Demand shocks and supply of schools: Insight from rainfall shocks in India

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Abstract

It has been well established in prior literature that rainfall shocks in agrarian economies result in negative household income shocks. These result in changes in demand for school education. This paper studies the effect of such demand shocks on supply of schools in a market with both private and public schools. Using an all India school level panel, we show that negative rainfall shocks increase the likelihood of private school closure but have no impact on public school closure. Entry of local government schools increases in response to shocks showing that these schools provide a buffer. We develop a simple model of a schooling market to interpret our results. To the best of our knowledge, this is the first study to document the impact of economic shocks on the education market. While not covering pandemic years our results shed light on possible changes in the schooling market due to the pandemic.

Keywords: Education; public schools; private schools; rainfall shocks; school supply

JEL Classification Numbers:H4, O2, I2

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1 Introduction

This paper examines the impact of negative economic shocks on the supply of schools in India. The Indian education market consists of both fee charging private schools, funded and managed privately, as well as public schools, which are funded and managed by the government. Public schools do not require significant out-of-pocket expenditure by households. Legally, private schools in India are required to be set up by charitable trusts or or other forms of non-profit organisations. Private schools, however, have come up with ways to get around this legal hurdle and there is considerable anecdotal evidence that these schools function like any profit making entity[1].

Public schools, on the other hand, are funded by the government and are not set up with the objective to earn profits. Given the ownership and management structure, this paper examines if private schools, which constitute 35% of total school supply, are vulnerable to economic shocks (specifically, negative income shocks to households) and, if public schools can provide a cushion against that vulnerability. Studying how supply of schools is likely to be affected by economic shocks can throw light on structure of education market. Additionally, from a policy perspective highlighting that economic shocks might cause disruption in education provision is important so that necessary mitigation strategies could be undertaken.

This paper uses rainfall shocks to capture negative economic shocks. Rainfall shocks in a rain-fed agrarian economy with poor irrigation infrastructure adversely affect agricultural yield impacting the livelihood of a large share of population. We study a reduced form relationship between rainfall shocks and supply of private schools as well as the response by public schools. Unlike public schools which are financed by the government, private school providers incur both fixed and running cost to setup and operate the school. As profit maximising agents, private schools cover this cost by setting the school fee (the 'price'). In the absence of access to formal credit markets(Kochar, 1997; Chaudhuri and Cherical, 2012), households choose whether to attend private school or public school not only based on the rate of return but also their current income and the school fee.

Thus, when a negative rainfall shock hits, it reduces rural household income, affecting the choice of school type. For some households, particularly those who are at the lower end of the income distribution, the income shock may make private schools unaffordable - after the profit maximising private school has responded optimally to the change in household income distribution. Existing work has shown that in years of rainfall shocks, children dropout of schools and join the labour market to cope up with the negative income shock (Jacoby and Skoufias, 1997). For private schools, the reduction in the number of students is expected to affect the revenue stream. If the reduced revenue is unable to cover the operating cost of the school, the school no longer remains profitable and is therefore likely to shut down. Our paper empirically tests this and a set of related hypotheses.

We also examine how public schools respond to the impact of the negative rainfall shocks on private schooling. While a negative income shock may lead to students' dropouts in public schools too, this is unlikely to affect the funding source of the government schools. Directly, public schools may thus not be affected. However, we do expect an indirect effect from closing down of private schools. Students who would like to continue education but can no longer afford private school fee are likely to move to existing public schools which entail much lower household expenditure on education. This increase in demand for public schools can result in a) increase in enrollment in existing public schools b) opening up of new public schools as existing public schools might not be able to accommodate the increased demand or may not serve the particular geographic market where the new demand originates from.

Even though we use rainfall shocks as indicators of adverse economic shocks, evaluating how such shocks can impact school supply is informative in its own right. Rainfall variability is likely to significantly increase in India and other developing countries due to climate change. As per sixth assessment report of the Intergovernment Panel on Climate Change (IPCC) extreme monsoon events are likely to increase in India and South Asia. Analysis of monsoon drought variability over a long period has also shown increase in intensity and area affected by droughts in India (Kumar, Rajeevan, Pai, Srivastava and Preethi, 2013; Sharma and Mujumdar, 2017). It has also been documented that droughts are becoming more frequent in agriculturally important coastal south-India, central Maharashtra, and Indo-Gangetic plains indicating higher food security and socioeconomic vulnerability in the region (Mallya, Mishra, Niyogi, Tripathi and Govindaraju, 2016). This coupled with the fact that agriculture employs close to 35% of labour force in the country and there is serious lack of irrigation infrastructure implies that rainfall shocks can have substantial impact on agriculture and rural incomes.

In trying to understand the impact of rainfall shocks on school supply decision, instead of simply working with the broad "public" and "private" school education category that has been commonly used in the literature, we look at a finer sub-classifications. The reason is that the broad categories mask important variation in funding sources which are important to consider for our analysis. In particular, the private school category encompasses three kinds of ownership and management structures.

There are private aided schools which receive financial aid from the government for their operation but are managed privately. The government sets the fee that these schools can charge which is usually minimal since they get financial aid from government. Given that these schools are supported by the government, we do not expect private aided schools to be vulnerable to economic shocks. These schools constitute 20% of total private schools in our data. The second category is recognised unaided private schools. These schools do not receive any financial aid from the government and rely on school fee for financing their operations. However, they are recognised by the government as education institutes which can impart school degrees to students[2]. Around 73% of private schools are unaided. Unrecognised unaided (also commonly known as unrecognised schools) private schools is a third category which, like recognised unaided schools, do not receive money from the government and charge school fee for their operation. However, they are not recognised by the government as they fail to adhere to minimum infrastructure standard set by the Right to Education Act (RTE) 2009. While as per the RTE, schools that are not recognised by the government should not function, a large number of unrecognised schools continue to remain in operation and therefore they are a part of our study. In fact around 7% of private schools in our data are unrecognised. These schools are usually smaller in size and cater to low income households as compared to recognised schools. Since recognised and unrecognised unaided schools completely rely on school fee, we expect these two types to be affected the most by economic shocks.

There is heterogeneity within public schools as well. There are central, state and local government schools which are funded and managed by central, state and local governments respectively. In addition, there are schools specifically set up for Scheduled Tribes, a marginalised indigenous community of India. Around 72% of public schools are funded by state governments, 22% are provided by local governments, 5% are tribal schools and 0.2% schools are central government schools. Since there are only a few central government schools, we exclude them from our analysis. Amongst public schools, we expect response of local government schools to shutting down of private schools to be quicker. Local governments have better information about the local calamities and conditions and are therefore expected to act faster as compared to higher levels of governments.

The paper uses an administrative dataset on schools compiled by Unified District Information System for Education (U-DISE) from 2012-13 to 2017-18 for information on closing and opening of schools. Initiated in 2012-13, U-DISE is an annual census of all schools in the country and contains detailed school level information on various characteristics including year of establishment, school management, school infrastructure, teachers hired and enrollment. Using the fact that it is mandatory for all schools to report information for U-DISE dataset, we consider a school as closed if it stops appearing in the U-DISE data after a particular year and continues to not report information for the rest of the sample period. While not appearing in the U-DISE could alternatively indicate discontinuation of reporting information for U-DISE rather than closing down of school, we conduct tests to rule this out. We consider a school as newly opened based on information on year of establishment of school provided in U-DISE. Thus, while our definition of school closure is based on our interpretation of disappearing of schools in UDISE, school opening is constructed using already available information on year of establishment in UDISE.

We measure rainfall shocks by using district level monthly rainfall data made available by the Indian Meteorological Department (IMD). Using this information we construct monthly standardised rainfall deviations from its long run average for each district. The count of the number of months in a Kharif season (major cropping season in India that starts in June and ends in October) in a district for which the standardised rainfall deviations in a district is below a pre-determined threshold is the measure of negative rainfall shocks.

Our results show that negative rainfall shocks increase the likelihood of closing down of private unaided recognised schools and unrecognised schools. We also document that private aided schools see a decrease in the likelihood of closing after a rainfall shock. This is expected given that aided schools are funded by government and so are not vulnerable to rainfall shocks. In fact they seem to be providing a cushion against the closing down of private recognised and unrecognised schools.

Our results also confirm that public schools, which are not dependent on school fee to cover their expenses, are not directly impacted by negative rainfall shocks. In addition, we examine if they have a higher likelihood of opening in response to shutting down of recognised and unrecognised private schools. In line with our expectation, our results suggest increased likelihood of opening of local government and tribal schools after the shock. This indicates that local government schools, as compared to state government schools, respond quickly and provide a cushion to students against the shutting down of fee charging schools.

In order to ensure that schools indeed "close" in response to shocks, and not just stop reporting information, we conduct a robustness test where we look at the impact of positive rainfall shocks on school opening of private schools. This is an analogous test to examining the impact of negative shock on school closing, but it does not rely on our definition of school closing. Our findings indicate that unrecognised schools are more likely to open up in response to positive shocks, corroborating that our results on school closure are not simply driven by failure to report information.

Additionally, in order to bolster our claim that the closing down of private schools and opening of public schools is driven by students switching to cheaper schools in response to negative shocks, we look at the data on school switches in the National Sample Survey (NSS) round conducted in 2014. NSS is a nationally representative survey of households in India which is conducted after every five years that collects detailed information on consumption expenditure. The round conducted in January to June 2014 has detailed information on education particular of households including school switches in the last year. Our results confirm that a deficient rainfall decreases the likelihood of switching to private schools and increases the switch to public schools.

In addition to studying school closure and opening, we also evaluate the impact of rainfall shocks on enrollment in public and private schools in the geographic neighbourhood of the closed down private schools. The direct expected impact is fall in average enrollment in nearby public and private schools due to an adverse income shock. But at the same time, we expect cheaper private schools as well as free of cost public schools to see increased enrollment from shutting down of the private school. We empirically estimate the overall impact on average enrollment in nearby schools. While our results show that the enrollment in private schools decreases, there is no impact of rainfall shocks on enrollment in public schools.

We also develop a simple model of a mixed schooling market - with both private and public schools - to interpret the empirical results in the paper. The model relies on modeling private schools as profit seeking. A simple, yet novel, result of the model is that the private school should *increase* its fee after the shock. While we cannot test for this in our data, we find support for this result in some surveys carried out during the school closure in COVID pandemic.

The rest of the paper is structured as follows: Section 2 briefly surveys the extant literature and this paper's contribution to it, section 3 provides the context, explains the data sources and presents summary statistics, section 4 presents the empirical framework, section 5 presents the results, section 6 presents a simple model and discussion to interpret the empirical findings and section 7 concludes.

2 Contribution to literature

The contribution of this paper is to highlight that economic shocks affect education market which consists of fee-charging private schools and free of cost government schools. The existing work in this area, on the other hand, has focused almost exclusively on studying the impact of economic shocks on demand for schooling measured in terms of school attendance and school enrollment decisions.

Jensen (2000); Björkman-Nyqvist (2013) document that households reduce human capital investment in children in order to insure against rainfall shocks. Duryea, Lam and Levison (2007), in the context of Brazil, show that unemployment shocks significantly increases the probability that a child fails to advance in school and enters the labour force. De Janvry, Finan, Sadoulet and Vakis (2006) show that fall in student enrollment in Mexico is much less when there is conditional cash transfers to households facing negative economic shocks. Ferreira and Schady (2009) conduct a literature survey and find that investment in human capital of children increases in response to negative economic shock in richer countries whereas school enrollment falls as a result of these shocks in poorer countries in Africa and Asia.

Existing studies in the Indian context indicate mixed results. Zimmermann (2020); Shah and Steinberg (2017) shows that school enrollment increases in response to negative rainfall shocks due to fall in outside employment opportunities and that there is increased switch to government schools after a positive rainfall shock. Maitra and Tagat (2019) on the other hand find increased participation in labour market and withdrawal from school in response to negative economic shock. They also find that women's opportunities for human capital accumulation are much more adversely affected than men.

We contribute to and complement this literature by showing that exogenous negative economic shocks lead to private school exits and public school entry. To the best of our knowledge, documentation of impact of economic shocks on the education market has not been done before. Our work is also significant in that we establish that the household responses studied by others may in part be driven by supply of schools. Some children may drop out of private schools not because they cannot afford it, but because the school shuts down. The fact that schooling choice is an equilibrium market outcome is not important in settings with majority public schooling, since the supply is not responding to market forces. But in settings like India where private schooling is a significant, it is critical to study outcomes as equilibrium outcomes.

3 Data and descriptive statistics

3.1 Rainfall data

We construct rainfall shocks in a district year using publicly available rainfall data from Indian Meteorological Department (IMD) website. The IMD provides data on rainfall received in a district month from 2008 to 2018. For each district we do the following:
a) First, calculate the average rainfall received in a month over 2008 to 2018 ($\overline{R_{dm}}$).
b) Second, calculate the deviation of rainfall in a district month year from the its average in a month normalised by its standard deviation ($z_{dmt} = \frac{R_{dmt} - \overline{R_{dm}}}{\sigma_{dm}}$) for 2012 to 2017 (the years for which we have U-DISE data)
The reason we construct these shocks at the monthly is level is because there is wide variation in median rainfall received (in millimeters) over different months [see figure 2]. Comparing rainfall received in a month with its historical average ensures that we do not compare rainfall prone district month pairs with district month pairs which usually receive low rainfall. The timing of rainfall is critical in agriculture and deficiency at the time of planting cannot be made up for later in the season. Using district month pairs takes care of this. Normalised rainfall deviations (z_{dmt}) range from -2.7 to 3 suggesting considerable variability in rainfall received in our data.

A month is classified as experiencing a rainfall shock if z_{dmt} is $<$-1.65. The reason we only consider negative rainfall shocks as adverse economic shocks is because they have been shown to be associated with a decline in area cultivated and production of wheat and rice, whereas positive rainfall shock has been shown to have a positive influence on production of crops(Maitra and Tagat, 2019).

3.2 School data

We use administrative data on schools maintained by Unified District Information System for Education (U-DISE) for information on school closure and opening. All schools in India are required to report information on school characteristics like infrastructure, number of teachers, enrollment and school management which is compiled by U-DISE[3]. U-DISE has been maintained since 2012-13 and we use this data to construct a school level panel from 2012-13 to 2017-18. We classify a school as closed if it stops appearing in U-DISE after a particular year and the year after which it stops appearing is classified as the year in which it closed down. If a school does not report data for a few years but returns in the sample in or before 2017, it is not categorised as closed. We do this to ensure that we do not wrongly categorise an event as school closure when it could be indicating failure to report the data. However, total private schools which fail to report in certain years is just 2% in our data, suggesting that such incidents are rare. Out of these schools, around 90% miss reporting information for one year (figure A.1). We use the information on year of establishment of schools in U-DISE data to classify a school as newly opened.

We merge the school closure and opening information from U-DISE with the rainfall shocks data. Since the U-DISE data is available yearly, we aggregate the monthly rainfall shocks at the year level. We do so by computing the number of months in the *kharif* season that experience negative rainfall shock. The *kharif* season is a major cropping season in India which starts in June and ends in October. The season significantly overlaps with the monsoon period in India (June to September). Since more than 70% of net area under cultivation in India is rainfed, rainfall shocks in the *kharif* season are likely to have a serious negative impact on agriculture income. We also check the robustness of our results to rainfall shocks in all months in a year.

3.3 Summary statistics

Our data show that the likelihood of a school closing down is 4% for a private school and 6% for a public school. Table 1 shows that the likelihood of a private school closing down is very high in 2012 (7%) and 2014 (6%). The same pattern is observed for public schools as well. The likelihood of a school opening in our sample is 4.4% for a private school and 1% for a public school. Table 1 also shows that of the schools that newly opened in our sample, most of the private schools opened in 2016 and 2017, whereas most of the newly opened public schools opened in 2013 and 2014.

Table 2 reports the summary statistics for rainfall shocks and shows that around 0.4 months or

12 days in a *kharif* season in our data received extreme rainfall (that is absolute value of z>1.65). This means that around 5% of the district years received extreme rainfall in at least three out of five *kharif* months. Negative rainfall shocks are rare events happening on average in 1%of district years in the data. Figure 2 shows that negative rainfall shocks affected a large number of districts in 2015 and 2016. The figure also shows that positive shocks are more frequent than negative shocks.

Table 3 reports average school characteristics for different categories of schools to showcase difference in attributes across different school types. We find that tribal, local, unrecognised and state schools are much smaller in terms of student enrollment as compared to other schools. Tribal, local and state schools are also predominantly rural schools. Amongst private schools, a large number of unrecognised schools (78%) exist in rural areas. Unaided recognised and unrecognised schools are much younger compared to all public schools. Also, number of teachers and classrooms in local, tribal and state schools are much lower. This is expected in part due to their smaller size. State, tribal and unrecogised schools fare poorly in terms of availability of electricity. Unrecognised schools also have the lowest likelihood of having a library.

Table 4 reports average characteristics of households making different school choices to highlight the association of household socio-economic conditions with school choice. We use 71st round of NSS data conducted in 2014-15, which particularly focused on household consumption expenditure on education, for this analysis. Note that while NSS data has information on finer categories within private schools, the data does not make any distinction between different kinds of public schools. Results show that the households that choose unaided schools have the highest income (proxied by their monthly per capita consumption expenditure) followed by those attending aided school. Households choosing unrecognised and public schools are the poorest in the sample. As expected, the school fee is highest in unaided schools and lowest in government schools. Note that school fee in unrecognised private schools is almost half the school fee in recognised private schools. Also since the average consumption expenditure of households choosing unrecognised schools is low, these households end up spending a large proportion of their expenditure on unrecognised school fee. Proportion of households involved in agriculture is slightly higher for households choosing unrecognised and state schools.

4 Empirical methodology

In a rain-fed agriculture dominant economy with limited access to formal credit, crop insurance and social safety net, rainfall shocks can be treated as exogenous shocks to rural incomes. The methodology to study the impact of rainfall shocks on education market is thus straight forward wherein we estimate the following regression equation:

$$Y_{i,d,t} = \theta + \alpha_i + \theta_t + \beta_1 negative\ shock_{d,t} + \beta_2 negative\ shock_{d,t} * unreco_i + \beta_3 negative\ shock_{d,t} * unaided_i + \gamma negative\ shock_{d,t} * urban_i + X'_{i,d,t}\delta + \eta_{i,d,t} \quad (1)$$

where $Y_{i,d,t}$ is a dummy indicating whether school i in district d closed after year t. $negative\ shock_{d,t}$ is the number of months in a *kharif* season in district d and year t for which $z_{d,m,t} <$ -1.65. To look at the differential impact of rainfall shocks on different school types, we interact rainfall shocks with $unreco_i$ and $unaided_i$, dummies indicating that school i is an unrecognised and recognised unaided school, respectively. We also include the interaction between rainfall shock and a dummy indicating if the school is in urban areas to understand if the impact differs in rural areas since rainfall shocks are expected to adversely affect rural households more.

The regression equation is estimated with school dummies which means that we track the same school over time to study the impact of negative rainfall shocks on school closure. Our regression equation also includes year fixed effects which capture country wide shocks to the likelihood of school closing that affect all the districts. Standard errors are clustered at the district level to allow shocks to school closing/opening to be correlated for schools within a district.

$X_{i,d,t}$ includes the following school level time varying controls: enrollment in primary and upper primary classes[4], total number of teachers and classrooms in a school and whether the school has library and electricity available. This ensures that we partial out the impact of school facilities and enrollment size on school closure. The coefficients βs give us the causal impact of rainfall shocks on closing of different categories of private schools.

To estimate the response of public schools to rainfall shocks and consequent shutting down of private schools, we estimate the following regression equation:

$$Y_{i,d,t} = \theta + \alpha_i + \theta_t + \beta negative\ shock_{d,t} + \gamma_1 negative\ shock_{d,t} * local_i + \gamma_2 negative\ shock_{d,t} * tribal_i + X'_{i,d,t}\delta + \gamma_2 negative\ shock_{d,t} * urban_i + \eta_{i,d,t} \quad (2)$$

$Y_{i,d,t}$ is a dummy indicating if a public school i in district d was established after year t. Like equation 1, we look at the differential impact of rainfall shocks on different school types. The coefficients of $negative\ shock_{d,t} * local_i$ and $negative\ shock_{d,t} * tribal_i$ indicate the differential impact of negative rainfall shock on local government schools and schools set up for Scheduled Tribes, respectively. β indicates the impact of rainfall shock on state government schools in rural areas.

5 Results

Regression results obtained from estimating equation 1 are reported in column 1 of Table 5. The coefficient of $negative\ shock$ suggests that the likelihood of an aided school closing down in rural areas is almost 1% point lower when one additional month in a district in *kharif* season suffers a negative rainfall shock. However, the coefficients of the interaction terms are positive suggesting that the impact of rainfall shocks in *kharif* months on recognised and unrecognised unaided school closure is differentially higher in comparison to aided schools. On average, the likelihood of closure is higher by 0.7% and 1.5% points for unaided and unrecognised schools when one additional month in *kharif* season suffers a negative rainfall shock. Given that the unconditional likelihood of unaided and unrecognised school closing down is 4 and 8%, this implies that the likelihood of school exit increases by around 19% as compared to average when a negative rainfall shock hits.

As explained earlier, aided schools are funded by government and unlike unaided and unrecognised schools they are not completely dependent on school fee for financing their operations. Unrecognised schools are particularly small rural schools with low fee levels and students who attend these schools tend to come from poor families. Given this, the finding that unaided and unrecognised schools close down during years of rainfall shocks whereas private aided schools are resilient to such shocks is not surprising. This result has important implications for policy. Even though there has been an exponential increase in private school demand over the past decade, our findings show that they are vulnerable to economic shocks and thus cannot be relied upon to achieve universal education, a stated aim of the Indian government.

We ensure that our results are not driven by state level policy changes. In order to reduce the adverse effects of economic shocks, state government might respond with mitigation policies, for example, regulation of the fees charged by the school[5]. Such events could be responsible for school shut down instead of student dropouts. We, however, show in column 2 that our coefficients only change marginally and our results qualitatively remain the same even after controlling for state year fixed effects.

The observed school closure could be indicative of volatility in school supply after adverse rainfall shocks, rather than drying up of income sources for private schools. If this is true, we would also observe high likelihood of opening up of private schools when a negative rainfall shock hits. Results reported in columns 3 and 4 however show that the likelihood of a private school opening up does not change in response to the shock. There is a lower likelihood of opening up of aided schools but this result is not robust to state-year fixed effects.

The coefficients on our control variables show that bigger schools, in terms of enrollment and number of teachers, have a lower likelihood of opening up. This is expected since schools which just start out tend to be smaller as compared to existing schools. We also see that these schools also have lower likelihood of closing down as compared to smaller schools.

Columns 1 and 2 of Table 6 present the impact of negative rainfall shocks on the likelihood of closing of different categories of public schools. We estimate this regression to check whether public schools, funded by governments, are directly impacted by negative economic shocks. We do not find systematic public school exits in response to rainfall shocks. However, the coefficient of the interaction between shock and tribal schools is positive in column 2, suggesting that as compared to other public schools tribal schools are vulnerable to these shocks. Since these schools primarily cater to Scheduled Tribes who are the most marginalised groups in the country with much poorer access to education opportunities as compared to other social groups, special attention must be given to ensure that tribal schools continue to be in existence when a negative economic shock occurs.

While our results suggest that there is no direct impact of rainfall shocks on provision of public schools, we expect indirect effect of closing down of fee charging private schools. We test for this indirect impact in columns 3 and 4 of Table 6 by looking at the impact of rainfall shocks on likelihood of opening up of new public schools. The estimates indicate that increase in the number of months experiencing negative rainfall shocks by two in a district increases the likelihood of a new local government and tribal school coming up by around 1% and 3% points respectively. Given that the average likelihood of a local government school opening is less than 1% and for tribal schools is 1.5%, the likelihood of a local and tribal school opening after negative shock increases considerably.

This suggests that local governments, which have better information about local calamities and realities respond to negative rainfall shocks by opening more schools to accommodate the increased demand for cheaper schooling. Given that these schools are much smaller and primarily rural (Table 3), their response to rural income shocks can act as a cushion against closing of fee charging recogised and unrecognised schools. Also note that the impact of negative rainfall shocks on opening up a state government school is negative suggesting that state government school do not seem to positively respond to the increased demand for public schools. This could also reflect that in times of poor economic shock, state government use state resources for disaster relief activities and provision of schooling takes a backseat.

Our indicator of school closure is constructed based on information on the year after which the school stops reporting. This makes our measure of school closure sensitive to the definition used. It is possible that private schools stop reporting information for U-DISE after a particular year and we mistakenly categorise that as school closure. However, this is likely to drive our results only if schools fail to report data more frequently in years of rainfall shock. This is plausible if poor rainfall makes reporting school information hard. While this seems unlikely, we, nevertheless, conduct a robustness check where we restrict our analysis to only those schools which got established before 2010. It is possible that the problem of not reporting information is more severe for newly established schools because of capacity constraints and logistical difficulties. We thus want to make sure that we look at schools that are older and more stable. Results reported in Tables in 7 and 8 show that there does not seem to be any change in the size and sign of coefficients, suggesting our reported results do not seem to be driven by information under reporting by newly established schools.

We conduct another robustness check wherein we look at the impact of positive rainfall shocks on likelihood of school opening for private and public schools. We define positive shock as the number of months in a *kharif* season in a district year for which $z_{d,m,t} > 1.65$. This test is based on the idea that if negative rainfall shocks result in school closures, positive rainfall years should increase the likelihood of private school opening since more households can afford the school fee. Unlike school closure, school opening is based on the information provided in U-DISE data and not on the definition we use. Additionally, there is no reason to expect systematic bias in the reporting of year of establishment in U-DISE for years with rainfall shock.

Results reported in column 1 of Table 9 show that there is an increased likelihood of unrecognised unaided schools setting up after a positive rainfall kharif season. While column 2 shows that the likelihood of local and tribal government schools opening up is lower when there is a positive shock. These results suggest that in years of good harvest, there is increased entry of private schools and low entry of public schools. These results corroborate our finding that private school closures happen in events of adverse economic shocks and that the result is not driven by failure to report information by private schools.

We also check the robustness of our results to considering rainfall shocks in all months in a year instead of $kharif$ months and our findings (results not reported) suggest that the results qualitatively remain the same.

5.1 Channel

We now provide evidence that it is the decreased demand for private schools that is driving private school exits after negative rainfall shocks. We do so by using information on school switches for currently school going children in the 71st education round of NSS. In particular, we estimate if improvement in rainfall results in increased switch from government school to private school. This would substantiate our claim that income shocks result in change in school choice for budget constrained households. The 71st round of NSS was conducted between January to June 2014 and so we use information on the month of the survey and the district in which the surveyed household resides to merge 2014 NSS data with 2013 rainfall data. We use the 2013 rainfall data because the question in NSS on school switches pertains to switches in the last academic year. We estimate the following regression equation:

$$switch\ to\ pvt_{i,d,m} = \alpha_d + \theta_m + \beta Z_{d,m} + \eta_{i,d,m} \tag{3}$$

Here $switch\ to\ pvt_{i,d,m}$ is a dummy indicating if the child i surveyed in month m in district d switched to private school, conditional on having switched in the last year. Since the survey period of NSS does not cover the *kharif* season, we simply use the standardised rainfall deviations in a district d month m as our independent variable. We control for district fixed effects, month fixed effects and cluster our standard errors at the district level. We expect better rainfall to increase switches to private schools and β to be positive.

Results, reported in Table 10, are consistent with our expectation. Column 1 shows that there is a 2% higher likelihood of switching to private schools if rainfall in the previous year increases by one standard deviation. Column 2 shows that the likelihood of switching from private to public school goes down with improvement in rainfall, as household ability to afford private school fee improves. These results support the hypothesis that private school closure is driven by demand shocks.

5.2 Impact on enrollment in nearby schools

Regression equations 1 and 2 estimates the supply response of schools on the extensive margin measured by their likelihood of exit and entry. In this section, we check the impact of rainfall shocks on the intensive margin as measured by average enrollment in schools which are geographically "close" to the shut down schools.

For existing private schools, while we expect enrollment to fall as a result of the income shock, there could be an upward pressure on enrollment if the students of the shut down private schools switch to other existing private schools. Similarly, for public schools, on the one hand, students, specially older ones, might dropout and join labour force to cope up with the negative shocks, on the other hand, some students might switch from fee charging private schools to free of cost government schools. Additionally, increase in number of local and tribal government schools could also put a downward pressure on average enrollment. We empirically resolve this ambiguity.

We call a school as "close" to the shut down school if it is situated in the same block. A block is a sub-division of a district created mainly for planning and development purpose. There are 5500 blocks in India and around 8 blocks on average in a district. Blocks are geographically neither too large to look at the response of "nearby" schools nor too small to miss out the response of relevant schools. We estimate the following regression:

$$Y_{b,d,t} = \alpha_b + \theta_t + \beta negative\ shock_{d,t} + \eta_{i,d,t} \tag{4}$$

Here $Y_{b,d,t}$ is the average enrollment in primary and upper primary classes in a school in a block 'b', district 'd' in year 't' . Note that schools which closed down during the study period are not a part of our analysis here. The regression equation has block and year fixed effects and standard errors are clustered at the district level. As before the coefficient of interest is β, which suggests the impact of rainfall shocks on average enrollment in nearby schools in the block. We estimate the above equation separately for different categories of schools to understand if the response differs by the school category.

Regression results obtained from estimating equation 4, for various categories of private schools, are reported in Table 11. Results show that average enrollment in upper primary classes decreases in response to rainfall shocks. Quantitatively, two additional *kharif* months experiencing negative rainfall shocks result in reduction in average enrollment in upper primary classes by 3.4 students, which is close to 5% reduction as compared to the average (70). However, we do not see any difference by finer categories of schools. This suggests that in addition to private school exits, enrollment size of existing private schools reduces. We also look at the impact on average enrollment in public schools in Table 12. Results suggest that while there is no impact on average enrollment for most schools, there is fall in enrollment in upper primary classes in tribal schools. The size of the coefficient suggests that there is a 4% decline in the average enrollment as compared to average.

6 A simple model and some discussion

In this section we sketch out a simple model to help interpret the empirical results from the previous sections. The key assumption, and innovation, in the model that drives its results is the modeling of private schools as profit seeking entities. As stated earlier, schools in India are required to be registered as non-profit entities. But that is far from the reality of how the schools actually operate. We therefore model them as profit seeking entities.

The setup consists of households indexed with i. Each household lives for two periods and in the first period has one school going child. The endowment of household i in the first period is y_i and $y_i \in [\underline{y}, \overline{y}]$, $y_i \sim U[\underline{y}, \overline{y}]$.

In the first period each household decides whether to send the child to a public or a private school. In the second period the child grows up and works and her income depends on the type of schooling taken in the first period. There is no other source of household income in the second period. Note that the household does not have access to any other saving technology. For simplicity we assume that there is one private school and one public school.

Given that we model public schools as non-market entities and their fees is normalised to zero the number of public schools does not matter. However, for private schools, the market structure is important since that will affect the prices - the school fees - they charge. We model the private school as a monopolist for simplicity - we discuss the implications of other market structures below.

6.1 Household choice

Households maximise their lifetime utility. In the first period they can either

1. Send the child to public school and consume their entire endowment or

2. Pay the school fees, send the child to private school and consume the remaining endowment.

In the second period the household consumes the entire income earned on the labour market. Note that the wage in the second period depends on the type of schooling in the first period. The utility function is assumed to have the log form

Formally, utility of household i is given by

$$U_i^{pub} = ln\ (y_i) + \beta\ ln(w_L) \tag{5}$$

if the child attends public school and

$$U_i^{priv} = ln\ (y_i - p) + \beta\ ln(w_H) \tag{6}$$

if the child attends private school.

Here p is the fee charged by the private school, β is the discount factor. w_H is the wage received by those with private school education and w_L is the wage received by those with public school education. Assume that $w_H > w_L > 0$. Given this last assumption every child in this model receives education.

Households will send their child to private school if $U_i^{priv} > U_i^{pub}$

$$ln(y_i - p) + \beta\, ln(w_H) > ln(y_i) + \beta\, ln(w_L) \tag{7}$$

We can solve this to identify the household that is indifferent between sending the child to private or public school. Let this household be indexed by its income $\tilde{y}$. Then

$$\tilde{y} = \frac{w_H^\beta}{w_H^\beta - w_L^\beta} p \tag{8}$$

It is easy to see that all HHs with income less than $\tilde{y}$ will send their children to public school and all those with incomes higher than $\tilde{y}$ will send their children to the private school. Given this and fact that the income distribution is uniform between $[\underline{y}, \overline{y}]$ we get the first result from the model

Proposition 1 *Given a private school fees of p, the demand for private schooling is given by*

$$\begin{aligned} q(p) &= \frac{\overline{y} - \tilde{y}}{\overline{y} - \underline{y}} \\ &= \frac{\overline{y} - \gamma p}{\overline{y} - \underline{y}} \end{aligned}$$

where $\gamma = \dfrac{w_H^\beta}{w_H^\beta - w_L^\beta}$. Thus the demand for private schooling is a linear function of the school fee.

6.2 School provision

In this model public schools are not active decision makers. The private school, given the demand function in proposition 1, sets the school fees to maximise its profits.

Given the demand function in proposition 1, we can write the inverse demand function for the private school as

$$p = a - bq$$
$$a = \frac{\overline{y}}{\gamma},\ b = \frac{\overline{y} - \underline{y}}{\gamma} \tag{9}$$

We assume that the cost of operating the private school has both a fixed component and a constant marginal cost. *The fixed cost covers not only costs like school building but also perhaps the costs of those teachers who are on some sort of contract - when we consider the time horizon of a few months or so.*. Thus the cost of operating the school is $C(q) = f + mq$. Here f is the fixed cost of operation and m is the marginal cost. The marginal costs could include electricity and maintenance charges, staff costs of non-contractual staff etc.

The school is thus maximising the following profit function

$$P_i(q) = (a - bq)q - f - mq \tag{10}$$

This implies a profit maximising quantity and price given in proposition 2 below.

Proposition 2 *In equilibrium the number of students studying in private school is* $\frac{\overline{y} - \gamma m}{2(\overline{y} - \underline{y})}$. *The private school fee is given by* $\frac{\gamma m - \overline{y}}{2}$

Proof: Straightforward unconstrained optimisation

In the long run *(depending on the type of private school this could be a few months)* it must also be the case that at this fees and this number of students privately educated result in positive profits.

Thus $P_i(q)$ as in equation 6 has to be positive. This implies

$$\frac{\overline{y} - \gamma m}{4(\overline{y} - \underline{y})} > f$$

6.3 The results of a shock

In this model what happens when an economic shock hits the households? Assume that the shock [like a rainfall shock] changes the endowment distribution of the households to $\sim U[\underline{y} - \delta, \overline{y} - \delta]$. Thus, the whole distribution shifts leftward by an amount δ while the density of the distribution remains the same.

What will be the impact of such a shock?

On demand for private schooling: The demand for private schooling after the shock is given by

$$\frac{(\overline{y} - \delta) - \gamma m}{2(\overline{y} - \underline{y})} = \frac{\overline{y} - \gamma m}{2(\overline{y} - \underline{y})} - \frac{\delta}{2(\overline{y} - \underline{y})}$$

Since $\delta > 0$, the demand for private schooling decreases after the shock.

On school fees: The school fees post the shock are given by

$$p = \frac{\gamma m - \overline{(y} - \delta)}{2} = \frac{\gamma m - \overline{y}}{2} + \frac{\delta}{2}$$

Again, since $\delta > 0$, the school fees increase after the shock.

On school closure: The condition for school closure in the aftermath of the shock becomes

$$\frac{(\overline{y} - \delta) - \gamma m}{4(\overline{y} - \underline{y})} > f \Longrightarrow \frac{\overline{y} - \gamma m}{4(\overline{y} - \underline{y})} - \frac{\delta}{4(\overline{y} - \underline{y})} > f$$

Thus, the condition for school closing weakens since the left hand side of the closure inequality is now lower. A large enough shock can thus cause schools to close down.

6.4 Discussion

The results from the model show that a negative shock to endowments in the first period can lead to a fall in demand for private schooling or to school closure - if the shock is large enough. The fall in demand is directly proportional to the size of the shock δ and inversely proportional to the range of the endowment distribution $\overline{y} - \underline{y}$. A higher range with the same mass implies that there is a smaller mass of HHs shifted from above the private schooling threshold to below it by the shock and hence a smaller impact on demand.

An interesting, and perhaps not so obvious, result of the model above is the increase in the school fees after the shock. This result is a direct consequence of modeling the private school as a unit price setting monopolist. A reduction in demand at the margin allows the monopolist to increase the price to what were the infra-marginal units in the original equilibrium.

Our data does not have enough information for us to empirically verify this finding from the model but there is tantalising support for it from some studies done during the COVID pandemic. For instance, an Oxfam study[6] said that 39% parents interviewed said that the private schools their child went to had increased school fees. The same report also finds higher dropouts from private schools and closure of some private schools.

The model presented above is simply meant to help interpret the main findings from the empirical work. Hence, it makes certain simplyfying assumptions that could be relaxed in later work in meaningful ways. We discuss two here.

First, we assumed a monopolistic market structure for private schools. Given that schools do have fixed costs of operation, a competitive market structure is not appropriate. This assumption has support in the data. The median number of private schools in a village in India is two. Thus we need to model schools as having some market power. How to model competition between private schools - in the presence of public schools - is a question that requires independent investigation and is beyond the scope of this paper. If we model the market as oligopolistic then it raises questions of the nature of that competition. What are schools competing on? Quantity or price? And is there a vertical differentiation between them? All these questions require more research than is within the scope of this paper. We believe that the monopolistic structure captures the essential feature of the market - the ability of the school to set prices.

The second assumption is on the nature of the shock. We have modelled it as a 'uniform' shock - both the rich and the poor are impacted to the same extent. That may not be the case. What if the shock only affects the poor? In the equilibrium of this model, only HHs above $\tilde{y}$ (see eq. 4) send the child to private school. So if there is a shock that only affects the 'poor', those below $\tilde{y}$ it will not impact the demand or price of private schooling. Of course, poverty here is relative and there are also low budget small private schools, especially in rural India, which cater to the richer among the poor. Our formulation of the shock thus captures the essence of what the reality of schooling in India is.

7 Conclusion and pandemic relevance

In this paper we document the impact of rainfall shocks on the schooling market in India using a panel data of schools from U-DISE. We show that adverse rainfall shocks lead to closure of unaided private schools, with the effect being especially pronounced for unrecognised schools, but have no impact on public schools. Local and tribal government schools respond to these shocks by more entry in years of negative economic shocks.

We also develop a simple model to interpret the empirical findings of the paper and show that, perhaps counter-intuitively, an economic shock can lead to an increase in private school fees - thus impacting even those households who continue to send the child to private school.

It is important here to understand the need to go beyond individual demand side responses to negative income shocks and study supply responses too. In India, private schooling is a major component of provision and a lot of this comes from smaller schools. Akin to small businesses these schools may not have the cash reserves to stay solvent if they cannot collect school fees. Thus these schools will be impacted and 'go under' when negative shocks hit the communities they serve.

In a lot of cases there may not be public schools available to absorb these students. And even when they are, transitions between schools maybe costly for students. Thus, overall these school closures may impose utility losses on students and households.

Our results have implications for policy making in education markets with mixed public and private provision. Our results show that it is the local schools that respond to the shocks and help cushion them and thus a focus on stronger and more responsive local education departments may become more important for a resilient schooling system as climate variability increases.

Calculation of possible impact of COVID on school closure

In this paper we have used rainfall shocks to identify the effect of correlated income shocks on the schooling market in India. While no systematic information for the COVID years is yet available, based on these results, one can expect that the pandemic would have resulted in similar effects on schools. Unlike localised rainfall shocks the pandemic is a country wide economic shock and therefore its impact on school closures may be of a larger magnitude.

Based on our estimates in this paper we carry out a simple calculation below to get a sense of the possible impact of COVID on school closure and student displacement. Our results show that on average an additional month of negative rainfall shocks increases the likelihood of school closure of recognised and unrecognised schools by 0.7% and 1.5% respectively.

Now, in our data rainfall shocks are rare and only impact about 1% of the districts in the country in any given year. However, the same is not true for COVID. This is a shock that affected all districts in the country. We can safely assume education markets to be geographically segregated - children typically attend schools in the geographic neighbourhood. A corollary to this is that the impact of a shock on education markets can be simply added across districts. So, if district A is hit by a shock it will result in school closure in that district independent of the events in other districts.

It follows thus that if the whole country was hit by a bad month [the economic shock] it would result in the closure of 0.7% of all recognised schools in the country and 1.5% of all unrecognised schools. What economic shock is COVID equivalent to in the context of our paper? We are simply trying to get a ball park number for the magnitude of the problem, so we assume that the COVID shock is **four** bad months of rainfall in the *kharif* season. This would be a severe drought situation - the whole monsoon season wiped out for the entire country - and would result in the closure of 2.8% of all recognised schools and 6% of all unrecognised schools. In 2017, the latest year for which we have data, there were 388,454 unaided recognised schools and 29,238 unrecognised schools in the country. Thus, the number of schools that would shut down will be $0.028 * 388454 + 0.06 * 29238 = 12,631$.

How many students will be displaced (either dropping out of education or switching schools) because of this school closure? In 2017, the average enrollment in a recogised school was 202 and that in unrecognised schools was 114. Using this along with the information on school closure gives the total number of displaced students as 2,397,100 (2,197,100 in recognised schools and 200,000 in unrecognised schools).

These numbers are not small. And the ability of the state to respond in a crisis like COVID is low anyway given the magnitude and scale of the shock.

Table 1: Summary statistics

Year	Private schools(‘000)	Public schools(‘000)	Private school closing	Public school closing	Private school opening	Public school opening
2012	316.8	1009.6	0.72	0.10	0.13	0.07
2013	327.3	1031.0	0.47	0.76	0.36	0.17
2014	375.3	1043.6	0.56	0.92	0.4	0.12
2015	383.7	1050.2	0.33	0.41	0.44	0.06
2016	393.2	1046.4	0.43	0.48	0.57	0.08
2017	417.7	1036.0	-	-	0.64	0.11

Notes: Column 1 reports the number of private schools (in 1000) in each year. Column 2 reports the number of public schools (in 1000) in each year. Columns 3 and 4 report the average likelihood of school closing for private and public schools, respectively. Columns 5 and 6 report the average likelihood of school opening for private and public schools, respectively.

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Shock	3,776	0.42	0.66	0	4
Negative shock	3,776	0.05	0.23	0	2
Shock - all months	3,805	1.16	1.13	0	7
Negative shock - all months	3,805	0.06	0.26	0	3

Notes: Shock is the number of months in Kharif season in a district for which absolute value of standarised rainfall deviations exceed 1.65. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65. *Shock - all months* is the number of months in a year in a district for which absolute value of standarised rainfall deviations exceed 1.65. *Negative shock - all months* is the number of months in a year in a district for which standarised rainfall deviations is less than -1.65.

Table 3: School characteristics across different types

	Private			Public			
Variable	Aided	Unaided	Unreco	Tribal	Local	Central	State
Pri Enrol	87.7	138.8	90.1	45.3	64.4	251.8	76.2
UpPri Enrol	114.2	62.8	23.9	26.9	23.8	187.2	38.6
Total enrol	201.9	201.6	114.0	72.2	88.2	439.0	114.8
Urban	0.32	0.38	0.22	0.05	0.08	0.48	0.07
Age (in years)	48.9	18.3	20.7	30.5	47.0	27.1	40.9
Teachers	10.3	8.7	6.3	3.0	3.9	22.2	4.4
Classrooms	5.6	7.4	5.4	3.0	3.8	13.4	4.0
Electricity	0.81	0.82	0.53	0.31	0.82	0.97	0.46
Library	0.88	0.76	0.45	0.81	0.87	0.93	0.81

*Notes:*The table reports average school characteristics for different school categories. *Pri Enrol* is the number of students in classes one to five in a school. *UpPri Enrol* is the number of students in classes six to eight in a school. *Total enrol* is the number of students in classes 1 to 8 in a school. *Urban* indicates if the school is in a urban locality. *Age* is calculated using year of establishment. *Teachers* is the total number of teachers in a school. *Classrooms* is the total number of classrooms in a school. *Electricity* indicates whether electricity is available in the school. *Library* is a dummy variable indicating presence of library in the school.

Table 4: Household characteristics across school types

Variable	Public	Aided	Unaided	Unreco
MPCE (in 2014 Rs.)	1354.4	2063.2	2147.1	1565.5
Course fee (in 2014 Rs.)	57.1	467.8	658.2	372.1
Course fee/MPCE	0.04	0.22	0.31	0.23
Proportion HH in agri	0.52	0.48	0.48	0.53

Notes: Columns 1, 2, 3 and 4 reports average characteristics for households who choose public, aided, unaided and unrecognised schools, respectively. *MPCE* is average monthly per capita consumption expenditure for a household. *Course fee* is the money spent by the household on studying the course. *Proportion HH in agri* is the proportion of households involved in agriculture.

Table 5: Negative rainfall shock and private school provision

VARIABLES	(1) School closing	(2) School closing	(3) School starting	(4) School starting
Negative shock	-0.013***	-0.007***	-0.004*	-0.004
	(0.000)	(0.001)	(0.097)	(0.112)
Negative shock*unaided	0.022***	0.011***	-0.002	-0.002
	(0.006)	(0.007)	(0.481)	(0.633)
Negative shock*unreco	0.028**	0.020***	-0.000	-0.000
	(0.015)	(0.006)	(0.985)	(0.961)
Negative shock*urban	0.002	0.002	0.001	0.004
	(0.586)	(0.429)	(0.556)	(0.133)
Pri Enrol	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
UpPri Enrol	-0.000	-0.000	-0.000*	-0.000*
	(0.122)	(0.575)	(0.060)	(0.068)
Teachers	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Classrooms	0.000**	0.000*	-0.002***	-0.003***
	(0.030)	(0.089)	(0.000)	(0.000)
Electricity	-0.002	-0.005*	-0.020***	-0.017***
	(0.600)	(0.093)	(0.000)	(0.000)
Library	0.008	0.002	-0.010***	-0.009***
	(0.289)	(0.729)	(0.000)	(0.000)
Observations	2,000,715	2,000,715	2,000,715	2,000,715
R-squared	0.039	0.102	0.024	0.043
School FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
StateXyear FE	NO	YES	NO	YES

Notes: School closing is a dummy variable indicating if the school has shut down. *School starting* is a dummy variable indicating if the school has opened in a given year. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65. *Unaided* is a dummy indicating if the school is a unaided private school. *Negative shock*unaided* is the interaction between *Negative shock* and *Unaided*. *Unreco* is a dummy indicating if the school is an unrecognised private school. *Negative shock*unreco* is the interaction between *Negative shock* and *Unreco*. *Negative shock*urban* is the interaction between *Negative shock* and a dummy indicating if the school is in an urban locality. *Pri Enrol* is the number of students in classes one to five in a school. *UpPri Enrol* is the number of students in classes six to eight in a school. *Total enrol* is the number of students in classes one to eight in a school. *Teachers* is the total number of teachers in a school. *Classrooms* is the total number of classrooms in a school. *Electricity* indicates whether electricity is available in the school. *Library* is a dummy variable indicating presence of library in the school. p values are in paranthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Negative rainfall shock and public school provision

VARIABLES	(1) School closing	(2) School closing	(3) School starting	(4) School starting
Negative shock	-0.013	-0.006	-0.005***	-0.002
	(0.166)	(0.496)	(0.008)	(0.213)
Negative shock*tribalsch	0.020	0.036*	0.018**	0.015*
	(0.277)	(0.064)	(0.028)	(0.051)
Negative shock*localsch	0.011	-0.001	0.008***	0.002
	(0.391)	(0.956)	(0.000)	(0.147)
Negative shock*urban	0.002	0.012	-0.001	0.001
	(0.796)	(0.212)	(0.409)	(0.619)
Observations	5,389,078	5,434,998	5,389,078	5,434,998
R-squared	0.015	0.080	0.008	0.041
School FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
StateXyear	NO	YES	NO	YES

Notes: School closing is a dummy variable indicating if the school has shut down. *School starting* is a dummy variable indicating if the school has opened in a given year. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65. *Tribalsch* is a dummy indicating if the school is a tribal school. *Negative shock*tribalsch* is the interaction between *Negative shock* and *tribalsch*. *Localsch* is a dummy indicating if the school is a local government school. *Negative shock*localsch* is the interaction between *Negative shock* and *localsch*. *Negative shock*urban* is the interaction between *Negative shock* and a dummy indicating if the school is in an urban locality. p values are in paranthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Negative rainfall shock and private school provision (schools established before 2010)

VARIABLES	(1) School closing	(2) School closing
Negative shock	-0.013***	-0.007***
	(0.000)	(0.001)
Negative shock*unaided	0.022***	0.011***
	(0.006)	(0.007)
Negative shock*unreco	0.024**	0.018**
	(0.026)	(0.013)
Negative shock*urban	0.001	0.001
Observations	1,787,980	1,787,980
R-squared	0.039	0.016
Controls	YES	YES
School FE	YES	YES
Year FE	YES	YES
StateXYear FE	NO	YES

Notes: School closing Pvt is a dummy variable indicating if the private school has shut down. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65. *unaided* is a dummy indicating if the school is a unaided private school. *Negative shock*unaided* is the interaction between *Negative shock* and *unaided*. *unreco* is a dummy indicating if the school is an unrecognised private school. *Negative shock*unreco* is the interaction between *Negative shock* and *unreco*. *Negative shock*urban* is the interaction between *Negative shock* and a dummy indicating if the school is in an urban locality. p values are in paranthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Negative rainfall shock and public school provision (schools established before 2010)

VARIABLES	(1) School closing	(2) School closing
Negative shock	-0.014	-0.006
	(0.145)	(0.452)
Negative shock*tribalsch	0.023	0.040**
	(0.211)	(0.044)
Negative shock*localsch	0.012	-0.000
	(0.352)	(0.994)
Negative shock*urban	0.002	0.012
	(0.774)	(0.199)
Observations	5,264,140	5,264,140
R-squared	0.015	0.082
Controls	YES	YES
School FE	YES	YES
Year FE	YES	YES
StateXyear	NO	YES

Notes: School closing is a dummy variable indicating if the school has shut down. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65. *Tribalsch* is a dummy indicating if the school is a tribal school. *Negative shock*tribalsch* is the interaction between *Negative shock* and *tribalsch*. *Localsch* is a dummy indicating if the school is a local government school. *Negative shock*localsch* is the interaction between *Negative shock* and *localsch*. *Negative shock*urban* is the interaction between *Negative shock* and a dummy indicating if the school is in an urban locality. p values are in paranthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Positive rainfall shock and school provision

VARIABLES	(1) School starting Pvt	(2) School starting Pub
Positive shock	-0.002	0.005***
	(0.330)	(0.000)
Positive shock*unaided	0.000	
	(0.827)	
Positive shock*unreco	0.009***	
	(0.001)	
Positive shock*urban	-0.003	-0.001*
	(0.152)	(0.088)
Positive shock*tribal		-0.005***
		(0.003)
Positive shock*local		-0.007***
		(0.000)
Observations	2,000,704	5,399,422
R-squared	0.024	0.009
School FE	YES	YES
Year FE	YES	YES
Controls	YES	YES

Notes: School starting Pvt is a dummy variable indicating if the private school has opened in a given year. *School starting Pub* is a dummy variable indicating if the public school has opened in a given year. *Positive shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is greater than 1.65. *unaided* is a dummy indicating if the school is a unaided private school. *Positive shock*unaided* is the interaction between *Positive shock* and *unaided*. *unreco* is a dummy indicating if the school is an unrecognised private school. *Positive shock*unreco* is the interaction between *Positive shock* and *unreco*. *Tribalsch* is a dummy indicating if the school is a tribal school. *Positive shock*tribalsch* is the interaction between *Positive shock* and *tribalsch*. *Localsch* is a dummy indicating if the school is a local government school. *Positive shock*localsch* is the interaction between *Positive shock* and *localsch*. *Positive shock*urban* is the interaction between *Positive shock* and a dummy indicating if the school is in an urban locality. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Rainfall shocks and school switch

	(1)	(2)
	Switched to pvt	Switched to gvt
Standardised rainfall	0.017*	-0.008^{+}
	(0.06)	(0.14)
District FE	Yes	Yes
Month FE	Yes	Yes
Observations	9567	9576

p-values in parentheses

Notes: Standardised rainfall is deviation of rainfall from its long run average for each district for the year 2013. *Switched to pvt* is a dummy variable indicating if the child switched to private school from public school in the last academic year. *Switched to gvt* is a dummy variable indicating if the child switched to public school from private school in the last academic year. Standard errors are clustered at district level

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Impact of rainfall shocks on nearby private schools

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pri Enrol	UpPri Enrol	Pri Enrol unaided	UpPri Enrol unaided	Pri Enrol unreco	UpPri Enrol unreco	Pri Enrol aided	UpPri Enrol aided
Negative shock	0.393	-1.705*	-0.636	-0.913	1.916	-0.474	1.026	-0.813
	(0.811)	(0.096)	(0.763)	(0.264)	(0.649)	(0.817)	(0.407)	(0.696)
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33727	33727	23039	23039	11282	11282	22158	22158

p-values in parentheses

Notes: Pri Enrol is the average enrollment in classes one to five in public schools in a block. *UpPri Enrol* is the average enrollment in public schools in classes five to eight in a block. *Pri Enrol unaided* and *UpPri Enrol unaided* denote average enrollment in unaided private schools in classes one to five and classes five to eight in a block, respectively. *Pri Enrol unreco* and *UpPri Enrol unreco* denote average enrollment in unrecognised schools in classes one to five and classes five to eight in a block, respectively. *Pri Enrol aided* and *UpPri Enrol aided* denote average enrollment in aided private schools in classes one to five and classes five to eight in a block, respectively. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Impact of rainfall shocks on nearby public schools

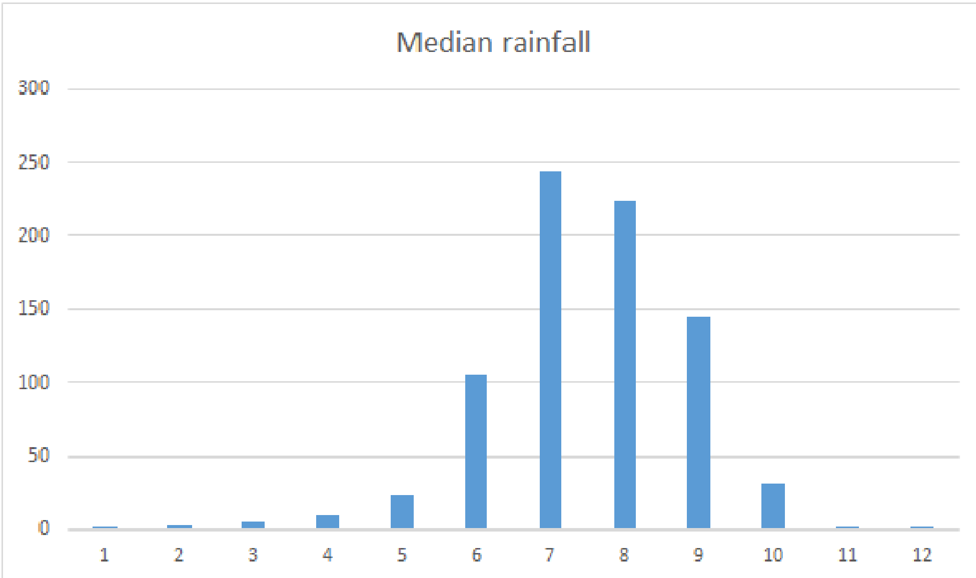
	(1) Pri Enrol	(2) UpPri Enrol	(3) Pri Enrol state	(4) UpPri Enrol state	(5) Pri Enrol local	(6) UpPri Enrol local	(7) Pri Enrol tribal	(8) UpPri Enrol tribal
Negative shock	0.341	-0.294	-0.503	-0.883	0.695	0.596	0.243	-1.253^{+}
	(0.518)	(0.370)	(0.402)	(0.295)	(0.251)	(0.222)	(0.767)	(0.104)
Block FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34546	34546	29980	16175	13970	4848	12909	12909

p-values in parentheses

Notes: Pri Enrol is the average enrollment in classes one to five in public schools in a block. *UpPri Enrol* is the average enrollment in public schools in classes five to eight in a block. *Pri Enrol state*, *UpPri Enrol state* denote average enrollment in state government schools in classes one to five and five to eight in a block, respectively. *Pri Enrol local*, *UpPri Enrol local* denote average enrollment in local government schools in classes one to five and five to eight in a block, respectively. *Pri Enrol tribal*, *UpPri Enrol tribal* denote the average enrollment in tribal schools in classes one to five and five to eight in a block, respectively. *Negative shock* is the number of months in Kharif season in a district for which standarised rainfall deviations is less than -1.65.

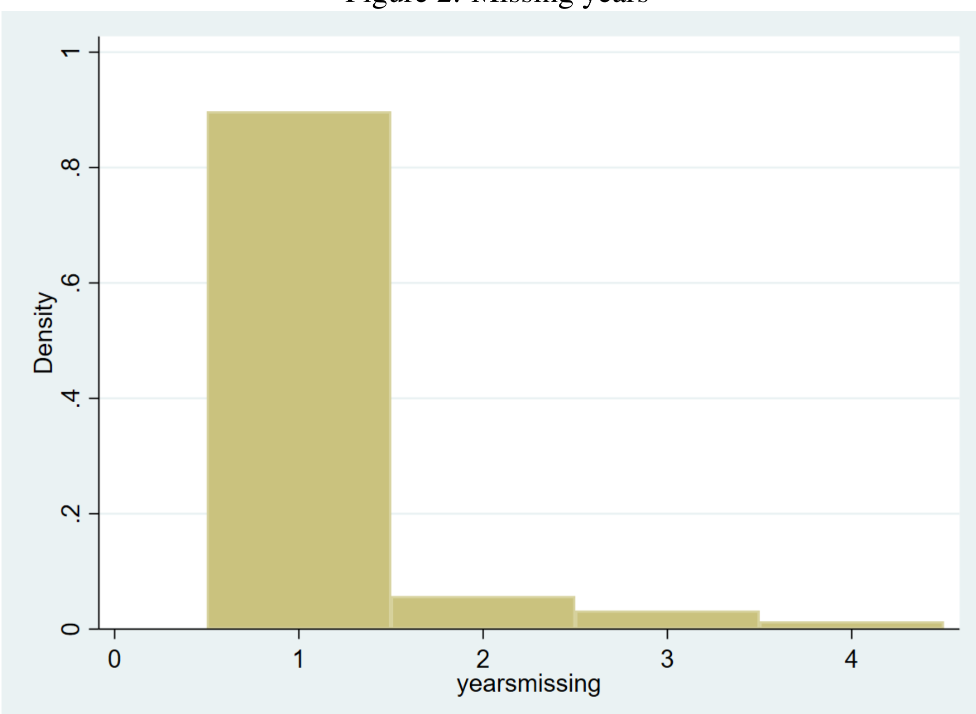
$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Monthly median rainfall



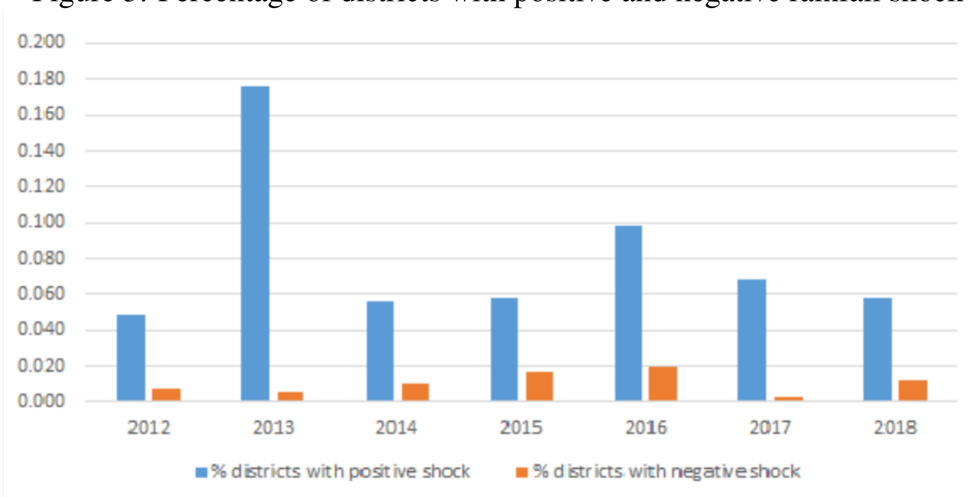
Note: X axis denotes months. The figure shows the median rainfall received in each month in a year.

Figure 2: Missing years



Note: The figure shows the distribution of number of years for which the school does not report information for UDISE.

Figure 3: Percentage of districts with positive and negative rainfall shock



Note: The figure shows the percentage of districts for which the standardised rainfall deviations is less than -1.65 (negative shock) and standardised rainfall deviations is greater than 1.65 (positive shock).

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