Do preschools add 'value'? Evidence on achievement gaps from rural India[1].

Sweta Gupta[2]

November 2020

[1] This working paper is based on a thesis chapter submitted for the degree of PhD. Economics at the University of Sussex. I would like to thank my supervisors, Dr. Sonja Fagernas and Prof. Peter Dolton, my PhD colleagues, the conference participants at UNU WIDER and German Economic Association Research Group on Development Economics. I am grateful to ASER Centre, New Delhi for making the data available to me for use in this paper and for my thesis – all data cleaning, analysis and results are my own and do not reflect on ASER Centre.

[2] PhD Economics Candidate, University of Sussex
Research Officer, Institute of Development Studies
sweta.gupta@sussex.ac.uk
s.gupta1@ids.ac.uk

Abstract

Despite a long-standing preschool policy and investment in preschool infrastructure in India, dating back to 1975, a rigorous evaluation of preschools in India remains virtually absent. Using data from three geographically and economically distinct states in India, the paper studies the immediate (1 year) impact of attending a preschool before starting primary school on cognitive, early language and numeracy skills. It additionally studies the heterogeneity in value-added of preschools by their management type. I find that there is a positive and significant premium of attending a preschool before starting primary school. However, the entire effect is driven by children who attend private preschools. There is considerable regional heterogeneity in the private-public gap in learning levels with Telangana exhibiting the highest private preschool premium. A descriptive study of the preschool quality by management type showed that private preschools have lower student-teacher ratios, longer hours of operation and a focus on formal instructional style of teaching. On the other hand, public preschools conduct more play-based activities. The results of this paper are particularly relevant in the backdrop of the new National Education Policy (Government of India, 2020), which stresses the need to improve foundational literacy and numeracy skills as early as in the preschool years. Given the findings of this paper, public preschools would need considerable overhaul to be able to deliver on closing the learning gaps. Moreover, the varying levels at which children start primary school based on their preschool experience highlight the need for educators to develop innovative pedagogical tools to effectively address learning heterogeneity within the classroom.

Keywords: Early Childhood, Education, Preschools, Value Added Models, Private
JEL Codes: I21, I28, O15

1. Introduction

UNESCO (2020) estimates that almost 80 percent of the children who remain unenrolled in preschools at the age of five are situated in low- and middle-income countries. However, what sets India apart is that despite being a developing country it boasts a preschool enrolment rate equivalent to that of high-income developed nations. Among the sample of children in this study, the preschool enrolment rate is as high as 89 percent for rural households. This is attributable to India's preschool policy which first came into play in 1975. In recent years, India has re-affirmed the importance of preschools in child development in its new National Education Policy (Government of India, 2020) promising that 'provisioning of quality early childhood development, care and education must thus be achieved as soon as possible, and no later than 2030' (para 1.1).

Despite such a long-standing preschool policy and investment in preschool infrastructure in India, a rigorous evaluation of preschools remains virtually absent. Singh and Mukherjee (2017) using Young Lives data from Andhra Pradesh and Telangana, find long-term effects of private preschool attendance on cognitive skills and subjective well-being at the age of 12. However, this study does not estimate the impact of having preschool exposure (public or private) versus none. Moreover, by looking at the impact of preschool exposure at age 12, it fails to consider the educational participation of the children between ages 6 and 12. A further limitation is the focus on data from Andhra Pradesh and Telangana; thus the paper fails to address the question of regional heterogeneity in preschool quality in a country as geographically diverse as India. For instance, the preschool funding guideline in India is skewed to benefit economically underdeveloped regions[3]. While the Central government contributes 90 percent of the construction and operational costs in these states, in other states (such as Andhra Pradesh and Telangana), the Central government contributes 75 percent of the construction cost and 60 percent of the operational cost.

In this paper, I seek to improve on the limited evidence on Indian preschools. I use data from three geographically and economically distinct states in India to provide a more representative evaluation of preschools. I study the immediate (1 year) impact of preschool attendance to minimise the risk of other educational inputs confounding the results. Moreover, I estimate the

[3] https://www.wcd.nic.in/sites/default/files/AR%202017-18%20Chapter%203.pdf

effect of attending a preschool versus having no preschool exposure. I complement this analysis with a study of private-public gap in learning.

Employing a lagged-score Value Added Model (VAM), I find that there is a positive and significant premium of attending a preschool before starting primary school on the achievement test. However, the entire effect is driven by children who attend private preschools. I find that children who attend public preschools before starting primary school do not have a significant advantage over children who start primary school with no preschool experience. There is considerable regional heterogeneity in the private-public gap in learning levels with Telangana exhibiting the highest private preschool premium.

The uniqueness of the Indian education system lies in the coexistence of two parallel sectors – a low cost fee-charging private and a free-of-cost public (government) sector. This introduces a degree of variability in the schooling trajectory followed by Indian children, and hence can potentially produce variability in learning levels.

Public preschools in India, commonly known as *anganwadis/balwadis* are part of the bigger umbrella program – Integrated Child Development Services (ICDS). The ICDS scheme has been in implementation since 1975 and performs six services – supplementary nutrition, preschool education, immunisation, health check-up, referral services, and nutrition and health education to mothers. There are 1.3 million ICDS centres across the country, with the policy stipulating that there be at least one centre in every village[4]. Public preschools are expected to cater to children in the age group 3 to 6 years of age, and contribute to the universalisation of primary education by providing necessary preparation for primary schooling.

Private preschools, on the other hand, are fee charging institutions, consisting of nursery and/or kindergarten classes. Their main draw is English language instruction. They are more formal in their structure and organisation with well-defined curricula and teaching hours.

The quality of public preschool education is often seen as poor, partly due to the Indian education policy failing to incorporate preschool education formally into its pedagogical framework. In reality, ICDS centres have come to be seen as health centres for children in early

[4] https://www.wcd.nic.in/sites/default/files/AR%202017-18%20Chapter%203.pdf

years, with the preschool function reduced to a free day care facility. A major shift in this realm comes with the new National Education Policy (2020), which will bring the preschool function of ICDS formally into what it terms as ‘school clusters’. This would imply that preschool education function of ICDS would shift from the Ministry of Women and Child Development to the Ministry of Human Resource Development[5]. This anticipated shift will integrate the preschool years with the rest of the education system in India, allowing the National Council of Educational Research and Training (NCERT)[6] to develop preschool curricula and pedagogy.

While variability in learning outcome due to the diverse private and public sector in education is well documented in India at the primary school level (Muralidharan and Sundararaman, 2015), very little is known at the school entry age or before that. Studies that document the learning gaps in the private and public sectors have overwhelmingly focussed on primary school without any knowledge of the early childhood years. One needs a careful assessment of the learning gap literature in India – whether these are gaps that arise due to primary school education or whether these are pre-existing gaps decreasing/increasing over time. From the policy perspective, it is vital to know when and where public spending should be focused to yield the highest return.

There is widespread recognition of the fact that early childhood factors and environment have a significant impact on future outcomes, cognitive and non-cognitive. Quality early childhood education can improve children’s learning skills and help with the transition to primary school (see Yoshikawa et al., 2013 for a review). Given such evidence, the less than satisfactory evaluation of preschool education in India is a major limitation. One of the main reasons for such an omission, is the lack of data in the education sector, and even more so in the preschool sector. The data set I use for this study is the only large-scale data set I know of which specifically aimed to collect information on preschools in India[7].

The paper also contributes to the wider literature on evaluation of universal preschool provision. This literature is sparse, even in developed countries and the results continue to be

[5] The Ministry of Human resource Development, India oversees all aspects of education – primary, secondary, higher education, technical and vocational training centres.

[6] NCERT currently oversees the development of curriculum, pedagogy, teacher training of all primary and secondary education in India.

[7] ASER recently conducted a national survey in 2019 of children’s enrolment status and skills with a focus on early years – ages 4 to 8. However, the survey does not have any information on the preschools themselves. It is also limited in its information on households.

mixed. While some studies find that universal preschool education is associated with improved literacy and numeracy skills at primary school entry age (for US, see Loeb et al., 2007; Fitzpatrick, 2008; for UK, see Melhuish et al., 2008; for Argentina, see Berlinski et al., 2009), others find that these positive effects dissipate as early as the end of first grade (for US, see Magnuson et al., 2007; for Quebec, see Baker et al., 2008).

2. Related Literature

Early years of life are critical for the acquisition of skills and concepts. While positive experiences are thought to be crucial in determining the formation of cognitive and non-cognitive skills (Cunha & Heckman, 2008), negative experiences in the form of poverty, malnutrition, and unstimulating home environment can be detrimental to cognitive, motor, and socio-economic skill development (Grantham-McGregor et al., 2007). Since skill begets skill and there is complementarity between inputs applied at various stages of growing up (Cunha et al., 2006) there is a strong case for intervention in the preschool years. Although certain socio-emotional functions and health can be observed even before the age of three (preschool starting age), most successful early childhood interventions begin in preschool years. These can also be complemented with earlier 'antenatal investment' (Doyle et al., 2009).

There is now a large body of literature which documents the effectiveness of early childhood interventions, particularly in the US (Heckman & Mosso, 2014). In the context of the US, much of the literature to explain when and why gaps in cognitive (and non-cognitive) achievement surface has focused on the racial bias (see Fryer & Levitt, 2004, 2006). The second theme in early childhood intervention research in the US has been to document the persistent positive impacts of such interventions into adulthood – for example, Perry Preschool Project in the US (Schweinhart et al., 2005), and Head Start Preschool intervention (Garces et al., 2002). While the results from these studies are useful, the programmes evaluated involved disadvantaged children from select cities in the US. The evidence on the impact of universal preschool policy remains scarce, and the evidence on short-run outcomes is mixed. While some studies find that universal preschool education is associated with improved literacy and numeracy skills at primary school entry age (for US, see Loeb et al., 2007; Fitzpatrick, 2008; for UK, see Melhuish et al., 2008), others find that these positive effects dissipate as early as the end of first grade (for US, see Magnuson et al., 2007; for Quebec, see Baker et al., 2008).

In developing countries, the evidence on evaluation of universal preschool is even more limited. Berlinski, Galiani, and Manacorda (2008) study the effect of preschool education on years of education using a Uruguayan household survey. They use the within household estimator exploiting the variation in education trajectories between siblings. The authors report that by the age of 15, children who had attended preschools accumulate 0.8 years of extra education when compared to their untreated siblings.

In another study from Argentina, Berlinski, Galiani, and Gertler (2009) investigate the impact of large scale expansion of universal preschool education on subsequent primary school performance, and find that one year of preschool education increases the average third grade test scores by 23 percent of the standard deviation.

In Cambodia, Rao et al. (2012) evaluate the effectiveness of the different early childhood programmes and find that ,while some programmes are more effective than others, some preschool experience is better than none at all. However, a recent study evaluating the impact of preschool construction in Cambodia on children's short-term cognitive and socio-emotional development finds that there are no impacts of preschool attendance (Bouguen et al., 2018). Further, they find that there are significant negative impacts of preschool attendance on children with the longest exposure to preschools.

In urban Ethiopia, Woldehanna (2016) using Young Lives data find that preschool attendance is correlated with better cognitive performance at the primary school starting age of five.

Other than the above-mentioned studies, there have been smaller sample studies. Mwaura et al. (2008) study the impact of preschool experience on cognitive achievement in a sample of 423 children in East Africa under a quasi-experimental framework. They find that children who went to Madrasa type preschools (faith-based organization) performed better than those who attended non-Madrasa type preschools or none. Moore et al. (2008) design a pre-post intervention-control framework to evaluate the effect of revised preschool versus a regular preschool in rural Bangladesh. In their sample of 138 children, they find that after seven months, children in the revised program performed better than those in the regular program, although the quality of the regular program had also improved. Most of these studies suffer from the problem of small sample and focus on comparing different type of preschools rather than a universal preschool programme.

A related strand of literature from developing countries looks at the impact of quality of preschools on child outcomes – for instance, the effect of teacher quality (Araujo et al., 2016 in Ecuador; Wolf et al., 2019 in Ghana; Yoshikawa et al., 2015 in Chile) and the effect of increasing preschool and parent communication (Ozler et al., 2016 in Malawi)

In the context of India, there are two papers that evaluate universal preschool provision. In Andhra Pradesh and Telangana, Singh and Mukherjee (2017) employ propensity score matching and find long-term effects of private preschool attendance on cognitive skills and subjective well-being at the age of 12. However, this study does not estimate the impact of having preschool exposure (public or private) versus none. Moreover, by looking at the impact of preschool exposure at age 12, it fails to consider the educational participation of the children between ages 6 and 12. A further limitation is the focus on data from Andhra Pradesh and Telangana; thereby, failing to address the question of regional heterogeneity in preschool quality in a country as diverse as India.

Another study using Young Lives data from Andhra Pradesh and Telangana, India, demonstrates that test score gaps between children in schools exist even at the school-entry age, and this gap can in part be attributed to attending a preschool and type of preschool attended (Singh, 2014). However, the author mentions that drawing causality is beyond the scope of his paper and is at most able to establish correlations. This paper serves as a valid starting point for my exercise – once established, that test score gaps exist even before starting primary school, I attempt to explain such a gap through preschool attendance and the management type of the preschools.

In this study, I seek to improve on the limited evidence on Indian preschools. First, I use data from three geographically and economically distinct states in India to provide a more representative evaluation of preschools. Second, I study the immediate (1 year) impact of preschool attendance to minimise the risk of other educational inputs confounding the results. Third, I estimate the effect of attending a preschool versus having no preschool exposure. I complement this analysis with a study of private-public gap in learning.

The focus on management type of preschools is motivated by the existing literature on the private-public achievement gap divide in India. The private sector in Indian education has been growing rapidly in the last two decades (Kingdon, 2007), and it is now well-known that there are significant gaps in the average achievement scores between private and public schools in India. Muralidharan and Kremer (2008) find that private unaided low fee-charging schools are widespread in rural India, particularly in areas where the public system is dysfunctional. This is a result of both demand-side variables (desire for English medium instruction, smaller classes, and more accountable teachers) and supply-side variables (availability of educated unemployed youth).

It has been found that private schools are associated with higher student achievement even after accounting for pre-existing differences in socio-economic background using a range of econometric methodologies. French and Kingdon (2010) use family fixed effects and within household variation to control for selection into private schools. Desai et al. (2009) use Heckman selection correction model using the existence of private school in the village as an exclusion restriction. Chudgar and Quin (2012) find positive effects of attending private primary schools while using regression analysis. However, when they conduct regressions on matched samples, the private school gain is less consistent across specifications. Muralidharan and Sundararaman (2015) do not find across the board gains of attending private schools in their experimental approach (school choice voucher scheme) and claim that private school children perform better in certain subjects (English and Hindi), but not in others (Telugu, Maths and Environmental Studies). Singh (2015) shows that private primary schools show significant positive gains in certain domains and age groups using Value Added Model, and that these results match up to the estimates of the experimental study of Muralidharan and Sundararaman (2015).

Most of these studies in India and beyond (with the exception of Singh & Mukherjee, 2017; Singh, 2014), have focused only on primary schools without any reference to prior preschool education. Given the widespread recognition of the importance of early childhood factors on future cognitive outcomes, this omission is a major limitation to the literature as it stands today.

I study the impact of preschool on cognitive achievement, and in particular, the differential impact of public versus private preschools. Since the question is similar to the literature which exists for primary schools in India, one could potentially use any one of the empirical strategies described earlier. However, family fixed effects are not satisfactory as parents can change their behavior based on preschool experience and it also requires assuming that there is perfect knowledge of intra-household allocation between siblings. Coming across a valid instrument which only affects school choice and not educational outcome is also a tall order. The instrument used by Desai et al. (2009) being, whether the village has a private facility, cannot satisfy the exclusion restriction. As noted, the presence of private facilities can be driven by demand side variables like the aspirations of parents and community. This would also affect the educational outcome.

An alternative identification strategy under-utilized in such research questions is one of lagged score Value Added Models (VAM). VAMs are used extensively in teacher and class effectiveness literature, particularly in the US. Overall evidence suggests that lagged score VAM estimates are valid and consistent, estimating average treatment effects with limited bias (see Kane & Staiger, 2008; Andrabi et al., 2011; Chetty et al., 2014; Guarino et al., 2015; Crawfurd & Elks, 2019).

2.1. Sampling

The data for this paper has been provided by ASER, India which had been collected as part of their 5-year longitudinal study, Early Childhood Education Impact Study[8]. This paper only covers two rounds of the data collection – the first round in September-December 2011 and the second round in October-December 2012.

The data covers three major states of India – Telangana, Assam, and Rajasthan. States were purposively selected to maximize differences in geographical location as well as demographic, socio-economic, and educational characteristics. Within each state, two districts were selected at random for inclusion in the study - Medak and Warangal in Telangana, Dibrugarh and Kamrup in Assam, and Ajmer and Alwar in Rajasthan. Within each district, a total of 50 villages were selected with a population of between 2000-4000. Given that the primary objective of this study was to examine the relationship between preschool and learning outcomes, sampling of villages was deliberately restricted to larger villages in order to maximize the likelihood of finding different types of preschool facilities (public and private) within a single village. Systematic random sampling was utilized in order to ensure that at least one village was included from each block in the district.

[8] http://www.asercentre.org/Keywords/p/342.html#br03d

Within each village, the objective was to select 50 children in the age group 3.5-4.5 years at the time of the first round (September-December 2011). Integrated Child Development Services (ICDS) records were used to create a sample of all children in the above-mentioned age group. These records are maintained by government (Anganwadi) workers in each village. If the number of children in the required age group exceeded 50, then 50 children were randomly selected. If this number was less than 50, then all the children in the village were selected. In theory, at most 2500 children should have been selected for each district. However, in practice this was not achieved. Table 1 shows the distribution of the sampled children across the six districts and three states. While 42 percent of the children are in Rajasthan, 31 percent are in Assam and 27 percent are in Telangana. Moving from Round 1 to Round 2 of the data collection, the study was able to track 89 percent of the children, with Rajasthan having the lowest attrition rate. This paper utilises the sample of 8124 children who are present in both Rounds 1 and 2.

Table 1. Distribution of sample by state and district

State	District	Sample Size at Round 1	Sample Size at Round 2	% of Round 1
Telangana	Warrangal	1031	931	90.3
	Medak	1477	1265	85.6
Assam	Kamrup	1662	1450	87.2
	Dibrugarh	1163	998	85.8
Rajasthan	Alwar	1896	1762	92.9
	Ajmer	1892	1718	90.8
Total		**9121**	**8124**	**89.1**

This table presents the sample size in each district surveyed at Round 1 and at Round 2. Round 1 was conducted in Sept-Dec 2011 and Round 2 was conducted roughly a year apart in Oct-Dec 2012.

2.2. Survey and Questionnaire

During 2011-2012, sampled children were visited four times, approximately once every three months. The first round of data collection occurred in September-December 2011 and the second round in October-December 2012. Between Rounds 1 and 2, two tracking visits occurred. Table 2 shows the information collected in each round.

Table 2. Timeline of survey and information collected

Survey instrument	**Round 1** Sep - Dec 2011	**Tracking Visit 1** Feb – Mar 2012	**Tracking Visit 2** Jul – Aug 2012	**Round 2** Oct - Dec 2012
Household questionnaire	X			
Assessment	X			X
Child tracking	X	X	X	X
Preschool questionnaire	X			X

The household questionnaire includes detailed information on the level of education of the parents, employment status, religion, caste, consumer durables owned by the household, sampled child's learning environment, and questions on parent's aspirations and expectations from preschool. The questions on parent's aspirations and expectations from preschool were only administered to parents where the child was enrolled in a preschool.

The child tracking was used to only track the enrolment status of the child – whether the sampled child was going to a preschool, or a primary school.

The preschool questionnaire was conducted for all preschools in the village, irrespective of whether the sampled child was enrolled in them or not. Key aspects of infrastructure, classroom teaching observation, and availability of learning materials for children were observed in each preschool facility visited. However, the data provided for this paper did not link the preschool to the sampled child. Additionally, no unique preschool identifier was used between Rounds 1 and 2, which implies that I cannot link the preschools from Round 2 with Round 1.

The assessment tool used for this study is the School Readiness Inventory (SRI). It was administered one-on-one by a trained field investigator to the children at home. The test was developed by the World Bank in conjunction with Centre for Early Childhood Education and Development, New Delhi. It is intended to test children's cognitive skill, and early language and numeracy skills[9]. Within these broad categories, the children were administered 24 items. Appendix A Table A.1 gives detail of the breakdown of the test.

I used a two-parameter logistic (2-PL) model of the Item Response Theory (IRT) to evaluate the performance of each item in uncovering the latent trait/skill parameter. Based on this model, I found Items 22 and 23 to perform poorly; and hence, excluded them for calculating the total score. Appendix A Section A.1 details the methodology used to construct the test score. While one can use test scores generated by IRT, for ease of interpretation, I do not do so in the main paper[10]. Instead, I assign a point for each of the 22 items administered and calculate the total test score. This is referred to as the raw score in the paper and ranges from 0 to 22. Second, I

[9]While most School Readiness instruments administered in early childhood studies also have dimensions on socio-emotional skills and motor skills (for e.g., see Yoshikawa et al., 2015; Wolf et al., 2019), the SRI tool administered in this study had a narrow focus on cognitive and language skills.
[10] In Appendix A Table A.3 and Table A.4, I report the main results using IRT constructed scores.

standardise this test score to have a mean of 0 and standard deviation of 1. This standardised score is used in all analyses. Children were assessed twice roughly a year apart. I shall refer to the test score from Round 1 as Lagged test score and the test score from Round 2 as Current test score.

2.3. Participation status

Table 3 summarises the participation trajectory of the sampled children from Round 1 to Round 2. Only 1.2 percent of the children remain unenrolled by Round 2 and all these children were from Rajasthan. 89 percent of the children were already attending a preschool at the time of the first data collection (Round 1). This is unsurprising as enrolment rates have been consistently high for India in the recent years – for instance, ASER Early Years Report (ASER Centre, 2020) documents that 84 percent of their nationally representative rural sample of 4-year old children were enrolled in preschool. Of these children in my data, most continued to attend a preschool in Round 2. 1861 children started attending a primary school after preschool - 95 percent of these children were in Rajasthan or Telangana. This is because the school starting age in Rajasthan and Telangana is 5 years, while it is 6 years in Assam. However, the slight anomaly, are the children (9 percent of the overall sample) who were already attending a primary school at Round 1 and continue to do so in Round 2. While officially these children would be too young to be attending primary school, it is common for the enforcement of formal school entry regulations to be lax[11]. Given the difference in educational norms and trends by states, I control for village fixed effects in all my analysis. The choice to have village instead of state fixed effects is to capture the differences in facilities provision by village.

[11] For example, see Singh (2020) where he documents that there is no regression discontinuity involving official school age entry for the Indian sample. Also, see ASER Early Years (ASER Centre, 2020) which documents 8 percent of their nationally representative rural sample at age 4 were enrolled in primary school.

Table 3. Distribution of sample by educational participation

Participation	Overall N	Overall %	Telangana	Assam	Rajasthan
Never enrolled	100	1.2	0	0	100
Attending a preschool	5402	66.5	1258	2350	1794
From preschool in Round 1 to primary school in Round 2	1861	22.9	787	98	976
Attending a primary school (with no preschool exposure)	761	9.4	151	0	610
Sample size	8124	100	2196	2448	3480

This table presents the sample size by each educational participation category, and also by the states. Attending a preschool category are children who have been attending a preschool in Round 1 and Round 2 and have not started primary school. From preschool in Round 1 to primary school in Round 2 are children who started going to a primary school between the 1-year apart data collection at Round 1 and Round 2. Attending a primary school are children who have never been to preschool and were attending a primary school in Round 1 and Round 2.

I categorise the children, ‘attending a preschool’, as children who have been to preschool (67 percent of the overall sample). The children ‘from preschool in Round 1 to primary school in Round 2’ are categorised as children who have been to preschool and school (23 percent of the overall sample). The children ‘attending a primary school’ are treated as children who have been to primary school (9 percent of the overall sample) without having ever attended a preschool. The last category are the children who are never enrolled (1 percent of the overall sample).

For additional analysis, I also categorise the children by the management type of preschools as shown in Table 4. 49 percent of those who were attending preschool, attended a private preschool – majority of these children are from Rajasthan. Children who attended a public preschool are mostly located in Assam. Most children, who start going to a primary school in Round 2 after preschool, come from a public preschool.

Table 4. Distribution of preschool goers by management type

	Overall	Telangana	Assam	Rajasthan
Attending private preschool	2649	881	451	1317
Attending public preschool	2753	377	1899	477
Attending private preschool and school	623	117	5	501
Attending public preschool and school	1238	670	93	475

The table provides a further breakdown for children who either are or have attended a preschool by management type. The 5402 children who have been attending a preschool in both Rounds 1 and 2 are further distinguished into 'attending a private preschool' and 'attending a public preschool'. The 1861 children who were attending a preschool in Round 1 and started going to a primary school in Round 2 are further distinguished as attending a private preschool and school; and attending a public preschool and school.

I keep children who have attended both preschool and primary school as a separate category because the change in test scores from Round 1 to Round 2 is now a function of both preschool and primary school input. Using the data from tracking visits, I confirm that these 1861 children would still have had substantial exposure to preschool between Rounds 1 and 2. Table 5 shows that no child switched to a primary school in February. Most children switch in July – this is expected because the academic calendar runs from June/July in Rajasthan and Telangana (and from January in Assam). Based on these tracking visits, I can confirm that these children would have had at least six months of preschool exposure after Round 1. Hence, it is reasonable to assume that the value added between Rounds 1 and 2 would be a function of both preschool and primary school.

Table 5. Switching from preschool to primary school

From preschool in Round 1 to primary school in Round 2	N
Switch occurs at tracking visit 1 (Feb-Mar 2012)	0
Switch occurs at tracking visit 2 (Jul-Aug 2012)	1215
Switch occurs at Round 2 (Sept-Dec 2012)	646
Sample size	1861

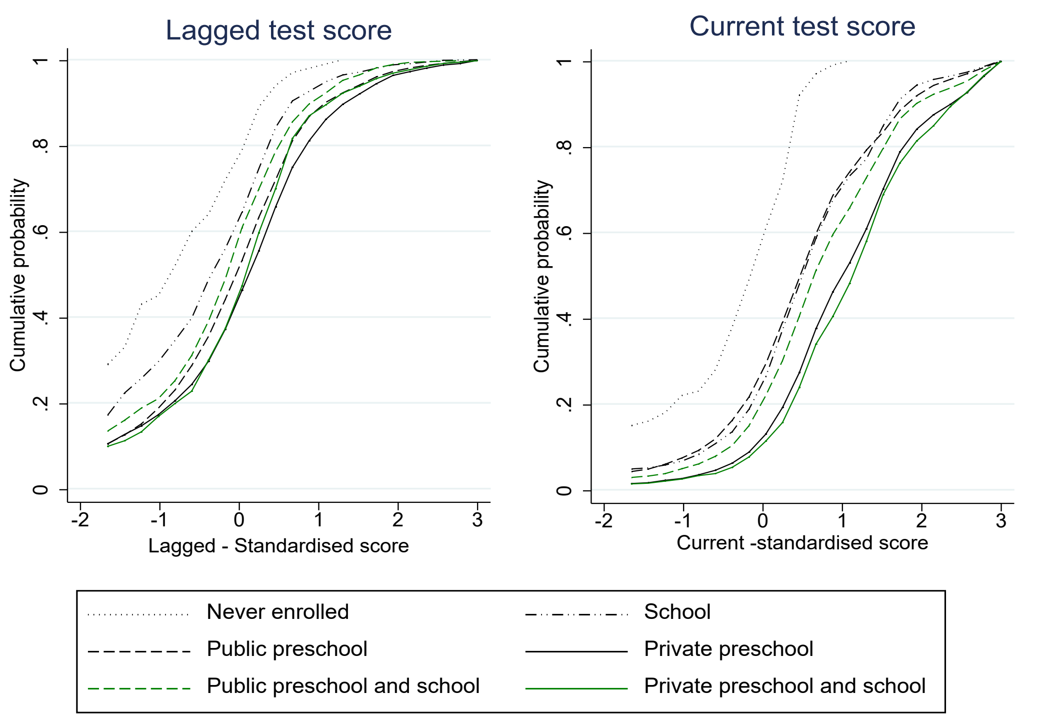
This table shows the approximate time when the 1861 children who were attending a preschool in Round 1 would have switched to a primary school.

2.4. Test scores

Figure 1 presents the distribution of the standardised score at Round 1 and Round 2 by participation status of the children. I distinguish the preschool goers further by management type. The test scores are presented by the following categories – never enrolled, going to a primary school (with no previous preschool exposure), going to a public preschool, going to a private preschool, going to a public preschool with primary school, and going to a private preschool with primary school.

Looking at the lagged test score, there emerges a clear hierarchy in selection – children who are not enrolled performing the worst, followed by children in primary school, then children in public preschool, and finally children in private preschool. When the children are tested again after one year in Round 2, all categories see a reduction in the proportion of children scoring very low. This could be a result of being tested on the same tool and the resulting familiarity or the effect of age. By Round 2, the primary school sample has caught up with the public preschool sample, with the two distributions almost overlapping. The public preschool goers who have started attending a primary school at Round 2 are slightly better off than those with only public preschool or with only primary school. The biggest gain in test scores come from the private preschool goers. The private preschool goers who may have attended at most six months of primary school before Round 2 testing are best performers in the sample.

Figure 1. Distribution of test scores by participation categories



I present further summary statistics on the test scores by particpation categories in Table 6. Looking at the raw test score, the average score for the overall sample is quite low at 7.8 (out of a total of 22) in Round 1 and just about half of the total at 11.8 in Round 2. There is a substantial proportion of children who score 0 on the test in Round 1 (12 percent of the overall sample). Most of these children are those who were not enrolled. This proportion drops across all particpation categories in Round 2. Additionally, while less than 1 percent of the overall sample score the full total of 22 in Round 1, in Round 2, 2.3 percent of the overall sample achieve a full score.

Table 6. Summary statistics on test score by participation categories

	Never enrolled	Primary School	Private preschool	Public preschool	Private preschool and school	Public preschool and school	Total
Round 1							
Raw score	4.46	6.36	8.55	7.89	8.26	7.19	7.84
Proportion scoring 0	0.29	0.17	0.11	0.11	0.10	0.14	0.12
Proportion scoring full	0	0.001	0.007	0.004	0.003	0	0.004
Standardised score	-0.714	-0.313	0.150	0.0101	0.0883	-0.138	0.0
Round 2							
Raw score	6.70	10.79	13.10	10.69	13.47	11.65	11.80
Proportion scoring 0	0.15	0.049	0.016	0.043	0.016	0.031	0.032
Proportion scoring full	0	0.013	0.034	0.015	0.032	0.020	0.023
Standardised score	-0.241	0.624	1.112	0.602	1.188	0.805	0.836
N	100	761	2649	2753	623	1238	8124

This table presents different statistics on the test score in Round 1 (lagged) and in Round 2 (current) by the educational participation categories. The categories are never enrolled, primary school with no preschool exposure, attending a private preschool in both Rounds 1 and 2, attending a public preschool in both Rounds 1 and 2, attending a private preschool before starting primary school, attending a public preschool before starting primary school, and the overall sample. The raw score is sum of correctly answered questions and ranges from 0 to 22. The standardised score is the raw score standardised using the Round 1 mean and standard deviation.

2.5. Sample characteristics

Table 7 reports the mean (and standard deviation) for the children by the participation categories. Column 1 reports the summary statistics for never enrolled; Column 2 for children in primary school (with no preschool exposure); Columns 3 for preschool (private and public) goers; Column 4 for private preschool goers; Column 5 for public preschool goers; Column 6 for children with both preschool (private and public) and primary school; Columns 7 and 8 differentiate the preschool participation among these children by private and public management types respectively; and Column 9 reports the summary statistics for the entire sample[12].

Older children are more likely to be in primary school or to have switched to primary school from preschool. Within preschools, private preschool goers tend to be marginally older than public preschool goers. Girls, muslims, scheduled caste, and scheduled tribe are less likely to have attended a private preschool. Children from scheduled caste and scheduled tribe are more

[12] In Appendix A, Section A.6, I present the results of a multinomial logit on choice of educational participation for a more nuanced exercise of understanding how the observable characteristics affect participation.

likely to attend primary school, while muslims are more likely to not be enrolled.

Parent’s education, wealth index, and consumer durable index are associated with private preschool attendance. The poorest families are most likely to send their child to a public preschool. If both parents are employed outside the household, the child is more likely to have attended a preschool, in particular a public preschool. This might be because public preschool are more informal in set up and they tend to be used as free crèche facilities in villages. Households having children’s reading material and play material are more likely to send the child to some educational institute as against not enrolling he child.

Table 7. Child and household characteristics by participation categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Preschool			**Mixed**		
	Never Enrolled	School	Total	Private preschool	Public preschool	Total	Private preschool and school	Public preschool and school	Full sample
Female	0.490	0.502	0.479	0.427	0.530	0.492	0.427	0.525	0.484
	[0.502]	[0.500]	[0.500]	[0.495]	[0.499]	[0.500]	[0.495]	[0.500]	[0.500]
Age in months	62.681	63.712	62.890	63.132	62.657	63.648	63.893	63.525	63.138
	[3.313]	[3.185]	[3.431]	[3.301]	[3.537]	[3.288]	[3.368]	[3.241]	[3.394]
Years of education - Father	4.960	5.506	6.279	7.747	4.866	5.500	7.398	4.545	6.012
	[4.452]	[4.546]	[4.699]	[4.653]	[4.293]	[4.898]	[4.956]	[4.582]	[4.743]
Years of education - Mother	0.630	1.970	4.180	5.144	3.254	2.794	3.909	2.233	3.612
	[1.905]	[3.282]	[4.412]	[4.701]	[3.896]	[3.792]	[4.195]	[3.439]	[4.244]
Both parents work outside of home	0.040	0.188	0.277	0.277	0.276	0.379	0.169	0.485	0.289
	[0.197]	[0.391]	[0.447]	[0.448]	[0.447]	[0.485]	[0.375]	[0.500]	[0.453]
Muslim (Base category: Hindu)	0.380	0.192	0.168	0.102	0.231	0.114	0.093	0.124	0.160
	[0.488]	[0.394]	[0.374]	[0.303]	[0.422]	[0.318]	[0.291]	[0.330]	[0.367]
Scheduled caste	0.160	0.233	0.136	0.127	0.145	0.228	0.141	0.272	0.167
	[0.368]	[0.423]	[0.343]	[0.333]	[0.352]	[0.420]	[0.349]	[0.445]	[0.373]
Scheduled tribe	0.100	0.129	0.091	0.067	0.114	0.114	0.108	0.118	0.100
	[0.302]	[0.335]	[0.287]	[0.250]	[0.318]	[0.318]	[0.310]	[0.323]	[0.300]
Backward castes	0.540	0.489	0.501	0.589	0.416	0.504	0.551	0.481	0.501
	[0.501]	[0.500]	[0.500]	[0.492]	[0.493]	[0.500]	[0.498]	[0.500]	[0.500]
Wealth index	-0.167	-0.167	0.026	0.458	-0.389	0.011	0.298	-0.133	0.002
	[0.872]	[0.862]	[1.031]	[0.967]	[0.913]	[0.936]	[0.980]	[0.879]	[0.995]
Ownership of durables index	-0.052	-0.068	-0.011	0.455	-0.459	0.082	0.271	-0.013	0.005
	[0.997]	[0.924]	[1.021]	[0.972]	[0.852]	[0.940]	[1.019]	[0.883]	[0.994]
HH has children's reading material	0.640	0.813	0.812	0.810	0.814	0.747	0.880	0.681	0.795
	[0.482]	[0.390]	[0.391]	[0.392]	[0.389]	[0.435]	[0.326]	[0.466]	[0.404]
HH has toys/games for child	0.140	0.229	0.372	0.440	0.305	0.325	0.379	0.298	0.345
	[0.349]	[0.420]	[0.483]	[0.497]	[0.461]	[0.469]	[0.485]	[0.458]	[0.475]
N	100	761	5402	2649	2753	1861	623	1238	8124

The child's age is in months at the time of testing in Round 2. Both parents work outside of home is a dummy variable which is 0 when either one of the parent stays at home. Scheduled caste, scheduled tribe and backward castes are dummy variables with general caste as the base category. The wealth index comprises of household building material (bricks as against mud/straw), having a toilet, piped water, electricity and using higher grade fuel (LPG as against kerosene or wood or cow dung) for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.

Table 8 provides the summary statistics on additional variables capturing child and parent motivation. Households are more likely to read a story to the child and help with learning if the child is in preschool rather than in primary school or never enrolled. However, if attending a preschool requires more home study, a household may be more likely to enage in such activities. While all information on these controls come from the Round 1 survey, as seen in Table 2, the children were already attending an institution in Round 1. Hence, it is likely that households have changed their input in response to the school/preschool input. Because of this concern, I do not use these variables in my main regressions, but only as robustness checks.

Additional questions relating to parent and child motivation were only adminitered to children in preschool. Parents who switch their child to a primary school by Round 2 report lower probability of engaging with preschool staff in Round 1. The proportion of parents wanting their child to learn to read and write is highest for children who go to a private preschool with primary school. Children who went to a private preschool and then a primary school are most likely to report liking going to a preschool. These additional questions are not used in the main regressions and only as robustness checks.

Table 8. Parent's and child's motivation by participation categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Preschool			**Mixed**		
	Never Enrolled	School	Total	Private preschool	Public preschool	Total	Private preschool and school	Public preschool and school	Full sample
Parent's motivation									
Reads story to child	0.040	0.089	0.393	0.308	0.475	0.204	0.199	0.206	0.317
	[0.197]	[0.285]	[0.489]	[0.462]	[0.499]	[0.403]	[0.400]	[0.405]	[0.465]
Helps with learning tasks	0.090	0.298	0.629	0.607	0.651	0.467	0.621	0.390	0.555
	[0.288]	[0.458]	[0.483]	[0.489]	[0.477]	[0.499]	[0.485]	[0.488]	[0.497]
Talk to staff about child's learning progress			0.329	0.318	0.339	0.275	0.345	0.239	
			[0.470]	[0.466]	[0.473]	[0.446]	[0.476]	[0.427]	
Wants child to read/write			0.775	0.760	0.789	0.760	0.827	0.726	
			[0.418]	[0.427]	[0.408]	[0.427]	[0.379]	[0.446]	
Child's motivation									
Child talks about preschool always			0.342	0.301	0.380	0.210	0.246	0.192	
			[0.474]	[0.459]	[0.486]	[0.407]	[0.431]	[0.394]	
Child talks about preschool sometimes			0.372	0.393	0.351	0.436	0.395	0.457	
			[0.483]	[0.488]	[0.477]	[0.496]	[0.489]	[0.498]	
Child likes going to preschool			0.610	0.598	0.622	0.538	0.748	0.433	
			[0.488]	[0.490]	[0.485]	[0.499]	[0.435]	[0.496]	
N	100	761	5402	2649	2753	1861	623	1238	8124

This table presents the mean and standard deviation in parenthesis on child and parent motivation variables by the educational participation categories. While all variables were administered to children attending preschool in Round 1, only a subset were administered to the full sample of children. All variables reported in this table come from Round 1 survey. Reads story to the child is a dummy variable which takes the value of 0 if no-one in the household reads story to the child at least once a week. Helps with learning tasks takes the value of 0 if no one in the household helps the child with homework at least once a week. Talks to staff about child's learning progress takes the value of 0 if the parent has not spoken to the staff in the past 3 months. The base category for the child talks about preschool always and sometimes is that the child never talks about the preschool.

3. Method

3.1. Value Added Model – theoretical derivation

The basis of the value-added model, used in recent literature, is a structural cumulative effects model developed by Boardman and Murnane (1979). Following Todd and Wolpin (2003) and Todd and Wolpin (2007), the general functional form is as follows,

$$T_{it} = T_t[F_i(t), S_i(t), X_i(\mathrm{t}), \mu_{i0}, \varepsilon_{it}] \qquad (1)$$

where T_{it} is a measure of achievement for child i at the end of the t-th year of life, F_i , S_i and X_i are the family, school and individual based input histories up to age *t* respectively, μ_{i0} is the time invariant individual endowment[13], and ε_{it} is a time varying error term.

Assuming the function in (1) is additively separable and non-age varying, we arrive at the cumulative effects model or the distributed lag model.

$$T_{it} = \alpha_1 F_{it} + \alpha_2 F_{i(t-1)} + \cdots + \alpha_{\mathrm{t}} F_{i1} + \beta_1 S_{it} + \beta_2 S_{i(t-1)} + \cdots + \beta_t S_{i1} + \gamma_1 X_{it} + \gamma_2 X_{i(t-1)} + \cdots + \gamma_t X_{i1} + \phi_t \mu_{i0} + \varepsilon_{it} (2)$$

It is important to note that linearity and additive separability are trivial assumptions to ease computability and interpretation. This is the most commonly used formulation of the cumulative effects model[14]. One can easily test if the functional form is mis-specified by introducing polynomials or using logarithmic transformation.

Second, non-age varying assumption implies that the impact of any input on achievement varies within the time period of application of the input and realization of achievement; however, it does not matter at which age or time period the input is applied. For example, it is assumed that the effect of a small class size at the age of 6 on achievement score at age 7 is the same as the effect of small class size at the age of 8 on the achievement score at age 9. This might seem like an unreasonable assumption, given the evidence for greater returns to investing in human capital in

[13] This can be thought of as genetic endowment or ability which is fixed at conception and does not vary over time. This is not to say that the effect of the endowment is fixed with time. The functional form allows ability to have different effects over time, that is, it allows for the notion that higher ability children may learn faster.

[14] An exception is Harris (2007) who uses a trans-log functional form.

the early years (see Cunha et al., 2006; Doyle et al., 2009). Although one can easily introduce extra interaction terms and allow for age varying intercepts, this is not ideal, due to loss of degrees of freedom and issues of multicollinearity.

It is important to note here that the μ_{i0} term in (2) remains untouched by the non-age varying assumption. The effect of ability can be interpreted in two ways in equation (2). First, ability can be thought of as fixed at conception, but having varying effects at different ages of the child, which is what ϕ_t would capture. Second, ability can be thought of as malleable and changing from the initial endowment. Given that ability cannot be observed, one cannot estimate the parameter on ability and observationally, both interpretations of the function of ability will give the same result.

Estimating equation (2) is difficult as data which tracks the child right from birth till current period and has information on inputs at every stage is impossible to come by. Also, one can easily see lag terms to be highly correlated with each other, giving little meaningful information to researchers and policy makers. If one is willing to assume geometric decay of prior inputs, and that this geometric decay parameter is the same for all prior inputs, we have $\alpha_t = \lambda\alpha_{t-1}; \beta_t = \lambda\beta_{t-1}; \gamma_t = \lambda\gamma_{t-1}$ where $0 \leq \lambda \leq 1$. The equation now becomes –

$$T_{it} = \alpha_1 F_{it} + \lambda\alpha_1 F_{it-1} + \cdots + \lambda^{t-1}\alpha_1 F_{i1} + \beta_1 S_{it} + \lambda\beta_1 S_{i(t-1)} + \cdots + \lambda^{t-1}\beta_1 S_{i1} + \gamma_1 X_{it} + \lambda\gamma_1 X_{i(t-1)} + \cdots + \lambda^{t-1}\gamma_1 X_{i1} + \phi_t\mu_{i0} + \varepsilon_{it} \qquad (3)$$

Subtracting $\lambda T_{i(t-1)}$ from both sides of equation (3), we have,

$$T_{it} = \lambda T_{i(t-1)} + \alpha_1 F_{it} + \beta_1 S_{it} + \gamma_1 X_{it} + (\phi_t - \lambda\phi_{t-1})\mu_{ij0} + \varepsilon_{it} - \lambda\varepsilon_{i(t-1)} \qquad (4)$$

The process described by geometric decay is well documented in literature – Banerjee et al. (2007) report that the 1-year treatment effect of educational intervention on test scores fade out by the 3rd year; Currie and Thomas (2000) and Lee et al. (1990) also show similar fading out of the Head Start preschool program, at least on achievement scores. If the effect of initial ability on achievement changes at a constant rate, then we finally have –

$$T_{it} = \lambda T_{i(t-1)} + \alpha_1 F_{it} + \beta_1 S_{it} + \gamma_1 X_{it} + v_i + \eta_i \qquad (5)$$

where $v_i = \phi\mu_{i0}$ and $\eta_i = \varepsilon_{it} - \lambda\varepsilon_{i(t-1)}$

Equation (5), is commonly known as the lagged score value added model (VAM). This is not the only specification of VAM in common use. The other two versions are the highly restrictive contemporaneous VAM which assumes immediate decay of prior inputs or $\lambda = 0$, and the gain score specification, which assumes that there is perfect persistence or $\lambda = 1$. While the former assumes that inputs in previous years have no impact in current year, the latter assumes that inputs in previous years have full (the same effect as they would have had in *t*-1) effect in current year. Hence, lagged score VAM is the least restrictive. I use the lagged score VAM as my main specification throughout the paper, while also reporting the results from contemporaneous VAM and perfect persistence VAM.

3.2. Value Added Model – estimated specification

This paper uses the lagged VAM as the main specification in the analysis.

$$T_{it} = \lambda T_{i(t-1)} + \beta_{\text{pre}}\text{preschool}_{\text{it}} + \beta_{\text{pri}}\text{primary school}_{\text{it}} + \beta_{\text{mixed}}\text{preschool and school}_{it} + \delta_1\text{village}_{\text{i}} + \alpha_1 F_{it} + \gamma_1 X_{it} + \eta_i \qquad (6)$$

where *preschool* is a dummy variable for having attended only preschool and not yet started primary school, *primary school* is a dummy variable for having attended only primary school with no preschool exposure, and *preschool and school* is a dummy variable for children who have started primary school after attending a preschool. The base category is for children who are not enrolled. The regression controls for village fixed effects (*village$_i$)* to ensure that differences in educational infrastructure provisioning at the village level is controlled for. The standard errors are clustered at the village level to account for the fact that sampling was not at random; deliberately choosing larger villages, and for spatial correlation within villages. I report equation (6) without household (F_{it}) and child (X_{it}) controls, and equation (6) with all controls. I also additionally report the results from contemporaneous VAM ($\lambda = 0$) and perfect persistence VAM ($\lambda = 1$).

The model in (6) is estimated using Dynamic OLS (DOLS). This estimation may be vulnerable to bias from two main sources. First, the identification of preschool and primary school effects relies on the assumption that the lagged test score is a sufficient proxy for the unobserved ability (v_i in eq (5)). This assumption may be violated if parents use more information than those captured in equation (6) while making a decision to send their child to an educational institute. It may also be violated if the unobserved ability does not decay at the same rate as the lagged achievement or if it has time varying effects. Since one cannot observe inherent ability, this is akin to saying that talented children learn faster. Both these cases would lead to an upward bias in our β coefficients of interest. Following Singh (2015) who uses DOLS estimation of lagged score VAM to study the differential impact of private and public primary school, I employ a series of robustness checks to ascertain if indeed there is a potential bias from lagged score being a poor proxy of innate ability.

Second, conditioning on lagged test score may introduce a measurement bias, which would attenuate the persistence coefficient (λ), and consequently bias the β coefficients of interest in an unknown direction. The precise bias on β coefficients will depend on the degree of correlation with lagged inputs, which are all now a part of the error term. Ideally, one would want to control for IQ or mental ability along with test scores (as suggested in Todd & Wolpin, 2003), as this would circumvent the measurement error. However, I am unable to do so since there is no data on IQ for my sample. Andrabi et al. (2011) discuss this issue in depth and show how correcting only for measurement error in their sample results in worse estimates for the variable of interest.

There may be concern around using DOLS estimation with lagged score as the lagged test score will be correlated with $\eta_i = \varepsilon_{it} - \lambda\varepsilon_{i(t-1)}$. However, as long as $\lambda < 1$, the DOLS estimation is asymptotically consistent. Indeed, the literature on VAM has found the persistence parameter to be less than 0.5 in most cases (see Andrabi et al., 2011; Kane & Staiger, 2008; Rothstein, 2010).

VAMs have been used extensively in the education literature, mostly in the US teacher value added empirical work. However, a separate strand studying the effects of different management type of schools and its impact is closest in application to this paper here. The work on effects of charter schools (for instance, see Hanushek et al., 2007; Sass, 2006) and the effects of private school (for instance, see Andrabi et al., 2011; Singh, 2015) have shown that VAMs are indeed a reliable identification tool.

Additionally, work by Guarino et al. (2015) on comparing different estimators of VAMs have stressed the superiority of DOLS as an efficient and consistent estimator. They assess the reliability of different VAMs estimators for recovering teacher effects using simulated data with a variety of non-random teacher-student assignment structure. They find that DOLS estimator performed robustly across most scenarios; better than other estimators, namely, Arellano-Bond panel data estimators, pooled OLS on gain score VAM specification, random effects model on gain score VAM, fixed effects model on gain score VAM, and average residual approach. They report that 'the main strength of this (*referring to DOLS)* estimator lies in the fact that, by including prior achievement on the right hand side, it controls whether directly or indirectly for grouping and assignment mechanisms' (Guarino et al., 2015, p.30). Hence, by allowing the lagged test score and the variable of interest to be correlated, DOLS takes care of the selection issue.

Andrabi et al. (2011) while studying the impact of private schools on cognitive achievement for Pakistan report that 'despite ignoring measurement error and unobserved heterogeneity, the lagged value-added model estimated by DOLS gives similar results for the private school effects as our more data intensive dynamic panel methods, although persistence remains overstated. The relative success of the lagged VAM can be explained by the countervailing heterogeneity and measurement error biases on persistence parameter and because lagged achievement can also act as a partial proxy for omitted heterogeneity in learning' (Andrabi et al., 2011, p.31).

More recently, Crawfurd and Elks (2019) tested the robustness of VAM models to predict school quality in Uganda and conclude the model to be robust to different specifications and controls. Moreover, VAMs can be a low-cost way of uncovering how much learning is happening in schools, particularly in low-income countries.

At this stage, I would like to draw a distinction between technology parameter (ceteris-paribus effect) and the policy effect (total effect) (Todd & Wolpin, 2003). Since VAMs are not the same as the cumulative effects structural model (equation (2)), one must remember that we are no longer estimating the technology parameter in the lagged score VAM. Thus, there is a need for caution as to which variables are included as controls – for example, one must not control for the channels through which private preschool choice would have an effect on learning because that would be part of the 'policy effect'. As soon as one controls for current family inputs or children's behavior, which might have changed due to the preschool choice, one is no longer calculating the average treatment effect, but the technology parameter. I will refrain from estimating the latter as there is not enough data or theory to guide the set of variables to be included.

One of the implications of this distinction, is that much of the criticism around VAM applied to teacher performance literature, primarily in the US, is due to researchers trying to evaluate teacher value added without controlling for change in the family input, resulting from being assigned to a low quality (or high quality) teacher. Since most of the papers engaged in calculating teacher value added (technology parameter) use school administration data, they have little information on households. In such a scenario, estimation involves assuming that household effect is time-invariant. Such an assumption would lead to misclassification of teachers. As shown by Guarino et al. (2015) and Sass et al. (2014), varying VAM specifications and estimation methods typically misclassify teachers, even though they provide reliable estimates of the average effect. As such, the scope of this paper is not to distill the individual preschool fixed effects, but to assess the average treatment effect of preschool. Thus, most of the criticism around VAM stemming from the application of this model to teacher value added is not valid for my exercise in this paper.

4. Results

4.1. Preschool value added

In Table 9, I present the results of value added by preschools as compared to not enrolled, primary school (with no preschool exposure) and both preschool and primary school. Not enrolled serves as the base category in these estimations. However, as noted in Table 3, only 1 percent of the sample are not enrolled, and they are all located in Rajasthan. There might be concern over the reliability of the estimates using this category. In Appendix A Table A.5, I report the regressions on a sub-sample excluding the not enrolled category. The estimates remain significant and qualitatively similar to those reported here.

In Table 9, Columns 1 and 2 assume instant decay of input and are the results from contemporaneous VAM. Columns 3 and 4 assume perfect persistence of past inputs. Columns 5 and 6 are my preferred specification of the lagged score VAM. Straightaway, we find that our coefficients of interest are biased upwards in contemporaneous VAM and biased downwards in a perfect persistence VAM. Columns 1, 3, and 5 have no controls. Columns 2, 4 and 6 have household and child level controls. The effects of controls are as expected and documented in the literature – girls and children belonging to socially disadvantaged groups perform worse on the test; older children, children from more educated parents and richer household perform better on the test.

Coming to the preferred specification (Column 6), there is a positive and significant effect of going to a preschool or a primary school or a preschool with primary school vis-à-vis children who are not enrolled anywhere. Going to a preschool increases the test score by 0.44 SD units, going to a primary school increases the test score by 0.53 SD units, and going to a preschool with primary school increases the test score by 0.67 SD units. These effects are large, but expected, as the base category are the children who have never been enrolled in any educational institute.

The more interesting comparison is children who attended primary school (with no exposure to preschool) and children who attended preschool. I find that there is no premium on test score of attending a preschool – in fact, these children perform worse than the children enrolled in primary school by 0.07 SD unit (significant at 5 percent). However, since teaching in primary school is more instructional and formal, and children are more familiar with test taking scenarios, it would be unfair to compare children who are yet to attend primary school with children who have been attending primary school for a while.

As discussed earlier in Section 3.3, some of the children who attended preschool also start going to primary school by Round 2. To truly gauge if attending a preschool before starting primary school has a premium, I compare the group of children with both preschool and primary school exposure to children with only primary school exposure. Children who attended preschool before starting primary school have a significant (at 1 percent) premium of 0.14 SD unit over children with only primary school experience. Hence, while it seems that preschool children lag behind in achievement tests at first glance, they seem to reap the benefits of their preschool experience when they enter primary school[15].

Table 9. Preschool VAM estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous VAM		Perfect persistence VAM		Lagged score VAM	
Lagged - Standardised score	0	0	1	1	0.276***	0.225***
					(0.019)	(0.017)
Preschool	0.657***	0.515***	0.196**	0.174*	0.530***	0.438***
	(0.081)	(0.085)	(0.093)	(0.095)	(0.079)	(0.083)
Primary school	0.625***	0.604***	0.245**	0.257**	0.520***	0.526***
	(0.085)	(0.088)	(0.100)	(0.101)	(0.083)	(0.086)
Preschool and school	0.837***	0.750***	0.378***	0.377***	0.711***	0.666***
	(0.084)	(0.087)	(0.097)	(0.098)	(0.082)	(0.086)
Constant	-0.687***	-2.249***	-0.240***	-0.392	-0.564***	-1.832***
	(0.079)	(0.239)	(0.091)	(0.279)	(0.077)	(0.226)
Controls added	No	Yes	No	Yes	No	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,124	8,124	8,124	8,124	8,124	8,124
R-squared	0.257	0.313	0.244	0.248	0.312	0.348
Preschool=School F-stat	0.411	3.987**	0.961	2.652	0.0413	4.215**
Preschool=Mixed F-stat	22.32***	44.16***	22.46***	26.88***	25.38***	44.21***
School=Mixed F-stat	18.38***	9.707***	5.311**	4.383**	15.80***	9.280***

All specifications control for village fixed effects. Standard errors are clustered at the village level. The table also reports the F-stat from testing equality of coefficient between preschool and primary school; between preschool and preschool with primary school (mixed); and between primary school and mixed. The variables of interest are preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), primary school (attending primary schools in Rounds 1 and 2 with no preschool exposure) and attending preschool before starting primary school. The base category is not enrolled. Columns 2, 4 and 6 have child and HH level controls – child's gender, child's age in months at Round 2, mother's education in years, father's education in years, whether both parents work outside of home, religion, caste, wealth index, consumer durables index, HH has child's learning material, HH has toys/games for child. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

4.2. Private preschool value added

There is well-documented evidence of the public-private divide in the Indian context (see French & Kingdon, 2010; Desai et al., 2009; Chudgar & Quin, 2012). Given the rapidly growing private sector in the Indian education landscape and the significant gaps in learning due to management type heterogeneity, I delve deeper into the preschool effect. Instead of looking at just the preschool variable, I now differentiate the children as going to a public or private preschool.

[15] There may be a concern that since the switch from preschool to primary school happens between Round 1 and Round 2, it could be due to an unobservable shock, which would no longer be captured by the controls and the lagged score. I re-run this analysis without the mixed (preschool and primary school) sample. The results are reported in Appendix A Table A.9. The results are qualitatively similar for the coefficients on preschool and primary school.

Table 10 presents the results of value added by preschool type[16]. Columns 1 and 2 assume instant decay of input and are the results from contemporaneous VAM. Columns 3 and 4 assume perfect persistence of past inputs. Columns 5 and 6 are my preferred specification of the lagged score VAM. I find that the coefficients of interest are biased upwards in contemporaneous VAM and biased downwards in a perfect persistence VAM. Columns 1, 3, and 5 have no controls. Columns 2, 4 and 6 have household and child level controls.

Coming to the preferred specification (Column 6), there is a positive and significant effect of going to a private preschool. Children from private preschool have a value-added premium of 0.62 SD units (significant at 1 percent) when compared to children from public preschool. Additionally, they score 0.13 SD units higher (significant at 1 percent) on the test than children with only primary school exposure.

On the other hand, attending a public preschool barely has a premium on achievement even when compared to children who are not enrolled – a insignificant premium of 0.08 SD unit. These children from public preschool do significantly worse on test scores when compared to their private preschool counterpart as well as the primary school category.

When one looks at children with both public preschool and primary school exposure, the value-added coefficient is 0.59 SD unit. This is not significantly different from that of children with only primary school experience. Hence, the effects of preschool that we saw in Section 5.1, were entirely driven by children who attend private preschools[17].

[16] In Appendix A Table A.6, I report the regressions on a sub-sample excluding the not enrolled category. The estimates remain significant and qualitatively similar to those reported here.

[17] There may be a concern that since the switch from preschool to primary school happens between Round 1 and Round 2, it could be due to an unobservable shock, which would no longer be captured by the controls and the lagged score. I re-run this analysis without the mixed (preschool and primary school) sample. The results are reported in Appendix A Table A.9. The results are qualitatively similar for the coefficients on private preschool, public preschool and primary school.

Table 10. Private preschool VAM estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous VAM		Perfect persistence VAM		Lagged score VAM	
Lagged - Standardised score	0	0	1	1	0.224***	0.198***
					(0.018)	(0.017)
Private preschool	0.942***	0.790***	0.339***	0.338***	0.806***	0.700***
	(0.079)	(0.083)	(0.097)	(0.098)	(0.079)	(0.083)
Public preschool	0.105	0.116	-0.058	-0.053	0.068	0.083
	(0.079)	(0.082)	(0.095)	(0.096)	(0.078)	(0.081)
Primary school	0.674***	0.645***	0.261***	0.272***	0.581***	0.571***
	(0.083)	(0.085)	(0.100)	(0.101)	(0.081)	(0.084)
Private preschool and school	1.157***	1.032***	0.373***	0.379***	0.981***	0.903***
	(0.090)	(0.094)	(0.105)	(0.106)	(0.087)	(0.091)
Public preschool and school	0.669***	0.638***	0.385***	0.399***	0.606***	0.591***
	(0.082)	(0.085)	(0.099)	(0.100)	(0.082)	(0.084)
Constant	-0.596***	-1.947***	-0.203**	-0.228	-0.508***	-1.606***
	(0.074)	(0.230)	(0.091)	(0.276)	(0.074)	(0.218)
Controls added	No	Yes	No	Yes	No	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,124	8,124	8,124	8,124	8,124	8,124
R-squared	0.331	0.356	0.255	0.257	0.367	0.382
Private preschool=School F-stat	32.83***	10.54***	2.272	1.517	25.29***	8.930***
Public preschool=School F-stat	105.9***	97.13***	29.19***	30***	97.32***	90.52***
Private preschool=Public preschool F-stat	384.9***	239.1***	72.83***	67.93***	317.8***	210.8***
Private preschool and school=School F-stat	62.66***	40.27***	2.840*	2.508	47.10***	31.71***
Public preschool and school=School F-stat	0.00927	0.0211	4.019**	4.182**	0.250	0.169

All specifications control for village fixed effects. Standard errors are clustered at the village level. The table also reports the F-stat from testing equality of coefficient between private preschool and primary school; between public preschool and primary school; between private and public preschool; between private preschool with primary school and primary school only; and between private preschool with primary school and primary school only. The variables of interest are private preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), public preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), primary school (attending primary schools in Rounds 1 and 2 with no preschool exposure), attending private preschool before starting primary school, and attending public preschool before starting primary school. The base category is not enrolled. Columns 2, 4 and 6 have child and HH level controls – child's gender, child's age in months at Round 2, mother's education in years, father's education in years, whether both parents work outside of home, religion, caste, wealth index, consumer durables index, HH has child's learning material, HH has toys/games for child The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

4.3. Preschool quality

Given that I find such a remarkable difference in test score by the management type of preschool, the natural line of inquiry is to understand the nature of these preschools. To this end, I use the preschool survey conducted in Round 1. A total of 1159 preschools were surveyed across 300 villages in my sample, of which, 76 percent are public preschools[18]. Table 11 reports the mean and standard deviation on selected indicators by management type, as well as the t-test of difference between these public and private preschool characteristics[19].

Overall, I find that private preschools have better physical infrastructure. Public preschools are more likely to have a kitchen, and this is due to the government mandated meal scheme in India, which does not apply to the private education sector. Public preschools are also more likely to have a building made of bricks rather that mud. This may be because public preschools are seldom housed together with other arms of ICDS providing facilities such as child nutrition, child immunisation, child health check-up, and nutrition and health education for mothers.

Private preschools have significantly lower student-teacher ratio than public preschools.
The classrooms in public preschools have better display materials – artwork and alphabet/number charts. They also are more likely to be equipped with toys and games for children. However, a key difference is in the variable where teachers were observed to be teaching. It may be the case that private preschools have more formal instruction akin to primary schools, while public preschools are more focussed on developing a child's socio-emotional or motor skills through play-based activities. Indeed, the National Policy on Education (Government of India, 1986), and the National Early Childhood Care and Education Policy (Government of India, 2013) have discouraged any formal instruction of the 3R's and emphasised play-based learning. This could explain the difference in the test score between the two management types. It also suggests a need for a more complete evaluation exercise using data that captures socio-emotional skills in the early childhood phase.

This difference in learning styles across the two management types is confirmed when I use the

[18] Here, I note that this data may be biased for several reasons. Not all preschools would have been surveyed, depending on whether these were open at the time of the visit and granted access to the investigators to conduct a survey. Private preschools may be more inclined to not grant such access; and the ones that did, could very well be 'better' quality. Indeed, substantially fewer private facilities were surveyed. See Appendix A, Section A.3 for details.

[19] Since the preschool data does not have unique identifier to link with the household survey, I am limited in my exercise and can only show the average characteristics by management type. I am unable to put these in a child level regression to study which aspect of preschool quality matters the most for the child's test score.

household survey. The household survey asked parents a range of questions on the activities that happened at the preschools. Again, I find that children in private preschools are more likely to engage in formal study with reading and writing activities. Children in public preschools are more likely to engage in play-based activities – artwork, singing songs, playing with toys or puzzles, and listening to stories. However, this may be set to change with the new National Education Policy (Government of India, 2020). The policy, while emphasising the use of play-based learning, posits one of the aims of preschool education as developing early literacy and numeracy. Children in private preschool also report spending more hours at the facility, on average 4.4 hours as compared to 3.6 hours in public preschools. The lower number of hours in public preschools is in violation of the government mandate of 4 hours of educational instruction in public preschools[20].

[20] While not captured by the survey, it is crucial to mention here that the Government of India allows the hiring of staff with no experience and no high school diploma as a teacher at public preschool. See https://icds-wcd.nic.in/icds.aspx. There is a route for these staff to get appropriate training. However, even assuming that this would be done in a timely fashion, the training is for a mere 26-day period.

Table 11. Selected characteristics of preschools by management type

	(1) Public preschool	(2) Private Preschool	(3) Total	(4) t-test (1)-(2)
Preschool Survey				
Student teacher ratio	14.226	9.437	13.204	4.789***
	[8.115]	[7.648]	[8.251]	
Building made of bricks/mortar	0.930	0.864	0.915	0.066***
	[0.255]	[0.343]	[0.280]	
Has a toilet	0.447	0.733	0.514	-0.286***
	[0.497]	[0.443]	[0.500]	
Has water facility	0.550	0.813	0.612	-0.264***
	[0.498]	[0.390]	[0.488]	
Has boundary wall	0.360	0.718	0.444	-0.358***
	[0.480]	[0.451]	[0.497]	
Has a playground	0.749	0.740	0.747	0.010
	[0.434]	[0.439]	[0.435]	
Has a kitchen	0.283	0.059	0.230	0.225***
	[0.451]	[0.235]	[0.421]	
Classroom has children's art display	0.542	0.223	0.467	0.318***
	[0.499]	[0.417]	[0.499]	
Classroom has learning charts	0.888	0.740	0.853	0.148***
	[0.315]	[0.439]	[0.354]	
Classroom has toys/games/puzzles	0.691	0.542	0.656	0.149***
	[0.462]	[0.499]	[0.475]	
Classroom has books	0.868	0.810	0.854	0.058**
	[0.339]	[0.393]	[0.353]	
Teacher was seen teaching	0.690	0.777	0.710	-0.087***
	[0.463]	[0.417]	[0.454]	
Teacher was seen playing games	0.528	0.176	0.445	0.352***
	[0.499]	[0.381]	[0.497]	
Teacher was seen using books	0.650	0.667	0.654	-0.017
	[0.477]	[0.472]	[0.476]	
N(preschools)	886	273	1159	
Household Survey				
Hours spent at preschool	3.562	4.442	3.959	-0.881***
	[1.252]	[1.053]	[1.246]	
Child gets food	0.620	0.264	0.460	0.356***
	[0.485]	[0.441]	[0.498]	
Child learns to read and write	0.694	0.804	0.744	-0.110***
	[0.461]	[0.397]	[0.437]	
Child plays games	0.537	0.430	0.489	0.107***
	[0.499]	[0.495]	[0.500]	
Child draws and colours	0.176	0.105	0.144	0.072***
	[0.381]	[0.306]	[0.351]	
Child sings songs and poems	0.176	0.142	0.161	0.034***
	[0.381]	[0.350]	[0.368]	
Child plays with toys and puzzles	0.039	0.024	0.032	0.016***
	[0.194]	[0.152]	[0.176]	
Child listens to stories	0.229	0.191	0.212	0.038***
	[0.420]	[0.393]	[0.408]	
N(children)	3991	3272	7263	

The first set of characteristics comes from a preschool survey conducted in Round 1. See Section **A.3** for details. The second set of characteristics comes from the household survey where parents would have answered these questions. The questions from household survey were only administered to sample of children attending preschool in Round 1. *** p<0.01, ** p<0.05, * p<0.1

4.4. State heterogeneity in value added

There can be considerable regional heterogeneity in preschool quality and hence, in the learning premium by the different states in India. This is driven by both, the variation in public preschool quality, and private preschool quality. Although the public preschools are governed by a central policy designed and implemented by the Ministry of Women and Child Development, the daily operation of these preschools is devolved at the state level. Most states are expected to raise at least 40 percent of the operational cost themselves. This can introduce a degree of variation in the quality of public preschools across the country.

While this heterogeneity exists even at the primary school level, I am restricted by the state-level distribution of the participation categories in my data set, and hence, can only explore the differences in preschools. As noted in Table 3, all children who are not enrolled come from Rajasthan; there are no children in Assam who attend primary school (without preschool exposure) and very few children in Assam who have switched from preschool to primary school. This is due to the primary school starting age being higher in Assam at six years as opposed to five years in the other states. Thus, in order to have adequate sample size in all three states, I restrict the analysis sample in this section to children who are attending preschool and have not yet started primary school. I distinguish these preschool goers by private-public management type, where going to a public preschool is the base category.

Table 12 presents the results of the lagged score VAM with full set of controls and village fixed effects for the sub-sample of children who are enrolled in preschool in Round 2 and have not yet started primary school. Column 1 estimates the value added of private preschool for the overall sample. Columns 2, 3 and 4 estimate the same specification for Rajasthan, Assam and Telangana respectively. I find that the private preschool premium is highest in Telangana, followed by Assam, and, lastly, Rajasthan. The findings here suggest that the limited empirical evidence on Indian preschools (Singh & Mukherjee, 2017; Singh, 2014) from Telangana, need to be interpreted with caution as the results from these studies may not hold universally for a country as diverse as India.

Table 12. State level heterogeneity in value added for only preschool sample

	(1) Overall	(2) Rajasthan	(3) Assam	(4) Telangana
Lagged - Standardised score	0.160***	0.352***	0.060***	0.082***
	(0.018)	(0.029)	(0.023)	(0.030)
Private preschool	0.628***	0.503***	0.633***	0.744***
(Base category: Public preschool)	(0.046)	(0.047)	(0.093)	(0.098)
Sample	Preschool (not started primary school)	Preschool (not started primary school)	Preschool (not started primary school)	Preschool (not started primary school)
Controls added	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Observations	5,402	1,794	2,350	1,258
R-squared	0.424	0.481	0.394	0.418

This table runs the lagged score VAM only on the subsample of children who attend preschool in both Rounds 1 and 2 and have not yet started primary school. All specifications control for village fixed effects and child and household level controls as in Table 9. Standard errors are clustered at the village level. The variables of interest are private preschool (attending private preschool in Rounds 1 and 2 and not yet started primary school). The base category is public preschool. *** p<0.01, ** p<0.05, * p<0.1

4.5. Robustness check - Ability bias

In this section, I investigate if VAM estimates suffer from bias due to child heterogeneity following Singh (2015). As discussed in Section 4.2, if child heterogeneity is left in the error term, it would cause the coefficient of interests as well the coefficient on lagged test score to be biased upwards. Child heterogeneity would be left in the error term if talented or motivated children learn faster, or if lagged test score is not a good proxy for ability. In either case, the lagged score VAM is no longer identified.

In the household questionnaire, the parents were asked "*Does the child speak about his day at the preschool?*" and "*If yes, how frequently?*". I use the information from these two questions to construct dummy variables for whether the child speaks of preschool always, sometimes, and never (base category). Another question was asked to the child *"Do you like going to preschool?"*. I have also used this information as a dummy variable. Both these could serve as a proxy for a child's motivation and enthusiasm to learn. Since these questions were asked for the preschool sample, I can only conduct a check on the validity of my estimates for the subset of preschool goers (89 percent of the sample) comprising of those who were in preschool at Round 2, and those who had switched to a primary school after attending preschool.

Table 13 reports the results of the preferred lagged score VAM specification with full set of household and child controls and village fixed effects. Column 1 runs the preferred specification on the subsample of preschool goers where the base category is going to a public preschool. Column 2 reports the results of the same specification, but additionally controls for child motivation variables.

Table 13. VAM estimates robustness check with child motivation variables

	(1) Current score	(2) Current score
Lagged - Standardised score	0.183***	0.172***
	(0.017)	(0.016)
Private preschool	0.623***	0.619***
	(0.043)	(0.043)
Private preschool and school	0.831***	0.805***
	(0.060)	(0.060)
Public preschool and school	0.513***	0.517***
	(0.048)	(0.048)
Child talks about preschool always		0.110***
		(0.035)
Child talks about preschool sometimes		0.126***
		(0.029)
Child likes going to preschool		0.091***
		(0.029)
Sample	Preschool	Preschool
Controls	Yes	Yes
Village fixed effects	Yes	Yes
Observations	7,263	7,263
R-squared	0.383	0.387

This table runs the lagged score VAM only on the subsample of children who are either attending preschool in both Rounds 1 and 2 and have not yet started primary school or have attended preschool before starting primary school. All specifications control for village fixed effects and child and household level controls as in Table 9. Standard errors are clustered at the village level. The variables of interest are private preschool (attending private preschool in Rounds 1 and 2 and not yet started primary school); private preschool with primary school and public preschool with primary school. The base category is public preschool only with no primary school. The base category for child talks about preschool always/sometimes is child never talks about preschool. *** p<0.01, ** p<0.05, * p<0.1

I find that while talking about preschool activities and liking to go to preschool has a significant and positive effect on test score, the coefficient on variables of interest is revised downward only marginally[21]. However, note that the coefficient on lagged test score itself moves downwards on

[21] The null hypothesis of equality of the coefficient on private preschool and school from the two columns is rejected at 1 percent. However, there is no significant difference between the coefficients on private preschool and public preschool with school in Columns 1 and 2.

adding child motivation variables in Column 2. Further, in Appendix A Table A.8, I investigate this bias following Singh (2015). I look at the correlation between the lagged test score and the child motivation variables and find child motivation variables to be strongly correlated with lagged test score. This suggests that lagged test score does serve as a proxy for child motivation. Thus, despite the child motivation variables being significant, the coefficient on the variables of interest does not change greatly.

4.6. Robustness check - Parent's Motivation

Another source of bias with regards to VAM is when selection into type of educational institute is based on more information than those captured by the model. In particular, if the lagged test score is not a good proxy for this unobserved decision-making conducted in the past, the model would not be identified, and it would suffer from a positive selection bias.

I use information from the household questionnaire that could serve as indicators for parent's motivation and aspirations. I have made use of four variables to capture parental aspirations – whether parents read stories to the child at least once a week, whether they help him/her with learning at least once a week, whether they have spoken to a preschool staff about their child's learning progress at least once in the past three months, and whether they would like their child to learn to read and write. While the first two questions were administered to all households, the last two were only administered to the subset of parents whose children were in preschool in Round 1.

Table 14 reports the results of the preferred lagged score VAM specification with full set of household and child controls and village fixed effects. Column 1 reports the results of the preferred specification, which we have seen previously in Table 10. Column 2 reports the results of the same specification, but additionally controls for two variables capturing parent's motivation. Column 3 runs the preferred specification on the sub-sample of preschool goers where the base category is going to a public preschool. Column 4 reports the results of the same specification as in Column 3, but additionally controls for all four indicators of parent's motivations. In Column 5, I run the same specification as in Column 3 by only adding indicators on talking to preschool staff and parents wanting their child to read and write. I do this because the variables 'reads story to the child' and 'helps with learning' could be an adjustment in parental inputs in response to the educational institute being attended. For example, if private preschools assign homework to children and in response to this, parents have to help the child with learning, then this variable is part of the private preschool effect. It becomes a mechanism through which private preschools have a positive impact. Hence, one would expect the coefficient on private preschool to adjust downwards, even if there was no selection bias.

Table 14. VAM estimates robustness check with parent's motivation variables

	(1) Current score	(2) Current score	(3) Current score	(4) Current score	(5) Current score
Lagged - Standardised score	0.198***	0.195***	0.183***	0.177***	0.178***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Private preschool	0.700***	0.690***	0.623***	0.617***	0.620***
	(0.083)	(0.083)	(0.043)	(0.043)	(0.043)
Public preschool	0.083	0.077			
	(0.081)	(0.081)			
Primary school	0.571***	0.569***			
	(0.084)	(0.084)			
Private preschool and school	0.903***	0.889***	0.831***	0.813***	0.817***
	(0.091)	(0.091)	(0.060)	(0.061)	(0.060)
Public preschool and school	0.591***	0.586***	0.513***	0.515***	0.515***
	(0.084)	(0.085)	(0.048)	(0.049)	(0.049)
Reads story to child		0.049		0.048	
		(0.031)		(0.032)	
Helps with learning tasks		0.059**		0.043	
		(0.027)		(0.029)	
Talk to staff about child's learning progress				0.035	0.044
				(0.029)	(0.029)
Wants child to read/write				0.075***	0.083***
				(0.029)	(0.028)
Sample	Full	Full	Preschool	Preschool	Preschool
Controls	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	8,124	8,124	7,263	7,263	7,263
R-squared	0.382	0.383	0.383	0.385	0.384

This table runs the lagged score VAM only on the full sample (Columns 1 and 2) and on the subsample of children who are either attending preschool in both Rounds 1 and 2 and have not yet started primary school or have attended preschool before starting primary school (Columns 3, 4 and 5). All specifications control for village fixed effects and child and household level controls as in Table 9. Standard errors are clustered at the village level. The variables of interest are private preschool (attending private preschool in Rounds 1 and 2 and not yet started primary school); public preschool only with no primary school, private preschool with primary school, public preschool with primary school, and primary school with no preschool exposure. The base category for Columns 1 and 2 is not enrolled. The base category for Columns 3, 4 and 5 is public preschool only with no primary school. Reads story to the child is a dummy variable which takes the value of 0 if no-one in the household reads story to the child at least once a week. Helps with learning tasks takes the value of 0 if no one in the household helps the child with homework at least once a week. Talks to staff about child's learning progress takes the value of 0 if the parent has not spoken to the staff in the past 3 months.*** p<0.01, ** p<0.05, * p<0.1

For the full sample (in Column 2), while 'helps with learning tasks' has a positive and significant impact, the change in the coefficients of interest is marginal[22]. Next when I look at the subsample of preschool goers only (in Column 4), parents wanting their child to read/write is positive and significant. However, the coefficient on variables of interest, once again, shows only a marginal change[23]. Moving to Column 5, where I do not control for variables that could be assumed to be parental inputs in response to attending a type of educational institute, I find that parents wanting their child to read/write to be positive and significant. The coefficients on variable of interest are not significantly different from those in Column 3. This indicates that the lagged test score is a sufficient proxy for past inputs including the parent's decision-making process regarding their child's enrolment (also see Appendix A Table A.8, for the significant correlation between the parent's motivation and lagged test score).

4.7. Robustness check – Excluding zeroes on test score

As seen in Table 6, 12 percent of the sample scored zero on the test in Round 1. This proportion reduces to 3 percent in Round 2. A concern arising from this change in the distribution at the lower end, is that I may be overestimating the value added of preschools. The change could have been because the children were older and more familiar with the test or less nervous at Round 2. In this section, I re-run the preferred lagged score VAM with controls and village fixed effects on a sub-sample of children who did not score zero in Round 1. Table 15 reports the results of this exercise[24].

Column 1 reports the results as seen in Column 6 of Table 9 for the full sample. Column 2 reports the results of the same specification but excludes children who scored zero on the test in Round 1. Column 3 reports the results as seen in Column 6 of Table 10 for the full sample differentiating preschools by management type. Column 4 reports the results of the same specification but

[22] The null hypothesis of equality of the coefficient on private preschool and private preschool with school in Columns 1 and 2 is rejected at 5 percent. However, there is no significant difference between the coefficients on public preschool, primary school, and public preschool with school in Columns 1 and 2.

[23] The null hypothesis of equality of the coefficient on private preschool in Columns 3 and 4 is rejected at 5 percent. The null hypothesis of equality of the coefficient on private preschool with school in Columns 3 and 4 is rejected at 1 percent. There is no significant difference between the coefficients on public preschool with school in Columns 3 and 4.

[24] Of the children scoring zero, the majority were not enrolled. Excluding the children who score zero in Round 1, also implies excluding 29 children from the base category of not enrolled. This means that the estimates are now based on 71 children in the not enrolled base category. Given this very small sample size, I re-run Table 2.15 excluding children who are not enrolled and using primary school (with no preschool exposure) as the base category in Appendix A Table A.11. The results are similar to those discussed here.

excludes the children who scored zero on the test in Round 1.

While the coefficient on variables of interest moves downwards (except that on *preschool),* the results remain significant and qualitatively similar. Thus, the main results are not an artefact of the test or testing environment but driven by the participation in preschool or primary school.

Table 15. VAM estimates excluding children scoring zero in Round 1

	(1) Current Score	(2) Current Score	(3) Current Score	(4) Current Score
Lagged - Standardised score	0.225***	0.240***	0.198***	0.209***
	(0.017)	(0.019)	(0.017)	(0.019)
Preschool	0.438***	0.441***		
	(0.083)	(0.094)		
Primary school	0.526***	0.507***	0.571***	0.553***
	(0.086)	(0.100)	(0.084)	(0.097)
Preschool and school	0.666***	0.656***		
	(0.086)	(0.096)		
Private preschool			0.700***	0.694***
			(0.083)	(0.094)
Public preschool			0.083	0.076
			(0.081)	(0.095)
Private preschool and school			0.903***	0.883***
			(0.091)	(0.102)
Public preschool and school			0.591***	0.575***
			(0.084)	(0.095)
Sample	Full	Excluding zeroes on lagged score	Full	Excluding zeroes on lagged score
Controls Added	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Observations	8,124	7,162	8,124	7,162
R-squared	0.348	0.348	0.382	0.383

This table presents the results of Table 2.9 (Column 1) and Table 2.10 (Column 3) for the full sample of children. In Columns 2 and 4, it re-runs the same specifications for the sub-sample of children excluding children who scored 0 on the tests in Round 1. All specifications control for village fixed effects and child and household level controls as in Table 2. 9. Standard errors are clustered at the village level. The variables of interest are private preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), public preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), primary school (attending primary school in Rounds 1 and 2 with no preschool exposure), attending private preschool before starting primary school, and attending public preschool before starting primary school. The base category is not enrolled. .*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

In this paper, I investigated the extent of value added of preschool attendance using data from three geographically and culturally distinct states in India. I find that children who attend preschool before starting primary school have a significant premium of 0.14 SD units in cognitive test scores as compared to children who attend primary school without any preschool exposure. On further investigation into the management type of the preschool, I find that this result is driven by those who attended private preschool. Children who attend public preschool before starting primary school are no better off than those who start primary school directly. I conduct a series of robustness checks to asses if lagged score VAM are sufficient proxies for child's and parent's motivation; if the results are an artefact of the test itself or testing environment, and find the results remain qualitatively similar in magnitude and significant.

I provide a descriptive study of the preschool quality by management type to understand the private preschool premium. Private preschools have lower student-teacher ratio, longer hours of operation and a focus on formal instructional style of teaching. On the other hand, public preschools conduct more play-based activities. While this may explain the difference in test scores, it stresses the importance of undertaking a more comprehensive evaluation of preschools in India.

The test used in this paper has a narrow focus on cognitive skills, early literacy and numeracy. However, empirical evidence shows that one of the main benefits of early childhood education lies in nurturing of a child's non-cognitive or socio-emotional skills (see Barnett, 1995, 2011, for a review). In this light, there is need to supplement the findings of this paper with outcome measures on non-cognitive skills. The play-based activities used in public preschools may nurture soft-skills, and it would be incorrect to conclude that they have no effect on child development based only on the results of this paper.

However, this paper contributes to the current literature on the private-public learning gap in India, which has so far neglected the effect of preschools on primary school performance. Additionally, the limited empirical evidence which exists on preschools in India is based on data from Telangana. I find that the private preschool premium displays considerable state level heterogeneity with Telangana adding the highest private preschool premium on test score and Rajasthan adding the least. Not only is the preschool funding guideline in India skewed to benefit economically underdeveloped regions, most states are expected to raise at least 40 percent of the operational costs themselves. This would imply a variation in public preschool quality depending the state's revenue generating capacity. States may also exhibit a variation in attitudes and norms around educational attainment which would in turn be another source of variation in the quality of educational institutions. As such, one needs to adopt caution to not interpret results from a single region in India to hold true for the entire country. More research is required using nationally representative data on preschools.

This study also contributes to the literature on evaluation of universal preschool provision. This literature is sparse, even in developed countries and the results continue to be mixed. While some studies find that universal preschool education is associated with improved literacy and numeracy skills at primary school entry age (for US, see Loeb et al., 2007; Fitzpatrick, 2008; for UK, see Melhuish et al., 2008; for Argentina, see Berlinski et al., 2009), others find that these positive effects dissipate as early as the end of first grade (for US, see Magnuson et al., 2007; for Quebec, see Baker et al.,2008).

The results of this paper are particularly relevant in the backdrop of a rapidly changing education policy in India. The new National Education Policy (Government of India, 2020) sees an important shift towards early years and stresses the need to improve foundational literacy and numeracy skills as early as in the preschool years. Given the findings of this paper, public preschools would need considerable overhaul to be able to deliver on closing the learning gaps.

The policy acknowledges that with lack of preschool exposure, a large proportion of children fall behind in learning levels, within a few weeks of starting Grade 1 (National Education Policy, Government of India, 2020, para 2.5), a concern that is reiterated in the findings of this paper. However, the policy fails to recognise that this gap in learning at school starting age is not as much due to lack of preschool exposure as it is due to lack of 'quality' preschool exposure. 89 percent of the sample in this paper attend some form of preschool. Hence, the bigger focus for policy is to improve the quality of public preschools in India. Further, the varying levels at which children start primary school based on their preschool experience, highlights the need for educators to develop innovative pedagogical tools that target children with lower levels of learning. 'Teaching at the Right Level' is one such pedagogical innovation developed by Pratham NGO which has been shown promising results (Banerjee et al., 2017; Banerji & Chavan, 2020).

6. Works Cited

Andrabi, T., Das, J., Khwaja, A. I., & Zajonc, T. (2011). Do value-added estimates add value? Accounting for learning dynamics. *American Economic Journal: Applied Economics*, 29-54.

Araujo, M. C., Carneiro, P., Cruz-Aguayo, Y., & Schady, N. (2016). Teacher quality and learning outcomes in kindergarten. *The Quarterly Journal of Economics, 131*(3), 1415-1453.

ASER Centre. (2020). *Annual Status of Education Report (Rural) 2019 Early Years*. Retrieved from New Delhi, India: http://img.asercentre.org/docs/ASER%202019/ASER2019%20report%20/aserreport2019earlyyearsfinal.pdf

Baker, M., Gruber, J., & Milligan, K. (2008). Universal child care, maternal labor supply, and family well-being. *Journal of political Economy, 116*(4), 709-745.

Baland, J.-M., Bonjean, I., Guirkinger, C., & Ziparo, R. (2016). The economic consequences of mutual help in extended families. *Journal of Development Economics, 123*, 38-56.

Banerjee, A. V., Cole, S., Duflo, E., & Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. *The Quarterly Journal of Economics, 122*(3), 1235-1264.

Banerjee, A., Banerji, R., Berry, J., Duflo, E., Kannan, H., Mukerji, S., Shotland, M., & Walton, M. (2017). From proof of concept to scalable policies: Challenges and solutions, with an application. *Journal of Economic Perspectives, 31*(4), 73-102.

Banerji, R., & Chavan, M. (2020). A twenty-year partnership of practice and research: The Nobel laureates and Pratham in India. *World Development, 127*, 104788.

Barnett, W. S. (1995). Long-Term Effects of Early Childhood Programs on Cognitive and School Outcomes. *The Future of Children, 5*(3), 25-50. doi:10.2307/1602366

Barnett, W. S. (2011). Effectiveness of early educational intervention. *Science, 333*(6045), 975-978.

Berlinski, S., Galiani, S., & Gertler, P. (2009). The effect of pre-primary education on primary school performance. *Journal of Public Economics, 93*(1–2), 219-234. doi:http://dx.doi.org/10.1016/j.jpubeco.2008.09.002

Berlinski, S., Galiani, S., & Manacorda, M. (2008). Giving children a better start: Preschool attendance and school-age profiles. *Journal of Public Economics, 92*(5–6), 1416-1440. doi:http://dx.doi.org/10.1016/j.jpubeco.2007.10.007

Boardman, A. E., & Murnane, R. J. (1979). Using Panel Data to Improve Estimates of the Determinants of Educational Achievement. *Sociology of Education, 52*(2), 113-121. doi:10.2307/2112449

Bouguen, A., Filmer, D., Macours, K., & Naudeau, S. (2018). Preschool and parental response in a second best world evidence from a school construction experiment. *Journal of human Resources, 53*(2), 474-512.

Ceniza, J. C., & Cereno, D. C. (2012). *Development of mathematic diagnostic test for DORSHS.* Available from http://www.doscst.edu.ph/index.ph[/academics/graduateschool/publication/category/5-volum-1-issue-1-2012?

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates. *American Economic Review, 104*(9), 2593-2632.

Chudgar, A., & Quin, E. (2012). Relationship between private schooling and achievement: Results from rural and urban India. *Economics of Education Review, 31*(4), 376-390.

Crawfurd, L., & Elks, P. (2019). Testing the feasibility of a value-added model of school quality in a low-income country. *Development Policy Review*, *37*(4), 470-485.

Cunha, F., & Heckman, J. J. (2008). Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of human Resources, 43*(4), 738-782.

Cunha, F., Heckman, J. J., Lochner, L., & Masterov, D. V. (2006). Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation. In E. Hanushek & F. Welch (Eds.), *Handbook of the Economics of Education* (Vol. Volume 1, pp. 697-812): Elsevier.

Currie, J., & Thomas, D. (2000). School Quality and the Longer-Term Effects of Head Start. *Journal of human Resources, 35*(4), 755-774.

Desai, S., Dubey, A., Vanneman, R., & Banerji, R. (2009). Private schooling in India: A new educational landscape. In *India Policy Forum 2008-09* (Vol. 5): Sage Publications India.

Doyle, O., Harmon, C. P., Heckman, J. J., & Tremblay, R. E. (2009). Investing in early human development: Timing and economic efficiency. *Economics & Human Biology, 7*(1), 1-6. doi:http://dx.doi.org/10.1016/j.ehb.2009.01.002

Fitzpatrick, M. D. (2008). Starting school at four: The effect of universal pre-kindergarten on children's academic achievement. *The BE Journal of Economic Analysis & Policy, 8*(1).

French, R., & Kingdon, G. (2010). *The relative effectiveness of private and government schools in Rural India: Evidence from ASER data* (No. 10-03). Department of Quantitative Social Science-UCL Institute of Education, University College London.

Fryer Jr, R. G., & Levitt, S. D. (2004). Understanding the black-white test score gap in the first two years of school. *Review of Economics and Statistics, 86*(2), 447-464.

Fryer, R. G., & Levitt, S. D. (2006). The black-white test score gap through third grade. *American Law and Economics Review, 8*(2), 249-281.

Garces, E., Thomas, D., & Currie, J. (2002). Longer-term effects of Head Start. *American Economic Review, 92*(4), 999-1012.

Government of India, M. o. H. R. D. (1986). *National Policy on Education 1986*. Retrieved from https://www.mhrd.gov.in/sites/upload_files/mhrd/files/upload_document/npe.pdf

Government of India, M. o. H. R. D. (2020). *National Education Policy.* Retrieved from https://www.mhrd.gov.in/sites/upload_files/mhrd/files/NEP_Final_English_0.pdf

Government of India, M. o. W. a. C. D. (2013). *National Early Childhood Care and Education Policy*. Retrieved from https://wcd.nic.in/sites/default/files/National%20Early%20Childhood%20Care%20and%20Education-Resolution.pdf

Grantham-McGregor, S., Cheung, Y. B., Cueto, S., Glewwe, P., Richter, L., Strupp, B., & Group, I. C. D. S. (2007). Developmental potential in the first 5 years for children in developing countries. *The Lancet, 369*(9555), 60-70.

Guarino, C. M., Reckase, M. D., & Wooldridge, J. M. (2015). Can value-added measures of teacher performance be trusted? *Education Finance and Policy, 10*(1), 117-156.

Hanushek, E. A., Kain, J. F., Rivkin, S. G., & Branch, G. F. (2007). Charter school quality and parental decision making with school choice. *Journal of Public Economics, 91*(5–6), 823-848. doi:http://dx.doi.org/10.1016/j.jpubeco.2006.09.014

Harris, D. N. (2007). Diminishing marginal returns and the production of education: An international analysis. *Education Economics, 15*(1), 31-53.

Harris-Fry, H., Shrestha, N., Costello, A., & Saville, N. M. (2017). Determinants of intra-household food allocation between adults in South Asia–a systematic review.

International Journal for Equity in Health, 16(1), 107.

Heckman, J. J., & Mosso, S. (2014). The economics of human development and social mobility. *Annu. Rev. Econ., 6*(1), 689-733.

Kane, T. J., & Staiger, D. O. (2008). *Estimating teacher impacts on student achievement: An experimental evaluation* (No. w14607). National Bureau of Economic Research.

Kingdon, G. G. (2007). The progress of school education in India. *Oxford Review of Economic Policy, 23*(2), 168-195.

Lee, V. E., Brooks-Gunn, J., Schnur, E., & Liaw, F.-R. (1990). Are Head Start Effects Sustained? A Longitudinal Follow-up Comparison of Disadvantaged Children Attending Head Start, No Preschool, and Other Preschool Programs. *Child Development, 61*(2), 495-507. doi:10.1111/j.1467-8624.1990.tb02795.x

Loeb, S., Bridges, M., Bassok, D., Fuller, B., & Rumberger, R. W. (2007). How much is too much? The influence of preschool centers on children's social and cognitive development. *Economics of Education Review, 26*(1), 52-66.

Magnuson, K. A., Ruhm, C., & Waldfogel, J. (2007). Does prekindergarten improve school preparation and performance? *Economics of Education Review, 26*(1), 33-51. doi:http://dx.doi.org/10.1016/j.econedurev.2005.09.008

Melhuish, E. C., Phan, M. B., Sylva, K., Sammons, P., Siraj-Blatchford, I., & Taggart, B. (2008). Effects of the home learning environment and preschool center experience upon literacy and numeracy development in early primary school. *Journal of Social Issues, 64*(1), 95-114.

Moore, A. C., Akhter, S., & Aboud, F. E. (2008). Evaluating an improved quality preschool program in rural Bangladesh. *International Journal of Educational Development, 28*(2), 118-131.

Muralidharan, K., & Kremer, M. (2008). Public and private schools in rural India. In R. Chakrabarti & P. Peterson (Eds.), *School Choice International*. Cambridge: MIT.

Muralidharan, K., & Sundararaman, V. (2015). The Aggregate Effect of School Choice: Evidence from a Two-Stage Experiment in India. *The Quarterly Journal of Economics, 130*(3), 1011-1066.

Mwaura, P. A., Sylva, K., & Malmberg, L. E. (2008). Evaluating the Madrasa preschool programme in East Africa: a quasi-experimental study. *International Journal of Early*

Years Education, 16(3), 237-255.

Özler, B., Fernald, L. C., Kariger, P., McConnell, C., Neuman, M., & Fraga, E. (2016). *Combining preschool teacher training with parenting education: A cluster-randomized controlled trial*: The World Bank.

Rao, N., Sun, J., Pearson, V., Pearson, E., Liu, H., Constas, M. A., & Engle, P. L. (2012). Is something better than nothing? An evaluation of early childhood programs in Cambodia. *Child Development, 83*(3), 864-876.

Rothstein, J. (2010). Teacher quality in educational production: Tracking, decay, and student achievement. *The Quarterly Journal of Economics, 125*(1), 175.

Sass, T. R. (2006). Charter schools and student achievement in Florida. *Education, 1*(1), 91-122.

Sass, T. R., Semykina, A., & Harris, D. N. (2014). Value-added models and the measurement of teacher productivity. *Economics of Education Review, 38*(0), 9-23. doi:http://dx.doi.org/10.1016/j.econedurev.2013.10.003

Schweinhart, L. J., Montie, J., Xiang, Z., Barnett, W. S., Belfield, C. R., & Nores, M. (2005). *Lifetime effects: the High/Scope Perry Preschool study through age 40* (No. 14). High/Scope Foundation.

Singh, A. (2014). Test score gaps between private and government sector students at school entry age in India. *Oxford Review of Education, 40*(1), 30-49.

Singh, A. (2015). Private school effects in urban and rural India: Panel estimates at primary and secondary school ages. *Journal of Development Economics, 113*, 16-32.

Singh, A. (2020). Learning more with every year: School year productivity and international learning divergence. *Journal of the European Economic Association, 18*(4), 1770-1813.

Singh, R., & Mukherjee, P. (2017). *Comparison of the effects of government and private preschool education on the developmental outcomes of children: evidence from Young Lives India* (No.167). Young Lives.

Todd, P. E., & Wolpin, K. I. (2003). On the specification and estimation of the production function for cognitive achievement. *The Economic Journal, 113*(485), F3-F33.

Todd, P. E., & Wolpin, K. I. (2007). The production of cognitive achievement in children: Home, school, and racial test score gaps. *Journal of Human capital, 1*(1), 91-136.

UNESCO. (2020). *Global Education Monitoring Report 2020: Inclusion and Education: All means All*. Paris: UNESCO.

Woldehanna, T. (2016). Inequality, preschool education and cognitive development in Ethiopia: Implication for public investment in pre-primary education. *International Journal of Behavioral Development, 40*(6), 509-516.

Wolf, S., Aber, J. L., Behrman, J. R., & Tsinigo, E. (2019). Experimental impacts of the "Quality Preschool for Ghana" interventions on teacher professional well-being, classroom quality, and children's school readiness. *Journal of Research on Educational Effectiveness, 12*(1), 10-37.

Yoshikawa, H., Weiland, C., Brooks-Gunn, J., Burchinal, M. R., Espinosa, L. M., Gormley, W. T., & Zaslow, M. J. (2013). *Investing in our future: The evidence base on preschool education*. Society for Research in Child Development.

Yoshikawa, H., Leyva, D., Snow, C. E., Treviño, E., Barata, M., Weiland, C., . . . D'Sa, N. (2015). Experimental impacts of a teacher professional development program in Chile on preschool classroom quality and child outcomes. *Developmental psychology, 51*(3), 309.

A. Appendix (Do preschools add 'value'? Evidence on achievement gaps from rural India)

A.1. School Readiness Inventory Test score construction

Table A.1 lists the 24 items administered to the children in Rounds 1 and 2. The classification of each item as per the competency has been provided by the developers of the tool (the World Bank in conjunction with Centre for Early Childhood Education and Development, New Delhi).

Table A.1. Description of test administered

Competency		Assessment activity	ITEM No.
Cognitive skills & concepts	Pre-number concept	Given pictures of four apple trees, children were asked to point to the one with the least and most apples.	1, 2
	Space Concept	Given two illustrations of children and houses, children were asked to point to the one in which the child was behind the house.	3
	Sequential thinking	Children were shown illustrations of water filling up a bucket and were asked to determine the correct sequence for the pictures.	4
	Classification	Children were asked to classify six creatures as either birds or animals.	5
	Number/object matching	Children were asked to match three numbers with pictures showing the same number of objects.	8,9,10
	Picture Identification	Children were asked to identify three different pictures.	11,12,13
	Pattern making	Children were asked to repeat and complete a pictorial pattern.	18,19
	Relative comparisons	Children were asked to point to a number (among 9, 3, 7, 8) that was less than the number 5.	24
Language skills & concepts	Following instructions	Children were asked to raise their hands. Next, the child was asked to pick up an object and bring it to someone.	6, 7
	Reading readiness, identifies beginning sound	Children were asked to identify the beginning sound of words and to match the two words with the same beginning sound.	14,15,16,17
	Sentence making	Children were asked to describe four photographs in complete sentences.	20, 21, 22, 23

I used Item Response Theory (IRT) to assess the performance of each of the 24 items in uncovering the latent ability parameter. The terminology 'ability' used in IRT is not the same as inherent ability, but only used to mean the skill or trait that the test intends to measure. Based on the observed probability of answering an item correctly in the data, the IRT estimates the difficulty and discrimination parameters for each item and hence, the latent ability for each individual. IRT models have been extensively used in the education literature, for example, in the construction of test score in international assessments such as TIMSS and PISA.

I used both the one-parameter logistic (1-PL) model and two-parameter logistic (2-PL) model to assess the reliabilty the test score. The 2-PL model is given by the following functional form, also known as the Item Characteristic Curve (ICC) –

$$P_q\left(X_{iq} = 1 \middle| \theta_i\right) = \frac{1}{1 + exp\left[-1.7a_q\left(\theta_i - b_q\right)\right]}$$

Where the probability of an individual i with ability θ_i to correctly answer a question q is given by two parameters – the difficulty parameter b_q, and the discrimination parameter a_q. The difference between 2-PL model and 1-PL model is that 1-PL model assumes that the discrimination parameter is constant across items, that is, $a_q = a$.

The discrimination parameter measures how well an item differentiates between high and low ability individuals. A positive discrimination parameter implies that higher ability individuals have a higher probability of answering the item correctly. A negative discrimination parameter would imply that a higher ability individual has a lower probability of answering the item correctly. Thus, in assessing the validity of an item, one would like the discrimination parameter (*a*) to be positive and high. Holding the discrimination parameter as constant across all items, as in the 1-PL model, implies that all ICCs have the same slope.

The difficulty parameter tells us how difficult an item is. Ceniza and Cereno (2012) provide the interpretation of the values of the difficulty parameter (*b*): Very Easy = Less than -2, Easy = -0.50 to -2.00, Average = -0.49 to 0.49, Difficult = 0.50 to 2.00 and Very Difficult = Greater than 2.00.

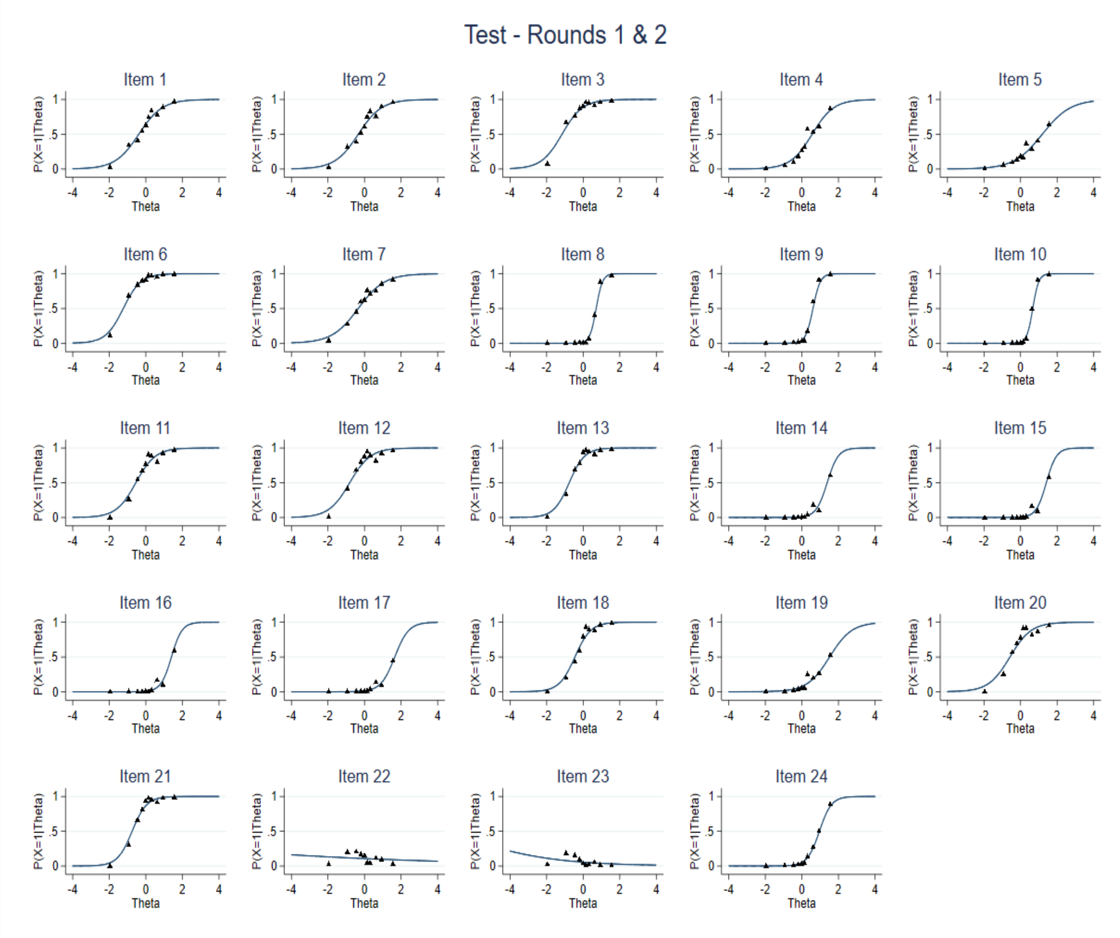
Using maximum likelihood estimator, I retrieve the difficulty and discrimination parameters for each of the 24 items on the test. I ran the IRT models on the combined Round 1 and 2 data. Table A.2 presents the results of these parameters from 2-PL and 1-PL model. First, the 2-PL model represents a better fit for the test as seen by the lower log likelihood value. However, even for the 1-PL model, the constant discrimination parameter is high and positive at 1.91. From the 2-PL model, I find that all values of discrimination parameter are positive. These results assure me that the test was reliable in differentiating between low and high ability children. Looking at the difficulty parameter, most items ranged from average to difficult levels. However, items 22 and 23 have very high values of difficulty parameter and low values on discrimination. Values higher than 3 on the difficulty parameter are mostly seen as suspicious and invalid. Hence, I drop items 22 and 23 from the test score construction.

Table A.2. Results of IRT 2 parameter and 1 parameter logistic model

	2-PL		1-PL	
Log likelihood	-157713		-165719	
Item No.	Discrimination	Difficulty	Discrimination	Difficulty
1	1.55	0.39	1.91	0.34
2	1.57	0.34	1.91	-0.30
3	1.78	-1.16	1.91	1.11
4	1.69	0.56	1.91	0.53
5	1.30	1.19	1.91	0.97
6	2.08	1.23	1.91	1.28
7	1.39	0.34	1.91	-0.27
8	5.76	0.71	1.91	0.96
9	5.00	0.61	1.91	0.79
10	6.14	0.67	1.91	0.90
11	1.86	0.55	1.91	0.54
12	1.76	0.81	1.91	0.77
13	2.37	0.76	1.91	0.85
14	3.31	1.38	1.91	1.74
15	3.60	1.41	1.91	1.82
16	3.46	1.40	1.91	1.79
17	2.62	1.66	1.91	1.92
18	2.30	0.45	1.91	0.51
19	1.64	1.52	1.91	1.42
20	1.72	0.58	1.91	0.55
21	2.50	0.75	1.91	0.86
22	0.12	17.79	1.91	1.64
23	0.38	7.37	1.91	2.08
24	3.04	0.96	1.91	1.16

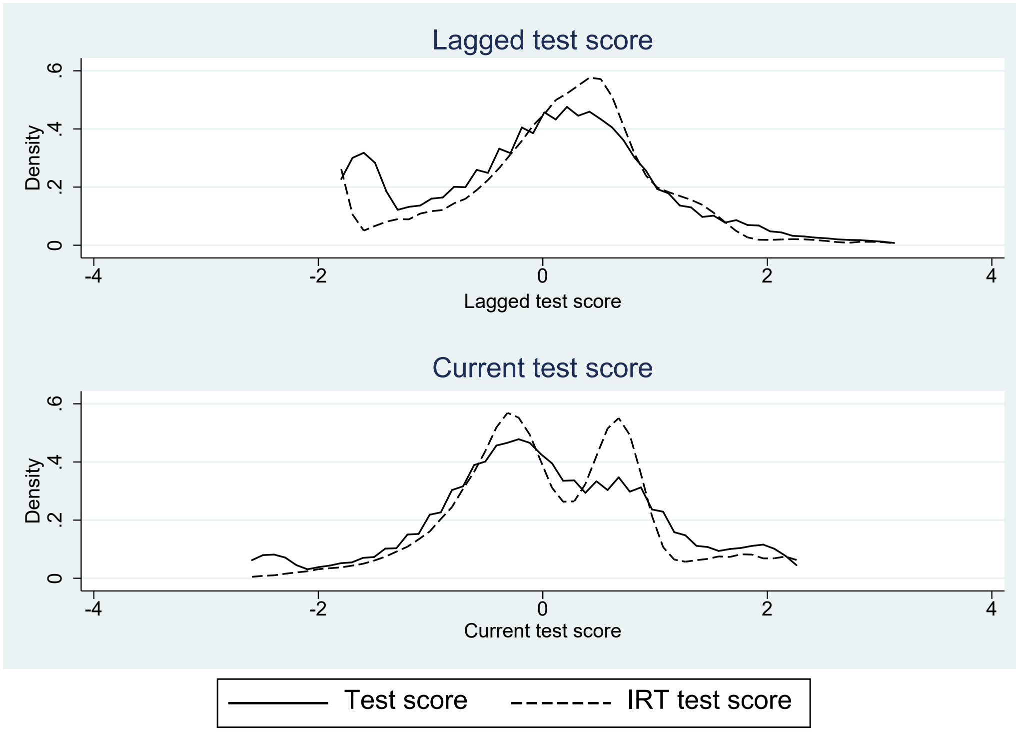
In Figure A.1, I graph the ICCs and the observed probability of answering an item correctly, to visually check the fit provided by the IRT 2-PL model. As is evident, suspiciously low proportion of children answered items 22 and 23 correctly, which leads to the IRT model predicting large values for the difficulty parameter.

Figure A.1. Item characteristics curves and observed probability



For simplicity, I used the standardised sum of scores over 22 items in my main analyses. In Figure A.2, I present the latent ability parameter using the IRT 2-PL model and how it compares with the standardised test scores used in the main paper. The latent ability parameter was also standardised to have a mean of 0 and standard deviation of 1. As we can see, the two distributions are similar. The current IRT score displays a bimodal tendency, and this is common when items are binary.

Figure A.2. Distribution of standardised test score and IRT estimated score



In Table A.3, I re-run the analysis from Table 2.9 using IRT constructed scores. The estimates using IRT scores are qualitatively similar to those using the standardised score in the main paper.

Table A.3. Preschool VAM estimates using IRT scores

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous VAM		Perfect persistence VAM		Lagged score VAM	
Lagged - IRT score	0	0	1	1	0.253***	0.208***
					(0.017)	(0.016)
Preschool	0.643***	0.510***	0.164	0.146	0.522***	0.434***
	(0.088)	(0.091)	(0.103)	(0.104)	(0.085)	(0.089)
Primary school	0.610***	0.589***	0.202*	0.215**	0.507***	0.511***
	(0.092)	(0.095)	(0.108)	(0.109)	(0.089)	(0.092)
Preschool and school	0.812***	0.729***		0.325***	0.688***	0.645***
	(0.090)	(0.093)		(0.107)	(0.087)	(0.091)
Constant	0.130	-1.412***	0.599***	0.517*	0.249***	-1.011***
	(0.086)	(0.232)	(0.100)	(0.277)	(0.083)	(0.220)
Controls added	No	Yes	No	Yes	No	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,124	8,124	8,124	8,124	8,124	8,124
R-squared	0.231	0.288	0.224	0.227	0.286	0.323

All specifications control for village fixed effects. Standard errors are clustered at the village level. The variables of interest are preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), primary school (attending primary schools in Rounds 1 and 2 with no preschool exposure), attending preschool before starting primary school. The base category is not enrolled. Columns 2, 4 and 6 have child and HH level controls – child's gender, child's age in months at Round 2, mother's education in years, father's education in years, whether both parents work outside of home, religion, caste, wealth index, consumer durables index, HH has child's learning material, HH has toys/games for child. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

In Table A.4, I re-run the analysis from Table 2.10 using IRT constructed scores. The estimates using IRT scores are qualitatively similar to those using the standardised score in the main paper.

Table A.4. Private preschool VAM estimates using IRT scores

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous VAM		Perfect persistence VAM		Lagged score VAM	
Lagged - IRT score	0	0	1	1	0.207***	0.184***
					(0.016)	(0.016)
Private preschool	0.912***	0.771***	0.295***	0.297***	0.784***	0.684***
	(0.086)	(0.089)	(0.105)	(0.106)	(0.084)	(0.088)
Public preschool	0.122	0.132	-0.065	-0.060	0.083	0.097
	(0.086)	(0.089)	(0.104)	(0.105)	(0.084)	(0.087)
Primary school	0.656***	0.627***	0.215**	0.229**	0.565***	0.554***
	(0.090)	(0.092)	(0.108)	(0.108)	(0.087)	(0.090)
Private preschool and school	1.109***	0.991***	0.296***	0.305***	0.940***	0.865***
	(0.094)	(0.098)	(0.113)	(0.113)	(0.090)	(0.094)
Public preschool and school	0.656***	0.625***	0.341***	0.356***	0.591***	0.576***
	(0.088)	(0.090)	(0.107)	(0.108)	(0.087)	(0.089)
Constant	0.216***	-1.126***	0.632***	0.665**	0.302***	-0.796***
	(0.081)	(0.222)	(0.100)	(0.274)	(0.080)	(0.212)
Controls added	No	Yes	No	Yes	No	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,124	8,124	8,124	8,124	8,124	8,124
R-squared	0.306	0.330	0.233	0.235	0.341	0.357
Private preschool=School F-stat	30.81***	10.44***	2.190	1.520	24.27***	8.982***
Public preschool=School F-stat	92.32***	84.06***	21.57***	22.63***	84.83***	78.55***
Private preschool=Public preschool F-stat	354.1***	230.3***	65.28***	61.89***	304.3***	208.5***
Private preschool and school=School F-stat	58.53***	37.80***	1.439	1.277	43.81***	29.51***
Public preschool and school=School F-stat	2.09e-06	0.00126	3.779*	3.893**	0.286	0.212

All specifications control for village fixed effects. Standard errors are clustered at the village level. The variables of interest are private preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), public preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), primary school (attending primary schools in Rounds 1 and 2 with no preschool exposure), attending private preschool before starting primary school, and attending public preschool before starting primary school. The base category is not enrolled. Columns 2, 4 and 6 have child and HH level controls – child's gender, child's age in months at Round 2, mother's education in years, father's education in years, whether both parents work outside of home, religion, caste, wealth index, consumer durables index, HH has child's learning material, HH has toys/games for child. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

A.2. **VAM excluding 'not enrolled'**

Since only 100 children are not enrolled and are all located in Rajasthan, I re-run the lagged score VAM excluding the not enrolled children and use children who attended primary school with no exposure to preschool as the base category. In Table A.5, I first report the lagged score VAM estimates on the full sample without controls (Column 1) and with controls (Column 2). In Columns 3 and 4, I report the lagged score VAM estimates on sample excluding the 100 not enrolled children. The coefficients on the variables of interest change marginally (by approximately 0.001 SD unit) and remain qualitatively similar.

Similarly, in Table A.6, I report the lagged score VAM estimates by management type excluding the not enrolled children. Columns 1 and 2 run the same lagged score VAM as reported in Table 10. The only difference is that I use primary school with no preschool exposure as the base category, instead of not enrolled. Columns 3 and 4 report the estimates on the sample excluding the 100 not enrolled children. The coefficients on the variables of interest change marginally and remain significant.

Table A.5. Preschool VAM estimates excluding never enrolled

	(1) Current Score	(2) Current Score	(3) Current Score	(4) Current Score
Lagged - Standardised score	0.276***	0.225***	0.275***	0.224***
	(0.019)	(0.017)	(0.019)	(0.017)
Not enrolled	-0.520***	-0.526***		
(Base category: Primary school only)	(0.083)	(0.086)		
Preschool	0.009	-0.088**	0.012	-0.087**
(Base category: Primary school only)	(0.046)	(0.043)	(0.046)	(0.043)
Preschool and school	0.190***	0.140***	0.190***	0.139***
(Base category: Primary school only)	(0.048)	(0.046)	(0.048)	(0.046)
Constant	-0.043	-1.306***	-0.041	-1.311***
	(0.040)	(0.226)	(0.040)	(0.227)
Controls added	No	Yes	No	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Sample	Full	Full	Excluding not enrolled	Excluding not enrolled
Observations	8,124	8,124	8,024	8,024
R-squared	0.312	0.348	0.304	0.342
Preschool=Mixed F-stat	25.38***	44.21***	24.65***	43.54***

All specifications control for village fixed effects. Standard errors are clustered at the village level. The variables of interest are not enrolled, preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), attending preschool before starting primary school. The base category is attending primary school with no preschool exposure. Columns 2, and 4 have child and HH level controls – child's gender, child's age in months at Round 2, mother's education in years, father's education in years, whether both parents work outside of home, religion, caste, wealth index, consumer durables index, HH has child's learning material, HH has toys/games for child. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

Table A.6. Private preschool VAM estimates excluding not enrolled

	(1) Current Score	(2) Current Score	(3) Current Score	(4) Current Score
Lagged - Standardised score	0.224***	0.198***	0.224***	0.197***
	(0.018)	(0.017)	(0.018)	(0.017)
Not enrolled	-0.581***	-0.571***		
(Base category: Primary school only)	(0.081)	(0.084)		
Private preschool	0.225***	0.129***	0.228***	0.130***
(Base category: Primary school only)	(0.045)	(0.043)	(0.045)	(0.043)
Public preschool	-0.513***	-0.488***	-0.510***	-0.486***
(Base category: Primary school only)	(0.052)	(0.051)	(0.052)	(0.051)
Private preschool and school	0.400***	0.332***	0.400***	0.331***
(Base category: Primary school only)	(0.058)	(0.059)	(0.058)	(0.059)
Public preschool and school	0.024	0.019	0.024	0.019
(Base category: Primary school only)	(0.048)	(0.047)	(0.048)	(0.047)
Constant	0.073*	-1.035***	0.076**	-1.039***
	(0.038)	(0.220)	(0.038)	(0.221)
Controls added	No	Yes	No	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Sample	Full	Full	Excluding not enrolled	Excluding not enrolled
Observations	8,124	8,124	8,024	8,024
R-squared	0.367	0.382	0.360	0.376
Private preschool=Public preschool F-stat	317.8***	210.8***	316.7***	208.5***

All specifications control for village fixed effects. Standard errors are clustered at the village level. The variables of interest are not enrolled, private preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), public preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), attending private preschool before starting primary school, and attending public preschool before starting primary school. The base category is primary school with no preschool exposure. Columns 2, and 4 have child and HH level controls – child's gender, child's age in months at Round 2, mother's education in years, father's education in years, whether both parents work outside of home, religion, caste, wealth index, consumer durables index, HH has child's learning material, HH has toys/games for child. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

A.3. **Preschool survey**

The data presented in Section 5.3 comes from the preschool survey conducted in Round 1. Not all preschools would have been surveyed, depending on whether these were open at the time of the visit and granted access to the investigators to conduct a survey. Private preschools may be more inclined to not grant such access, and the ones that did, could very well be 'better' quality. Additionally, if a preschool was located outside the village, the facility would not have been surveyed. This is more likely to be a private preschool which would be located outside a village in order to cater to the catchment area of several nearby villages.

In Table A.7, I present the information on number of preschools surveyed by state. As suspected, on average, the study surveyed three public preschools per village and only one private preschool per village. In Assam, on average, four public preschools were surveyed per village, the highest among the three states. This is expected as the current funding guidelines for North-eastern states (of which Assam is one) is that the Central government would contribute to 90 percent of the construction and operational costs[25]. Compare this to the guideline for Rajasthan and Telangana where the Central government contributes to 75 percent of the construction cost and 60 percent of the operational cost.

While, one would assume that the number of private facilities to be lower than public facilities in each village, there is an element of bias introduced by the survey itself. For instance, the data shows that one village in Assam and four villages in Rajasthan had no public preschool. This cannot be true as the household survey clearly indicates that children in these village were going to a public preschool. Additionally, the government mandate is to have at least one public preschool in an area of 800 children under the age of six years, or a 'mini' public preschool in an area of 150-300 children under the age of six years[26].

Second, according to the preschool survey, 10 villages in Rajasthan, 68 villages in Assam, and 64

[25] www.icds-wcd.nic.in/icds.aspx
[26] www.icds-wcd.nic.in/icds.aspx

villages in Telangana have no private preschool. However, from the household survey, I find that in all the 10 villages in Rajasthan, in 45 out of the 68 village in Assam, and in 58 out of the 64 villages in Telangana , children are enrolled in private preschools. Thus, the preschool survey was neither a census of the preschool facilities in the village, nor representative of these facilities.

Table A.7. Preschools surveyed per village

	(1) Rajasthan	(2) Assam	(3) Telangana	(4) Total
Average number of preschools surveyed per village	4.136	4.406	3.163	3.902
	[1.627]	[2.499]	[1.266]	[1.930]
Average number of public preschool surveyed per village	2.272	3.990	2.745	2.983
	[1.021]	[2.231]	[1.169]	[1.711]
Average number of private preschool surveyed per village	1.864	0.417	0.418	0.919
	[1.221]	[0.706]	[0.608]	[1.127]
Village has at least 1 public preschool surveyed	0.961	0.990	1.000	0.983
	[0.194]	[0.102]	[0.000]	[0.129]
Village has at least 1 private preschool surveyed	0.903	0.323	0.357	0.535
	[0.298]	[0.470]	[0.482]	[0.500]
Number of villages	100	100	100	300

A.4. **Lagged test score proxy for motivation**

Table A.8. Regression of lagged test score on controls, child motivation and parent's motivation

	(1) Lagged score	(2) Lagged score	(3) Lagged score	(4) Lagged score
Reads story to child	0.118***	0.071*	0.062	0.029
	(0.040)	(0.043)	(0.038)	(0.041)
Helps with learning tasks	0.293***	0.186***	0.183***	0.106***
	(0.032)	(0.035)	(0.031)	(0.035)
Talk to staff about child's learning progress		0.108***		0.068**
		(0.032)		(0.031)
Wants child to read/write		0.100***		0.095***
		(0.032)		(0.031)
Child talks about preschool always		0.193***		0.165***
		(0.040)		(0.040)
Child talks about preschool sometimes		0.120***		0.108***
		(0.031)		(0.030)
Child likes going to preschool		0.153***		0.141***
		(0.032)		(0.031)
Female			-0.105***	-0.097***
			(0.020)	(0.021)
Age in months			0.024***	0.023***
			(0.003)	(0.003)
Years of education - Father			0.005**	0.005*
			(0.002)	(0.003)
Years of education - Mother			0.015***	0.014***
			(0.003)	(0.003)
Both parents work outside of home			-0.087**	-0.080**
			(0.037)	(0.037)
Muslim (Base category: Hindu)			-0.129***	-0.118**
			(0.048)	(0.053)
Scheduled caste			-0.167***	-0.172***
			(0.050)	(0.054)
Scheduled tribe			-0.256***	-0.222***
			(0.059)	(0.063)
Backward castes			-0.137***	-0.128***
			(0.041)	(0.044)
Wealth index			0.023	0.022
			(0.017)	(0.017)
Ownership of durables index			0.056***	0.052***
			(0.014)	(0.016)
HH has children's reading material			0.069**	0.025
			(0.031)	(0.034)
HH has toys/games for child			0.054*	0.036
			(0.032)	(0.034)
Constant	-0.200***	-0.398***	-1.584***	-1.663***
	(0.018)	(0.032)	(0.221)	(0.231)
Sample	Full	Preschool	Full	Preschool
Controls	No	No	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Observations	8,124	7,263	8,124	7,263
R-squared	0.290	0.300	0.318	0.324

All specifications control for village fixed effects. Standard errors are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1

A.5. **Results for sub-sample without mixed (preschool and primary school) category – only non-switchers**

Table A.9. Lagged score VAM estimates excluding mixed category sub-sample

	(1) Current score	(2) Current score	(3) Current score	(4) Current score
Lagged - Standardised score	0.266***	0.212***	0.213***	0.186***
	(0.019)	(0.018)	(0.019)	(0.018)
Preschool	0.524***	0.435***		
	(0.082)	(0.086)		
Primary school	0.482***	0.495***	0.549***	0.542***
	(0.087)	(0.091)	(0.085)	(0.088)
Private preschool			0.810***	0.704***
			(0.082)	(0.085)
Public preschool			0.073	0.089
			(0.079)	(0.083)
Female		-0.083***		-0.049**
		(0.021)		(0.021)
Age in months		0.020***		0.017***
		(0.004)		(0.004)
Years of education - Father		0.015***		0.011***
		(0.003)		(0.003)
Years of education - Mother		0.018***		0.014***
		(0.003)		(0.003)
Both parents work outside of home		-0.079*		-0.058
		(0.040)		(0.039)
Muslim (Base category: Hindu)		-0.120**		-0.061
		(0.058)		(0.058)
Scheduled caste		-0.183***		-0.100**
		(0.049)		(0.049)
Scheduled tribe		-0.080		-0.011
		(0.066)		(0.063)
Backward castes		-0.050		-0.025
		(0.039)		(0.038)
Wealth index		0.039**		0.009
		(0.017)		(0.016)
Ownership of durables index		0.071***		0.047***
		(0.017)		(0.017)
HH has children's reading material		0.022		0.020
		(0.031)		(0.031)
HH has toys/games for child		0.048		0.028
		(0.030)		(0.029)
Constant	-0.544***	-1.775***	-0.474***	-1.552***
	(0.079)	(0.260)	(0.076)	(0.249)
Sample	No mixed	No mixed	No mixed	No mixed
Village fixed effects	Yes	Yes	Yes	Yes
Observations	6,263	6,263	6,263	6,263
R-squared	0.341	0.380	0.401	0.417
Preschool=School F-stat	0.729	1.748		
Private preschool=School F-stat			28.45***	12.04***
Public preschool=School F-stat			74.52***	70.30***
Private preschool=Public preschool F-stat			300.5***	193.3***

This table reports the results of Table 2.9 and Table 2.10 excluding the children who switch from preschool to primary school between Rounds 1 and 2. All specifications control for village fixed effects. Standard errors are clustered at the village level. The variables of interest are private preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), public preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), and primary school with no preschool exposure. The base category is not enrolled. The child's age is in months at the time of testing in Round 2. Both parents work outside of home is a dummy variable which is 0 when either one of the parent stays at home. The base category for scheduled caste, scheduled tribe and backward castes is general caste. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

A.6. **A discussion of choice**

I run a multinomial logit model on the choice of educational participation. The categories of participation are – never enrolled, going to a primary school only, going to a public preschool only, going to a private preschool only, going to a public preschool with primary school, and going to a private preschool with primary school. The model includes full set of child and household level controls available for the entire sample. It includes state dummies (base category being Rajasthan) to capture the difference in educational norms and trends by state.

In Table A.10, I report the probability of selecting a participation category for each covariate, instead of the log odds ratio or relative risk ratio. Both, odds ratio and relative risk ratio, are conditional on the base category, making interpretations between categories difficult. For direct comparisons, I present the average marginal effect of covariates on each participation category.

The results confirm the patterns that emerged from the descriptive statistics reported in Section 3.5. Girls, Muslims, and children from socially disadvantaged groups (lower caste categories) are less likely to attend a private preschool. Older children are more likely to be in primary school or to have switched from preschool to primary school. Older children are also more likely to be in a public preschool.

Parent's education, wealth index and consumer durable index are positively associated with private preschool attendance. If both parents are employed outside the household, the child is more likely to attend a public preschool and less likely to attend a private preschool.

Households having reading material at home is negatively associated with public preschool attendance and positively with primary school attendance. Parents are also more likely to help the child with learning tasks at home if the child attends private preschool.

Children in Assam and Telangana are less likely to attend primary school than children in Rajasthan. Children in Assam are more likely to attend public preschools, while in Telangana , they are more likely to attend private preschools.

Table A.10. Average marginal effects on educational participation estimated from multinomial logit model

	(1) Never enrolled	(2) Primary school	(3) Public preschool	(4) Private preschool	(5) Public preschool and school	(6) Private preschool and school
Female	0.008	0.012*	0.025***	-0.059***	0.022***	-0.007
	(0.006)	(0.006)	(0.009)	(0.011)	(0.008)	(0.004)
Age in months	-0.001	0.002***	-0.009***	-0.001	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of education - Father	-0.001**	0.000	-0.003***	0.006***	-0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of education - Mother	0.002*	-0.002	-0.008***	0.012***	-0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Both parents work outside of home	0.002	0.000	0.042***	-0.064***	0.026**	-0.005
	(0.011)	(0.011)	(0.012)	(0.015)	(0.010)	(0.011)
Muslim (Base category: Hindu)	0.010	0.025***	0.095***	-0.118***	0.026***	-0.037***
	(0.007)	(0.008)	(0.010)	(0.009)	(0.009)	(0.009)
Scheduled caste	-0.009	0.033***	0.091***	-0.132***	0.055***	-0.039***
	(0.010)	(0.010)	(0.014)	(0.014)	(0.015)	(0.009)
Scheduled tribe	-0.009	0.031**	0.070***	-0.101***	0.018	-0.010
	(0.011)	(0.012)	(0.017)	(0.015)	(0.018)	(0.009)
Backward castes	0.004	0.002	0.032***	-0.024**	0.006	-0.021***
	(0.008)	(0.007)	(0.012)	(0.010)	(0.013)	(0.006)
Wealth index	0.003	-0.018***	-0.039***	0.060***	-0.011**	0.005
	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.003)
Ownership of durables index	-0.003	-0.011***	-0.009	0.031***	0.002	-0.011***
	(0.003)	(0.004)	(0.006)	(0.006)	(0.005)	(0.003)
HH has children's reading material	-0.028***	0.037***	-0.029***	-0.004	-0.011	0.035***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.009)	(0.008)
HH has toys/games for child	0.009	0.010	-0.050***	0.006	0.010	0.014***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.005)
Reads story to child	0.001	-0.024**	0.013	-0.004	0.018*	-0.004
	(0.009)	(0.010)	(0.012)	(0.012)	(0.010)	(0.007)
Helps with learning tasks	-0.021**	-0.015**	-0.036***	0.043***	-0.021**	0.049***
	(0.009)	(0.006)	(0.010)	(0.011)	(0.010)	(0.007)
Assam	0.031***	-0.158***	0.577***	-0.194***	-0.103***	-0.153***
	(0.010)	(0.009)	(0.010)	(0.011)	(0.009)	(0.009)
Telangana	-0.007	-0.087***	0.002	0.078***	0.106***	-0.092***
	(0.011)	(0.013)	(0.011)	(0.020)	(0.015)	(0.012)
Observations	9,121	9,121	9,121	9,121	9,121	9,121

The table reports the marginal effects post running a multinomial logistic regression on the educational participation categories. Standard errors were bootstrapped and clustered at the village level. The child’s age is in months at the time of testing in Round 2. Both parents work outside of home is a dummy variable which is 0 when either one of the parent stays at home. The base category for scheduled caste, scheduled tribe and backward castes is general caste. The wealth index comprises of household building material, having a toilet, piped water, electricity and using higher grade fuel for cooking. The durables index comprises of ownership of TV, fan, fridge, cycle, scooter, phone.*** p<0.01, ** p<0.05, * p<0.1

A.7. **Robustness check – excluding zeroes and not enrolled**

Table A.11. VAM estimates excluding children scoring zero in Round 1 and not enrolled

	(3) Current Score	(4) Current Score	(7) Current Score	(8) Current Score
Lagged - Standardised score	0.224***	0.239***	0.197***	0.209***
	(0.017)	(0.019)	(0.017)	(0.019)
Private preschool			0.130***	0.140***
(Base category: Primary school only)			(0.043)	(0.048)
Public preschool			-0.486***	-0.477***
(Base category: Primary school only)			(0.051)	(0.056)
Private preschool and school			0.331***	0.330***
(Base category: Primary school only)			(0.059)	(0.062)
Public preschool and school			0.019	0.020
(Base category: Primary school only)			(0.047)	(0.051)
Preschool	-0.087**	-0.066		
(Base category: Primary school only)	(0.043)	(0.047)		
Preschool and school	0.139***	0.148***		
(Base category: Primary school only)	(0.046)	(0.050)		
Sample	Excluding not enrolled	Excluding not enrolled and children scoring zero on lagged score	Excluding not enrolled	Excluding not enrolled and children scoring zero on lagged score
Controls added	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes
Observations	8,024	7,091	8,024	7,091
R-squared	0.342	0.342	0.376	0.378

This table presents the results of Table 2.9 (Column 1) and Table 2.10 (Column 3) for sub-sample of children excluding not enrolled. In Columns 2 and 4, it re-runs the same specifications for the sub-sample of children excluding children who scored 0 on the tests in Round 1. All specifications control for village fixed effects and child and household level controls as in Table 2. 9. Standard errors are clustered at the village level. The variables of interest are private preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), public preschool (attending preschool in Rounds 1 and 2 and not yet started primary school), attending private preschool before starting primary school, and attending public preschool before starting primary school. The base category is primary school with no preschool exposure. .*** p<0.01, ** p<0.05, * p<0.1