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Private Preschools and Test Score Gaps in Rural India

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Abstract

There is a large body of literature which documents the effectiveness of early childhood interventions, such as preschools. While such evidence is available from the developed countries, similar evidence in the developing countries' context is scarce. Moreover, there has been no rigorous evaluation of *preschools* in the Indian context. In this paper, I present the *first* estimates of the effect of private and public preschools on test score, using a unique data set from 3 geographically and culturally distinct states in India (Rajasthan, Andhra Pradesh, Assam). I estimate a value-added model, while controlling for household characteristics, parent's aspirations, and child's motivation. I complement the results from VAM with difference in difference matching methods. The effect of private preschools remains significant and positive (0.10-0.13SD) across all formulations. This paper contributes to the existing literature in India on the differential impact of private and public *primary schools*, by explaining that some of the difference in later years can be attributed to participation in the early years.[2]

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1 Introduction

The preschool system in India, as anywhere else, is the first step towards education. What makes the preschool setting or the educational landscape in India unique, is the co-existence of low cost fee-charging private and free of cost public (government) sector. This introduces a degree of variability in the education trajectory followed by Indian children, and hence produces huge 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. Public preschools are expected to cater to children in the age group 3 to 6 years of age, and contribute to the universalization of primary education, by providing necessary preparation for primary schooling. However, the quality of preschool education is frequently seen as poor.

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

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 & Sundararaman, 2013), very little is known at the school entry age or before that. Studies that document and explore the learning gaps in the private and public sectors have overwhelmingly focussed on primary school without any knowledge of prior education in preschools.

There is widespread recognition of the fact that early childhood factors and environment have a significant impact on future outcomes, cognitive and non-cognitive. 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 was aimed to collect information on preschools in India.

In this paper, I attempt to address this gap in literature and study the differences in test scores which exist even before starting primary school, due to the public-private divide in education in India. Specifically using the ASER data on Early Childhood Care and Education collected in 2011-12, I present the estimates from Value Added Models (VAM) of the effect of private preschool on test scores. VAM is identified by the inclusion of lagged test score as an independent variable. However, in some cases lagged test scores may be poor proxies for previous inputs, specifically parent's aspirations. They may also not perfectly

measure ability. While I test my specification for parent's aspirations and child motivation, I unfortunately cannot rule out the bias due to unobserved ability in VAM.

2 Literature Review

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.). Since skill begets skill and there is complementarity between inputs applied at various stages of growing up (Cunha, Heckman, Lochner, & Masterov, 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 3 (preschool age), most successful early childhood interventions begin in preschool years. These can also be complemented with earlier "antenatal investment" (Doyle, Harmon, Heckman, & Tremblay, 2009).

There is now a large body of literature which documents the effectiveness of early childhood interventions, particularly in the US (J. J. 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 Jr and Levitt (2004); Fryer and Levitt (2006)). The second theme in early childhood intervention research in the US, has been to evaluate the persistence of such interventions into later years and their effect on adult outcomes – for eg, Perry Preschool Project in the US (Schweinhart et al., 2005); Head Start Preschool intervention(Garces, Thomas, & Currie, 2000).

While a large body of evidence in this area is available from the developed countries, similar evidence in the developing countries' context is scarce. Moreover, even the evidence that exists in the developed countries, evaluates the effect of preschool interventions which were targeted at the socio-economically disadvantaged children. To the best of my knowledge, there are four papers which study the impact of universal preschools, two of which are set in the background of developing countries.

Cascio (2009) exploits the variation in grants provided by some states in the US to school districts offering kindergarten programs in 1960s and 70s to find that kindergarten reduces the chances of dropout during later school years, particularly for the white children.

Magnuson, Ruhm, and Waldfogel (2007) using Early Childhood Longitudinal Study (a nationally representative sample of children entering kindergarten in 1998-99) show that preschool education in the US is associated with higher reading and mathematics score in primary school. They employ OLS with rich set of controls, teacher fixed effects, propensity score matching, and IV method to estimate the impact of preschool. While the first three methods give similar results, IV approach gives a much higher impact, making the exclusion restriction questionable. They use state spending on kindergarten as the IV. However, it can be argued that states which spend more on preschool facilities would also be investing in other resources crucial for early childhood development.

Berlinski, Galiani, and Manacorda (2008) study the effect of preschool education school attendance and years of education using Uruguayan household survey which collects retrospective information on preschool attendance . They use within household estimator which makes use of the variation in education trajectories between siblings. They report that by age of 15, children who had attended preschools accumulate 0.8 years of extra education when compared to their untreated siblings.

Berlinski, Galiani, and Gertler (2009) investigate the impact of large scale expansion of universal pre-primary education on subsequent primary school performance in Argentina and find that 1 year of preschool education increases the average third grade test scores by 23% of the standard deviation.

In the context of developing countries, other than the two above mentioned studies, there have been smaller sample studies. Mwaura, Sylva, and Malmberg (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 preschool performed better than those who attended non-Madrasa type of preschool or none (the two comparison groups). Moore, Akhter, and Aboud (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 7 months in operation, 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 lack of rigorous estimation methods, casting the result of effective preschool in doubt.

In the context of India, there is no study which looks at the effect of preschools on cognitive achievement, to the best of my knowledge. Singh (2014) demonstrates that test score gaps between children in private and public 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. However, he clearly mentions that drawing causality is beyond the scope of his paper, and is at most able to establish correlations. However, this 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 by private and public preschool attendance.

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 between the average learning scores of children in private and public schools in India. Muralidharan and Kremer (2006) 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, Dubey, Vanneman, and Banerji (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) also 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 EVS). 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). All these studies and more, which evaluate the gaps in learning between students in private and public sectors in India, thus far, 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 attempt to 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 strategy described earlier. However, family fixed effects are not satisfactory as parents can change their behavior based on preschool experience and it also requires to assume 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 satisfactorily satisfy the exclusion restriction. As already noted earlier, 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 Value Added Models (VAM). VAMs are used extensively in teacher and class effectiveness literature, particularly in the US. VAMs produce unbiased and consistent results under some strict assumptions (discussed in Section 5). However, overall evidence seem to point that the bias from VA estimates are very limitedKane and Staiger (2008) while analyzing results from an experiment in Los Angeles that assigned children randomly across classrooms, report that teacher effects estimated from lagged score VAM yielded similar unbiased results. . Andrabi, Das, Khwaja, and Zajonc (2011) while documenting the evidence of public-private school test score gap in Pakistan, point that VA estimates obtained from OLS provide similar results as VA estimates from data extensive GMM estimation methods. Chetty, Friedman, and Rockoff (2013) find no evidence of bias in VA estimates when studying the long term impact of teachers on adult outcomes.

3 Data

3.1 Sampling

The data for this paper has been provided by ASER, India which had been collected as part of their 5 year longitudinal study on Early Childhood Care and Education. This data only covers the first year of the study September, 2011-December, 2012. The data covers 3 major states of India – Andhra Pradesh (now, known as Telangana), Assam and Rajasthan. States were purposively selected to maximize differences in geographical location as well as demographic, socioeconomic and educational characteristics (Figure 1).

Figure 1

Within each state, two districts were selected at random for inclusion in the study: Medak and Warangal in Andhra Pradesh, 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 is 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.

Within each village, the objective was to select 50 children in the age group 3.5-4.5 years of age at the time of the first visit (September-December, 2011). Integrated Child Development Services (ICDS) survey records were used to create a sample of all children in the above mentioned age group. These records are maintained by government (Anganwadi – public preschool) 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 were selected. In theory, 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 6 districts and 3 states. While 43% of the children are in Rajasthan, only 27% of the children are in Andhra Pradesh.

Table 1

State	District	Sample Size	%
Andhra Pradesh	Warrangal	1265	15.57
	Medak	931	11.46
Assam	Kamrup	998	12.28
	Dibrugarh	1450	17.85
Rajasthan	Alwar	1762	21.69
	Ajmer	1718	21.15
Total		**8124**	**100**

3.2 Survey and Questionnaire

During 2011-12, sampled children were visited 4 times, approximately once every 3 months. The first visit was conducted in Sept-Dec, 2011; the second in Feb-March 2012; the third in Jul-Aug, 2012 and the fourth in Oct-Dec, 2012. Table 2 shows the information collected in each of the visits -

Table 2

Survey instrument	**Visit 1** Sep - Dec 2011	**Visit 2** Feb – Mar 2012	**Visit 3** Jul - Aug 2012	**Visit 4** Oct - Dec 2012
Village questionnaire	✓			
Household questionnaire	✓			
Assessment	✓			✓
Child questionnaire	✓	✓	✓	✓
Preschool questionnaire	✓	✓	✓	✓

The village questionnaire collected basic information such as village population and number of households. It also records whether the village has access to *pucca* roads, electricity, post office, banking services, private schools, public schools, preschools, etc. While the former information was obtained from the sarpanch (president of the government local body), the latter was recorded on the basis of investigator's observation.

Household questionnaire includes detailed information on the level of education of the parents, the primary source/s of income, religion, caste, consumer durables owned by the household, sampled child's learning environment, parent's knowledge of preschool functioning, questions on aspirations and expectations of the parents from preschool.

The child questionnaire was used to only track the child – whether the sampled child was going to a preschool, changed preschools, moved to a primary school.

The Preschool questionnaire was conducted for all preschools in the village in Visits 1 and 2, irrespective of whether the sampled child was enrolled in them or not. During Visits 3 and 4, only those facilities where sampled children were participating were visited. Key aspects of infrastructure, staffing, enrolment, and availability of materials for children were observed in each ECE facility visited. If the preschool was open and had children present during the survey visit, field teams also recorded basic information on the nature of the activities taking place.

The assessment tool used for this study, the School Readiness Inventory (SRI), was developed by the World Bank and is intended to test children's cognitive and language skills and concepts. Within these broad categories, the tool tests children on a range of competencies which are broken down into ten specific tasks. The maximum score assigned to each task varies from 1 to 6, depending on the complexity of the task. The test as a whole has a total score of 40 points, which has been standardised. Table A 1 in Appendix A gives detail of the breakdown of the assessment tool. Children were assessed twice, in Visit 1, which I shall refer to as lagged test score; and in Visit 4, which I shall refer to as current test score.

3.3 Data – A caveat

At this stage, it is important to emphasize that since this data is purely an observational data, it poses some problems in modelling the effects of preschool. Specifically, there is one simplification I make. Not all children in the data set have been to preschool. Table 3 gives a breakdown of the participation status of the children. Less than 2% of the sample has never been to a preschool or any other educational institution during the period of the survey. Another 10% of the sample did not go to a preschool – however, these children were seen at a primary school. Given that the setting of the survey is rural and laws are not strictly enforced, it is not a surprise that less than 5 year old children could be in school. This is not to say they were formally enrolled, and, if fact, there is nothing in the data set which could help me ascertain the formal participation status of these 800 children. It is common practice in rural India to attend schools with older siblings. For the purpose of this paper, I only engage with 88% who were in a preschool.

Table 3[3]

Preschool Participation	Freq.	Percent
No educational institution	109	1.34
Preschool	7,174	88.31
No preschool - straight to Primary	836	10.29
Total	8,119	100

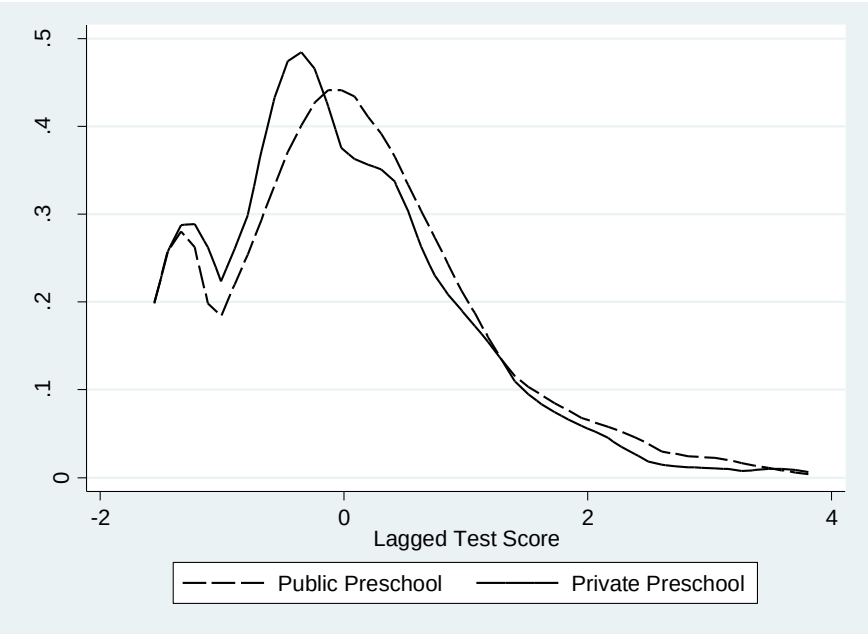
Second, 93% of 7174 children were already in preschool when they were tested for the first time in Visit 1. Since there were no retrospective questions asked, I cannot determine as to how long these children had been going to preschool. However, I do not see this as a serious issue because if one were to believe that the lagged test score was sufficient proxy for past inputs, then I can still get robust estimates of value added by private preschool over 1 year (2011-12).

4 Summary Statistics

As mentioned in Section 3.2, the test score used for this study has a raw score scale from 0 to 40. For the purpose of this paper, I have standardized the scores. Figure 2 and Figure 3 show the distribution of the standardized lagged (Visit 1) and current (Visit 4) respectively. It is interesting to note that the distribution of lagged test score for public and private going children in Figure 2 is similar for scores greater than the mean. The public preschool sample has a lower proportion in lower scores as compared to the private preschool sample. There is also a high proportion of children with 0 raw scores in both, public and private preschool sample.

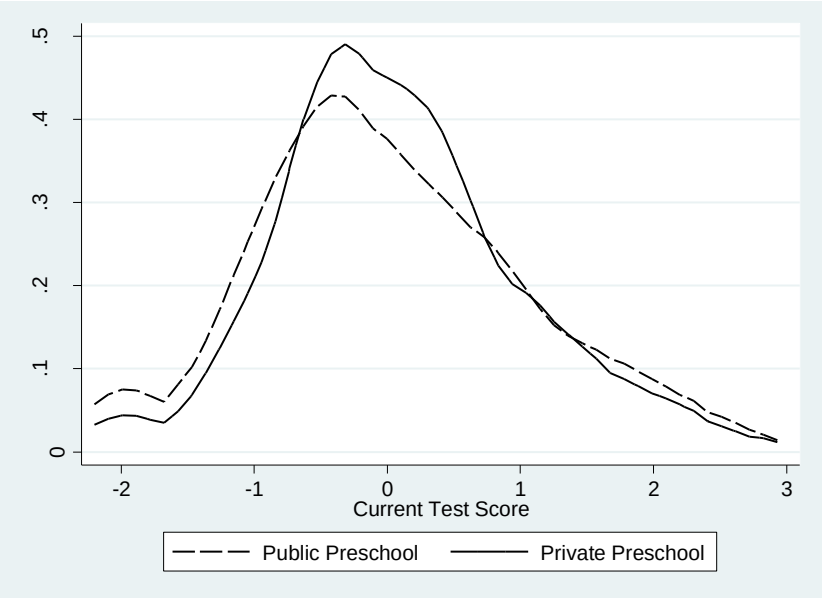
[3] The total sample should add up to 8124. However, for 5 observations in the data, I was unable to match their trajectory from Visit 1 through to Visit 4. This was due to missing or contradicting information in multiple visits.

Figure 2



In Figure 3, when the children were tested again after 1 year, both public and private preschool sample have shown an improvement with a rightward shift in the mass. The proportion of zero's have also diminished greatly. For lower test scores and around the mean, the private preschool sample is doing better than the public preschool sample. But then again, for the higher scores, both samples look fairly similar.

Figure 3



I have also looked at the test score standradised by the age (in months). The relevant figures can be found in Appendix B. For the sake of completeness, I have included the distribution by 3 categories[4] – no preschool, private, and public preschool in Appendix B. Since there is no major difference in distribution of the test scores standardised by age vis-à-vis test scores standardised for the overall sample, I use the latter in all sections.

Table 4

	Public	Private	Diff	p-value	N - Public	N - Private
Test Scores						
Raw lagged test score	11.832	10.791	1.040	0.000	5,307	1,663
Raw current test score	17.275	17.713	-0.437	0.060	5,307	1,663
Lagged test score - standardised	0.090	-0.042	0.132	0.000	5,307	1,663
Current test score - standardised	0.034	0.087	-0.053	0.060	5,307	1,663
Child and Household Characteristics						
Age in months	62.998	63.195	-0.197	0.053	5,290	1,660
Female	0.501	0.427	0.074	0.000	5,297	1,662
Muslim	0.172	0.117	0.055	0.000	5,101	1,595
Scheduled Caste	0.169	0.128	0.041	0.000	5,307	1,663
Scheduled Tribe	0.109	0.064	0.045	0.000	5,307	1,663
Other backward	0.475	0.582	-0.107	0.000	5,307	1,663
Years of Edu - Father	5.975	8.662	-2.686	0.000	4,912	1,502
Years of Edu - Mother	3.891	4.769	-0.878	0.000	4,949	1,547
Consumer Durable Index	2.449	3.308	-0.859	0.000	5,131	1,609
Primary Income: Contract Labor	0.459	0.444	0.015	0.287	5,186	1,603
Mother employed	0.421	0.166	0.255	0.000	4,767	1,556
Months in primary school	0.847	0.847	0.000	0.997	5,307	1,663
Parent's motivation						
Reads story to child	0.385	0.224	0.161	0.000	5,307	1,663
Helps with learning	0.594	0.579	0.015	0.270	5,307	1,663
Reason for Preschool - Prepare for Primary School	0.377	0.327	0.051	0.000	4,821	1,427
Talk to staff about child's progress	0.370	0.325	0.044	0.002	4,774	1,402
Child's Motivation						
Talks about preschool always	0.339	0.217	0.122	0.000	5,307	1,663
Talks about preschool sometimes	0.396	0.380	0.016	0.237	5,307	1,663
Likes going to preschool	0.646	0.719	-0.074	0.000	4,859	1,421

Table 4 reports the summary statistics for the children by the preschool type. It also reports the t-test of difference in means. Older children are more likely to be in private preschool. Girls, muslims, scheduled castes, scheduled tribe, other backward castes are less likely to be in a private preschool. The base category for muslim is hindu; for scheduled caste, schedule tribe, and backward caste is general category. Parent's education and consumer durable index [5]are associated with private preschool attendance. If the primary source of income in the family is casual labour, the child is more likely to be in public preschool.

[4] No preschool category clubs together no educational institution and only primary school categories, as detailed in Table 3.

[5] Consumer durable index is based on consumer durables – television, phone, fridge, fan, cycle, scooter and car.

However, this difference is insignificant. If the mother is employed outside the household, the child is more likely to be in public preschool. Public preschool are more informal in set up, and they tend to be used as crèche in villages.

Variables such as reading story, help with learning, and wants to prepare the child for primary school capture parental aspirations and motivation, while the last few variables capture the child's motivation and enthusiasm about going to preschool.

It is important to understand the variable "months in primary school" – over the one year period of the survey, some children had enrolled into a primary school. Since between the 2 testing period, there were 2 visits to track the child's participation status, I can observe when the child enrolled in primary school. Again, no retrospective questions were asked and I cannot ascertain the exact number of months. However, if the child started going to school in Visit 3, I deduce the number of months in primary school as the time between Visit 4 and Visit 3. This does imply that I am underestimating by at most 3 months, for the child could have started going to primary school anytime between Visit 2 and Visit 3. If the child starts going to primary school in Visit 4, I assume the duration to be 1 month, underestimating by at most 2 months.

Only 28% (1995 children) of the sample had started going to primary school by second testing period (Visit 4). As seen in Table 5, 90% of 1995 children were in Rajasthan or Andhra Pradesh. Also the enrollment starts Visit 3 (more so in Visit 3 than Visit 4) onwards. This is because of the academic calendar and the school starting age in these states. While Rajasthan and Andhra Pradesh have the new academic calendar starting over June-July, coinciding with Visit 3 in the survey, Assam does not start new academic year till January. Additionally, while the school starting age in Rajasthan and Andhra Pradesh is 5, it is 6 years in Assam. [6] By the time of the second testing period (Visit 4), some children are beyond 5 years of age, but at most 5.5 years.

Table 5

	State		
Enrolled in School	Rajasthan	Assam	Andhra Pradesh
Never	1,714	2,256	1,210
Visit 2	2	0	7
Visit 3	727	87	635
Visit 4	253	103	180

[6] While the national policy on education in India (Right to Education Act, 2009) envisages the school starting age to be 6+ years, this is not strictly followed in all states. This information is obtained by talking to the local surveyors in these states, and is not based on any formal guidelines.

It is important to control for the time at primary school, in order to confidently attribute the gain in scores to preschools. Additionally, I control for the states as well, as they differ not only in their geography and culture, but also in their educational policy.

5 Empirical Specification

5.1 Value Added Model – derivation and assumptions

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,

$$T_{ija} = T_a\left[F_{ij}(a), S_{ij}(a), X_{ij}(a), \mu_{ij0}, \varepsilon_{ija}\right] \qquad (1)$$

Where T_{ija} is a measure of cognitive achievement for child *i* in household *j* at age *a*, $F_{ij}(a)$, $S_{ij}(a)$ and $X_{ij}(a)$ are the family, school and individual based input histories up to age *a* respectively, μ_{ij0} is the time invariant individual endowment[7], and ε_{ija} is a time varying error term. $T_a[.]$ allows for impact of inputs and individual fixed endowment to vary with age.

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

$$T_{ija} = \alpha_1 F_{ija} + \alpha_2 F_{ij(a-1)} + \cdots + \alpha_a F_{ij1} + \beta_1 S_{ija} + \beta_2 S_{ij(a-1)} + \cdots + \beta_a S_{ij1} + \gamma_1 X_{ija} + \gamma_2 X_{ij(a-1)} + \cdots + \gamma_a X_{ij1} + \phi_a \mu_{ij0} + \varepsilon_{ija} \qquad (2)$$

It is important to note that linearity and additive separability are but trivial assumptions to ease computability and interpretation. This is the most commonly used formulation of the cumulative effects model[8]. 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 the input on achievement varies within the time period of application of 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 the early years (see Cunha et al. (2006) and 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. However, the assumption can be tested under the null of joint insignificance of the interaction terms.

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[7] 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.

[8] An exception is Harris (2007) who uses a translog functional form.

The μ_{ij0} term in (2) requires more careful thought and interpretation, particularly if this includes ability. Non-age varying assumption does not restrict the impact of ability. The effect of ability can be interpreted in 2 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_a would capture. Second, ability can be thought of malleable and changing from the initial endowment at conception. 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 (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 we assume geometric decay of inputs, that is, the impact of an input applied at a particular age on achievement score will be smaller as the distance between the two increases. Hence we have $\alpha_a = \lambda_F \alpha_{a-1}$; $\beta_a = \lambda_S \beta_{a-1}$; $\gamma_a = \lambda_X \gamma_{a-1}$ and $0 \leq \lambda \leq 1$. The process described by geometric decay is well documented in literature - Banerjee, Cole, Duflo, and Linden (2005) report that the 1-year treatment effect of educational intervention on test scores fade out by the 3rd year; Currie and Thomas (1998) and Lee, Brooks-Gunn, Schnur, and Liaw (1990) also show similar fading out of the Head Start preschool program, at least on achievement scores.

If now, following Todd and Wolpin (2003) we assume *uniform* geometric decay, that is $\lambda_F = \lambda_S = \lambda_X = \lambda$, then subtracting $\lambda T_{ij(a-1)}$ from both sides of equation (2), we have,

$$\begin{aligned} T_{ija} - \lambda T_{ij(a-1)} = {} & \alpha_1 F_{ija} + F_{ij(a-1)}(\alpha_2 - \lambda\alpha_1) + \cdots + F_{ij1}(\alpha_a - \lambda\alpha_{a-1}) + \beta_1 S_{ija} \\ & + S_{ij(a-1)}(\beta_2 - \lambda\beta_1) + \cdots + S_{ij1}(\beta_a - \lambda\beta_{a-1}) + \gamma_1 X_{ija} + X_{ij(a-1)}(\gamma_2 - \lambda\gamma_1) + \cdots \\ & + X_{ij1}(\gamma_a - \lambda\gamma_{a-1}) + (\phi_a - \lambda\phi_{a-1})\mu_{ij0} + \varepsilon_{ija} - \lambda\varepsilon_{a-1} \end{aligned} \tag{3}$$

Applying the assumption of uniform geometric decay equation (3) reduces to

$$T_{ija} = \lambda T_{ij(a-1)} + \alpha_1 F_{ija} + \beta_1 S_{ija} + \gamma_1 X_{ija} + (\phi_a - \lambda\phi_{a-1})\mu_{ij0} + \varepsilon_{ija} - \lambda\varepsilon_{ij(a-1)} \tag{4}$$

One could, in theory, test the assumption of geometric decay by estimating equation (2) and using Wald-type test to test the following null hypothesis (Sass, Semykina, & Harris, 2014)

$$H_0: \frac{\alpha_1}{\alpha_2} = \cdots = \frac{\alpha_{a-1}}{\alpha_a}$$

Sass et al. (2014) test the null hypothesis that the input specific decay is geometric against the alternative that the decay is not geometric for a particular input and find that they cannot reject the null.

Next, in order to test the assumption of common geometric decay, one may include inputs from the lagged year into equation (4) and test for joint significance of the lagged inputs. If the geometric decay were same across all inputs, one would assume that the lagged test score would capture all the effect from the lagged inputs. However, if after controlling for the lagged test score, the lagged inputs have a significant effect on the current test score, one would be led to believe that the assumption of uniform decay is violated. Sass et al. (2014) show that this assumption is violated in their sample, by conducting the test described. Todd and Wolpin (2007) display that a “value added plus” specification is an improvement over equation

(4) in their study. Thus, in order to conduct a more wholesome exercise, one should ideally follow up (4) with an extension where the one year lagged inputs have also been included. Recent work by Cunha and Heckman (2008) on the formulation of production function for cognitive and non-cognitive skill development may be described as "value added plus" specification.

At this stage, I must mention that the value added plus specification holds little meaning in my analysis. This is because I am not looking at the impact of a specific school input, for e.g. class size, which would have different values in time period *t* and *t-1*. Since my research paper looks at the impact of private preschool, a value added plus specification would be relevant only if the research question were to look at the switch in preschool from public to private (or private to public) from time period *t-1* to *t*.

Before proceeding onto the estimation of equation (4), it is important to note here that equation (4) is what is commonly known as the lagged score formulation of the value added model (VAM). This is not the only specification of VAM in common use. One other version is the highly restrictive contemporaneous VAM which assumes immediate decay of prior inputs or $\lambda = 0$. Another commonly used VAM is gain score specification, which assumes that they 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.

5.2 Value Added Model – estimated specification

$$T_{ija} = \lambda T_{ij(a-1)} + \alpha_1 F_{ija} + \beta_1 S_{ija} + \gamma_1 X_{ija} + (\phi_a - \lambda\phi_{a-1})\mu_{ij0} + \varepsilon_{ija} - \lambda\varepsilon_{ij(a-1)} \quad (4)$$

I can now re-write equation (4) specific to my question, which is to study the impact of private preschools on cognitive achievement as

$$T_{ia} = \lambda T_{i(a-1)} + \alpha_1 X_{ia} + \beta_1 private + (\phi_a - \lambda\phi_{a-1})\mu_{i0} + \varepsilon_{ia} - \lambda\varepsilon_{i(a-1)} \quad (5)$$[9]

Where $X_{ia}$is a vector of individual and household level inputs; and *private* is the dummy variable for attending private preschool vis-à-vis public preschool.

The model in (5) is estimated using Dynamic OLS (DOLS) estimation. DOLS would give consistent estimates only under certain conditions. The unobserved ability (μ_{i0}) is assumed to decay at the same rate as the other inputs. This implies that the lagged test score is a sufficient proxy for ability. However, if ability does not decay at the same rate as other inputs or if higher ability children learn faster, this term would end up in the error term and result in biased estimates.

Second, the variable *private* must not be correlated with the error term, conditional on the controls and lagged test score. Although one might expect the lagged test score to be correlated with $\varepsilon_{i(a-1)}$, as long as the variable of interest, *private*, is correlated with the error term via the lagged test score, DOLS estimators would be consistent.

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[9] The subscripts j has been dropped only for notational ease. Also, in my dataset there is at most one child per household and hence, household sub-scripts do not hold much value.

However, if parents had more information than those captured by the variables included in the regression when selecting the type of preschool for their child, then the variable *private* will be correlated with the error term and biased.

In summary, there are 2 potential source of bias when estimating equation (5) using DOLS. The first stems from child heterogeneity ending up in the error term. This might be due to ability not exhibiting a decay rate similar to other inputs, or due to parents using more information about their child that what is captured by the lagged test score in making the preschool choice, or due to talented/motivated children learning faster. The second stems from the lagged test score being a poor proxy and/or measured with an error.

Focusing on the persistence coefficient (coefficient on the lagged test score), the measurement error will bias the coefficient downwards, commonly known as the attenuation bias; and the child heterogeneity will bias it upwards.

Furthermore, the bias in the persistence coefficient will lead to a bias in the coefficient of interest (β_1). If the lagged test score is measured with an error, we will leave a part of the true lagged achievement score in the error term. So one would expect β_1 to be biased downward if the biased persistence parameter is greater than the true persistence parameter. The precise bias on β_1 will depend on the degree of correlation with lagged inputs which are all now a part of the error term. Thus, the direction of the bias on β_1 due to measurement error is unknown.

β_1 will be biased upwards if there is child heterogeneity in the error term. Thus, correcting only for measurement error in the sample and ignoring the child heterogeneity issue, might be worse for the model estimates, overall. 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.

Ideally one would want to control for IQ along with test scores, as this would circumvent measurement error as well as the error arising from unobserved ability. However, I am unable to do so since there is no data on IQ for my sample.

As for child heterogeneity or ability, if one assumes that this is time invariant, then one could use child fixed effects or first differencing models. However, both these require that strict exogeneity assumption holds and hence, one cannot use them in equation (5) specification with the lagged test score as an independent variable. Hence, one would have to either use a gains formulation of VAM (assume $\lambda = 1$) or one can difference equation (5) and instrument the 1 year lagged score with double or three times lagged scores. This would obviously require a bigger panel with at least 3 years of data (or 3 testing points). However, none of these methods allow for ability to have time-varying effects. Additionally, Sass et al. (2014) show that the strict exogeneity assumption is violated by each of the methods described above in their study. I do not have multiple time periods to implement more robust panel data methods.

This is not to say that DOLS estimates are unreliable. Guarino, Reckase, and Wooldridge (2014) assess the reliability of different VAMs for recovering teacher effects using simulated data with a variety of non-random teacher-student assignment structure and find that DOLS model performed robustly across most scenarios; better than other estimators, namely, Arellano-Bond panel data estimators, POLS on gain score VAM specification, RE on gain score VAM, FE on gain score VAM, and average residual approach. They

find 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 wither directly or indirectly for grouping and assignment mechanisms." Hence, DOLS by allowing the lagged test score and the variable of interest to be correlated, takes care of the selection issue.

Andrabi et al. (2011) while studying the impact of private schools on cognitive achievement for Pakistan sample 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)).

Hence, the model that I would be estimating to calculate the value added by private preschool on test score, under the assumption that selection into preschool is identified after controlling for lagged test score and other covariates is given by –

$$T_{ia} = \alpha_1 X_{ia} + \lambda T_{i(a-1)} + \alpha_2 Private_i + \alpha_3 Village_i + \alpha_4 State_i + error \qquad (6)$$

Eq (6) denotes the lagged score VAM. As outlined earlier, I shall estimate the above equations using OLS (or Dynamic OLS); and for now I am assuming that there is no measurement error, and child heterogeneity. I shall return to the latter in Section 7. T_{ia} is the test score of the child in 2012; $Private_i$ is the dummy variable for whether the child was in private preschool in 2011/12; $Village_i$ and $State_i$ are dummy variables for the village and the state the child is from respectively[10]; X is a vector of individual child and household characteristics and $T_{i(a-1)}$ is the lagged test score as measured in 2011.

5.3 Value Added Model – a note on interpretation

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. We are estimating the policy effect. Following Todd and Wolpin (2003), let us consider a simple theoretical model

$$A_2 = \mathrm{g}(S_1, F_1, F_0, \mu)$$

$$F_1 = \theta(A_1, S_1 - \overline{S_1})$$

Where A_i stands for achievement at the start of grade *i,* S_1 stand for school inputs in grade 1, F_i stands for family inputs in grade *i,* μ stands for student heterogeneity. This model says that achievement at the start of Grade 2 depends on prior school and family inputs. Family inputs in turn, depend not just on achievement, but also parent's expectation of school input quality (denoted by $\overline{S_1}$). For example, if a child

[10] All regressions cluster the standard errors at the village level.

is allocated to a poor teacher, then parents may try to compensate by spending more time with child at home on learning.

In such a model if one were to ask about the effect of an unanticipated change (randomized) in school input in grade 1, the answer can be provided by finding the total derivative of A_2 (Todd & Wolpin, 2003)

$$\frac{dA_2}{d(S_1 - \bar{S_1})} = \frac{\delta g_1}{\delta S_1} + \frac{\delta g_1}{\delta F_1} * \frac{\delta F_1}{\delta (S_1 - \bar{S_1})} \qquad (7)$$

Thus a randomized experiment uncovers this "policy effect" – the average total effect of a change in input on cognitive achievement of the children participating in the experiment. In order to get the technology parameter, one must be able to evaluate the last term in equation (7); and this can only be achieved if one has knowledge of the family input decision rule. Since there is no theoretical model which would help us understand the effect of preschool choice on family inputs, it is hard to understand which variables should be included in the regression equation (5), in order to estimate the technology parameter.

Thus, there is a need for caution as to which variables are included as controls – in particular, 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 ATE, but the technology parameter. I will refrain from estimating the latter as there isn't enough evidence or theory to convincingly argue which variables must 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 poor (or good) 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. (2014) 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 choice. Thus most of the criticism around VAM stemming from the application of this model to pay related teacher value added, is not valid for my exercise in this paper here.

6 Results - VAM

In Table 6, I present the results of lagged score VAM. Column 1 gives the mean difference in the test score of children between private and public preschool, while controlling for the village and state the child is from. Column 2 additionally controls for the age. Column 3 adds the lagged test score – the effect of private preschool goes down to 0.19 SD units (or 19% of SD of test score). Column 4 is simple OLS estimation of contemporaneous VAM with no lagged structure and full set of child and household controls. This model assumes that there is full decay of past inputs, causing our variable of interest, the

private preschool to be biased upwards. Column 5 reports the results from DOLS estimation of lagged VAM. The coefficient on private school dummy is reduced to 0.13 SD unit from 0.17 SD unit, confirming that immediate decay of inputs does not hold.

Going to a private preschool has a positive and significant effect on test score for children – it increases by 0.13 SD unit or 17% of the SD. Older children perform better on the test, but the effect is very small (.01 SD). Being a female child has a small (0.05 SD) negative effect on test score. Parent's education and the asset index of the house have a highly significant and positive effect on test scores. Being a muslim has a negative and significant impact on test scores.

By the end of 2012, when the children were tested again, some had progressed to school owing to their month of birth and academic calendar. One extra month of being in primary school increases the test score by 0.06 SD. This is a cause of worry for the value added estimate of private preschool, as it introduces the issue of unequal dosage of preschool within the sample. One needs to think about the interpretation of private preschool variable now in terms of duration of exposure. Some children could have started school earlier and been at a preschool for shorter duration. In such a case, the coefficient of private school dummy is not just averaging the effect over treatment (private) and control (public), but also the duration of the treatment. Since I am limited by my data and have no information on the length of preschool exposure, I am unable to refine the private preschool dummy further or even comment on the direction of the bias.

Table 6

	(1)	(2)	(3)	(4)	(5)
Dependent Variable - Current test score				VAM - contemporaneous	VAM - Lagged
Private Preschool	0.265***	0.258***	0.193***	0.168***	0.129***
	(0.0422)	(0.0423)	(0.0397)	(0.0385)	(0.0368)
Age in Months		0.0226***	0.0169***	0.0186***	0.0143***
		(0.00392)	(0.00367)	(0.00366)	(0.00346)
Female				-0.0695***	-0.0524**
				(0.0233)	(0.0226)
Muslim				-0.139**	-0.117**
				(0.0539)	(0.0541)
Scheduled Caste				-0.0773	-0.0658
				(0.0528)	(0.0522)
Scheduled Tribe				-0.0345	0.000990
				(0.0680)	(0.0663)
Other backward				0.0295	0.0426
				(0.0449)	(0.0440)
Yrs of edu - father				0.0145***	0.0126***
				(0.00335)	(0.00324)
Yrs of edu - mother				0.0283***	0.0246***

				(0.00362)	(0.00350)
Consumer Durable Index				0.0824***	0.0723***
				(0.0104)	(0.0102)
Primary Income: Casual/Contract Labor				-0.0745***	-0.0739***
				(0.0272)	(0.0263)
Mother employed				-0.0569	-0.0492
				(0.0432)	(0.0419)
Months in primary school				0.0643***	0.0613***
				(0.0134)	(0.0131)
Lagged test score			0.228***		0.182***
			(0.0202)		(0.0181)
State Controls	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes
Observations	5,730	5,730	5,730	5,730	5,730
R-squared	0.342	0.347	0.379	0.398	0.417

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses, clustered at village level

6.1 How huge is the private preschool effect?

A private preschool effect of 0.13 SD unit is 6% of the mean. Since there limited number of studies in developing countries, and none, in the Indian context, it is difficult to compare this effect with other results in literature. The closest research question to my paper is by Singh (2014) who uses Young Lives data to study the effect of test score gaps that exist at the school entry age (4.5-6yrs). He does so by controlling for different trajectories followed by the children, public preschool, private preschool, public school, private school, and a combination of the two. Although the results are not directly comparable, he reports an effect of 0.25 SD unit for private preschool on CDA score; and 0.2 SD unit on PPVT score. He admits that these estimates are mere correlations, and as such, one can see why the effects are reduced for my sample when I control for lagged test score. Alternatively, Berlinski *et al* (2009) found that the effect of preschool on third grade test mathematics test scores to be 0.24 SD unit or 8% of the mean.

7 Robustness Checks

7.1 Child Heterogeneity

In this section, I revisit the problem of child heterogeneity. As discussed earlier, if child heterogeneity is left in the error term, it would cause the coefficient of private preschool as well the lagged score to be biased upwards. Child heterogeneity could be left in the error term if talented or motivated children learn faster, or if lagged test score is not a perfect measure of 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, never (base category). Another question was asked to the child *"Do you like going to preschool?".* I have also used this information as dummy variable. Both these could serve as a proxy for a child's motivation and enthusiasm to learn.

Table 7

	(1)	(2)
Dependent Variable - Current test score	VAM - Child's motivation	Original VAM
Private Preschool	0.136***	0.145***
	(0.0410)	(0.0415)
Talks about preschool always	0.162***	
	(0.0416)	
Talks about preschool sometimes	0.142***	
	(0.0359)	
Likes going to preschool	0.0849***	
	(0.0314)	
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
State Controls	Yes	Yes
Village Controls	Yes	Yes
Lagged test score	Yes	Yes
Observations	5,192	5,192
R-squared	0.417	0.413

Robust standard errors in parentheses, clustered at village level
*** p<0.01, ** p<0.05, * p<0.1

In Table 7, while we find that talking about preschool activities and liking to go to preschool has a significant and positive impact on test score, the effect of private preschool is not greatly altered. In column 2, I re-estimate the full lagged score VAM as in Column 5 of Table 6. This is done as the sample size has changed by including child motivation variables. To summarise, it does seem that there is an element of child heterogeneity which is not captured by the lagged test score. However, it only affects the coefficient of interest by 0.01 SD unit.

7.2 Tracking (Parent's Motivation)

Another major concern raised by Rothstein (2010) with regards to VAM was the issue of tracking or sorting. While evaluating teacher value added models, he pointed out that VAMs are not efficient in handling sorting of students by head teachers into classrooms. For instance, higher ability students might

be assigned to better teachers. In my model, such a bias would imply that parents purposely sort their children into private preschools using more information than just the lagged test score. If that were the case, the model would not be identified and it would still suffer from selection bias.

I test if my results are robust to dynamic sorting by parents, by making use of information from the household questionnaire which could serve as proxy for parent's motivation and aspirations. In Table 8, I present the results of lagged score VAM with these new variables in Column 1. Column 2 reports the previously estimated lagged score VAM on the new sample size.

I have made use of 4 variables to capture parental aspirations and interest – whether parents read stories to the child, whether they help him/her with learning, whether they want to prepare their child for primary school, and whether they have spoken to preschool staff about their child's learning progress.

Once again, despite 1 of the 4 variables having a significantly positive effect on test score, the coefficient on private school dummy changes, but marginally – from 0.15 SD to 0.14 SD.

Table 8

Dependent Variable - Current test score	(1) VAM - Parent's motivation	(2) Original VAM
Private Preschool	0.136***	0.152***
	(0.0417)	(0.0420)
Reads story to child	0.0378	
	(0.0348)	
Helps with learning at home	0.0547	
	(0.0337)	
Reason for Preschool - Prepare for Primary School	0.108**	
	(0.0445)	
Talk to staff about child's progress	0.0519	
	(0.0325)	
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
State Controls	Yes	Yes
Village Controls	Yes	Yes
Lagged test score	Yes	Yes
Observations	4,945	4,945
R-squared	0.405	0.402

Robust standard errors in parentheses, clustered at village level
*** p<0.01, ** p<0.05, * p<0.1

7.3 Lag structure of VAM

Finally, I estimate the lagged score VAM with third-order polynomial lag structure as done by Singh (2015), Chetty et al (2013) and Kane and Staiger (2008). The results are remain unchanged. These are presented in the Appendix in Table C 2.

8 Alternative Specification

8.1 Propensity score matching - model

The most important concern in understanding the effect of private preschools vis-à-vis public preschool, is one of self-selection, and it is the most challenging to deal with. Self-selection bias occurs in my analysis because participation in a particular preschool is not random. If we were to believe that the lagged score VAM does not take care of the selection problem and produces biased estimates, one could estimate the average treatment effect using Propensity Score Matching.

While traditional matching estimators match each treated observation to observably similar control observation, they are justified by the assumption that the outcome is independent of treatment conditional on observables. As such if the main issue with the VAM were one of selection on unobserved ability, traditional cross-sectional matching would suffer from the same problem. The only improvement in such a case would be one of functional form.

However, if the unobservable was time invariant, or in this case, if we were to assume that ability is fixed, then one could use a difference-in-difference (DID) matching strategy as outlined by J. J. Heckman, Ichimura, and Todd (1997) and J. Heckman, Ichimura, Smith, and Todd (1998). A traditional DID model measures the impact of the treatment by the difference in outcome before-after and between treated and control.

Following Smith and Todd (2005), cross sectional matching would give unbiased result under the conditional mean independence condition,

$$E(Y_0|Z, D = 0) = E(Y_0|Z, D = 1) = E(Y_0|Z)$$

Where Y_0 is the outcome of the control group, Z is the observable characteristics, and D is the dummy for treatment.

Similarly for DID matching estimator, the conditional mean independence condition is,

$$E(Y_{0t} - Y'_{0t}|Z, D = 0) = E(Y_{0t} - Y'_{0t}|Z, D = 1)$$

Where t and t' are pre and post treatment periods respectively.

Since conditioning on all relevant covariates would result in a high dimension of Z, Rosenbaum and Rubin (1983) suggested the use of balancing scores. One such balancing score is the propensity score which measures the probability of participating in a program given the observable characteristics, Z.

$$P(Z) = P(D = 1|Z)$$

Where P(Z) is the propensity score and D is the dummy for having received the treatment, that is, of going to a private preschool. For the binary treatment case, where probability of participation versus non-participation is to be estimated, logit and probit models usually yield similar results (Caliendo & Kopeinig, 2005). Hence, the choice is not too critical, even though the logit distribution has more density mass in the bounds.

The decision to send the child to a particular preschool is made by the parents at the individual child level (or household level, since each household has 1 child in my data). This decision, I would argue is based on child and household level characteristics, rather than preschool or other village level characteristics. First, preschools characteristics are not observed by the parents before decision. Parents may have a perception of the school facilities and the school type – public or private serves also as a proxy for parents' expectation of quality. Second, all villages have at least 1 preschool in my sample. This is because larger villages were chosen in order to ensure both preschool types, for this study. Hence, the possibility of supply side restriction is ruled out.

Since I have data on 2 time periods, I would be implementing a variant of DID model. The conventional DID model assumes that the coefficient of the lagged or pre-treatment outcome as one. However, I will run an "unrestricted" model (LaLonde, 1986) with the lagged test score on the right hand side (as done for VAM). A potential cause of concern would be that the lagged test score in my data is strictly not a pre-treatment variable – children were tested for the first time when most of them were already in preschool. However, I would argue that first, controlling for the lagged test score conditions out all the differences between controls and treated prior to 2011. Second, the treatment in my case does not have the same conventional meaning – going to a public or private preschool is an ongoing process. Hence, the question is then one of the effect of private preschool on test score *over the sampled year* (2011-2012).

Once the propensity score has been obtained, I carry out matching using four methods – Nearest Neighbour, 5-Nearest Neighbour, Kernel Density, and Radius Matching with a caliper of 0.01. Matching is carried out with replacement where an untreated observation (public preschool) may be matched with more than one treated observation (private preschool).

Kernel-weights give higher weights to the closer matches of non-participants; 5-nearest neighbour provide uniform weights; and radius matching provides equal weights within a caliper. Using only 1 nearest neighbour may produce bad matches as high score participants may be matched with low score participants. This concern is subsumed by allowing for matching with replacement and multiple neighbours. Furthermore, kernel density matching is employed which uses more information and relies on non-parametric matching.

8.2 Propensity score matching - results

Table 9 reports the results from logit of going to a private preschool. Being female reduces the probability of going to private school – most rural household enroll male child into private preschool as these are fee requiring institutions and the male child is perceived as the bread earner who requires "better" education than females.

Table 9

VARIABLES	(1) Private
Age in months	0.00227
	(0.00997)
Female	-0.237***
	(0.0716)
Muslim	-0.623***
	(0.115)
Scheduled Caste	-0.676***
	(0.136)
Scheduled Tribe	-0.701***
	(0.161)
Other backward	-0.192*
	(0.105)
Years of Education - Father	0.0666***
	(0.00959)
Years of Education - Mother	0.0489***
	(0.0101)
Consumer Durable Index	0.113***
	(0.0285)
Primary Income: Casual/Contract Labor	0.0498
	(0.0741)
Mother employed	-0.432***
	(0.122)
Lagged test score	0.131***
	(0.0393)
State Controls	Yes
Observations	5,730

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Being muslim as compared to hindu reduces the chance of being in a private preschool. Similarly, being from the general caste as against scheduled caste or scheduled tribe or backward class, increases your chance of being in a private preschool. Hindus and General caste are associated with higher levels of socio-economic status which may explain a higher chance of such kids to be enrolled in fee requiring private institutions.

Father's and mother' education increase the chance of child going to a private preschool. If the mother works outside the house, the child is more likely to go to a private preschool. This may be due the informal nature of public preschool, which may be perceived by parents as a day care facility.

Table 10 finally reports the ATE and the ATT of going to a private preschool on test score. Standard errors for nearest neighbor and 5-nearest neighbor are Abadie and Imbens (2006) corrected standard errors. As for radius and kernel matching, bootstrapping was implemented. Matching was done only on common support. For graph of common support, see Appendix D - Figure D 1. Around 200 observations are lost due to the common support restriction, which is less than 4%.

Using any of the 4 matching methods, I find significant positive ATT of going to a private preschool, except for nearest neighbor matching. The results are lower than VAM by approximately 0.03 SD. ATE is significant only when using kernel matching, and the results are fairly similar to ATT.

Table 10

	Nearest Neighbour	5 - Nearest Neighbour	Radius	Kernel	Sample Size
Model : Outcome variable Gain in test score (DID)					
ATE	0.084	0.081	0.09	0.099**	5494
	(0.071)	(0.067)	(0.055)	(0.045)	
ATT	0.073	0.103**	0.104**	0.104**	5494
	(0.052)	(0.052)	(0.045)	(0.044)	

9 Conclusion

In this paper, I investigated the extent of learning gaps between private and public preschool going children in rural areas. I have tried at best to estimate the causal effect of private preschool using VAM where the identification comes from lagged test score, and also DID matching strategy where identification comes from matching on estimated propensity of being in private preschool as though the assignment were random. While VAM may still suffer from selection on unobserved ability of test score are imperfect measures of ability, DID matching strategy would eliminate time invariant ability. As such one can think of the results from DID matching strategy as lower bound to any overestimation by VAM.

Children going to private preschool do significantly better (0.1 SD to 0.13 SD) than those in public preschools, even after controlling for individual and household characteristics, and lagged test scores. I have conducted various robustness checks – standardizing test scores by age (Appendix C - Table C 1), controlling for parent's aspirations (Section 7.2), controlling for child motivation (Section 7.1), using alternative lag structure (Section 7.3), and using DID matching strategy (Section 8). The results remain significant and positive to all different specifications.

This is the first rigorous evaluation of preschool system in India. These results contribute to the current literature on the private public learning gap in India, which have so far concentrated only on primary education. I believe it is possible that in the absence of data on preschool attendance, studies focusing on primary schooling in India could possibly wrongly attribute the difference in test scores to primary education. It could be the case that any such gap is due to differences in preschool attendance and that

such divergences persist beyond preschool years into primary school. As such, one of the policy implications of a comprehensive exercise taking into account both preschool and primary school attendance, could be investment in preschool education for remediation of unwanted gaps in future outcome.

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Appendices

Appendix A

Table A 1

Competency		**Assessment activity**	**Score**
Cognitive skills & concepts	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.	1
	Pre-number concept	Given pictures of four apple trees, children were asked to point to the one with the least and most apples.	2
	Number/object matching	Children were asked to match three numbers with pictures showing the same number of objects.	3
	Relative comparisons	Children were asked to point to a number (among 9, 3, 7, 8) that was less than the number 5.	2
	Sequential thinking	Children were shown illustrations of water filling up a bucket and were asked to determine the correct sequence for the pictures.	5
	Pattern making	Children were asked to repeat and complete a pictorial pattern.	5
	Classification	Children were asked to classify six creatures as either birds or animals.	6
Language skills & concepts	Following instructions	Children were asked to raise their hands, and then to pick up an object and bring it to someone.	4
	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.	6
	Sentence making	Children were asked to describe two photographs in complete sentences.	6
TOTAL			40

Appendix B

Figure B 1 and Figure B 2 show the distribution of test scores by preschool type. The test scores have been standardized by age.

Figure B 1

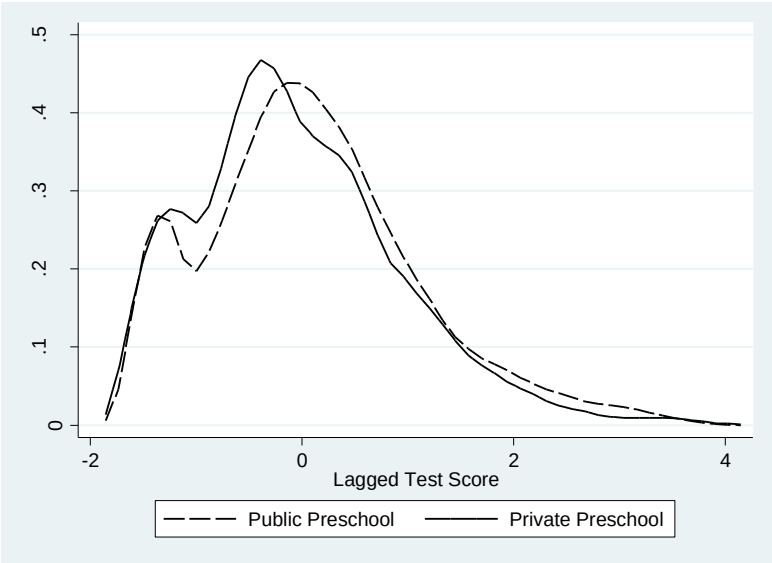

Figure B 2

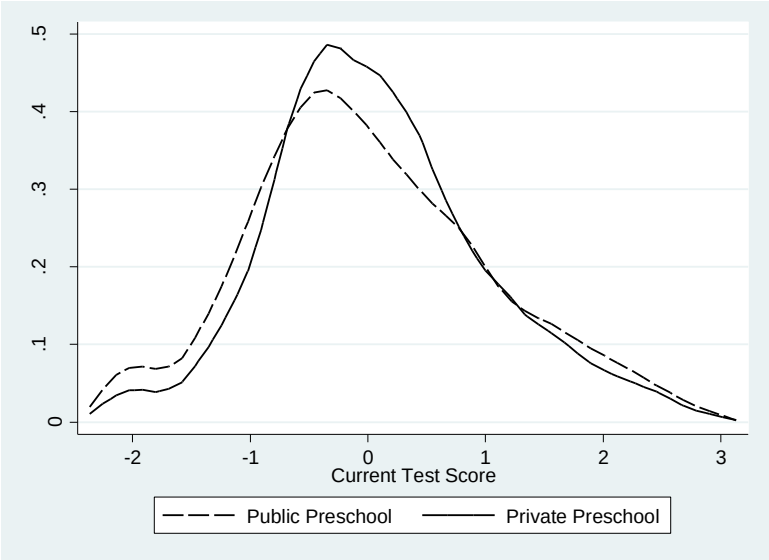

Figure B 3 and Figure B 4 show the distribution of test score (standardized by age) for 3 categories – no preschool, private and public preschool. No preschool category clubs together no educational institution and only primary school categories, as detailed in Table 3.

Figure B 3

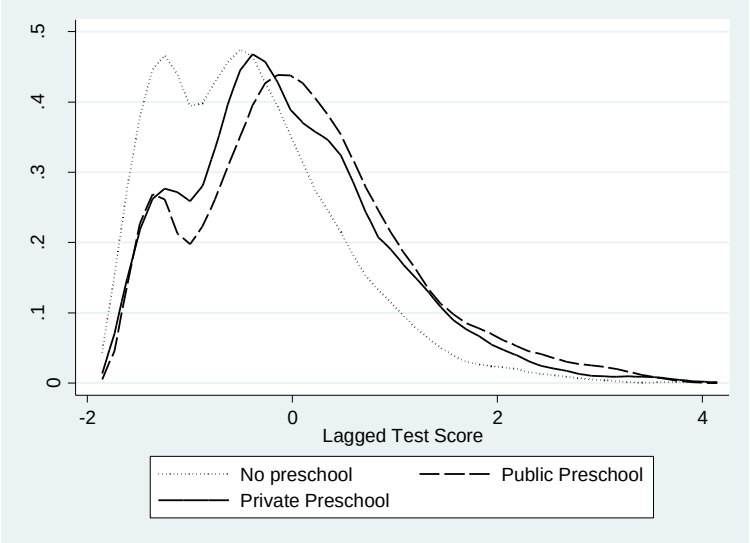

Figure B 4

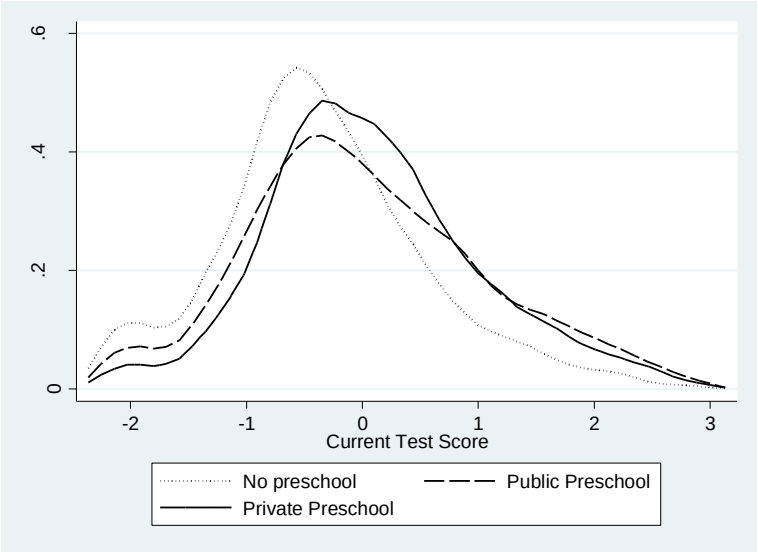

Table B 1 provides the mean by all 3 categories – no preschool, private preschool, and public preschool. No preschool category clubs together no educational institution and only primary school categories, as detailed in Table 3

Table B 1

	No preschool mean	Public Preschool mean	Private Preschool mean	Total mean
Test Score				
Raw lagged test score	7.87	11.83	10.79	11.14
Raw current test score	14.23	17.28	17.71	17.00
Lagged test score - standardised	-0.41	0.09	-0.04	0.00
Current test score - standardised	-0.34	0.03	0.09	0.00
Child and household characteristics				
Age in months	63.47	63.00	63.19	63.10
Female	0.48	0.50	0.43	0.48
Muslim	0.22	0.17	0.12	0.17
Scheduled Caste	0.22	0.17	0.13	0.17
Scheduled Tribe	0.12	0.11	0.06	0.10
Other backward	0.51	0.47	0.58	0.50
Years of Education - Father	6.17	5.98	8.66	6.55
Years of Education - Mother	2.06	3.89	4.77	3.85
Consumer Durable Index	2.54	2.45	3.31	2.64
Primary Income: Casual/Contract Labor	0.58	0.46	0.44	0.47
Mother employed	0.18	0.42	0.17	0.34
Months in primary school	0.00	0.85	0.85	0.83
Parent's motivation				
Reads story to child	0.08	0.39	0.22	0.32
Helps with homework	0.28	0.59	0.58	0.55
Reason for Preschool - Prepare for Primary School	0.15	0.38	0.33	0.35
Talk to staff about child's progress	0.15	0.37	0.33	0.34
Child's motivation				
Talks about preschool always	0.11	0.34	0.22	0.29
Talks about preschool sometimes	0.25	0.40	0.38	0.38
Likes going to preschool	0.61	0.65	0.72	0.66

Appendix C

Table C 1 - VAM with test score normalized by age.

Variable	(1) Test score standardised by age	(2) Test score standardised by age	(3) Test Score (Original VAM)
Private Preschool	0.131***	0.132***	0.129***
	(0.0367)	(0.0369)	(0.0368)
Age in Months		-0.000551	0.0143***
		(0.00342)	(0.00347)
Female	-0.0547**	-0.0549**	-0.0529**
	(0.0226)	(0.0227)	(0.0226)
Muslim	-0.116**	-0.115**	-0.117**
	(0.0534)	(0.0541)	(0.0541)
Scheduled Caste	-0.0705	-0.0710	-0.0659
	(0.0527)	(0.0526)	(0.0522)
Scheduled Tribe	0.00134	0.00301	0.00266
	(0.0661)	(0.0665)	(0.0664)
Other backward	0.0433	0.0432	0.0419
	(0.0440)	(0.0442)	(0.0440)
Yrs of edu - father	0.0127***	0.0127***	0.0126***
	(0.00323)	(0.00323)	(0.00324)
Yrs of edu - mother	0.0243***	0.0245***	0.0246***
	(0.00355)	(0.00355)	(0.00351)
Consumer Durable Index	0.0711***	0.0705***	0.0722***
	(0.0102)	(0.0102)	(0.0102)
Primary Income: Casual/Contract Labor	-0.0738***	-0.0745***	-0.0743***
	(0.0264)	(0.0265)	(0.0263)
Mother employed	-0.0499	-0.0461	-0.0492
	(0.0420)	(0.0421)	(0.0419)
Months in primary school	0.0622***	0.0622***	0.0616***
	(0.0126)	(0.0127)	(0.0129)
Lagged test score - age corrected	0.185***	0.185***	
	(0.0183)	(0.0183)	
Lagged test score			0.183***
			(0.0181)
State Controls	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes
Observations	5,724	5,724	5,724
R-squared	0.412	0.412	0.417

Robust standard errors in parentheses, clustered at village level

*** p<0.01, ** p<0.05, * p<0.1

Table C 2 – Testing for different specification of lag structure

Dependent Variable - Current test score	(1) Vam - Lag structure	(2) Original VAM
Private Preschool	0.129***	0.129***
	(0.0367)	(0.0368)
Lagged test score	0.195***	0.182***
	(0.0240)	(0.0181)
Lagged test score ^2	-0.0113	
	(0.0168)	
Lagged test score^3	-0.00130	
	(0.00617)	
	(0.237)	(0.236)
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
State Controls	Yes	Yes
Village Controls	Yes	Yes
Observations	5,730	5,730
R-squared	0.418	0.417

Robust standard errors in parentheses, clustered at village level
*** p<0.01, ** p<0.05, * p<0.1

Appendix D

Figure D 1 – Common Support for matching (Table 10)

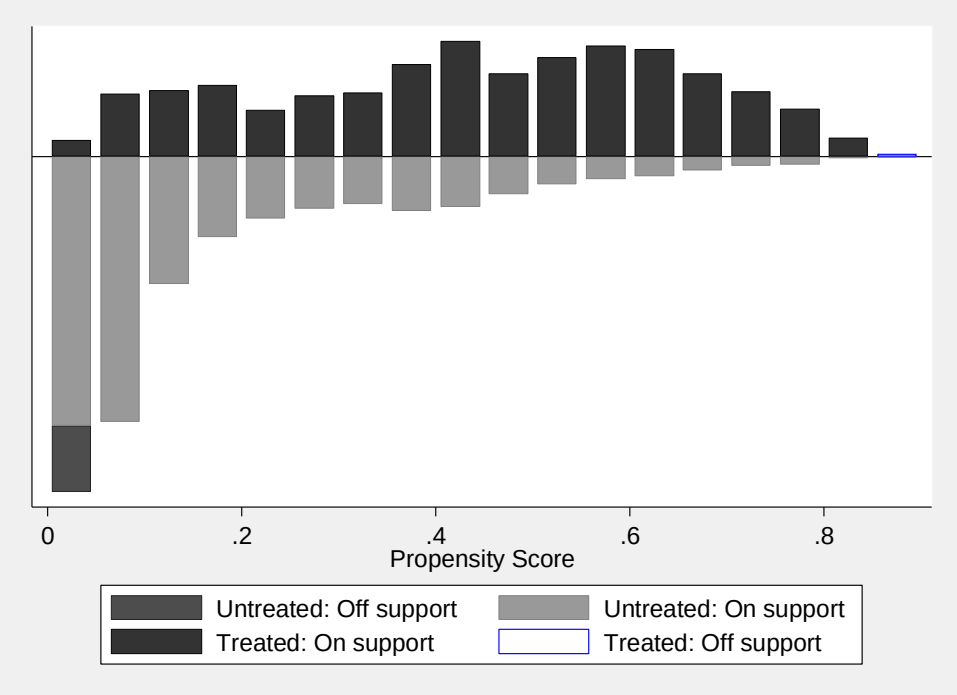

Table D 1 – Balancing test before and after matching

Variables		Treated	Control	%bias
Age in months	Unmatched	63.22	62.98	6.8
	Matched	63.22	63.28	-1.8
Female	Unmatched	0.43	0.50	-13.5
	Matched	0.43	0.42	1.9
Muslim	Unmatched	0.12	0.15	-9.3
	Matched	0.12	0.11	1.6
Scheduled Caste	Unmatched	0.13	0.18	-14.2
	Matched	0.13	0.13	-0.8
Scheduled Tribe	Unmatched	0.07	0.11	-14.9
	Matched	0.07	0.06	1.2
Backward caste	Unmatched	0.60	0.51	18.1
	Matched	0.60	0.61	-1.8

Father's edu	Unmatched	8.70	6.09	59.1
	Matched	8.68	8.67	0.4
Mother's Edu	Unmatched	4.77	3.95	18.6
	Matched	4.75	4.69	1.5
Consumer Durable Index	Unmatched	3.32	2.57	54.5
	Matched	3.31	3.30	0.9
Income: Casual Labour	Unmatched	0.44	0.46	-3.1
	Matched	0.45	0.44	0.6
Mother employed	Unmatched	0.16	0.41	-56.1
	Matched	0.17	0.17	-1.2
Lagged test score	Unmatched	-0.04	0.09	-13.1
	Matched	-0.04	-0.05	0.3

Table D 2 – Propensity score without lagged score

VARIABLES	(1) Private
Age in months	0.00643
	(0.00989)
Female	-0.254***
	(0.0713)
Muslim	-0.634***
	(0.115)
Scheduled Caste	-0.703***
	(0.136)
Scheduled Tribe	-0.752***
	(0.160)
Other backward	-0.200*
	(0.105)
Years of Education - Father	0.0674***
	(0.00958)
Years of Education - Mother	0.0501***
	(0.0101)
Consumer Durable Index	0.118***
	(0.0284)
Primary Income: Casual/Contract Labor	0.0424
	(0.0740)

Mother employed	-0.431***
	(0.122)
State Controls	Yes
Observations	5,730

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D 3 – Cross Sectional Matching (without lagged test score)

	Nearest Neighbour	5 - Nearest Neighbour	Radius	Kernel	Sample Size
Model (1) : Outcome variable Current test score					
ATE	0.087	0.125**	0.143*	0.147***	5524
	(0.068)	(0.064)	(0.051)	(0.054)	
ATT	0.086*	0.107***	0.123***	0.131***	5524
	(0.048)	(0.037)	(0.037)	(0.037)	

Figure D 2 – Common Support for cross sectional matching (without lagged test score)