



# The educational experiences of Indian children during COVID-19

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## ABSTRACT

We explore the educational experiences of Indian children during the COVID-19 pandemic, using time-use and household expenditure data from a panel of over 110,000 households with school-aged children. We find that both 12–18-year old's average learning time and their average households' expenditure on education more than halved following the March 2020 school closures. Both had barely recovered by the end of 2021 throughout a period of phased but incomplete school reopenings. Interpreting the changed patterns of educational investments through a simple model of skill formation suggests skill inequalities between cohorts may increase, while implications for within-cohort inequalities are ambiguous. Children from households who experienced more-severe economic shocks during the pandemic saw larger losses in inputs although heterogeneity by socio-economic characteristics is more mixed. Overall, differences in losses across subgroups are dwarfed the average losses: every subgroup we analyze experienced average falls in learning time and educational expenditure, respectively, of at least 42 % and 60 %.

## 1. Introduction

Over the last several decades, low and middle-income countries have made extraordinary progress towards universal basic education. In India, the setting of this paper, primary and secondary gross enrolment rates rose from 78.7 % to 108.6 % and from 24 % to 73.9 % between 1971 and 2015, respectively (World Bank, 2021a).<sup>1</sup> Enthusiasm about these advances have been somewhat tempered by the 'learning crisis': the finding that many children, despite attending school, are failing to acquire basic literacy and numeracy skills (World Bank, 2017). However, despite not being as prodigious as advances in access, advances in quality and attainment are certainly not negligible. Adult literacy rates in India rose from 41 % in 1981 to 72 % in 2015, mirroring similar trends that have been observed throughout the Global South (Miller et al., 2016).

Against this backdrop, COVID-19 has dealt an enormous blow to the education of India's approximately 380 million children and adolescents of school age.<sup>2</sup> As in many low-and-middle-income countries (LMICs), India faced particular challenges including that many schools struggled to provide virtual alternatives to in-person teaching, and many families lacked the technology, space, and equipment necessary for children to study effectively at home (World Bank, 2021b). Moreover, the scale of the public health disaster was particularly large in India (Anand et al., 2021) and, relatedly, its school closures were amongst the longest in the world.<sup>3</sup> Likewise, very high rates of private-school enrolment (44 % for primary school, 52 % for secondary in 2019) mean that shocks to household incomes may have severed children's access to their school if families cannot afford to keep up with fees.<sup>4</sup>

This paper documents the impact of COVID-19 on the educational experiences of Indian school-aged children. 18 % of the world's children

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<sup>1</sup> Gross enrolment rates are defined as the number of children in school divided by the number of children of school age. Therefore, rates can be above 100% in the case of early and/or late enrolment or grade repetition.

<sup>2</sup> Total population aged 4–19 taken from the 2011 census accessed from: <https://censusindia.gov.in/nada/index.php/catalog/1541>.

<sup>3</sup> The UNSECO school closure tracker reports that schools in India have been fully closed for 25 weeks and partially closed for 57 weeks, the joint-second longest duration of any country in the world after Uganda (UNESCO, 2021).

<sup>4</sup> Private schooling figures from UNESCO Institute for Statistics. Accessed via: <https://data.worldbank.org/indicator/SE.PRIV.ZS?locations=IN>

under the age of 15 live in India and so as well as being a hugely important group in their own right, understanding the experiences of Indian children is crucial to understanding the global educational impacts of the pandemic.<sup>5</sup> We study the pattern of educational experiences up until the end of 2021, using panel data of over 110,000 Indian households with school-aged children. We focus on two main themes: learning experiences and inequalities between groups of children. To examine learning experiences, we look at changes in *material investments* as well as changes in secondary students' *learning time* – both of which can be considered key inputs in a human capital production function. To examine inequalities between groups, we sketch out this function explicitly, adopting a model in which children's skills in each period are a function of past skills and time and material investments in the previous period. We use this model to interpret the changes in the variances and covariances of these investments over the pandemic, and to suggest what these changes might mean for inequalities between different groups of children.

At the aggregate level, we find that children's average learning time fell dramatically during the pandemic, from around 5.5 h a day between September 2019 – February 2020 to around 2 h a day after the initial school closures in March 2020. This is a fall of over 60 %. Families' average education expenditure also declined substantially, falling to less than a third of pre-pandemic benchmarks in both absolute terms and relative to total household expenditure. This includes large falls in school fees (which the vast majority of households stopped paying completely), books and stationary and private tutoring. Alarming, learning time and expenditures only recovered slightly over the next 21 months, despite the phased school reopening's during the latter half of 2021. We make use of state-by-month variation in school closure policies to examine how these shaped investments. We find that while successive degrees of reopenings were associated with larger investments, the magnitudes appear relatively small. Overall, between March 2020 and December 2021, we estimate that the average child lost 1627 h of learning time. These findings suggest a substantial degree of learning loss, a finding that has been documented by ASER (2023) and by Singh et al. (2023).

Between cohorts, we find that falls in time investments were somewhat greater for younger adolescents while falls in material investments fell to fairly uniform levels across the 12–18 age distribution.<sup>6</sup> The longer-run impacts of these slightly larger falls for younger adolescents may be amplified if, as has been suggested by recent literature (e.g. Fuhmann et al. 2015; Anderson, 2021), this is a period of particular developmental sensitivity. Within cohorts, implications for inequalities appear more ambiguous. While the variance of certain investments increased (increasing inequality), this may be offset by time investments becoming less correlated with their past values during the pandemic. We also examine heterogeneity by a rich set of sociodemographic and economic characteristics. The overwhelming message here is that the huge drops experienced by every single subgroup we analyze dwarfs any differences between groups. We do see that children in households who experienced particularly severe economic shocks during COVID-19 saw particularly large falls in investments.

This paper contributes to a burgeoning literature on the impact of COVID-19 school closures on the educational experiences of children. Empirical work in lower-income countries (e.g. Ardington et al., 2021; Wolf et al., 2022; Akmal et al., 2020; King et al., 2021; Whizz Education, 2021; Kosaretsky, Zair-Bek, Kersha, & Zvyagintsev, 2021; Lichand et al., 2022; ASER Pakistan, 2021) and higher-income countries (e.g. Engzell et al., 2020; Cattani et al., 2021; Maldonado & De Witte, 2021) alike has found evidence of huge disruptions to children's learning. It is worth

noting that despite the fact that larger classes, sparser access to technology, lower and more unreliable connectivity, and less well-funded school systems may have led to more pronounced effects in lower income countries (World Bank, UNESCO and UNICEF, 2021), much of the empirical research on lower-income contexts has been limited by datasets which are small, cross-sectional, or highly unrepresentative. Our nationwide panel dataset allows us to paint a detailed and comprehensive picture of the educational impacts of COVID-19 in India.

In the context of India specifically, there are two studies that warrant particular mention. Both examine the impacts of COVID-19 on children's learning *outcomes*. First, the 2022 ASER (ASER, 2023) study surveyed the learning levels of 700,000 children across rural India and is able to compare these measures to those collected in the 2018 round. It finds that in 2022, children's reading levels had fallen below 2012 levels while their basic arithmetic had fallen below 2018 levels. Consistent with our findings that many households had stopped paying private school fees even as those schools were reopening, it finds a large movement of children from private into government schools. Second, Singh et al. (2023) examines a panel of 19,000 children in rural Tamil Nadu and document huge initial losses of around 0.7 of a standard deviation in math and 0.34 in language followed by a large but incomplete recovery of learning of two-thirds of the gap once schools reopened.

We view our examination of the patterns of educational *inputs* during COVID-19 as complementary to this work on *learning outcomes*. First, carefully documenting impacts on inputs can help understand the mechanisms behind impacts on both current and future learning outcomes. Second, shocks to educational inputs may have long-lasting impacts on future human capital over-and-above what is captured by measures of current human capital. This might be due to complex dynamics in the educational production function (e.g. Todd and Wolpin, 2007), or due to input shocks shaping future investment decisions of parents or schools over-and-above the feedback coming from the shock to learning outcomes (e.g. Berry et al., 2020). Third, we consider that the scale and scope of the panel data we use makes this study a useful complement to work on learning outcomes. The nationwide scope means we are able to examine geographic heterogeneity while the panel aspect of our data means we can study the evolution of investments for the same group of children. Our detailed information at both the individual and household-level allows us to test for heterogeneity across a broad range of categories, including age, gender, region, caste, and income. The panel nature of our data also allows us to map children's learning time losses to their pre-pandemic levels, and explore the impact of within-household shocks during the pandemic, such as parental job or income losses. We note, finally, that an important limitation of our study is that we do not have access to data after the end of 2021 which means that we cannot track how the same children transition once schools fully reopened.

This paper is structured as follows: Section 2 provides an overview of the impact of COVID-19 in India and the educational policy response; Section 3 describes our data; Sections 4 and 5 describe our findings on learning experiences and inequalities; Section 6 concludes.

## 2. COVID-19 and school closures in India

The first COVID-19 case in India was documented in Kerala on January 27th 2020 (Andrews et al., 2020). On 24th March 2020, in response to escalating case numbers, the Indian government ordered a national lockdown, mandating the closure of all schools and alternative educational institutions. Overall, 320 million learners were affected – the highest number of any country in the world (UNICEF, 2020).

States were given considerable discretion to design their own remote learning strategies, although most opted to follow the guidance issued by the National Council of Education and Training (NCERT). This initial guidance was based on the premise that “almost everyone owns a mobile” (NCERT, 2020a), and hence teachers were encouraged to distribute lessons via WhatsApp or, for children without reliable internet access,

<sup>5</sup> Figure from comparing the world population aged 0-14 with India's (2021 World Bank estimates). Data accessed from: <https://data.worldbank.org/indicator/SP.POP.0014.TO?locations=IN-1W>.

<sup>6</sup> We only have time use data for children aged 12 or over.

via SMS messages or phone calls. To reach children without access to phones, NCERT also started telecasting two-hour long lessons for different grades throughout the day on its official TV channel (van Capelle et al., 2020). Radio-based instruction was generally eschewed, due to low rates of radio ownership in India.

In August 2020, the Ministry of Education and NCERT released a new set of learning guidelines which recognized the need for different delivery methods for children with less access to technology (NCERT, 2020b). However, schools remained closed, in contrast to the phased reopenings implemented in many parts of the world (UNESCO, 2021). It was not until October 2020 that the federal government gave states permission to reopen primary and secondary schools, although it continued to specify distance learning as the preferred mode of teaching (Government of India, 2020). Most states continued with distance learning and, by January 2021, schools still remained closed to all year groups in half of Indian states (Education World, 2021). Past research has shown that the stringency of states' school closures was positively correlated with the stringency of other covid-control measures, such as workplace closures and the cancelation of public events (Nagesh et al., 2022). Variation between states' stringency appears related both to the severity of the pandemic locally and to the political considerations, for instance, many states observed upticks in restrictions during election periods (Nagesh et al., 2022).

Gradual reopenings were abruptly reversed in April 2021, when India experienced an unprecedented wave of COVID infections and deaths (Anand et al., 2021). From July 2021, partial reopenings resumed, although with considerable variation between states. By October 2021, schools were only fully open in around half of states, with all states operating some form of social distancing protocols such as mask wearing, classroom caps, and year group rotations throughout the week. The phased reopening was once again reversed in January 2022, when some states reclosed their schools in response to the omicron variant. Between March 2020 and March 2022, schools in India were fully or partially closed for 82/104 weeks— the joint-second longest duration of any country in the world (UNESCO, 2021). In Section 4.3, we make use of statewise variation in the timing of these reopenings to explore their impacts on investments.

### 3. Data

To examine children's educational experiences, we use a unique thrice-yearly panel of 236,000 Indian households collected by the Centre for Monitoring the Indian Economy (CMIE). Beginning in 2014, the CMIE panel is selected with the aim of being representative of the Indian population when used with the appropriate sampling weights, which we use in all analysis.<sup>7</sup> While there are ongoing debates about whether the CMIE sample is biased towards richer households (Dreze and Somanchi, 2021; CMIE, 2021),<sup>8</sup> we consider the immense coverage and panel nature of the dataset make it a valuable resource for learning about children's experiences during the pandemic. Nevertheless, we stop short of interpreting our results as perfectly representative of Indian children's experiences.

The CMIE survey contains detailed information on individual demographics, time use, household asset ownership, income, and expenditure. Data collection continued during the pandemic, as the thrice-yearly face-to-face household surveys were replaced by telephone surveys, which

retained the full set of questions. This continuity of data collection with the same panel of households provides real-time insights into the learning experiences of children during COVID-19, avoiding the difficulties associated with missing data and data based on recall (Bell et al., 2019).

To paint a picture of children's learning experiences during COVID-19, it is important to understand the nature of attrition throughout the pandemic, since selective attrition could produce biased and misleading estimates. Due to the logistical challenges of transitioning to phone surveys,<sup>9</sup> CMIE randomly excluded around 24 % of households from being targeted for the survey during the COVID-19 waves. Since these households were excluded at random, this should not affect the representativeness of the data collected during these waves. Theoretically more worrying are the 10 % of households that were uncontactable or refused to participate between March 2020 and August 2021. Reassuringly, this figure is only slightly higher than the pre-pandemic benchmark of 8 %, although concerns about selection would still arise if the pandemic changed the composition of households that attrited.

To empirically assess this, we compare the observable characteristics of households in our sample before COVID-19 with those in the sample during COVID-19. As Table A1 shows, both samples look similar in terms of the location of respondents, their education, employment, income, and household structure. As a robustness check, we also re-estimate our main results using the inverse-probability of attriting from the sample based on key observable characteristics as weights, which are combined with the survey weights provided by CMIE.<sup>10</sup> We also re-estimate our results on a fully balanced sample for whom we have data for each wave between September 2019 and December 2021. In all cases, our results do not substantially differ, suggesting our pandemic sample was not fundamentally different from the original. Figs. A9 through A12 show this robustness analysis; we see no substantive differences between these and our main results.

To explore the impact of COVID-19 on the learning experiences of Indian school children, we examine how their learning time and educational expenditures evolved throughout the pandemic. Both the quantity of learning time and the quantity and quality of material resources have been shown to promote learning (Attanasio et al., 2020a).

To measure learning time, we use information from CMIE's time use module, which asks how individual members spent a representative day in the last week. The time use module was introduced in September 2019, which gives us over 5 months of data before the March 2020 school closures. We focus on the education category, which captures all time spent on learning-related activities. Individual time use is asked about for all members of a household over the age of 12, and hence our learning time estimates are reflective of the experiences of most upper-primary-school, secondary-school and upper-secondary school children.<sup>11</sup> We note that for a small proportion of individuals, all or the vast majority of time is inputted as "other". We consider these to be inattentive cases where the timeuse data is likely unreliable. Thus, in each wave, we drop observations where the time coded as "other" is above the 90th percentile (which corresponds to roughly 16/24 or more hours recorded as "other").<sup>12</sup>

<sup>9</sup> When the first lockdown was announced, CMIE initially decided that only senior team members were qualified enough to conduct phone interviews, effectively reducing the enumerator team from over 200 to 70.

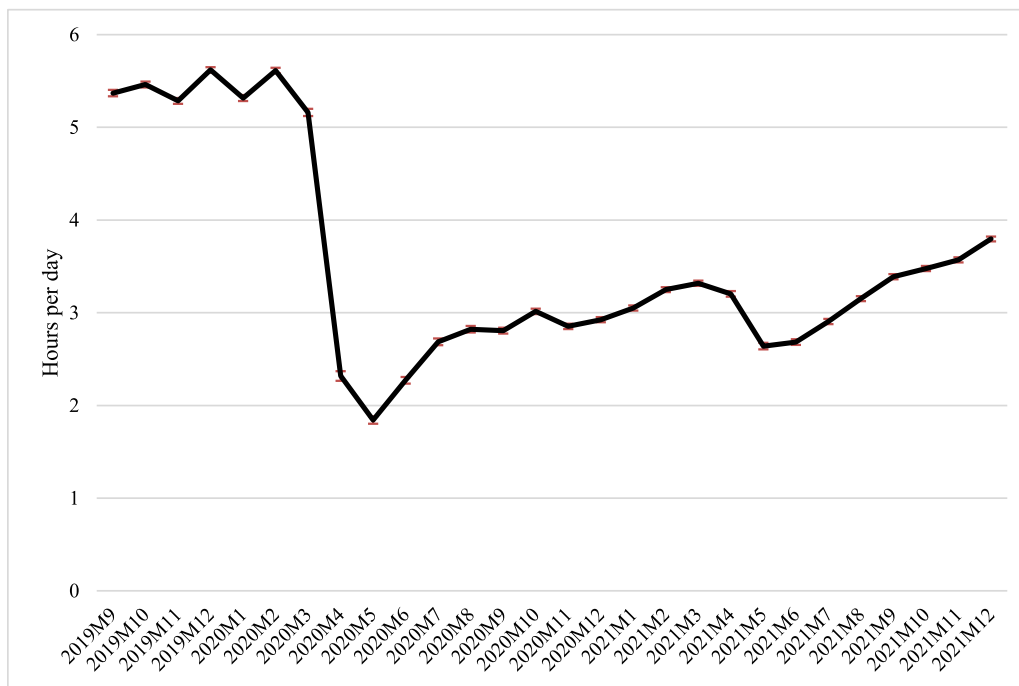
<sup>10</sup> Each of our main specifications uses the CMIE survey weights, which account for the fact that some areas of India (e.g. Andaman and Nicobar Islands) cannot be surveyed for practical reasons (Vyas, 2020b).

<sup>11</sup> Age 12 roughly corresponds to 6<sup>th</sup> standard, which is the second year of upper-primary school.

<sup>12</sup> We drop the same proportion of observations in each round since we consider it plausible that the pandemic resulted in a real increase in the time appropriately categorized as "other". We note that only the absolute levels and not any of the covid-19 related proportional impacts are sensitive to this choice. Descriptives without this trimming can be found in the earlier working paper version.

<sup>7</sup> Households were randomly selected for inclusion in the sample from within strata. See Vyas (2020a) and CMIE (2021) for more details of the stratification and sampling process.

<sup>8</sup> Dreze and Somanchi argue that CMIE's approach over-samples houses on main roads/streets, and hence likely over-represents richer households. While CMIE argue that this is based on a misunderstanding of their sampling strategy, they have agreed to examine the geographic distribution of its sample to more thoroughly test this.



**Fig. 1.** Average daily learning time, September 2019 – December 2021.

Notes: Figure plots unsmoothed month-by-month average learning time, alongside 95 % confidence intervals, for 12–18-year old's across all states. Estimated using CMIE survey weights.

To measure educational expenditures, we focus on four major areas: expenditure on school fees, books and stationery, private tuition fees, and other educational expenditure.<sup>13</sup> We then additionally consider expenditure on internet and cell fees which, although not necessarily related to education, could be indicative of spending to aid children's access to remote learning

#### 4. Learning experiences

##### 4.1. Learning time

Fig. 1 plots average daily learning time for children between 12 and 18, regardless of whether or not they were formally enrolled in and attending school. Before the first lockdown was announced, children spent an average of 5.5 h per day on learning activities – broadly equivalent to a school day, once breaks and registration are accounted for. However, in April and May 2020, this fell to around 2 h a day. This amounts to a fall of over 60 %. Critically, average learning time barely recovered during the period our data covers, increasing to 3 h 20 min a day by early 2021 but then dipping again with the onset of the second wave. We explore the persistence of this fall over this period more in Section 4.3 where we disaggregate average learning time by school reopening experiences. Appendix Fig. A2 suggests that children's time spent in doing domestic work, indoor entertainment and sports increased during the pandemic.

This fall in aggregate learning time was driven by changes to both the intensive and extensive margin. Amongst the children registering some learning time, average hours fell from 5.9 h pre-pandemic to 3.7 h per day. The percentage of children doing 0 h of learning also rose from 8.7 % to 15.9 %. These children have likely endured substantial learning losses and some may have disengaged from schooling entirely, raising concerns about increased student dropout. We do not detect a noticeable

increase in the number of school-age children listed as out-of-school in the CMIE data. This is consistent with the finding of the ASER 2022 (ASER, 2023) survey although we note that the CMIE data we use perhaps stop too early to give a definitive answer on this question since mandatory in-person attendance had not yet resumed at the end of our analysis period.

Overall, then, this fall represents an enormous amount of lost learning time for India's approximately 380 million children and adolescents of school age. Against a pre-covid benchmark of 5.5 h of learning time a day, this fall amounts to 1627 lost hours which is equivalent to 296 5.5 h days. It is notable that the magnitude and persistence of the fall appears to far outstrip what has been observed in richer countries.<sup>14</sup> What's more, these patterns stand in contrast to patterns observed in other spheres of life in India. Data from Google mobility trends in India show that, compared to a February 2020 benchmark, the number of people geolocated in workplaces fell by 60 % in April 2020 following the first national lockdown (see Fig. A3). However, unlike with learning time, this trend recovered rapidly, almost returning to pre-pandemic levels before the second wave.

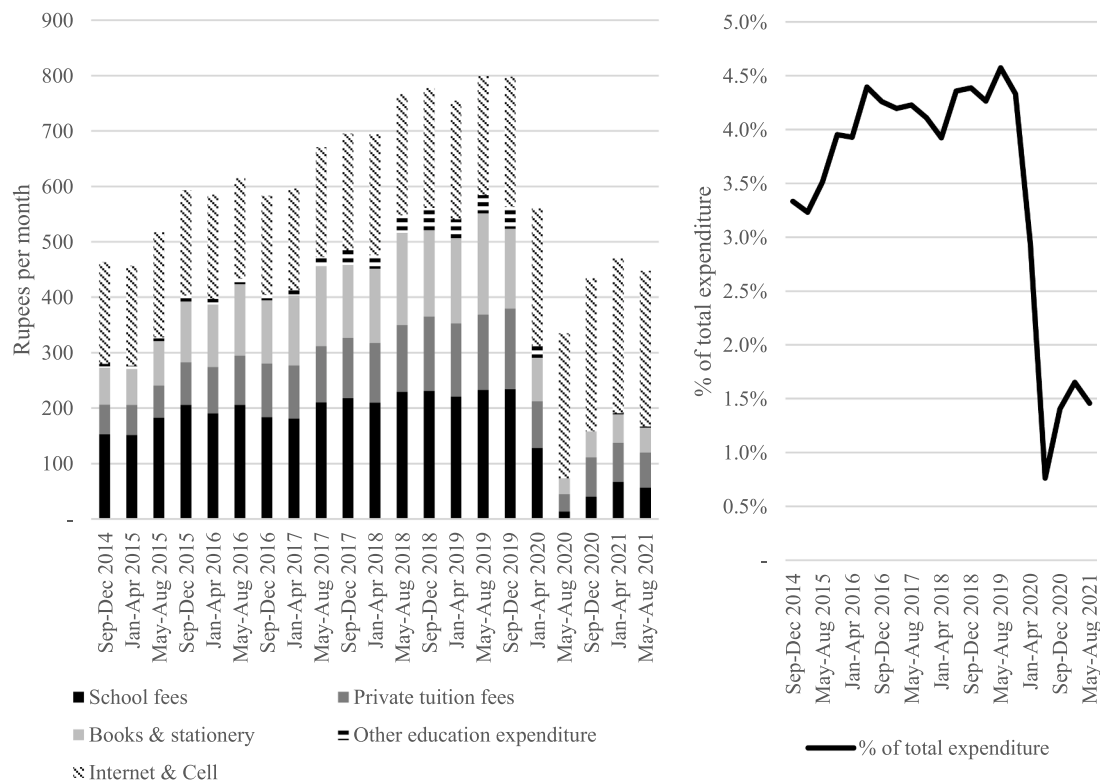
##### 4.2. Learning resources

In addition to large falls in the quantity of time children spent learning, the pandemic reshaped how children could spend their learning time. Children lost access to all classroom-based learning activities and the educational resources that schools provide, such as stationery and textbooks. They therefore became reliant on educational resources within their own home, as well as technology devices such as

<sup>13</sup> Other educational expenditure is a 'catch-all' category, that captures everything otherwise related to learning activities.

<sup>14</sup> For instance, in the UK – one of the few countries with comparable pre- and post-pandemic learning time estimates – children spent around 6 hours per day on learning activities before the pandemic, broadly in line with their Indian counterparts. However, in April and May 2020, this fell to 4.5 hours – far higher than in India – and, crucially, by the time of the second lockdown in January 2021, learning time had almost recovered to pre-pandemic levels (Cattan et al., 2021).





**Fig. 2.** Education expenditure.

Notes: Left figure plots average monthly educational expenditure by CMIE wave, broken down by category. Right figure plots average monthly education expenditure (excluding internet and cell) as a percentage of the household's total monthly expenditure. Sample is all households with a school-aged child (6–18). Estimated using CMIE survey weights.

mobiles and tablets to access newly-introduced digital modes of instruction. As a result, the pandemic could have led to an increase in private educational expenditures from parents, as they sought to compensate for the resources children had lost through not being in school (Jang & Yum, 2021). On the other hand, both perceived complementarities between learning time and materials and the huge financial shocks experienced by many households may have reduced educational expenditures, with likely consequences on the quality of time that children spent learning.

To examine this, the left-hand graph in Fig. 2 plots, month by month, average education expenditure for households with school-aged children (aged 6–18). It records our four major areas: expenditure on school fees, books and stationery, private tuition fees, and other educational expenditure. It then additionally plots expenditure on internet and cell fees. To assess the relative contribution, Fig. 3b also plots total educational expenditures as a proportion of overall household expenditures.<sup>15</sup>

As Fig. 3 shows, Indian households with school-aged children substituted away from spending on their education during the pandemic, in both absolute and relative terms. We see a very stark decline in school fee payments which further analysis suggests is almost entirely due to households paying zero fees during the closures. In Fig. A6, we see that while in January 2020 31 % of households with a child aged 6–18 paid positive school fees, this had dropped to just 2 % by April 2020 and remained below 8 % throughout the sample period. This is consistent with findings by ASER (2023) of a movement of children away from private schools and into government schools. It is striking to note that expenditure on other inputs also saw a drastic decline. For

example, spending on textbooks and stationery fell by 84 % between September–December 2019 and September–December 2020. As a fraction of total household expenditures, average educational expenditure fell from 4.6 % to 0.8 % over the same period. Expenditure on internet and mobile data rose during the pandemic – which could represent an alternative channel through which parents supported their children's education (Bacher-Hicks et al., 2021) – though it is not possible to disaggregate this category into the type of internet usage to confirm this.

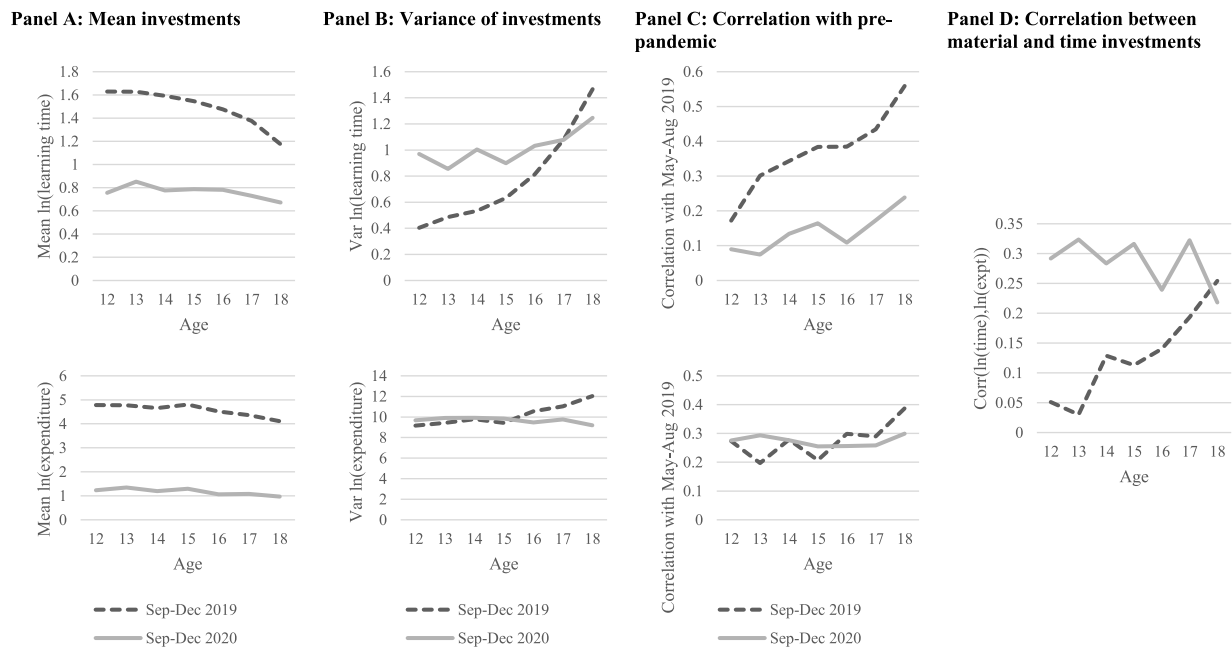
These trends help shed light on the patterns documented in Fig. 1. A key reason why learning time failed to recover may have been that – unlike in higher-income contexts – more financially constrained parents were less able to provide the inputs necessary to help their children adapt to remote learning. Beyond this, Fig. 3 provides further evidence that the quality – not only the quantity – of children's learning time was likely severely affected.<sup>16</sup>

#### 4.3. Variation by school reopening policies

We next explore how school reopening policies may have affected educational inputs. In particular, we use state-by-month measurements

<sup>15</sup> To supplement this, Figure A4 and A5 show how average household income and the average composition of household expenditure changed during the pandemic, to capture what households transitioned towards.

<sup>16</sup> Given the Indian government's focus on digital-based learning during COVID-19, a key consideration is whether students had access to the technologies that would enable this. This is documented extensively in the Annual Status of Education Report (ASER) 2021: a survey of children aged between 3–16 in rural areas which, since COVID, has focused extensively on technology access. In 2021, only 68% of children had access to a smartphone at home, and only 27% had it always available. Lack of available hardware is compounded by a lack of internet access: in June 2020, a survey by the Indian telecom authority estimated that the number of internet subscribers per 100 of the population was just 55 – considerably lower than other large developing countries like Indonesia and Nigeria (World Bank, 2021d).



**Fig. 3.** Comparison of moments of log investments, September-December 2019 and September-December 2020.

Notes: Figure compares various moments between Sept-Dec 2019 (in black, dashed) and Sept-Dec 2020 (in grey, solid). Panel A plots mean (log) investments, Panel B plots the variance of log investments and Panel C plots the correlation of investments with investments in May-August 2019. Top row plots log learning time (in hours) while the bottom line plots log educational expenditure (in rupees). In Panel C, we restrict the sample to households with 2 pre-COVID observations. For the expenditure figures, we report education expenditure in households including children of ages 12–18. Panel D plots the correlation between logged learning time and logged expenditure. Estimated using CMIE survey weights

of school closure policy as recorded by the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). In this data there are four categories of policies: (i) require closing all levels, (ii) require closing (only some levels or categories, eg just high school, or just public schools), (iii) *recommend* closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations, and (iv) No measures. Table 1 shows the results of regressing our measures of educational inputs on categories (ii) through (iv) with schools being fully closed being the omitted category. We run these regressions just on observations from March 2020 onwards (i.e. the covid period).

Beginning with learning time, against an average of 3 h of learning per day for children when schools were completely closed, Column (1) of Panel A shows that relaxing restrictions was associated with an increase in learning time, which reached 4.1 h per day when schools were fully reopened. However, column (2) shows that some of this increase appears to be simply due to time effects: learning time increased modestly in all states, even those that didn't reopen schools. Moreover, column (3) which adds state fixed effects suggests that some of the correlation between (full) reopenings and learning time is driven by it being the states that already had higher learning being the ones that were most likely to (fully) reopen. Once we have accounted for state and month effects, the results suggest that within this timespan, periods of full reopenings (which were often brief and subsequently reversed) were associated with only a half an hour increase in children's learning time. Partial reopenings appear not to have shifted learning time at all. Appendix Fig. A7 plots the timeseries in average learning times by state, superimposed onto temporal variation in closure policies and suggests that learning time may have been more responsive to school reopenings in some states (e.g. Tamil Nadu) than others (e.g. Madhya Pradesh).

Moving onto expenditures, Panel B repeats the same regressions using, respectively, indicators of whether households paid any school fees and total monthly educational expenditures. Since we have this data for a shorter timespan, we see very few observations with no measures in place and thus we combined categories (iii) and (iv). The results show

that both the proportion of households paying fees and total educational expenditures increase upon (partial) school reopenings. The estimates for category (iv), recommended closures or open with significant operational differences, is robust to including state and month effects and suggests that this policy was associated with a 5.3 percentage point increase in the proportion of households paying school fees and an Rs. 81 increase in educational expenditures. These increases are fairly sizeable relative to a mean of 3.7 % of households paying fees and a mean expenditure of Rs. 123 when schools were fully closed during the covid period.

Overall, then, these results paint a mixed picture of the impacts of school re-openings during this timeframe. We see statistically significant movements in inputs but these are modest in size, especially for learning time. When they reopened, most schools implemented protocols to facilitate social distancing. For example, in Delhi and Uttar Pradesh, schools were able to reopen with a 50 % classroom cap, causing many to operate a shift system with a shortened school day (The Economic Times, 2021). This may have been significantly disruptive for children, while at the same time crowding out their school's ability to provide adequate remote instruction. Given the return to school was voluntary, many parents may have also opted to not send their children back to school due to ongoing fears about COVID-19.<sup>17</sup> Though our dataset is not able to assess this (since we do not observe whether learning time took place at home or in school), a parliamentary standing committee meeting in January 2022 revealed school attendance of just 50 % in Assam and 40 % in Uttar Pradesh after their schools reopened (Indian Express, 2022).

On the subject of statewide heterogeneity more broadly, Appendix Fig. A8 plots statewide falls in educational investments against COVID-19 death rates. We find evidence that those states with higher

<sup>17</sup> Several journalistic accounts have cited ongoing anxiety about the pandemic as a major barrier preventing parents from sending their children back to school (The Print 2021; Indian Express 2021).

**Table 1**

Variation in children's learning time (in hours) by state-level school closure policies.

	Panel A: Learning time (hours)		
	(1)	(2)	(3)
Required closures (all levels), omitted category	0 (.)	0 (.)	0 (.)
Required closures (some levels only)	0.191*** (0.0122)	-0.140*** (0.0176)	0.0234 (0.0163)
Recommended closures or open with significant operational differences	0.614*** (0.0215)	0.0379 (0.0282)	0.00403 (0.0275)
No measures	1.115*** (0.0245)	0.660*** (0.0302)	0.417*** (0.0338)
Month Fixed Effects		Y	Y
State Fixed Effects			Y
Observations	327247	327247	327247
Mean when fully closed	2.98	2.98	2.98

	Panel B Paying positive school fees		Monthly educational expenditure (Rs.)	
	(1)	(2)	(3)	(4)
Required closures (all levels), omitted category	0 (.)	0 (.)	0 (.)	0 (.)
Required closures (some levels only)	0.0353*** (0.00145)	0.0150*** (0.00109)	46.41*** (1.875)	15.28*** (1.786)
Recommended closures or open with significant operational differences	0.0634*** (0.00617)	0.0529*** (0.00453)	85.79*** (8.532)	81.28*** (7.507)
Month Fixed Effects		Y		Y
State Fixed Effects		Y		Y
Observations	903035	903035	878997	878997
Mean when fully closed	0.036	0.036	122.6	122.6

Notes: Table presents OLS coefficients for regressing educational inputs on contemporaneous state-specific school opening policies. Standard errors in parentheses, clustered at the household level. Regressions use sample weights. Sample for panel A is all children aged 12–18. Sample for panel B is all households with a school-aged child (6–18).

recorded death rates also had, on average, higher falls in educational investments. We interpret this finding with caution: it is difficult to say whether this is due to the real burden of disease being related to reductions in educational investments or whether, alternatively, recorded death rates are heavily related to institutional capacity which could have affected the severity of lockdowns.

## 5. Heterogeneities and implications for human capital

In this section, we examine how the impacts of COVID-19 on educational investments varied across children. We consider inequalities within and between cohorts, as well as between children from different demographic and socioeconomic backgrounds.

In addition to examining heterogeneity in the levels of educational investments per se, we also explore, tentatively, the longer-run implications of these patterns for inequalities in human capital. Given the dynamics inherent in learning and skill formation, the impact of COVID-19 on both the average level of and inequalities in adult skills is likely to depend on the interaction between pre-pandemic investments and investments during COVID-19. To this end, we use a simple Cobb-Douglas model of human capital formation to help us understand how children's different experiences during COVID-19 might affect their adult skills. Rather than providing a rigorous account of the human capital production process, we view this as a helpful framework to guide our thinking. Structural estimates suggest that a Cobb-Douglas production function is a reasonable approximation of the process of skill accumulation (Agostinelli & Wiswall, 2016; Attanasio et al., 2020a; Attanasio et al., 2020b). In particular, we consider a model in which children's skills in each period are a function of past skills and time and material

investments in the previous period, combined through a Cobb-Douglas aggregator. We assume that child  $i$ 's skills at age  $a + 1$  ( $Y_{i,a+1}$ ) are determined by their skills in the previous period ( $Y_{i,a}$ ), their time ( $T_{i,a}$ ) and material investments ( $M_{i,a}$ ) in the previous period, and an idiosyncratic mean-zero error term ( $e^{\epsilon_{i,a}}$ ). Formally, we assume:

$$Y_{i,a+1} = Y_{i,a}^{\alpha} M_{i,a}^{\beta} T_{i,a}^{\gamma} e^{\epsilon_{i,a}} \quad (1)$$

$\alpha$  describes the persistence of human capital, and  $\beta$  and  $\gamma$  describe the sensitivity to material and time investments. We assume diminishing returns to all inputs and assume  $\alpha$ ,  $\beta$  and  $\gamma$  are all less than 1. To capture the idea of sensitive periods, we allow  $\beta$  and  $\gamma$  to depend on the age of the child ( $a$ ). We assume that school age begins at  $a = 0$  and continues until  $a = A$ .

This model suggests that adult skills can be approximated by the sum of *logged* investments across the whole of childhood, weighted by the productivity of these investments at different ages and the persistence of skills across time:

$$\ln Y_{i,A} = \alpha^A \ln Y_{i,0} + \sum_{a=0}^{A-1} \alpha^{A-1-a} (\beta_a \ln M_{i,a} + \gamma_a \ln T_{i,a} + \epsilon_{i,a}) \quad (2)$$

For simplicity, and because our focus is on the role of changing investments, we assume that both  $Y_{i,0}$  and  $\forall_a e^{\epsilon_{i,a}}$  are independent of each other and the entire stream of investments.

Under this independence assumption, it follows that:

$$E(\ln Y_{i,A}) = \alpha^A E(\ln Y_{i,0}) + \sum_{a=0}^{A-1} \alpha^{A-1-a} (\beta_a E(\ln M_{i,a}) + \gamma_a E(\ln T_{i,a})) \quad (3)$$

$$\begin{aligned}
\text{Var}(\ln Y_{i,A}) &= \alpha^{2A} \text{Var}(\ln Y_{i,0}) + \sum_{d=0}^{A-1} \alpha^{2A-2-2d} (\beta_d^2 \text{Var}(\ln M_{i,d}) + \gamma_d^2 \text{Var}(\ln T_{i,d})) \\
&+ \sum_{d=0}^{A-1} \alpha^{2A-2-2d} \text{Var}(\varepsilon_{i,d}) \\
&+ \sum_{d=0}^{A-1} \sum_{d'=0, d' \neq d}^{A-1} \alpha^{2A-2-d-d'} \text{Cov}(\beta_d \ln M_{i,d} + \gamma_d \ln T_{i,d}, \beta_{d'} \ln M_{i,d'} + \gamma_{d'} \ln T_{i,d'})
\end{aligned} \tag{4}$$

We use this framework to guide our thinking about how changes in the distribution of educational investments during COVID-19 might change both the mean and dispersion of the adult skills of affected children. We consider how each of these moments might have changed relative to a counter-factual of no COVID-19 shock. For simplicity, we assume COVID-19 covers a single period in the human capital accumulation process. We also assume that all future investments after COVID-19 stay exactly the same, which abstracts from future catch-up policies or compensatory investments from parents.

We start by considering between-cohort inequalities, exploring how patterns differed by the age that children were when COVID-19 hit, and consider how these differences might feed through to differences in adult skills. We then turn to within-cohort inequalities by examining the dispersion of investments within each cohort, and the extent to which time and material investments during COVID-19 are correlated with one another and with pre-COVID investments.

### 5.1. Inequalities between cohorts

If we define cohorts by the age they are when COVID-19 hits, then for the cohort that is age  $a = c$ , the eventual skill loss (relative to the counterfactual  $\bar{Y}$ ) is:

$$\begin{aligned}
\Delta E(\ln Y_{A,i,c}) &\equiv E(\ln Y_{A,i,c}) - E(\ln \bar{Y}_{A,i,c}) \\
&= \alpha^{A-1-c} (\beta_c \Delta E(\ln M_{i,c}) + \gamma_c \Delta E(\ln T_{i,c}))
\end{aligned} \tag{5}$$

If we take the pre-covid period as a counterfactual for the covid period in the absence of the pandemic, Panel A of Fig. 3 suggests that  $\Delta E(\ln M_{i,c}) < 0, \forall c$  and  $\Delta E(\ln T_{i,c}) < 0, \forall c$ : i.e. both average time and average material investments fell during COVID-19 for all cohorts. This immediately implies that every cohort of school age during COVID-19 will have lower adult skills than under the counterfactual.

This expression additionally implies that the impacts on a cohort  $c$ 's average adult skills will be particularly pronounced if: (i) average shocks to their investments were larger (i.e. if  $\Delta E(\ln M_{i,c})$  or  $\Delta E(\ln T_{i,c})$  is particularly large); (2) COVID-19 occurred at a more critical time in their lives (i.e. if  $\beta_c$  and/or  $\gamma_c$  is particularly large). The degree of persistence in the process of human capital formation ( $\alpha$ ) will determine the degree to which impacts on cohorts who were young during COVID-19 will persist to later ages.

Panel A of Fig. 4 plots mean logged investments by age across two periods: September–December 2019 (before COVID-19) and September–December 2020 (during COVID-19). We see that, compared to children of their same age one year earlier, younger children experienced a slightly larger fall in learning time, although the magnitude of these differences are small relative to the size of the falls experienced by all age cohorts. There is no obvious heterogeneity by age in educational expenditures. The extent to which this larger drop in learning time for cohorts aged 12–14 will translate into particular losses in adult skills for these cohorts will depend on how sensitive these periods are and the

persistence of the process of learning. There is growing evidence that, in addition to early childhood, early adolescence is also a critical period where human capital development is highly sensitive to investments and to adversity (Furhmann et al., 2015; Anderson, 2021).<sup>18</sup> This might suggest that the eventual learning harms to those who were early adolescents during the pandemic could be particularly severe. However, we note that we cannot be certain about how the losses to learning time and material resources that we document map into losses in the specific types of inputs that adolescent development is most sensitive too. Moreover, we note that the presence of other social and institutional factors, such as graduating into poor labor market conditions, may result in particular disadvantages for older cohorts too (Oreopoulos et al., 2012).

It remains unknown what the gradients in Panel A look like at younger ages. On the one hand, younger children may require fewer specialist materials for their learning and hence might have made more progress at home. On the other hand, lacking basic literacy skills, younger children may have struggled more with self-study. This would resonate with studies elsewhere, which have found higher degrees of skill loss during COVID-19 amongst the early grades (ASER Pakistan, 2021; Lichand et al., 2022; Hevia et al., 2022; Whizz Education, 2021).

### 5.2. Inequalities within cohorts

We now turn our attention to how COVID-19 might have affected inequalities in education and skills within cohorts. Within cohorts, our framework suggests that COVID-19's impact on the dispersion of log adults skills in cohort  $c$  is:

$$\begin{aligned}
\Delta \text{Var}(\ln Y_{i,A,c}) &= \alpha^{2A-2-2c} (\beta_c^2 \Delta \text{Var}(\ln M_{i,c}) + \gamma_c^2 \Delta \text{Var}(\ln T_{i,c})) \\
&+ \sum_{d=0, d \neq c}^{A-1} \alpha^{2A-2-d-c} \Delta \text{Cov}(\beta_d \ln M_{i,d} + \gamma_d \ln T_{i,d}, \beta_c \ln M_{i,c} + \gamma_c \ln T_{i,c})
\end{aligned} \tag{6}$$

This expression suggests that, ceteris paribus, that an increase in any of the following would cause an increase in within-cohort inequality: (i) the variance of logged investments; (ii) the correlation of logged investments with their past (or future) values; and (iii) the covariance between logged investments. Panels B through D in Fig. 3 plots each of these moments, disaggregated by age.

For younger children (12–14 when COVID-19 hit) there was an increase in the overall variance of their educational investments (particularly time investments) during the pandemic (Panel B), as well as their time and material investments becoming more correlated (panel D). Other things being equal, these changes, imply an increase in the dispersion of final educational attainment within our framework. On the other hand, Panel C indicates that time investments during the pandemic became less correlated with their past values. If investments are partially substitutable between periods, this will put downward pressure on the variance of adult skills, since it reduces the extent to which the COVID-19 shocks were compounding pre-existing inequalities. For older

<sup>18</sup> In India, centralized public exams are sat in Class 10 and Class 12, when children are aged 16 and 18 (assuming no delayed entry or repetition).



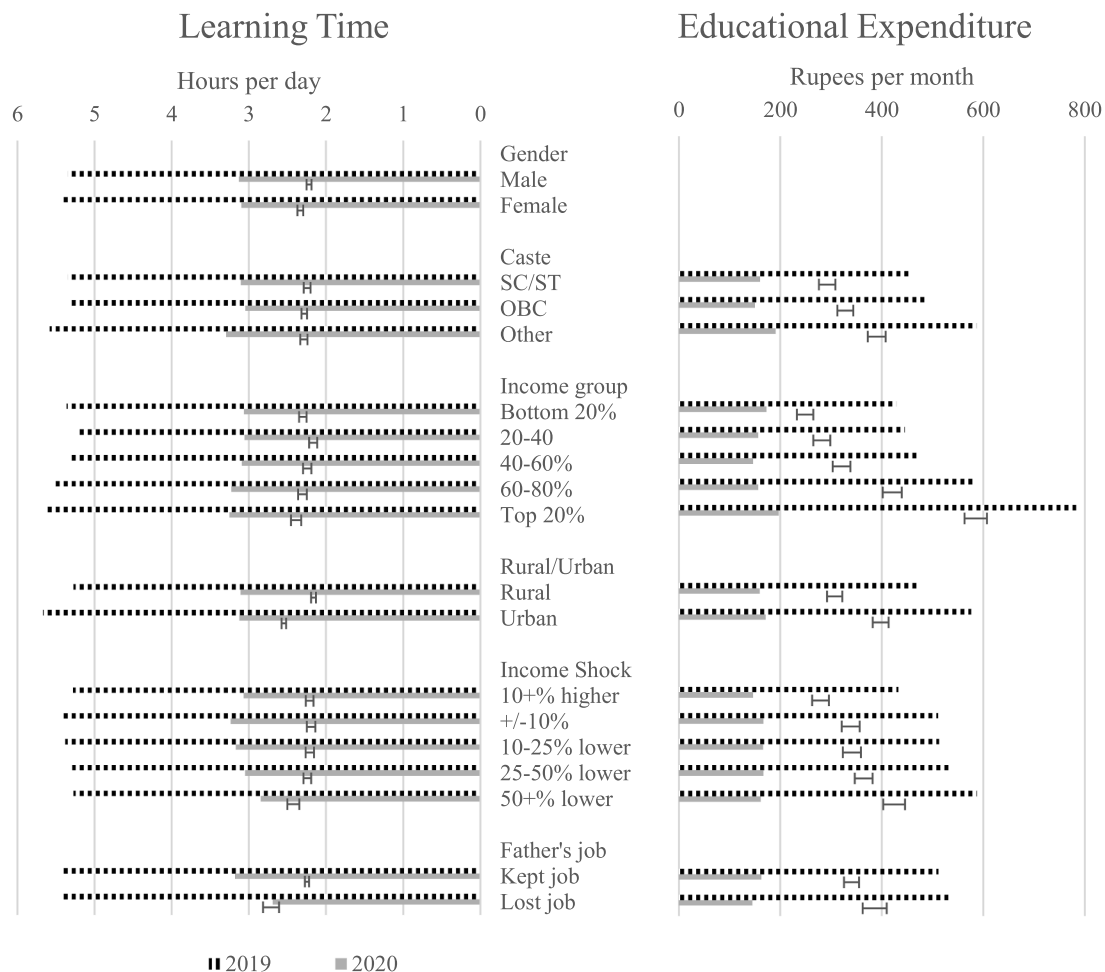


Fig. 4. Heterogeneity by gender, socioeconomic status, and COVID-19 economic shocks.

Notes: Figure shows differences in daily learning time and monthly household education expenditure between September 2019–February 2020 and March 2020–December 2021. 95 % confidence intervals for the difference in averages time and expenditure for each category displayed underneath. Learning time sample is 12–18-year olds across all states; expenditure sample is all households with school-age children (6–18). Estimated using CMIE survey weights.

children (16–18), the variance of educational inputs decreased during COVID-19 (Panel B) which, together with investments becoming less correlated with their past values (Panel C) push in the direction of decreasing the within-cohort dispersion of adult skills. Overall, the lack of unanimity in the direction of these effects makes the pandemic's effect on within-cohort inequalities ambiguous.

### 5.3. Inequalities between demographic and socioeconomic groups

Fig. 4 looks at how average time and material investments changed during the pandemic for children from a range of different demographic and socioeconomic backgrounds, including by gender, caste, household income quintile, whether the household is rural or urban, and by economic shocks faced by the household during COVID-19. We compare investments between September 2019–February 2020 (pre-school closures) to those recorded March 2020–December 2021.

The most striking message from Fig. 4 is that all subgroups experienced enormous falls in both time and material investments. Every single subgroup we analyze experienced an average fall in learning time of between 42 and 50 %, and an average fall in educational expenditures of between 60 and 75 %. We find that all subgroups were doing an average of fewer than 3.25 h per day of learning in autumn 2020, and all subgroups reported household-level monthly educational expenditures of less than 200 rupees. This is around one third of the unconditional average from 2019.

Digging into the heterogeneous patterns in more detail, we see that girls and boys appear to have very similar hours of learning time both before and during the pandemic. This pattern is reasonably similar across states (Appendix Table A3). This is consistent with recent data showing that school enrolment rates of girls and boys have nearly converged in India (ASER India, 2021). While there is strong evidence of son preference in India – with male children often receiving superior parental investments (e.g. Barcellos et al., 2014) – the time children spent on learning may have come at little opportunity cost to parents, and hence this preference was less likely to manifest itself. In addition, norms prohibiting girls from playing in public spaces (Andrew et al., 2022) may have meant girls spent more time at home during the pandemic, making learning activities relatively more appealing. This might have been offset by their higher responsibility for household chores, although we do not find evidence that the gender gap in domestic chores amongst 12–18-year old's significantly increased after March 2020. Unfortunately, since we only have household-level expenditure data we cannot analyze how per-child educational expenditures differed by children's gender.

Turning to caste, we see that children from more disadvantaged caste groups (SC/ST and OBC) recorded fewer hours of learning time before the pandemic and fewer hours during it than children from more advantaged caste groups with their absolute fall in learning hours being fairly similar. Children from more advantaged castes have higher household educational expenditures both before and during COVID-19.

More advantaged castes faced higher absolute (and logged) falls than more disadvantaged castes.

We see a similar picture for heterogeneity by pre-COVID income. Children from more advantaged households were recording more hours of learning time both before the pandemic and during it. Children from the poorest households saw slightly larger absolute falls than those from the middle of the income distribution. Those from the top of the income distribution saw the largest falls (in levels and logs). Turning to educational expenditures, richer households spent far more (almost double) on educational expenditures before the pandemic. These households saw the largest falls in both levels and logs so that expenditures during COVID-19 look remarkably similar between income quintiles.

Finally, the last two categories show that children from household's that suffered greater economic shocks during the pandemic saw greater absolute falls in both inputs. Children from households that suffered a larger relative income fall during COVID<sup>19</sup> lost out on more learning time and education expenditure, while children whose father lost their job during the pandemic also lost more of both inputs, despite similar pre-pandemic levels. These events may have strained family relationships (Abiona & Koppensteiner, 2018) or parental mental health (Rohde et al., 2016), both of which may have created a home environment un conducive to home learning. The fact that greater economic shocks led to reduced educational investments is important, since it may represent a key mechanism through which COVID-19 will have lasting, intergenerational consequences.

## 6. Conclusions

This paper examines the educational impacts of COVID-19 in India using large-scale, nationwide panel data. We find sharp decreases in children's learning time and educational expenditure during the pandemic, with learning time falling to less than 2 h a day immediately after the first school closures were announced. These figures had only slightly recovered by the end of 2021, despite the phased school reopenings that took place in the latter half of 2021. Based on our monthly estimates during COVID-19, and a pre-pandemic benchmark of 5.5 h of learning per day, we estimate that, as of December 2021, children have lost 1627 h (296 days of 5.5 h) of learning time on average. This likely understates the true extent of the loss of quality learning time, given that the transition to distance learning and the sharp decreases in household educational expenditure will have adversely affected the quality of this time. While some groups, such as those households who were hit particularly hard by the economic shock from covid, suffered even larger losses, the main findings from our heterogeneity analysis is that the magnitude of losses across all groups appear to dwarf variation across groups. We anticipate that the patterns of input losses we have documented with have long lasting implications for the education and life-chances of the affected cohorts for years and decades to come.

## CRedit authorship contribution statement

**Alison Andrew:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Adam Salisbury:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization.

## Data availability

The authors do not have permission to share data.

<sup>19</sup> To measure relative income shock, we take the percentage difference in average household income between March 2019 – February 2020 (i.e. before the first lockdown) and average income between March 2020 – February 2021.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.econedurev.2023.102478](https://doi.org/10.1016/j.econedurev.2023.102478).

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