0.002	0.002
	(0.018)	(0.019)	(0.020)	(0.001)	(0.003)	(0.004)
Observations:	429	429	427	427	429	429
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.378	0.493	0.572	0.013	-0.028	0.024
	(0.463)	(0.464)	(0.526)	(0.013)	(0.069)	(0.138)
Δ slope	-0.001	0.003	-0.002	0.000	0.004	-0.005
	(0.033)	(0.032)	(0.041)	(0.000)	(0.004)	(0.008)
Observations:	380	380	374	374	380	380
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.11: 2018-2019: Impact of Late School Enrollment on Child Health - (Amazon Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.328	0.118	-0.404	0.007	-0.003	0.033
	(0.382)	(0.386)	(0.566)	(0.184)	(0.024)	(0.078)
Δ slope	-0.017	-0.021	-0.076**	0.025**	0.006	0.006
	(0.025)	(0.026)	(0.036)	(0.013)	(0.004)	(0.004)
Observations:	278	278	277	277	278	278
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	-0.842	-0.209	-0.644	0.124	-0.080	-0.203
	(0.611)	(0.483)	(0.539)	(0.211)	(0.055)	(0.146)
Δ slope	0.001	0.007	-0.005	0.009	0.003	-0.002
	(0.029)	(0.026)	(0.032)	(0.011)	(0.004)	(0.006)
Observations:	263	263	262	262	263	263
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Early Child Development

Table S3.12: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Male Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.060	-0.399	0.349	-0.081	-0.502**
	(0.253)	(0.263)	(0.258)	(0.230)	(0.232)
Δ slope	0.006	0.004	-0.008	0.009	-0.015
	(0.015)	(0.018)	(0.017)	(0.012)	(0.013)
Observations:	626	626	626	625	624
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.293	-0.075	0.251	0.117	0.449
	(0.292)	(0.253)	(0.306)	(0.154)	(0.303)
Δ slope	0.028**	0.009	-0.035**	-0.037***	-0.013
	(0.014)	(0.013)	(0.016)	(0.009)	(0.015)
Observations:	590	589	589	590	589
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.13: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Female Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.047	0.355**	-0.099	0.075	0.074
	(0.206)	(0.173)	(0.231)	(0.132)	(0.147)
Δ slope	-0.007	0.006	-0.002	-0.019***	-0.000
	(0.011)	(0.008)	(0.010)	(0.007)	(0.007)
Observations:	633	632	633	633	633
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.155	0.010	0.096	-0.215	0.015
	(0.176)	(0.109)	(0.180)	(0.155)	(0.169)
Δ slope	0.029	0.010	0.002	0.017	0.002
	(0.020)	(0.010)	(0.017)	(0.014)	(0.015)
Observations:	591	591	591	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.14: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (More than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	-0.047	-0.052	0.339	0.106	-0.104
	(0.266)	(0.169)	(0.229)	(0.169)	(0.157)
Δ slope	-0.015	0.030**	-0.015	-0.007	-0.006
	(0.017)	(0.014)	(0.017)	(0.011)	(0.012)
Observations:	553	553	553	553	552
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.084	0.076	0.176	0.133	0.217
	(0.230)	(0.187)	(0.208)	(0.129)	(0.193)
Δ slope	0.052**	-0.004	-0.053**	-0.026**	-0.016
	(0.025)	(0.015)	(0.023)	(0.013)	(0.018)
Observations:	591	591	590	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.15: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Less than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.105	0.111	-0.119	-0.116	-0.288*
	(0.200)	(0.179)	(0.210)	(0.150)	(0.169)
Δ slope	0.002	-0.003	0.003	-0.007	-0.002
	(0.011)	(0.008)	(0.009)	(0.007)	(0.009)
Observations:	706	705	706	705	705
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.367	-0.067	0.241	-0.296	0.213
	(0.271)	(0.134)	(0.248)	(0.216)	(0.269)
Δ slope	0.012	0.018**	0.010	-0.002	0.004
	(0.016)	(0.009)	(0.014)	(0.011)	(0.015)
Observations:	590	589	590	590	589
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.16: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Public School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 4					
Jump	0.174	-0.074	0.154	-0.154	0.219
	(0.154)	(0.087)	(0.148)	(0.133)	(0.143)
Δ slope	0.027***	0.010	-0.018	-0.009	-0.008
	(0.010)	(0.008)	(0.012)	(0.008)	(0.011)
Observations:	927	926	926	927	926
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.17: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Private School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 4					
Jump	0.509	0.097	0.170	0.227	0.222
	(0.513)	(0.451)	(0.523)	(0.237)	(0.485)
Δ slope	0.033	-0.021	-0.023	-0.050	0.021
	(0.088)	(0.049)	(0.075)	(0.049)	(0.074)
Observations:	254	254	254	254	254
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.18: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.042	-0.105	0.054	0.152	-0.244
	(0.175)	(0.155)	(0.182)	(0.161)	(0.159)
Δ slope	0.016	0.009	-0.009	-0.011	-0.010
	(0.012)	(0.011)	(0.012)	(0.010)	(0.011)
Observations:	679	678	679	678	678
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.247	-0.099	0.555**	-0.029	0.435*
	(0.272)	(0.176)	(0.238)	(0.170)	(0.248)
Δ slope	0.016	0.001	-0.031*	-0.020*	0.009
	(0.013)	(0.011)	(0.018)	(0.010)	(0.017)
Observations:	617	616	616	617	617
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.19: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Non-poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.048	0.252	0.070	-0.134	-0.120
	(0.306)	(0.271)	(0.285)	(0.195)	(0.222)
Δ slope	-0.019	0.007	-0.006	-0.000	-0.002
	(0.014)	(0.009)	(0.014)	(0.009)	(0.008)
Observations:	580	580	580	580	579
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.272	0.044	-0.171	-0.112	0.054
	(0.219)	(0.159)	(0.215)	(0.167)	(0.202)
Δ slope	0.047*	0.017	0.021	0.001	-0.009
	(0.024)	(0.016)	(0.020)	(0.016)	(0.020)
Observations:	564	564	564	564	563
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.20: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Coast Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	-0.003	-0.010	0.199	-0.040	-0.173
	(0.309)	(0.262)	(0.282)	(0.179)	(0.213)
Δ slope	-0.010	0.014	-0.011	-0.020***	-0.008
	(0.014)	(0.011)	(0.014)	(0.007)	(0.009)
Observations:	552	552	552	552	550
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.627*	0.323	0.168	-0.099	0.249
	(0.327)	(0.261)	(0.304)	(0.204)	(0.310)
Δ slope	0.027	0.014	-0.010	-0.006	0.001
	(0.022)	(0.018)	(0.019)	(0.013)	(0.018)
Observations:	539	538	539	539	539
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.21: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Andes Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	-0.088	0.048	0.100	0.177	-0.343**
	(0.188)	(0.153)	(0.170)	(0.186)	(0.161)
Δ slope	0.013	0.004	0.001	0.002	-0.011
	(0.011)	(0.009)	(0.011)	(0.010)	(0.010)
Observations:	429	429	429	428	429
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.049	-0.398**	0.121	-0.116	0.113
	(0.200)	(0.177)	(0.208)	(0.166)	(0.226)
Δ slope	0.035**	-0.003	-0.024	-0.029**	-0.004
	(0.015)	(0.018)	(0.017)	(0.012)	(0.017)
Observations:	380	380	379	380	379
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S3.22: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Amazon Sample, bw: 31-days) - Sample Weights and Triangular Kernel - No controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.380	0.141	-0.256	-0.099	0.022
	(0.248)	(0.187)	(0.271)	(0.225)	(0.194)
Δ slope	-0.016	0.006	-0.008	0.016	0.013
	(0.016)	(0.014)	(0.018)	(0.015)	(0.014)
Observations:	278	277	278	278	278
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	-0.240	-0.228	0.041	0.135	0.403*
	(0.284)	(0.184)	(0.318)	(0.263)	(0.223)
Δ slope	0.008	-0.005	-0.026	-0.007	-0.027*
	(0.014)	(0.010)	(0.016)	(0.012)	(0.016)
Observations:	262	262	262	262	262
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	No	No	No	No	No

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

S4 Heterogeneity analysis with controls

Child Health

Table S4.1: 2018-2019: Impact of Late School Enrollment on Child Health - (Male Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.348	-0.465	-0.598	0.154	0.043	-0.094
	(0.386)	(0.441)	(0.556)	(0.148)	(0.026)	(0.152)
Δ slope	0.023	0.050	0.009	0.005	-0.001	0.005
	(0.029)	(0.033)	(0.034)	(0.008)	(0.001)	(0.010)
Observations:	626	626	622	622	626	626
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.532	0.540	0.488	-0.056	-0.047	-0.213
	(0.885)	(0.881)	(0.772)	(0.176)	(0.045)	(0.290)
Δ slope	0.000	0.009	-0.024	0.005	0.004**	-0.003
	(0.031)	(0.032)	(0.027)	(0.007)	(0.002)	(0.010)
Observations:	591	591	587	587	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.2: 2018-2019: Impact of Late School Enrollment on Child Health - (Female Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.247	0.398	-0.036	-0.068	-0.028	0.080
	(0.396)	(0.361)	(0.323)	(0.110)	(0.023)	(0.109)
Δ slope	-0.007	-0.002	-0.010	0.009	0.004**	0.003
	(0.019)	(0.020)	(0.016)	(0.006)	(0.002)	(0.006)
Observations:	634	634	630	630	634	634
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.216	0.303	-0.385	0.110	-0.003	-0.031
	(0.379)	(0.392)	(0.381)	(0.114)	(0.033)	(0.105)
Δ slope	0.031	0.029	-0.029	0.002	-0.002	0.001
	(0.038)	(0.035)	(0.032)	(0.012)	(0.003)	(0.010)
Observations:	592	592	587	587	592	592
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.3: 2018-2019: Impact of Late School Enrollment on Child Health - (More than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.514	-0.443	-0.709	0.068	-0.017	-0.046
	(0.386)	(0.335)	(0.558)	(0.193)	(0.024)	(0.151)
Δ slope	-0.009	0.019	0.057*	-0.003	0.003	0.006
	(0.031)	(0.031)	(0.029)	(0.011)	(0.002)	(0.009)
Observations:	554	554	548	548	554	554
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.160	0.170	-0.151	0.083	-0.001	-0.121
	(0.540)	(0.539)	(0.482)	(0.136)	(0.039)	(0.172)
Δ slope	0.035	0.030	0.007	-0.001	0.002	-0.001
	(0.037)	(0.036)	(0.033)	(0.011)	(0.003)	(0.010)
Observations:	592	592	587	587	592	592
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.4: 2018-2019: Impact of Late School Enrollment on Child Health - (Less than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.316	0.363	0.158	-0.025	0.026	0.040
	(0.326)	(0.355)	(0.309)	(0.100)	(0.021)	(0.102)
Δ slope	0.015	0.024	-0.033**	0.011**	0.001	0.004
	(0.019)	(0.021)	(0.015)	(0.005)	(0.002)	(0.006)
Observations:	706	706	704	704	706	706
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.630	0.730	-0.006	0.022	-0.041	-0.067
	(0.616)	(0.636)	(0.485)	(0.151)	(0.034)	(0.154)
Δ slope	-0.001	0.015	-0.028	0.004	0.001	-0.004
	(0.028)	(0.029)	(0.028)	(0.010)	(0.002)	(0.009)
Observations:	591	591	587	587	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.5: 2018-2019: Impact of Late School Enrollment on Child Health - (Public School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 4						
Jump	-0.036	0.028	-0.394	0.158	-0.019	-0.090
	(0.318)	(0.313)	(0.337)	(0.114)	(0.033)	(0.085)
Δ slope	0.019	0.030	-0.019	0.007	0.002	0.000
	(0.021)	(0.021)	(0.019)	(0.007)	(0.002)	(0.006)
Observations:	928	928	922	922	928	928
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.6: 2018-2019: Impact of Late School Enrollment on Child Health - (Private School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 4						
Jump	1.210	1.423	0.834	-0.304	-0.016	-0.152
	(1.251)	(1.352)	(1.033)	(0.215)	(0.018)	(0.433)
Δ slope	-0.076	-0.131	-0.078	0.004	0.000	-0.011
	(0.122)	(0.133)	(0.118)	(0.026)	(0.001)	(0.043)
Observations:	255	255	252	252	255	255
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.7: 2018-2019: Impact of Late School Enrollment on Child Health - (Poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.192	0.225	-0.442	-0.071	0.002	0.087
	(0.285)	(0.278)	(0.390)	(0.130)	(0.030)	(0.076)
Δ slope	-0.013	0.002	0.004	0.007	0.004*	-0.003
	(0.019)	(0.020)	(0.029)	(0.010)	(0.002)	(0.005)
Observations:	680	680	676	676	680	680
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.226	0.083	0.076	-0.005	-0.082	-0.147
	(0.513)	(0.473)	(0.493)	(0.106)	(0.054)	(0.113)
Δ slope	0.019	0.017	-0.019	0.011**	0.002	-0.001
	(0.023)	(0.022)	(0.021)	(0.005)	(0.002)	(0.007)
Observations:	617	617	614	614	617	617
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.8: 2018-2019: Impact of Late School Enrollment on Child Health - (Non-poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.221	-0.282	0.015	0.181	0.004	-0.104
	(0.571)	(0.612)	(0.610)	(0.169)	(0.004)	(0.202)
Δ slope	0.022	0.040	-0.008	0.002	0.000	0.013
	(0.027)	(0.029)	(0.020)	(0.007)	(0.000)	(0.009)
Observations:	580	580	576	576	580	580
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.374	0.621	-0.258	0.116	0.010	-0.054
	(0.520)	(0.577)	(0.483)	(0.159)	(0.034)	(0.185)
Δ slope	0.002	0.005	-0.011	-0.011	-0.002	-0.007
	(0.045)	(0.046)	(0.040)	(0.014)	(0.003)	(0.015)
Observations:	566	566	560	560	566	566
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.9: 2018-2019: Impact of Late School Enrollment on Child Health - (Coast Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	0.170	0.087	-0.422	0.055	0.002	0.004
	(0.597)	(0.562)	(0.672)	(0.209)	(0.006)	(0.203)
Δ slope	0.019	0.046	0.010	0.003	0.001	0.006
	(0.031)	(0.030)	(0.023)	(0.008)	(0.000)	(0.009)
Observations:	553	553	548	548	553	553
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.530	0.438	-0.018	0.044	0.007	-0.123
	(0.752)	(0.759)	(0.553)	(0.180)	(0.015)	(0.212)
Δ slope	0.015	0.022	-0.016	0.001	-0.000	-0.001
	(0.039)	(0.038)	(0.034)	(0.012)	(0.001)	(0.013)
Observations:	540	540	538	538	540	540
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.10: 2018-2019: Impact of Late School Enrollment on Child Health - (Andes Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.113	-0.180	-0.149	0.001	0.006	-0.020
	(0.297)	(0.323)	(0.248)	(0.015)	(0.046)	(0.071)
Δ slope	0.007	0.007	0.021	0.001	0.002	0.000
	(0.017)	(0.019)	(0.017)	(0.001)	(0.003)	(0.005)
Observations:	429	429	427	427	429	429
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	0.556	0.624	-0.048	0.025	-0.018	0.036
	(0.511)	(0.539)	(0.519)	(0.026)	(0.085)	(0.161)
Δ slope	0.000	0.005	-0.055*	0.001	0.004	-0.004
	(0.031)	(0.032)	(0.030)	(0.001)	(0.004)	(0.008)
Observations:	380	380	374	374	380	380
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.11: 2018-2019: Impact of Late School Enrollment on Child Health - (Amazon Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	WAZ	WHZ	Hemoglobin	Anemia	Underweight	Overweight
Panel A: Age 3						
Jump	-0.165	0.209	-0.120	-0.048	-0.015	0.052
	(0.303)	(0.372)	(0.426)	(0.162)	(0.024)	(0.083)
Δ slope	-0.009	-0.018	-0.029	0.017	0.005	0.006
	(0.021)	(0.024)	(0.027)	(0.010)	(0.004)	(0.004)
Observations:	278	278	277	277	278	278
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4						
Jump	-0.644	-0.116	-0.320	0.106	-0.091	-0.199
	(0.558)	(0.496)	(0.458)	(0.192)	(0.062)	(0.144)
Δ slope	-0.000	0.006	-0.003	0.007	0.004	0.001
	(0.025)	(0.023)	(0.024)	(0.009)	(0.003)	(0.005)
Observations:	263	263	262	262	263	263
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Early Child Development

Table S4.12: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Male Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.035	-0.391	0.370	-0.114	-0.492**
	(0.238)	(0.250)	(0.249)	(0.214)	(0.226)
Δ slope	0.005	0.002	-0.009	0.012	-0.011
	(0.015)	(0.018)	(0.016)	(0.011)	(0.012)
Observations:	626	626	626	625	624
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.477	-0.097	0.197	0.018	0.518
	(0.368)	(0.330)	(0.379)	(0.160)	(0.385)
Δ slope	0.020	0.009	-0.033**	-0.027***	-0.016
	(0.014)	(0.011)	(0.015)	(0.008)	(0.014)
Observations:	590	589	589	590	589
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table S4.13: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Female Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.117	0.350*	-0.215	0.150	0.064
	(0.207)	(0.182)	(0.231)	(0.137)	(0.150)
Δ slope	-0.007	0.006	-0.002	-0.018**	0.000
	(0.010)	(0.008)	(0.011)	(0.007)	(0.007)
Observations:	633	632	633	633	633
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.222	0.039	0.044	-0.177	0.027
	(0.188)	(0.124)	(0.183)	(0.171)	(0.179)
Δ slope	0.029	0.010	0.003	0.016	0.001
	(0.019)	(0.011)	(0.016)	(0.014)	(0.016)
Observations:	591	591	591	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table S4.14: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (More than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.024	-0.055	0.309	0.213	-0.054
	(0.262)	(0.184)	(0.244)	(0.178)	(0.158)
Δ slope	-0.011	0.027**	-0.018	0.001	-0.001
	(0.015)	(0.013)	(0.016)	(0.011)	(0.011)
Observations:	553	553	553	553	552
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.248	0.103	0.081	0.129	0.093
	(0.249)	(0.238)	(0.236)	(0.139)	(0.227)
Δ slope	0.041**	-0.006	-0.045**	-0.024**	-0.012
	(0.021)	(0.013)	(0.019)	(0.010)	(0.016)
Observations:	591	591	590	591	591
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.15: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Less than mother's age median Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.108	0.113	-0.163	-0.118	-0.286*
	(0.186)	(0.165)	(0.199)	(0.138)	(0.156)
Δ slope	0.001	-0.003	0.003	-0.004	-0.003
	(0.011)	(0.008)	(0.009)	(0.007)	(0.008)
Observations:	706	705	706	705	705
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.391	-0.083	0.173	-0.278	0.209
	(0.274)	(0.134)	(0.245)	(0.212)	(0.267)
Δ slope	0.013	0.017*	0.008	-0.002	0.005
	(0.015)	(0.009)	(0.013)	(0.010)	(0.015)
Observations:	590	589	590	590	589
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.16: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Public School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 4					
Jump	0.261	-0.053	0.100	-0.116	0.229
	(0.172)	(0.097)	(0.157)	(0.141)	(0.158)
Δ slope	0.026***	0.009	-0.018	-0.009	-0.008
	(0.010)	(0.007)	(0.011)	(0.007)	(0.011)
Observations:	927	926	926	927	926
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.17: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Private School Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 4					
Jump	0.592	0.171	0.132	0.192	0.161
	(0.526)	(0.483)	(0.558)	(0.236)	(0.521)
Δ slope	0.013	-0.028	-0.019	-0.040	0.019
	(0.074)	(0.047)	(0.065)	(0.037)	(0.067)
Observations:	254	254	254	254	254
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 4-year-old children. We were not able to identify the treatment status by school type for 3-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.18: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.006	-0.097	0.041	0.094	-0.261*
	(0.159)	(0.139)	(0.163)	(0.141)	(0.148)
Δ slope	0.017	0.007	-0.009	-0.008	-0.006
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Observations:	679	678	679	678	678
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.364	-0.095	0.537*	0.021	0.506*
	(0.316)	(0.212)	(0.293)	(0.190)	(0.300)
Δ slope	0.018	0.001	-0.033**	-0.017*	0.008
	(0.014)	(0.011)	(0.017)	(0.010)	(0.017)
Observations:	617	616	616	617	617
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.19: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Non-poor Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.148	0.218	0.049	-0.099	-0.043
	(0.306)	(0.298)	(0.298)	(0.212)	(0.229)
Δ slope	-0.021	0.006	-0.006	-0.000	-0.002
	(0.013)	(0.009)	(0.014)	(0.009)	(0.008)
Observations:	580	580	580	580	579
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.308	0.077	-0.208	-0.141	-0.001
	(0.232)	(0.165)	(0.219)	(0.166)	(0.209)
Δ slope	0.043*	0.014	0.022	0.004	-0.006
	(0.022)	(0.014)	(0.020)	(0.015)	(0.019)
Observations:	564	564	564	564	563
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. The poverty variable is constructed using categories 1 (very poor) and 2 (poor) from the wealth index variable as indicated in the Demographic and Family Health Survey. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.20: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Coast Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.102	-0.019	0.207	-0.023	-0.123
	(0.304)	(0.273)	(0.288)	(0.196)	(0.223)
Δ slope	-0.009	0.015	-0.011	-0.020***	-0.008
	(0.014)	(0.011)	(0.014)	(0.007)	(0.009)
Observations:	552	552	552	552	550
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.638*	0.356	0.186	-0.140	0.206
	(0.350)	(0.275)	(0.307)	(0.199)	(0.316)
Δ slope	0.022	0.010	-0.011	-0.001	0.002
	(0.021)	(0.016)	(0.018)	(0.012)	(0.016)
Observations:	539	538	539	539	539
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.21: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Andes Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	-0.091	0.057	0.068	0.183	-0.342**
	(0.180)	(0.143)	(0.162)	(0.169)	(0.148)
Δ slope	0.013	0.001	-0.000	0.007	-0.005
	(0.011)	(0.009)	(0.011)	(0.010)	(0.009)
Observations:	429	429	429	428	429
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	0.156	-0.393*	0.078	-0.124	0.089
	(0.220)	(0.206)	(0.246)	(0.184)	(0.254)
Δ slope	0.036**	-0.003	-0.022	-0.029**	-0.004
	(0.015)	(0.016)	(0.017)	(0.012)	(0.016)
Observations:	380	380	379	380	379
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4.22: 2018-2019: Impact of Late School Enrollment on Early Childhood Development (ECD) - (Amazon Sample, bw: 31-days) - Sample Weights and Triangular Kernel - All controls

	Tantrums	ARD	PWB	Imitation	TIN
Panel A: Age 3					
Jump	0.327	0.149	-0.241	-0.090	-0.112
	(0.223)	(0.177)	(0.242)	(0.202)	(0.145)
Δ slope	-0.014	0.005	-0.009	0.015	0.015
	(0.014)	(0.012)	(0.017)	(0.013)	(0.012)
Observations:	278	277	278	278	278
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Panel B: Age 4					
Jump	-0.280	-0.241	0.066	0.138	0.376
	(0.264)	(0.174)	(0.308)	(0.267)	(0.230)
Δ slope	0.013	-0.002	-0.027*	-0.007	-0.027*
	(0.013)	(0.009)	(0.015)	(0.012)	(0.015)
Observations:	262	262	262	262	262
Bandwidth:	±31.00	±31.00	±31.00	±31.00	±31.00
Polynomial:	Linear	Linear	Linear	Linear	Linear
Controls	Demographic	Demographic	Demographic	Demographic	Demographic
Controls	Geographic	Geographic	Geographic	Geographic	Geographic

Note: Standard errors are clustered at district level. Sample weights and a triangular kernel are selected. Panel A reports the results for 3-year-old children, whereas Panel B presents the corresponding results for 4-year-old children. Results from a fuzzy regression discontinuity design are presented. We use a 31-day bandwidth around the cutoff. Controls include child's age in months, child's sex, altitude, time in school, and urban residence. We also include survey fixed effects. Jump indicates the effect of late enrollment. Each column represents a dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

S5 First stage by year, 2009-2019

Figure S5.1: First Stage by Year - Age 3 (2009–2019)

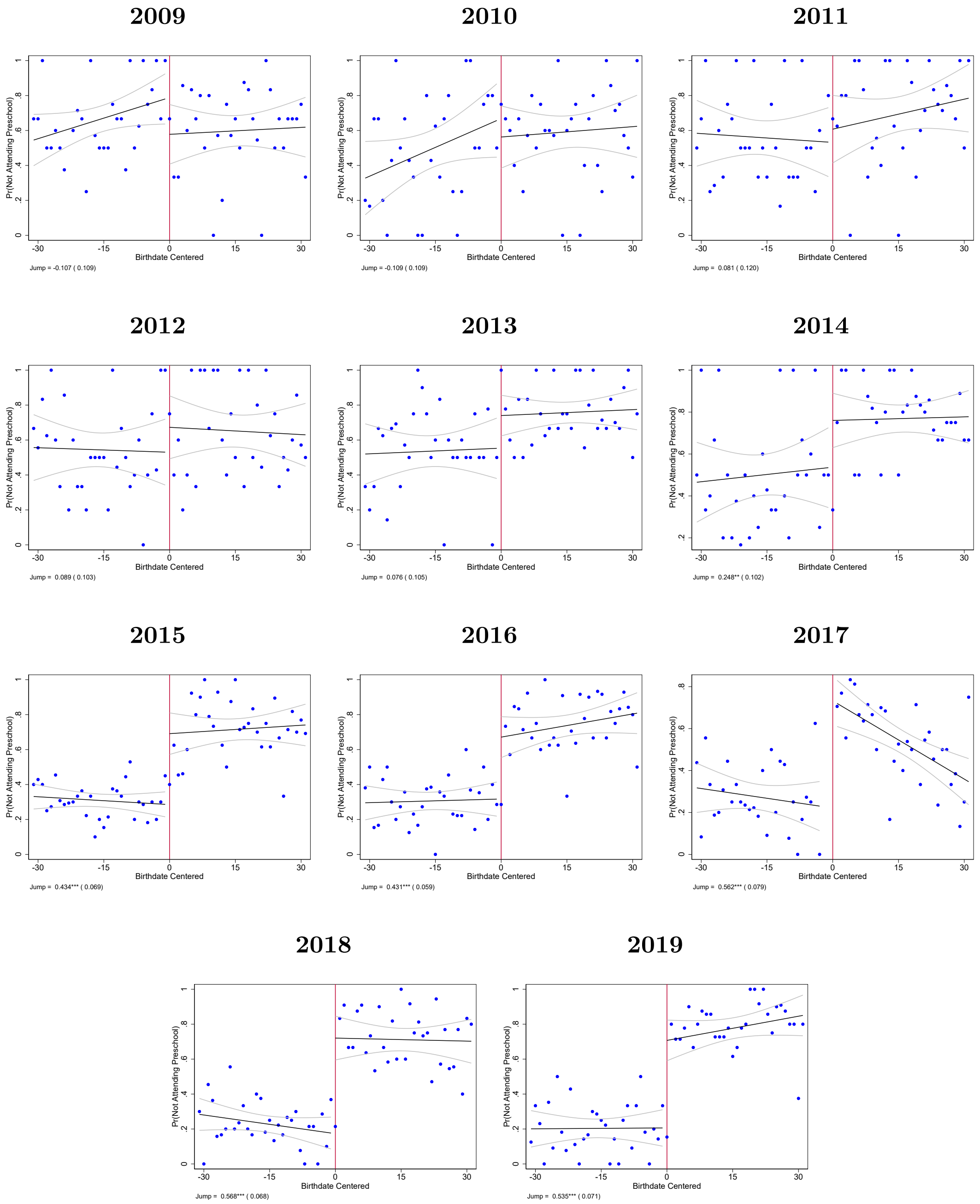
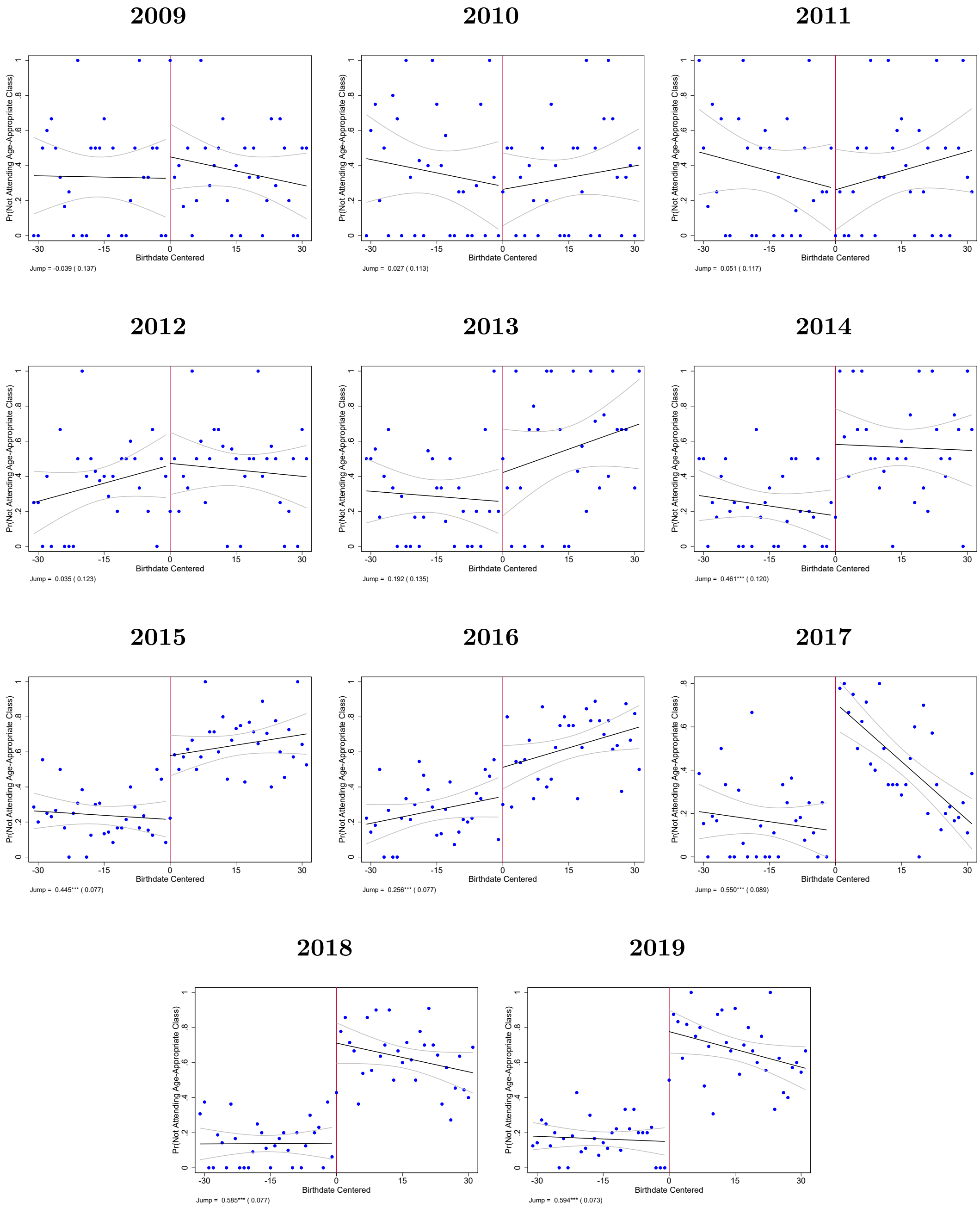


Figure S5.2: First Stage by Year - Age 4 (2009–2019)



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