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EMPIRICAL ARTICLE

CHILD DEVELOPMENT

# School readiness losses during the COVID-19 outbreak. A comparison of two cohorts of young children

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**Abstract**
The COVID-19 context has created the most severe disruption to education systems in recent history. Its impact on child development was estimated comparing two cohorts of 4- to 6-year-old Uruguayan children: control ($n$ = 34,355, 48.87% girls) and COVID cohort ($n$ = 30,158, 48.95% girls) assessed between 2018 and 2020 in three waves, by a routinely administered school readiness instrument in public preschools. Ethnicity information is not available. For the COVID cohort, losses were observed in Motor and Cognitive development, Attitudes towards learning, and Internalizing behavior (range 0.13 – 0.27 SD). Losses were less pronounced among children from higher socioeconomic schools. These results extend the literature on the consequences of the pandemic on learning and early child development.

## INTRODUCTION

### Early childhood development and COVID-19

The COVID-19 pandemic is a major sociohistorical event that continues to severely disrupt people's lives (Benner & Mistry, 2020). In the past, researchers have shown that other large scale events (e.g., the SARS and N1H1 epidemics, the 2008 recession, the great depression, and World War II) were powerful enough to divert children from normative developmental trajectories with long-lasting effects (Almeida & Wong, 2009; Benner & Mistry, 2020). For example, children who received less education during WWII experienced adverse effects 40 years later (Ichino & Winter-Ebmer, 2004). The impact of such societal events is even more potent at ages where typical developmental turning points occur, such as school entry at age four or the transition from childhood into adolescence (Almeida & Wong, 2009; Benner & Mistry, 2020). Our study focuses on developmental losses among children who transitioned into school entry during the COVID-19 pandemic.

In the context of COVID-19, school closures are likely the most relevant factor disrupting the lives of young children, a factor traditionally responsible for learning losses that has affected 94% of learners worldwide (United Nations, 2020). However, it is impossible to isolate the impact of school closures on learning or developmental losses (Bacher-Hicks & Goodman, 2021). Instead, we should consider the pandemic as a myriad of interactive factors contributing to hardships among young learners (Bacher-Hicks & Goodman, 2021) related to the impact of the pandemic on children's families (e.g., job loss, financial losses, remote working, illness, death, stress, mental health, and improvised parenting practices), teachers (e.g., stress, the sudden switch to online learning), social lives (e.g., loss of social contact), and access to services (e.g., daycare, delayed healthcare visits; Ananat & Gassman-Pines, 2020; Bacher-Hicks & Goodman, 2021; Rothstein, 2020). Nevertheless, even

**Abbreviations:** DiD, differences-in-differences; MANOVA, multivariate analysis of variance; SES, socioeconomic status.

without the added burden of societal catastrophes, studies evidenced that routine school closures during the summer months provoke learning losses (e.g., Alexander et al., 2007). As a whole, we expect that the current pandemic context would negatively impact young children's school readiness, but there is no research on the topic to our knowledge. In light of this large gap, the effect of the pandemic on early childhood development needs to be a priority for researchers (Benner & Mistry, 2020; Yoshikawa et al., 2020).

Recent studies suggest that the pandemic has a negative impact on school performance among older children and adolescents. When elementary schools closed for 8 weeks in the Netherlands, children lost the equivalent of 20% of what would be achieved during a typical school year (Engzell et al., 2021). Another study examined achievements in reading and math among three million elementary school children. When comparing children who were exposed to the pandemic to a reference group that was not, the authors found that scores in math dropped 5%–10% but reading scores did not significantly differ (Kuhfeld et al., 2020). Among children in Belgium, scores in math ($SD$ = .19) and Flemish language ($SD$ = .29) dropped more in a cohort of children exposed to the pandemic than in a reference cohort (Maldonado & De Witte, 2020). On the basis of the extant literature, we expect that the pandemic negatively impacted school readiness among young children. This is important because school readiness is associated with achievement during elementary school (Duncan et al., 2007, 2020) and later on (Watts et al., 2014). Other studies evidenced that isolation and interpersonal relationships impacted areas of children's mental health, well-being (Araújo et al., 2020; Guerrero, 2021; Liu et al., 2021; Loades et al., 2020; Spiteri, 2021), and physical activity (Gobbi et al., 2020). This could threaten the United Nations (2021) Sustainable Development Goal 4 promoting *inclusive and equitable quality education and promote lifelong learning opportunities for all*, especially among children with underprivileged backgrounds.

## Widening achievement gaps and inequity

Before the pandemic, large achievement gaps distinguished learners according to household income (e.g., Chmielewski & Reardon, 2016; Papay et al., 2020). These gaps are exacerbated because of the differential impact the pandemic has on children according to factors related to their socioeconomic status (SES). For example, low-income parents are more likely to be essential workers, with the risk of increased COVID-19 transmission, and not be able to care for their children during confinement periods. Also, low-income households are less likely to have a quality internet connection which is necessary for online learning. Financial strain also makes it less likely that parents can afford private tutoring to compensate for school closures (Bailey et al., 2021). Furthermore, children from lower-income households are more likely to experience overcrowding in small houses, food insecurity, unstable home life, and mental health issues, including trauma, anxiety, and depression (Masonbrink & Hurley, 2020). These children suffer more from the impact of school closures, thus increasing achievement disparities (Atteberry & McEachin, 2021; Stewart et al., 2018).

These disparities translate directly to inequity in learning losses during the COVID-19 pandemic. When 200 education researchers were asked to project the extent to which the achievement gap will widen among school-age children in the year following the pandemic, respondents estimated that scores in reading would widen from 1 $SD$ point to 1.25, and that the standard deviation in math scores would widen to 1.30. Furthermore, respondents projected that these alarming disparities would last 2 years after the onset of the pandemic (Bailey et al., 2021). Researchers in the Netherlands found that the negative impact on learning was 55% larger among students who had less educated parents (Engzell et al., 2021). In Chetty et al.'s study (2020), achievement fell by 30% for higher-income students and then quickly bounced back after schools reopened, whereas achievement fell by 50% among lower-income students and stayed low throughout the school year. In the context of COVID-19, inequity in school readiness losses among underprivileged preschoolers is expected (e.g., Benner & Mistry, 2020; Yoshikawa et al., 2020), but has never been studied to our knowledge. Quantifying these disparities can inform public policy and help allocate the necessary resources to the most vulnerable students.

## The current study

In Uruguay and elsewhere the unprecedented COVID-19 pandemic led to the suspension of face-to-face classes. Nonetheless, deaths per capita in Uruguay were among the lowest in South America by the end of 2020, which, unlike in other countries, allowed educational authorities to restore face-to-face activities during the last period of the year, including the administration of a nationwide school readiness assessment that has been implemented regularly since 2018 within public schools. This scenario provided the setting for a natural experiment on the impact of the COVID context (e.g., school closures, economic crisis) on child development. To our knowledge, no research has quantified the impact of the pandemic on preschoolers' development. Though all children may be suffering developmentally in the context of COVID-19, those from less privileged communities would be the hardest hit. Accordingly, this study aims to provide insights into the heterogeneity of this impact across different socioeconomic settings. Even if this study did not undergo preregistration, on the basis of the extant literature we expected to find moderate-to-small losses in school readiness among the COVID Cohort, and that these losses would be larger among children in schools from lower-SES districts. Thus, this study can be considered confirmatory.

## The context of the current study

### The impact of the pandemic in Uruguay

Reactions to the COVID-19 pandemic differed across countries and our study was conducted in Uruguay. Uruguay is situated in South America and has a small-density population of 3.5 million inhabitants and moderate-to-high life expectancy at birth (77.1 years, 44th in global rank; World Health Organization, 2021). In reaction to the pandemic, the Uruguayan government communicated recommendations to citizens (guidelines for hand sanitization, masks, social distancing, self-isolation, etc.) and framed public campaigns with messages to act responsibly. Though the government never legally imposed a lockdown, other restrictions were implemented including on social gatherings and international travel. In the first months of the pandemic, many restaurants and shops were closed and were allowed to reopen progressively around June 2020. Public offices reopened in April – May for strictly necessary purposes, but most of the work shifted to distance. In that context, unemployment rose approximately 1 percentage point from March to October. There was a clear impact on the economy with GDP falling 5.9% in 2020 (BCU, 2021). The active COVID-19 cases per capita in Uruguay remained low until the end of December 2020 when numbers started to rise.

### Timeline of school closures in Uruguay

The World Health Organization declared that the COVID-19 outbreak was a public health emergency of international concern on January 30, 2020. China was the first country to close schools in mid-February, and by mid-March, about 135 countries were affected by school closures (UNESCO, 2020). Uruguay implemented a certain degree of school attendance during 2020 because of the good epidemiological situation. In Uruguay, the school year runs from March to mid-December rather than from September to June. Schools were open as usual for the first 2 weeks of March 2020 and then faced the first nationwide school closures. Distance learning was implemented using home devices and virtual educational platforms from “Plan Ceibal”. Plan Ceibal is a governmental socioeducational project in Uruguay, widely accepted by families and education communities, that supports education through technology. It was created in 2007 and inspired by the One Laptop Per Child project (One Laptop Per Child, 2021). Nonetheless, the coverage of Plan Ceibal within the preschool system is limited (e.g., devices are not delivered to preschoolers), making distance learning particularly challenging for very young learners.

Under these conditions, classes were held entirely online for 3 months (mid-March through mid-June), with the exception of a small number of children attending schools in the low-density populated rural areas, which reopened in April 22. Afterward, children were able to return gradually to face-to-face classes on a voluntary basis. On June 15, 2020, nonmandatory in-person classes were held and most children attended school twice or three times a week in compliance with sanitary measures (e.g. reduced class size and increased social distancing). Home-schooling was used to compensate for the reduced hours. This scenario carried on from June 15 to August 2020 when schools were able to hold in-person activities depending on the number of children enrolled and the physical size of the school building. On October 13, 2020, face-to-face education was fully restored and continued until the school year ended (Presidencia de la República, 2021). A typical school year in Uruguay lasts 185 days (ANEP, 2021). In 2020, schools were open on average 80.6 days, but variability was high (56–113 days for percentiles 10 and 90, respectively). In Uruguay, children in age 5 classrooms attended school 53.1 days on average (ANEP, 2021), and 104 school days were lost. These numbers are by far better than those of Latin America and the Caribbean, which had an average of 158 days of school closures, and South Asia with 146 days (Unicef, 2021).

In Uruguay, education is mandatory starting at age 4, and coverage for preschool and primary school is almost universal. By 2018, 94% of 4- and 99% of 5-year-olds attended preschools (INEEd, 2019). Education providers can be either public, which means government-funded and managed schools that provide free education, or private, which rarely are free but can sometimes provide scholarships (e.g., some Catholic schools in low-income districts). Traditionally, the main provider of education has been the national government, with a strong network of public schools including in low-populated rural areas. In 2020, the public preschool and primary school system reached coverage of 81.7% of all children (ANEP-DGEIP, 2021). Teachers should have an official tertiary degree. Until 2017, there was no differentiation between primary and preschool teachers undergraduate education, in a 4-year curriculum focused on primary education content. As of 2017, a new 4-year degree was created for early education with a curriculum aligned with the idea of stimulating child development rather than predominantly teaching academic content (ANEP-CFE, 2016).

# METHOD

## Participants and procedure

We used longitudinal cohort data collected through the School Readiness-Child Development Inventory-Inventario de Desarrollo Infantil (INDI, by its Spanish acronym) among children attending public schools in Uruguay. Children's information (age and gender) and information about schools' SES (quintile) were also provided from an anonymized administrative dataset in agreement with the educational authority Consejo Directivo Central (CODICEN). This source of data does not collect information about ethnicity. However, according to the last Uruguayan census, 93.9% of individuals self-reported European ancestry, 8.1% reported being Afro-Uruguayan, and 5.1% reported Indigenous ancestry (Cabella et al., 2013). Note that self-reporting multiple ethnic identifications was allowed.

We included two cohorts of children aged 4- to 6-years old enrolled in Uruguayan public preschool in age 4 and 5 classrooms. The 2019–2020 cohort of children was naturally exposed to the COVID-19 pandemic at age 5 (mainly focused on school closures) and will be referred to as the "COVID cohort." The 2018–2019 cohort was used as a reference group or "control cohort" since the children were not exposed to the pandemic at age 5. Table 1 shows a timeline of the Uruguayan school year, COVID-19 mitigation measures impacting school closures, and features the three waves of data collection in each cohort. Wave 1 of data collection was carried out among 4-year-old children in the first semester of the school year (age 4 classroom). Wave 2 of data was collected in the second semester (age 4 classroom). Note that at wave 1 and wave 2 neither the control cohort nor the COVID cohort was exposed to the pandemic. Wave 3 was collected 1 year after wave 2 (age 5 classrooms) at a time where the COVID cohort had been naturally exposed to the pandemic (year 2020), whereas the control cohort had not (year 2019).

Nearly 40,000 children per cohort were administered at least one assessment at waves 1, 2, or 3. However, we discarded participants from analyses if they were missing at least one assessment at waves 2 or 3. This led us to discard 13% of the control cohort and 23% of the COVID cohort, leading to a final sample of 34,355 and 30,158 participants, respectively (Table 2). Within the COVID cohort, attrition was due to children who lacked an assessment at wave 2 (24%), wave 3 (71%), or both wave 2 and 3 (i.e., only wave 1 assessment, 5%). There were more missing data in the COVID cohort, notably at wave 3, because, within the context of the health emergency, teachers were given the option to opt-out of evaluating a given child, and more children did not attend school.

We analyzed the impact of attrition on mean INDI scores. We found that children who did not complete wave 3 had slightly lower average INDI scores at waves 1 and 2. On the other hand, those who were excluded because of a lack of assessment in wave 2, most often had higher means than those who were evaluated. The differences in both cases are small, and do not affect the general average, that is, the means in waves 2 and 3 for the total cohort and valid cases are not statistically significantly different (see Supporting Information 1).

Across waves and cohorts, data were reported from 1554 schools with an average of 26.24 children per center. Data on gender, age, socioeconomic school quintiles, and school typologies for the two cohorts are provided

**TABLE 1** Timeline of data collection and COVID mitigation measures in the school context

| Date | Semester | COVID measures | Control cohort | COVID cohort |
|---|---|---|---|---|
| Year 2018 | | | | |
| March–July | Semester 1 | N/A | Age 4, wave 1 | |
| August–December | Semester 2 | N/A | Age 4, wave 2 | |
| Year 2019 | | | | |
| January–February 2019 | Vacation | N/A | | |
| March–July 2019 | Semester 1 | N/A | | Age 4, wave 1 |
| August–December 2019 | Semester 2 | N/A | Age 5, wave 3 | Age 4, wave 2 |
| Year 2020 | | | | |
| January–February | Vacation | None | | |
| March 1–15 | Semester 1 | Schools open | | |
| March 15–June 15 | Semester 1 | Schools closed[a] | | |
| June 15–July | Semester 1 | Partial opening | | |
| August–October 14 | Semester 2 | Partial opening | | |
| October 15–December | Semester 2 | Schools open | | Age 5, wave 3 |

Abbreviation: N/A, not applicable.

[a]Except for schools in rural areas that reopened on April 24.

in Table 3. In order to assess the equivalency of cohorts across these characteristics, we used Student's *t* tests (numerical variables) and Pearson's chi-squared test (categorical variables). We found statistically significant differences in age between the COVID and Control cohort. This was due to small differences in the period of assessment across waves and years. No sex differences were found in the distribution by cohort. The cohorts significantly differed on school quintiles and by school typology.

**TABLE 2** Children assessed with INDI and reasons for sample exclusion, by cohort

| | Control cohort | COVID cohort |
|---|---|---|
| Children with at least one assessment at wave 2 and 3 | 39,359 | 39,329 |
| Attrition wave 2 and 3 | 265 | 432 |
| Attrition wave 2 | 3601 | 2195 |
| Attrition wave 3 | 1138 | 6544 |
| Total attrition | 5004 | 9171 |
| Total children assessed at wave 2 and 3 (final sample in differences-in-differences analyses) | 34,355 | 30,158 |
| Total children assessed at wave 1, 2 and 3 | 33,255 | 29,823 |

**TABLE 3** Distributions of age, sex, school quintile, and school typology for each cohort

| | Control cohort | COVID cohort | Statistic |
|---|---|---|---|
| Mean age in months (*SD*) | | | |
| Wave 1 | 53.57 (3.47) | 53.78 (3.52) | $-7.96^{***}$ |
| Wave 2 | 60.18 (3.49) | 59.69 (3.52) | $17.91^{***}$ |
| Wave 1 | 71.65 (3.49) | 71.88 (3.52) | $-8.16^{***}$ |
| Girls (%) | 48.87 | 48.95 | −0.2 |
| School quintile (%) | | | |
| Q1 | 17.9 | 17.5 | 0.03 |
| Q2 | 20.5 | 20.4 | $3.32^{**}$ |
| Q3 | 18.9 | 18.2 | $5.04^{*}$ |
| Q4 | 18.6 | 20 | $7.16^{**}$ |
| Q5 | 22.3 | 22.3 | 0.26 |
| No data | 1.8 | 1.6 | $11.5^{***}$ |
| Type of school (%) | | | |
| Simple (4 h a day) | 39.47 | 38.05 | $13.65^{***}$ |
| Full day (8 h a day) | 21.96 | 21.74 | 0.47 |
| Extended (4 h +lunch) | 2.54 | 3.42 | $42.87^{***}$ |
| APRENDER | 23.23 | 23.54 | 0.87 |
| Other (e.g., teacher training, rural) | 12.79 | 13.25 | $2.93^{*}$ |
| *N* | 34,355 | 30,158 | |

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

## Measures

*Sociodemographic information* was collected using an administrative source including age, gender, and the schools' SES quintile (1 = lowest, 5 = highest). The National Administration of Education (ANEP) assigns quintiles to schools based on the average socioeconomic information of the enrolled children's families. Thus, it is possible but unlikely that children coming from low-income families are enrolled in a high-SES rating school and vice-versa.

*The School Readiness—Child Development Inventory (INDI)* was used. INDI is a norm-referenced, teacher-reported school readiness assessment carried out in the educational context. It is implemented by the authorities to improve school readiness practices and better target educational and health protection measures for vulnerable children. Teachers receive a 2-h annual training on administration and the use of the automatic reports system for educational interventions. Further reading of the manuals is strongly recommended as they provide specific details for scoring, and interpreting reports. Teachers can also attend optional courses throughout the school year. To administer INDI, teachers observe the child's frequency of specific behaviors in certain developmental milestones, during a typical school day within a period of 3–4 weeks. Most items are observational, but some require individualized testing for scoring (e.g., "Holds the pencil properly") with specifically designed activities and response options. Teachers score indicators on a digital platform using a 6-point frequency Likert scale ranging from "never" to "always." Teachers can also indicate any reasons that prevent evaluation (e.g., frequent absences, severe developmental difficulties; see Supporting Information 2). Detailed information about scoring is available on the digital platform where teachers complete the INDI and in the administration manual.

INDI accounts for four developmental domains, some of which include subscales (Vásquez-Echeverría et al., 2021): (a) Cognitive development is composed of Language (including oral comprehension and production, phonological awareness, and early literacy skills, e.g., *Understands a short story*; 7 items), Logical-mathematical skills (early numeracy skills such as verbal counting, recognizing number symbols, shapes, and manipulating quantities, e.g., *Recognizes numbers between 1 and 10*, 6 items), Self-projection (including perspective-taking abilities, as in the case of episodic memory, foresight and theory of mind; Buckner & Carroll, 2007, e.g., *Anticipates what he will need in the future*, 6 items), and Executive functioning (including mainly attentional and self-regulation skills, e.g., *Is able to wait for turns*, 6 items). Cognitive subscales scores are summed up to yield a Cognitive development total score; (b) Motor development (mostly composed of content tapping fine-motor skills such as pencil-grip and gross-motor skills such as locomotion, e.g., *Holds the pencil properly*, 6 items); (c) three orthogonal subscales compose Socioemotional development: Internalizing behaviors (behavior problems such as anxiety, sadness or behavioral inhibition, e.g., S*pends time alone*, *isolated from the group*, 5 items), Externalizing behaviors (behavior problems such as verbal or physical aggression, defiant attitudes toward teachers and peers, e.g., *Verbally assaults his/her peers*, 4 items), and Prosocial behaviors (cooperative and empathic attitudes, e.g., *Shares toys and materials*, 5 items). No composite socioemotional score is provided, and (d) Attitudes toward learning (including school adaptation, motivation, and creativity, e.g., *Shows curiosity and interest in class*; 6 items). The INDI version used in the current study is adapted to children aged 49–79 months old (age 4 and age 5 classrooms) and totals 52 items. The INDI Automatic Reports System provides feedback about child performance on each domain and subscale comparing individual results with a normative sample using four categories: risk, monitoring zone, on track, and outstanding. Previous studies suggested that INDI scores have good-to-excellent internal consistency ($\alpha$ range .73–.93), test–retest stability ($r$ range .80–.99), and inter-rater reliability (intraclass correlation coefficient range .71 to .95) coefficients, as well as convergent validity estimates (Vásquez-Echeverría, 2020). INDI was administered to preschoolers nationwide from 2018 to 2020. Though the administration of INDI is not compulsory, it was administered to 94.8% of preschoolers in 2018, 96.1% in 2019, and 70.3% in 2020. More information about the INDI assessment system can be found at https://indi.psico.edu.uy/en.

## Data analysis

To study the impact of the COVID-19 pandemic on developmental markers, we compared levels of development across the two cohorts of children (COVID cohort and control cohort). This counterfactual scenario allowed us to infer what we would expect if the children had not been exposed to the pandemic.

We estimated the health emergency's impact on developmental markers using differences-in-differences analysis (DiD; Angrist & Pischke, 2009). This regression-based approach was used to compare developmental changes of the two cohorts across the three waves of data collection while reducing bias from unobserved variables. DiD analysis operates on the assumption that scores would evolve in the same way across the two cohorts of data (parallel trends), had the treatment or event (e.g., pandemic) not occurred. This quasi-experimental design is appropriate for testing the impact of a situation that would otherwise be impossible or unethical to provoke, such as a pandemic exposure (Wing et al., 2018). The difference between trends of the two cohorts is then quantified as a marker of the pandemic's impact.

The impact estimator is the difference in scores between waves 3 and 2 of the COVID cohort, minus the differences in the scores between waves 3 and 2 of the Control cohort. The model's equation for a given child, including control variables can be defined as in Equation (1):

$$y_{it} = \beta_0 + \beta_1 C_i + \beta_2 X_{it} + \delta_0 T_{it} + \text{DiD } T_{it} \times C_i + u_{it}, \quad (1)$$

where $i = 1, n$ and $t = 2, 3$; $y$ is the outcome variables for each child $i$ at wave $t$, $C_i$ is a dummy that indicates if the child belongs to the COVID cohort, $T_{it}$ is a dummy that indicates if the observation $y$ of child $i$ correspond to wave $t = 3$. The coefficient of interest, DiD, multiplies the interaction term $C \times T$; which is equivalent to a dummy variable that indicates if the observations are from the COVID cohort at wave 3. $X$ stands for the control variables that may vary across measurement occasions $t$, and $u$ is the error term. Our model controlled for children's age-in-months, sex, the school SES quintile, and cluster robust standard errors estimate at the group (class) level. In these analyses, we used standardized estimates to convey effect sizes following Ferguson's (2009) criteria (i.e., .2, .5, and .8 as small, moderate, and strong effects, respectively).

In order to reduce possible bias in DiD estimations and check the robustness of results of the main model, we conducted analyses under different specifications: (a) model without controls; (b) balanced model with propensity score matching, to control for the imbalance of cohorts samples by school type, school SES quintile, children's age-in-months and sex; (c) fixed-effect models, to control for the scores' nestedness and non-random variance within schools. For this model, only schools with at least 10 participants were selected.

We examined heterogeneous effects by the school SES quintile, sex, and previous development by using tertiles of development at wave 2. To explore the variability of impact estimates between schools, a mixed-effects model (where impact estimates will be allowed to vary across schools) was conducted.

Additionally, we provided descriptive statistics of the evolution of developmental profiles with intra- and inter-individual comparisons. Development was categorized as *high risk*, *monitoring zone*, or *on-track* based on INDI normative data corrected for age in months. We expected to find a higher proportion of children with high risk or in the monitoring zone at wave 3 in the COVID cohort in comparison to the control cohort.

# RESULTS

## Preliminary analyses

We compared the mean scores for INDI domains and subscales at each of the three measurement waves. Descriptive statistics for each wave and cohort are presented in

Table 4. With a visual inspection of the means at waves 1 and 2, we observed a similar trend before measurements in age 5 classrooms. To further check this assumption, we performed a DiD model following Equation (1) with $t = 1, 2, 3$. DiD estimates obtained for the prepandemic interaction were all nonsignificant, except for Executive functioning at the $p < .01$ threshold ($DiD_{pre} = 0.06$, $p = .002$). Internalizing behavior ($DiD_{pre} = -0.04$, $p = .04$) and Attitudes toward learning ($DiD_{pre} = 0.05$, $p = .02$) were significant at the $p > .05$ threshold, with coefficients close to zero.

In order to compare differences between cohorts, we expressed the effect size of differences with Cohen's *d* (see Figure 1 for cognitive and motor scores, and Supporting Information 3). The COVID cohort scored slightly higher than the control cohort at waves 1 and 2. At wave 3 (when the COVID cohort was exposed to the pandemic) lower scores were observed in the COVID cohort, except for internalizing behaviors. Furthermore, effect sizes were most often larger at wave 3 than at waves 1 or 2, especially for externalizing behaviors ($d = .29$) and motor skills ($d = .21$). Effect sizes in the .10 to .20 range were observed for Language, Logical-mathematical skills, Self-projection, and Cognitive development such that the COVID cohort scored lower than the control cohort.

## DiD modeling

### General estimation

We evaluated the impact of the COVID-19 pandemic on childhood development using the DiD approach. Regression analyses were carried out following our main specification (controlling for age, gender, and the school's SES quintile) and without those controls (see Table 5). Analyses showed that the COVID cohort had statistically significant losses, with standardized DiD estimates above .20 in all INDI cognitive subscales: Language, Logical-mathematical skills, and Self-projection, except for Executive functioning (0.10). Concerning dimensions, Motor development and Cognitive development showed losses above 0.20, followed by Attitudes toward learning (0.14). Internalizing behaviors increased (0.13), whereas Externalizing behaviors decreased (0.22), suggesting that the COVID cohort exhibited less aggressive and frustrated behaviors than the control cohort. No significant differences were observed in Prosocial behaviors. These results held even after controlling for age, gender, and the school SES quintile.

To check the robustness of the DiD modeling, we used propensity score matching to control for the imbalance of cohorts in the main demographic and socioeconomic variables, and fixed effects to account for nested data across schools. Balance of treatment and control groups were used as covariates (Supporting Information 4). We found that estimates were robust to different specifications (see Figure 2 for impact estimates). In order to enhance statistical parsimony, the main specification (model with controls) was selected for further analyses and interpretation. Fixed effects model selection would also require excluding some schools with fewer children from the analysis.

Impact estimates across schools were calculated using a linear mixed model. Figure 3 shows that losses varied substantially across schools in Cognitive and Motor development, and in some schools there were even gains. This pattern is also observed in cognitive and socioemotional subscales and in Attitudes toward learning (see Supporting Information 5). Schools with gains were distributed across all school SES quintiles. Gains in Cognitive development were more frequent in higher-SES schools, but these differences were not statistically significant.

Next, considering the moderate to high correlation between subscale scores, we selected INDI scores with negative impact estimates above the minimum practical significant effect of .20 to conduct a multivariate analysis of variance (MANOVA; Supporting Information 6). Dependent variables included the standardized differences of the scores between waves 3

**TABLE 4** Means (and *SD*s) of INDI's scores in all domains and subscales for each wave and cohort

| | Wave 1 | | Wave 2 | | Wave 3 | |
|---|---|---|---|---|---|---|
| Cohort | Control | COVID | Control | COVID | Control | COVID |
| Language | 23.44 (10.47) | 24.25 (10.46) | 34.92 (13.90) | 35.10 (13.58) | 44.75 (14.25) | 42.23 (14.60) |
| Logical-mathematical | 17.3 (8.35) | 18.19 (8.33) | 28.44 (10.97) | 28.64 (10.59) | 37.7 (9.99) | 36.11 (10.59) |
| Self-projection | 25.25 (9.05) | 26.36 (8.69) | 32.6 (9.35) | 33.05 (8.89) | 37.83 (8.54) | 36.33 (8.78) |
| Executive functioning | 31.32 (8.26) | 31.87 (8.57) | 35.03 (7.66) | 35.93 (8.05) | 38.3 (7.61) | 38.65 (7.15) |
| Internalizing | 10.18 (4.89) | 10.02 (4.77) | 9.09 (4.35) | 8.83 (4.19) | 8.3 (3.93) | 8.48 (4.12) |
| Externalizing | 14.97 (8.72) | 14.85 (8.52) | 14.57 (8.52) | 14.20 (8.30) | 13.91 (8.24) | 11.76 (6.25) |
| Prosocial | 24.15 (6.48) | 24.53 (6.23) | 27.41 (6.19) | 27.83 (6.02) | 29.2 (5.83) | 29.4 (5.50) |
| Cognitive development | 59.04 (19.65) | 61.25 (19.47) | 81.79 (23.85) | 82.76 (23.29) | 99.97 (23.20) | 96.42 (23.80) |
| Motor development | 20.16 (5.32) | 20.66 (4.97) | 24.75 (4.89) | 24.95 (4.61) | 27.57 (3.90) | 26.73 (4.23) |
| Attitudes *t*/learning | 27 (7.15) | 27.31 (7.02) | 30.52 (7.15) | 30.91 (6.95) | 32.74 (6.86) | 32.43 (6.76) |

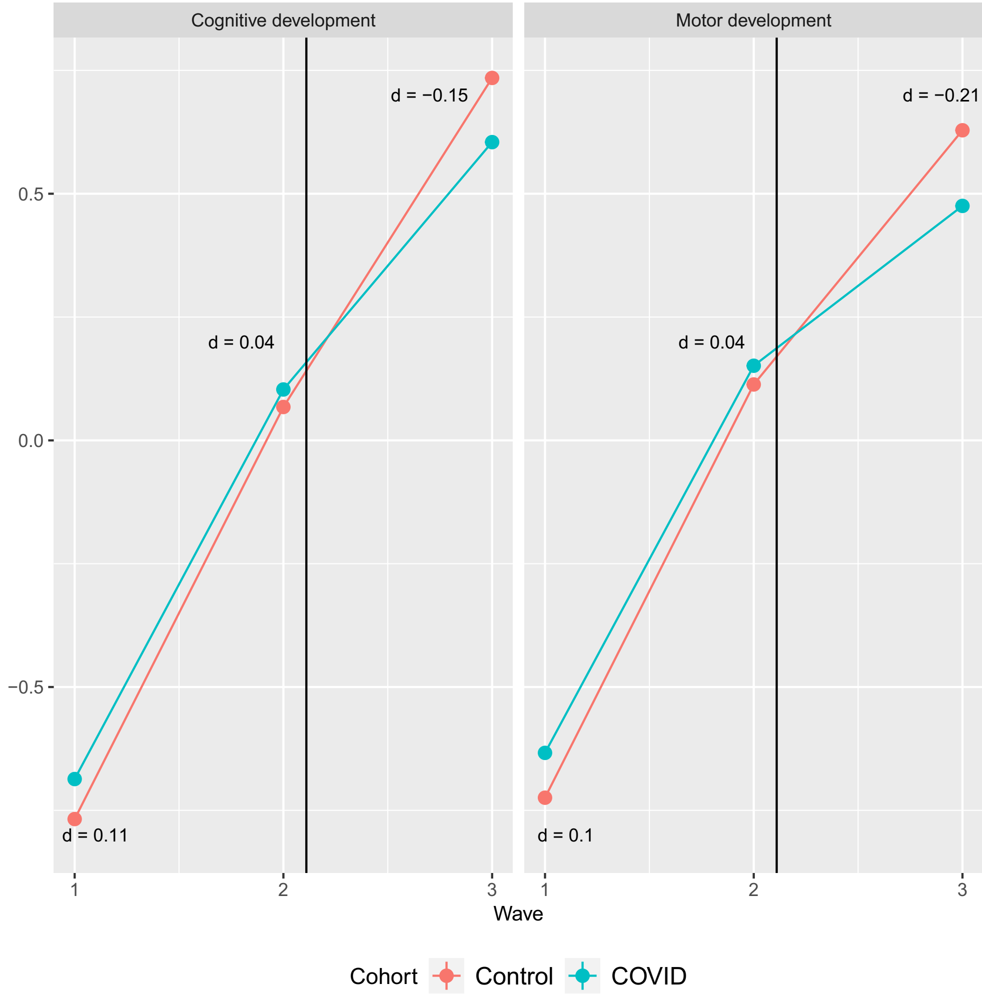


**FIGURE 1** Standardized means for the COVID and Control cohorts (and effect sizes of the differences) at each wave, for cognitive and motor development scores

**TABLE 5** Cohorts comparison according to differences-in-differences estimates without controls and controlling for age, gender, and socioeconomic status (main specification)

| | Unstandardized estimates (*SE*) | | Standardized estimates (*SE*) | |
|---|---|---|---|---|
| | Bivariate | Regression-controls added | Bivariate | Regression-controls added |
| Language | −2.69 (−0.46)*** | −3.31 (−0.45)*** | −0.18 (0.03)*** | −0.22 (0.03)*** |
| Logical-mathematical | −1.79 (−0.30)*** | −2.34 (−0.29)*** | −0.16 (0.02)*** | −0.21 (0.02)*** |
| Self-projection | −1.95 (−0.29)*** | −2.32 (−0.29)*** | −0.21 (0.03)*** | −0.25 (0.03)*** |
| Executive functioning | −0.55 (−0.23)** | −0.74 (−0.23)*** | −0.07 (0.03)** | −0.10 (0.02)*** |
| Prosocial behaviors | −0.23 (−0.21) | −0.33 (−0.20) | −0.04 (0.03) | −0.06 (0.03) |
| Internalizing behaviors | 0.44 (−0.13)*** | 0.52 (−0.13)*** | 0.11 (0.03)*** | 0.13 (0.03)*** |
| Externalizing behaviors | −1.78 (−0.20)*** | −1.76 (−0.19)*** | −0.22 (0.02)*** | −0.22 (0.02)*** |
| Cognitive development | −4.51 (−0.72)*** | −5.72 (−0.69)*** | −0.18 (0.02)*** | −0.23 (0.02)*** |
| Motor development | −1.05 (−0.14)*** | −1.24 (−0.14)*** | −0.23 (0.02)*** | −0.27 (0.03)*** |
| Attitudes *t*/learning | −0.69 (−0.21)*** | −0.98 (−0.21)*** | −0.10 (0.03)*** | −0.14 (0.02)*** |

*Note:* Negative values indicate skills loss in the COVID cohort, except for Internalizing and Externalizing behaviors in which negative values indicate improvement.

Abbreviation: *SE*, standard error.

$^{**}p < .01$; $^{***}p < .001$.

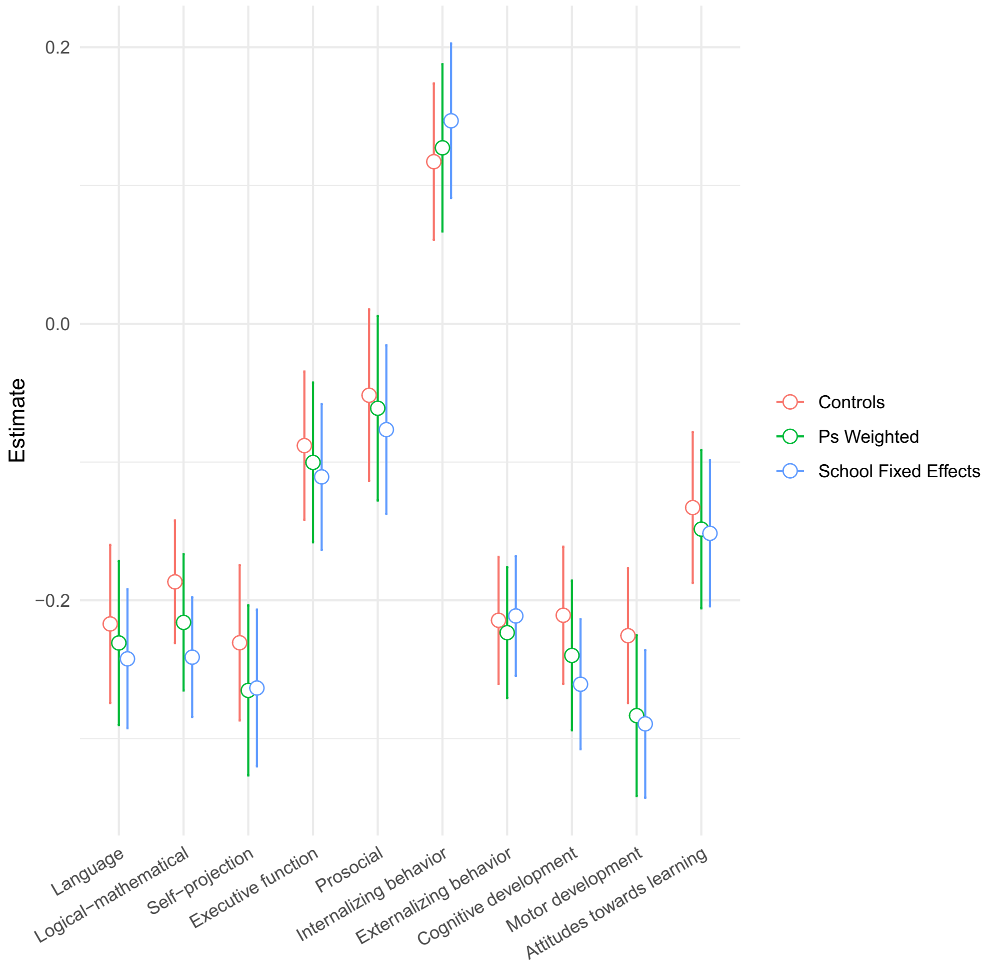


**FIGURE 2** Differences-in-differences estimates of impact of COVID-19 on INDI domains and subscales. Red dots represent the main specification (estimations with controls). Green dots represent the estimations using propensity matching and the blue dots represent the estimation using fixed effects at the school level. Negative coefficients represent a reduction in developmental performance according to the expected trend, except for Internalizing and Externalizing behaviors where negative scores indicate an improvement compared to the expected performance

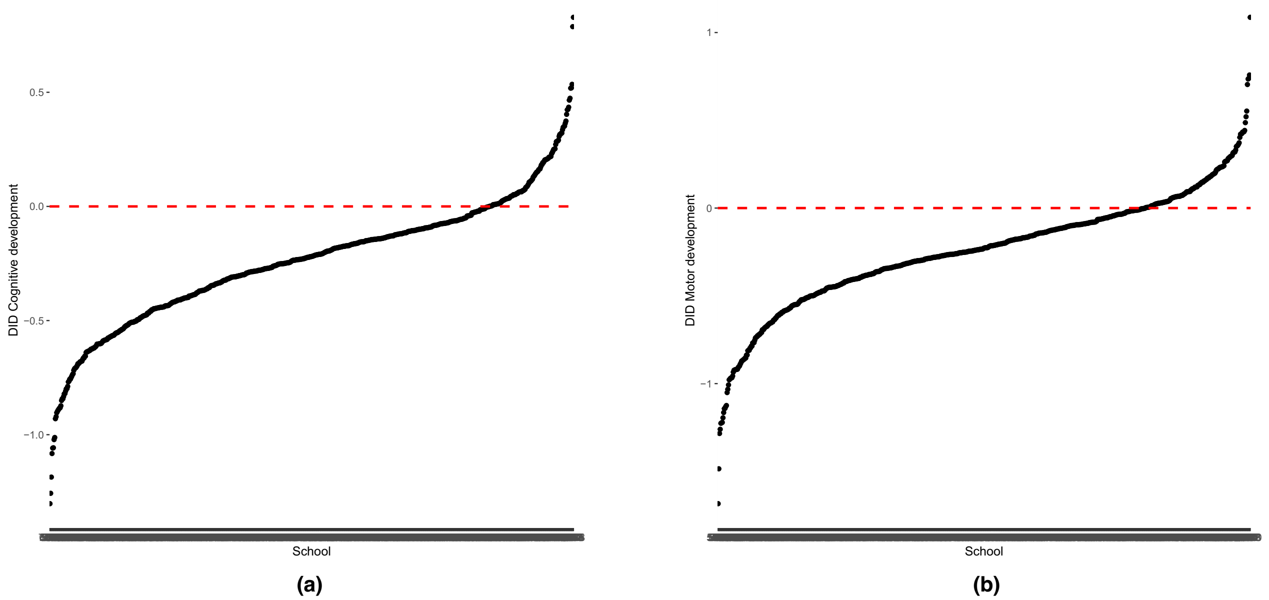


**FIGURE 3** Variability of impact estimates at the preschool level for Cognitive (a) and Motor development (b). Negative values (below the red line) represent the preschools where the COVID-cohort showed losses

and 2 for Language, Logical-Mathematical skills, Self-projection, and Motor development. The cohorts were used as independent factors. The MANOVA results revealed significant differences across the two cohorts on all the dependent variables ($F$ (4, 50.951) = 279.12, $p < .001$).

## Estimation by school ses, previous developmental level, and sex

We conducted analyses to investigate if the school's SES moderated developmental trajectories. Schools were categorized into five quintiles, with higher quintiles indicating the more privileged school districts. In the COVID cohort, Language and Logical-mathematical skills showed losses in the four lowest SES quintiles, whereas very small and non-significant declines were observed in the highest SES districts (quintile 5). Losses in Self-projection, Motor development, and Cognitive development were observed across all quintiles. Though larger impacts were observed among children attending centers from quintiles 2 and 3, followed by quintiles 1 and 4, and lastly quintile 5, few of these differences were statistically significant (see Figure 4). More specifically, significant differences were only observed between quintile 3 and 5 in Language, Logical-mathematical skills, and Cognitive development. Interestingly, socioeconomic gaps in school readiness increased. For example, the effect size of the differences between Q1 and Q5 in the COVID cohort between Wave 2 and Wave 3 increased from $d = .33$ to $d = .45$ in Language, from $d = .50$ to $d = .55$ in Logical-mathematical subscale, and from $d = .21$ to $d = .23$ in Motor development. Descriptive statistics by quintile can be found in Supporting Information 7.

Next, we compared impacts according to previous development (categorized by tertiles of performance at wave 2) and sex (Supporting Information 8). Children with lower levels of development at age 4 suffered the most from school closures in all dimensions, except for Executive functioning. Nonetheless, statistically significant differences between tertiles were observed only in Logical-mathematical skills and Motor development, whereas all other differences were non-significant. No sex differences were observed except for a statistically significant effect of Externalizing behaviors (boys

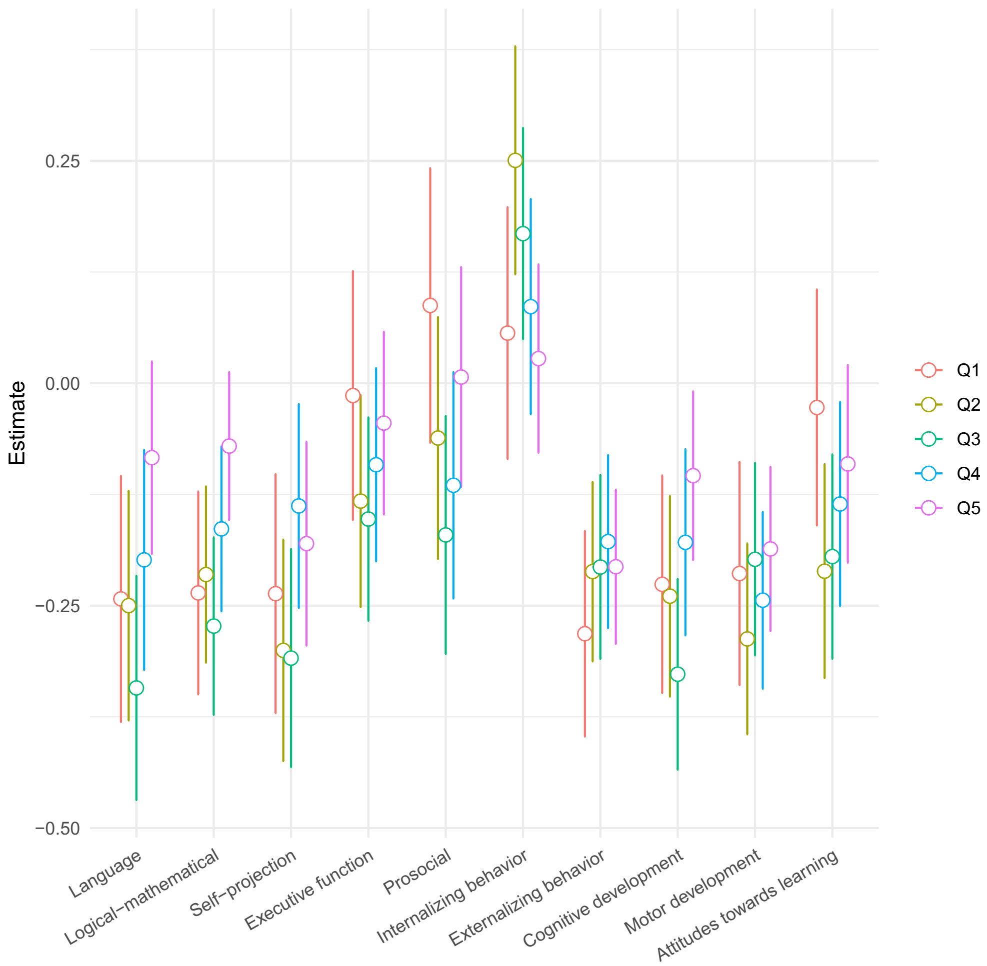


**FIGURE 4** Differences-in-differences estimates of the impact of COVID-19 on INDI domains and subscales by school quintile. Statistical controls include sex and age-in-months

had more reduction). Descriptive statistics by sex and prior developmental scores can be found in Supporting Information 7.

### Analyses by developmental profiles

We further estimated developmental profiles for each INDI score at waves 1, 2, and 3 for the COVID and control cohorts (Supporting Information 9). When comparing waves 1 and 2, the COVID cohort had a significantly higher percentage of children meeting global developmental expectations (i.e., outstanding and on-track profiles) than the control cohort. At wave 3, the percentage of children who met developmental expectations was significantly lower in the COVID cohort, except for Externalizing behaviors, which was significantly higher.

Next, we carried out intra-individual analyses for children to track their trajectory from wave 2 to 3 (1-year interval). The trajectory for each child was categorized as favorable, unfavorable, or stable for each domain and subscale, based on the normative data used for the INDI reports system. We found that in the COVID cohort the percentage of children with an unfavorable development was significantly higher whereas the percentage of favorable development was significantly lower. This applied to all domains and subscales, except for Externalizing behaviors where we found a statistically significant effect in the opposite direction (see Supporting Information 10).

## DISCUSSION

We investigated the impact of the COVID-19 pandemic on school readiness among preschoolers using two large representative cohorts of Uruguayan children and three waves of data collection. We added novelty to the extant literature in the following ways. First, because we compared a cohort of students who attended preschools through the pandemic to a control cohort who was not exposed to restrictions. Second, we used teachers' assessments carried out in the school setting rather than parental reports or online educational platforms. Third, we evaluated cognitive, motor, and socioemotional development simultaneously. Fourth, we focused on the development of preschool-age children whereas most research to date has focused on other age groups or education levels.

### Impact of the pandemic on child development

We found that children who were in preschool during the pandemic experienced negative outcomes in multiple developmental domains. This converges with extant literature documenting learning losses in the context of the COVID-19 pandemic among school-age children (Engzell et al., 2021; Kuhfeld et al., 2020; Maldonado & De Witte, 2020), but we were the first to our knowledge to document the impact on school readiness among preschoolers. Though we cannot attribute developmental losses to school closures specifically, our findings also converge with studies documenting detrimental effects on learning of school closures during summer recess (Alexander et al., 2007; Bao et al., 2020; Gershenson, 2013) or emergencies leading to school closures (for a review see Araújo et al., 2020). We found the cognitive and motor development of children was suffering the most, followed by their attitudes toward learning. Within cognitive functioning, Self-projection, Language and Logical-mathematical skills showed the largest losses but effect sizes were small. Nevertheless, these losses could pose a threat to educational achievement later in life. For instance, literature on school readiness highlights that early math and literacy performance are strong predictors of academic outcomes in primary school (Duncan et al., 2007, 2020). Indeed, health and economic crises may have repercussions on the life course years later (Benner & Mistry, 2020). Furthermore, these areas of functioning may be the most difficult to compensate for at home because they require teaching expertise, age-appropriate activities and materials, and are highly dependent on the quality of stimulation from caregivers (e.g. Anders et al., 2012). Time-structured activities and events were reduced during the pandemic, which could impact the development of self-projection. Similarly, stay-at-home measures led to a drastic decrease in physical activity (Gobbi et al., 2020), which may explain the underdevelopment of motor skills. As there have been few to no studies on the impact of the pandemic on these developmental areas, it would be relevant to develop further research on the topic among preschool-age children.

Most surveys in early childhood have focused on the pandemic's impact on socioemotional development (Guerrero, 2021). Likewise, we accounted for internalizing, externalizing, and prosocial behaviors. Our study evidenced that the COVID-19 context had a small but significant negative impact on anxious and avoidant internalizing behaviors. These findings converge with other studies carried out among children (Liu et al., 2021). Avoidant and anxious behaviors in children could be an indirect result of increased parental stress, deregulation of daily life (Hiraoka & Tomoda, 2020; Tso et al., 2020), or increased teacher stress (Bacher-Hicks & Goodman, 2021). Unexpectedly, the COVID cohort exhibited less externalizing behaviors when compared to the control group. This might be explained in part by the fact that most often socioemotional assessments and reports of behavioral problems were based on parental observations during confinement periods (Glynn et al., 2021; Guerrero, 2021; Liu et al., 2021), rather than on teacher evaluations within school settings. Alternatively, the school reopening conditions in Uruguay could explain the lower prevalence of externalizing behaviors because they implied a lower child–teacher ratio and increased supervision of social interactions (NICHD Early Child Care Research Network, 2004; van Verseveld et al., 2019). Similarly, a cross-sectional study carried out among Canadian children and adolescents found that youth reported lower levels of bullying and aggression during COVID-19 in comparison to prepandemic levels (Vaillancourt et al., 2021).

We found that the impact of the pandemic on school readiness losses varied considerably across preschool centers. This variation converges with literature on learning losses during summer recesses (Atteberry & McEachin, 2021) and school closures due to the COVID-19 pandemic (Engzell et al., 2021). In the current context, aspects of online learning during closures (e.g., frequency of videoconferencing, parental adherence to distance learning, and availability and quality of bandwidth), and of schools reopening (e.g. space constraints to comply with social distancing protocols, safety-protocols due to possible or confirmed COVID-19 cases) differed across schools to some extent. Also, the quality of developmental stimulation at home could vary across families and school neighborhoods. Further research would be necessary in order to pinpoint the factors within each school that could explain why there was such variation. Another interesting and unexplored line of research could focus on children who benefited from the pandemic. For example, the COVID-19 context may have provided a higher quality developmental environment for some children because it could increase the quality and frequency of interaction between family members, improve the socioemotional climate and provide a closer follow-up of educational activities, especially among higher-SES families. However, our study showed little evidence in favor of a SES-based explanation of gains.

## Impact of the pandemic across SES and previous development

After observing differences in trajectories across the two cohorts, we took an interest in the impact of schools' SES and found significant differences. Specifically, we found that developmental losses for children in the highest quintile were less pronounced, especially in language and math skills. Likewise, previous studies revealed higher learning losses among primary school-age children with lower SES in the context of COVID-19 (Engzell et al., 2021; Maldonado & Witte, 2020). The effect of lower SES on developmental losses is well documented and there is an array of explanations of why underprivileged children would be more negatively impacted by the pandemic and school closures. First, routine school closures during summer recess have more of an impact on children of lower-SES (Alexander et al., 2007), suggesting that the effect is impacted by school closures specifically. In the context of the pandemic, a high-quality home environment or family stimulation (e.g., literacy practices at home, age-appropriate toys, and materials) may absorb some of the negative effects among children from privileged families (Anders et al., 2012; Bao et al., 2020). In contrast, low-income families would adhere less to online education because they lack equipment or motivation (Kruszewska et al., 2020). The pandemic has put an additional financial strain on families, especially among those with lower SES (Bailey et al., 2021; Clark et al., 2020). For the most disadvantaged, food insecurity is a major threat to childhood development in Latin America (Guerrero, 2021) and on an international scale (Sharma et al., 2020). A higher risk of psychosocial problems among children of low-income families is well documented (e.g., Tso et al., 2020) and could be exacerbated in the context of the pandemic.

Relatedly, children who were struggling the most when in age 4 classrooms displayed larger developmental losses thus increasing the achievement gap. A similar finding was reported in previous studies (Engzell et al., 2021; Kuhfeld et al., 2020). Prior to the pandemic, the home environment of these children could have lacked appropriate stimulation, and attending school would be particularly critical to compensate. Furthermore, once the pandemic was underway, their families may have been among those who suffered the most (e.g., food insecurity, economic hardships, parental stress).

## Strengths, limitations, and future directions

Major strengths of our study included the novelty of studying young children, the large sample size, the presence of a control group not exposed to COVID-19, and our use of teacher reports even in this pandemic context. However, multiple limitations should be noted. First, we cannot be certain of what aspects of the COVID-19 pandemic specifically impacted school readiness (e.g., school closures, parental and teacher stress, access to computers, etc.). We accounted for the school SES, but we were not able to measure family SES or income, nor account for the economic and psychosocial hardships of families during the pandemic (e.g., unemployment). There was more attrition in the COVID cohort than in the control cohort that may bias (underestimate) the impact of the pandemic on school readiness, as more vulnerable children were more likely to have dropped out. We did not account for the family's adherence to distance learning, differences in teaching strategies, the number of hours of online instruction, or the number of days children attended school after reopenings. If available, these variables would be worth considering in the future. Teachers' assessments may have been biased because of work stress and shifts in their perception of expected behaviors due to the pandemic. The interpretation of results on internalizing behaviors, attitudes toward learning, and especially executive functioning scores should be taken cautiously because the significant effect of the pretreatment interaction may signal an issue with the assumption of parallel trends. The current study was carried out using large, national cohort data from Uruguay, but may not generalize to other contexts, as characteristics of school closures, mitigation measures, and other COVID-19-related socioeconomic impacts differed across regions. As this is the first study on preschoolers to our knowledge, it would be beneficial to conduct similar research around the world.

# CONCLUSIONS AND IMPLICATIONS

Based on our findings, we can draw the general conclusion that the COVID-19 pandemic harmed multiple domains of childhood development, especially within cognitive and motor domains. Inequalities in school readiness already present in the Uruguayan population (Vásquez-Echeverría et al., 2021) appear to have been exacerbated, as children living in the most privileged districts were more protected from the impact of the COVID crisis, and children who were already struggling at age 4 before the onset of the pandemic suffered the most compared to their expected trajectory.

This increased inequity in developmental losses can directly inform public policy to focus on helping children in their transition to primary school. For example, as motor and cognitive development were the most impacted, it would be important for school teachers to focus on these domains in the upcoming school years. Our findings imply that teachers and caregivers need to focus on children from underprivileged backgrounds or those who were struggling before the onset of the pandemic. This advice was given to teachers in Uruguay during the latest 2021 INDI teacher training program, in order to help mitigate the negative impact of the pandemic on school readiness. Public policies may also benefit from allocating resources to families in underprivileged school districts (e.g., financial aid for childcare or private tutors to increase instructional time).

Further research on how the pandemic impacts the cognitive and motor development of young children needs to be conducted because our study was the first to our knowledge and generalization may be dubious. Exposure to the COVID-19 pandemic incorporates a myriad of confluent factors that differ considerably across time, cultures, and geographical locations. Therefore, it would be critical to conduct further research in order to ascertain the extent to which findings generalize outside of Uruguay. Considering the epidemiological situation of Uruguay during 2020, the mild restrictions, and other favorable educational policies (e.g., shorter school closures compared to many other countries, social policies, and a strong culture of technology in education), it would not be surprising if the impact of the pandemic on early childhood development in other countries was larger, and even more exacerbated among underprivileged children.

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## SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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