

# Understanding Private School Performance in Rural Pakistan

Nick Eubank

October 28, 2012

## **Abstract**

The emergence of rural, secular, affordable private schools across South Asia is one of the most potentially promising educational sector developments in decades. Yet the question of whether private schools are actually superior to government schools remains unsettled. Observational studies consistently show that private school students outperform government school students, but it is unclear whether this is because (a) private schools provide students with a better education, or because (b) more talented students attend private schools. This paper presents a novel empirical regularity from Pakistan – that private school superiority declines dramatically with village caste fractionalization – and examines its compatibility with these two theories. It concludes that this regularity implies at least 50% of the difference between government and private school test scores can be explained by differences in student composition, not teaching quality.

# 1 Introduction

Developing countries – particularly those in South Asia – have experienced explosive growth in private schools. From 2000 to 2005 in rural Pakistan, for example, “the number of private schools in Pakistan increased from 32,000 to 47,000 and by the end of 2005, one in every 3 enrolled children at the primary level was studying in a private school.” (Andrabi et al., 2007, p. vi). Similarly 20-24% of rural students in India report attending a private school in 2005 (Pratham, 2005). Moreover, the students in these private schools consistently outperform their government school counterparts, even when controlling for observable student characteristics (Jimenez et al., 1991; Jimenez and Lockheed, 1995; Pratham, 2005; Andrabi et al., 2011; Desai et al., 2009; Tooley and Dixon, 2003; Alderman et al., 2003, 2001). This has given rise to the hope that private schools may someday circumvent reform-resistant government schools and finally deliver quality educations to the hundreds of millions of children in rural India and Pakistan. Yet while observational studies give hope that private schools may be the answer to the stagnation of education reform, the question of whether private schools really deliver a superior education remains – perhaps to a surprising degree – undecided.

The difficulty is that there are two very different explanations for the superiority of private school students with very different implications, and separating the two has proven exceedingly difficult.

The first explanation is that private school students differ from government school students in some unobservable way. Most studies of private schools are observational in nature, and while they are able to control for many important factors – like parental education and household wealth – this still leaves open the door to more subtle sorting. Addressing this exact question, Banerjee (2009) recently observed:

The reason why it is always been a challenge to answer this question is that there is an identification problem. [...] It basically comes down to the question, “Are children who get sent to private schools different from those who are not?” This is a problem at every level – within a family, within a neighborhood, within a district within a state. [...] You worry that the child who gets sent to the public school rather than the private school by a family that can afford both, might have certain characteristics that are driving the choice.

Of course efforts have been made to address the possibility of student “sorting.” Randomizing school assignments is untenable, but in two major cases private school vouchers have been randomly assigned. Even these randomizations have proven problematic, however. Angrist et al. (2002) examines a voucher lottery system in Colombia and finds a small

positive effect of vouchers, but inference is clouded by the fact that voucher students who performed poorly were at risk of losing their vouchers, making it impossible to separate this incentive effect from the private school effect. And several studies have been conducted of a voucher system in Chile, but as Bellei (2008) notes, the slight private-school advantage these studies show may be down to the fact that private school admissions are selective and poorly performing students can be expelled from private schools, making it difficult to disentangle selectivity from school effects.

Advocates of private schools argue that not only are observational studies able to control for many factors, but there is also evidence to explain *why* private schools outperform government schools. In particular, they point out that private schools appear to address the biggest problem in government schools: low effort. High absenteeism and low accountability in government schools has been well documented (Muralidharan and Kremer, 2008; Chaudhury et al., 2006), but appears less prevalent in private schools. The reason, many argue, is that in private schools good teachers are better paid, and poor teachers are let go (Andrabi et al., 2007). This line of reasoning is also buoyed by a growing body of literature that suggests that what matters for success is not the availability of educational “inputs” (like qualified, well paid teachers or good facilities), but incentive schemes that reward effort on the behalf of teachers. (Hanushek, 1997, 2003; Banerjee et al., 2007).<sup>1</sup>

Private schools are superior, in other words, because they have incentive systems that induce greater teacher effort.

This paper evaluates these two theories – the “incentive” theory and the “sorting” theory – on the basis of their ability to explain a novel empirical regularity. Using data from 112 villages in rural Pakistan, this paper shows that private school dominance varies with village fractionalization. In particular, it shows that as the level of caste fractionalization in a village increases, the degree to which private schools outperform government schools declines by 50%.

As this paper will argue, this finding appears to be incompatible with the “incentive” story as there is no evidence that the way teachers are paid in either government or private schools varies between high and low fractionalization villages. By contrast, there is relatively strong evidence to suggest that the way students “sort” between schools does vary with ethnic fractionalization, and that this change in sorting is consistent with the

---

<sup>1</sup>This reasoning is not entirely supported by the evidence. For example, while private schools generally outperform public schools in the US and many have attributed that to better incentive structures, private-run government charter schools (which presumably have a similar incentive system but do not necessarily have the saw draw for educationally minded families) have not fared so well. (Fuller, 2002) And while a number of studies of randomly-assigned private-school vouchers suggest that the private school effect may be real, even these studies have been complicated by a number of problems which make inference difficult.

convergence in test scores seen in the data.

This finding is unlikely to put to rest the debate over whether private schools are superior to government schools. Indeed, private school students continue to outperform government school students even in the most homogenous villages, just by a dramatically smaller margin. But even after using some of the most sophisticated econometric methods available, this paper still establishes (as a “lower bound”) that sorting explains a very large portion of the public-private test score gap. This should give analysts pause when examining other empirical results that claim to fully control for sorting.

The novelty of this approach lies not in the introduction of a new empirical regularity, but in the introduction of a new regularity that operates at a different level of analysis than previous studies. Most education work takes children, households, or schools to be the unit of analysis, but to date this approach has failed to answer even these most basic questions. By bringing in not just a new source of exogenous variation, but rather an entirely new *level* of variation, this approach will hopefully not only bring new perspective to these issues, but also provide a model for future work.

This paper is organized out as follows: Section 2 provides an overview of the data and methods employed in this analysis. Section 3 introduces the empirical regularity around which this paper is organized – that as caste fractionalization increases, the difference between government and private school performance declines. Section 4 examines some of the evidence that private schools are better educators and shows it cannot explain the convergence of test scores in high fractionalization villages. Section 5 that shows public-private test score convergence *can* and most likely *is* explained by a change in how children sort across schools. It also provides a number of possible explanations for the question of why, if their dominance is illusory, private schools are still able to fill their classrooms with fee-paying students. And finally Section 6 discusses the strengths and weaknesses of these findings, and how they might best be interpreted.

## **2 Data and Methodology**

This analysis is based on panel data from the Learning and Educational Attainment in Punjab Schools (LEAPS) survey, administered jointly by the World Bank, Pomona College, and Harvard University with the assistance of the Government of Punjab. The LEAPS survey was conducted in 112 villages in the Punjab districts of Attock, Faisalabad, and Rahim Yar Khan annually from 2003-2007. The data consists primarily of two panels of students – one (initiated in 2003 with an initial population of 12,110 children)

which followed students for four years, and one (initiated in 2005 with an initial population of 11,852 students) which followed students for two years. Each panel represents the universe of enrolled students in sample villages in Class 3 in both government and private schools.

Students in both panels were administered annual exams in English, math, and Urdu. In addition, approximately half of students were administered demographic surveys which include questions on parental education and household wealth. These exams were designed and piloted by the LEAPS team, and subsequently standardized using Item Response Theory (IRT) methods. The test scores presented here are the normalized IRT results, which have a mean of zero and standard deviation of one among students in Class 3.

In addition to testing and surveying students, the LEAPS survey also collected data on schools, teachers, and a random sample of 10 households per village with children of school-eligible age. Further, some data were also obtained from a listing census conducted in sample villages prior to the start of the LEAPS survey that include basic demographic information on all households, allowing for the computation of accurate village level statistics.

## 2.1 Measuring Test Scores

### 2.1.1 Measuring Child Learning

To measure learning, this analysis employs the lagged-value-added model, which has increasingly become the norm in the education research (Gordon et al., 2006; McCaffrey et al., 2003; Hanushek, 2003). The lagged-value-added model incorporates the assumption that current knowledge is an additive function of all current and past inputs and an i.i.d. stochastic error term. This can be written formally as:

$$Y_{i,t} = \alpha_t X_{i,t} + \alpha_{t-1} X_{i,t-1} + \cdots + \alpha_1 X_{i,1} + \epsilon_{i,t} \quad (1)$$

where  $Y_{i,t}$  is child  $i$ 's test scores at time  $t$  and  $X_{i,t}$  is a vector of child, school, and village controls at time  $t$ . As data on past inputs are usually unavailable, however, they are generally subsumed into a lagged dependent variable included as a control. In this case the lagged-value-added model can be re-written as:

$$Y_{i,t} = X_{i,t}\alpha + Y_{i,t-1}\beta + \epsilon_{i,t} \quad (2)$$

Where  $Y_{i,t-1}$  is assumed to capture all past inputs and unobservable heterogeneity across students. The specification given by Equation 2 is the model primarily employed in this paper. As the interest of this analysis is on the difference between government and private school students, primary interest is on a dummy for school type included in the vector of controls  $X_{i,t}$ .

Three aspects of this specification are worth emphasizing. First, while the inclusion of a lagged dependent variable effectively controls for unobserved differences that affect differences in test *levels*, it cannot control for unobserved heterogeneity that affects learning *rates*. It is for this reason that while superior to other available methods, value-added analyses can not fully overcome selection issues.<sup>2</sup>

Second, the  $\beta$  term can be interpreted as the “persistence parameter” in that it estimates the degree to which past learning may carry forward. A value of one is equivalent to assuming that children do not forget past lessons, while a value of zero corresponds to students forgetting all past lessons each year. While imposing a persistence parameter of one may seem reasonable – it amounts to regressing the difference in test scores between time  $t$  and time  $t - 1$  on controls – a growing literature has shown that the test score gains of short term interventions often “die out” over time, suggesting that not all that is learned is retained (Banerjee et al., 2007; Glewwe et al., 2010; Currie and Thomas, 1995; Rothstein, 2010). Andrabi et al. (2011) shows that imposing the restriction that  $\beta = 1$  biases learning estimates.

Finally, lagged test scores are generally measured with error, which leads to an often significant attenuation bias in the estimate of  $\beta$  and biased estimates of other coefficients (Kane and Staiger, 2002; Chay et al., 2005; Andrabi et al., 2011). Thus keeping with best practices, lagged test scores from all three subjects – English, Urdu, and math – are included in all specifications to instruments for the primary lagged test score of interest.

Note further that all child-level results are presented using heteroskedastic-robust standard errors clustered at the level of the village.

---

<sup>2</sup>Some analysis have turned to second-differencing the data and focusing on students who change schools (Andrabi et al., 2011), but these analyses have their own limitations, among them limited sample sizes (given that changes between types of school are relatively infrequent in most surveys) and the assumption that school changes are not the result of some unobserved shock (i.e. that school switches are not accompanied by contemporaneous with other changes – a potentially problematic assumption given the relative infrequency with which students change schools).

### 2.1.2 Village-Level Estimates

In addition to estimating learning differences at the level of the child, the primary analysis of this paper is also estimated at the level of the village. To do so, Specification 2 is augmented with with fixed effects for each village-school type combination, as below:

$$Y_{i,t} = X_{i,t}\alpha + Y_{i,t-1}\beta + \mathbb{I}_{i,j,type,t}\gamma_{j,type} + \epsilon_{i,t}$$

Where  $\mathbb{I}_{j,type}$  is a vector of dummies for the village  $j$  of child  $i$  in school type  $type \in \{private, government\}$  at time  $t$ . The difference between the village private-school dummy coefficients and the village government-school dummy coefficients are then extracted as a village-level estimate of the government-private test score gap. These village-level gaps are then regressed against a series of village-level controls, include village fractionalization, wealth, size, land fractionalization, and adult literacy variables  $Z_j$  reported at the level of the village  $j$ , as below:

$$Gap_j = Z_j\delta + \eta_j$$

### 2.1.3 Teacher-Value Added Estimates

A similar method is employed when estimating the contribution of individual teachers to child learning. Specification 2 is again employed with the addition of fixed effects for each individual teacher, as below:

$$Y_{i,t} = X_{i,t}\alpha + Y_{i,t-1}\beta + \mathbb{I}_{i,k,t}\zeta_k + \epsilon_{i,t}$$

where  $\mathbb{I}_k$  is a vector of dummies for whether student  $i$  was taught by teacher  $k$  in year  $t$ . The fixed effect coefficients  $\zeta_k$  are then extracted as an estimate of teacher  $k$ 's contribution to student learning in various regressions. Teacher regressions are all weighted by the number of students taught by a given teacher, both because our interest is in the experience of the average child and because value-added estimates for teachers with small classes are extremely imprecise and are otherwise prone to skew results.

### 3 Caste Fractionalization and Test Score Convergence

This section presents the empirical regularity around which this paper is organized: that private-public test scores converge in fractionalized villages. Before presenting this result, however, a brief digression on the nature of “caste” in Punjab. Those with a familiarity with the concept of caste in Pakistan can jump ahead to Section 3.2.

#### 3.1 Caste in Punjab

Caste – known variously as *biraderi* or *zaat* – is a central aspect of rural social identity in Pakistan, especially in Punjab. While *biraderi* is a somewhat distinct concept from the idea of “caste” in India, “it retains a very important feature of the [Indian subcaste] – that of an inherent, inbuilt hierarchy that governs social interactions. Society is hierarchically ordered with the Syeds at the top, followed by the landowning castes, then by the service castes or kammis, and finally by the Musallis, who occupy the lowest rung of the social ladder. This ordering dictates much of the social life in a Punjabi village and is most profound in the notions of community cooperation, where solidarity is strongest within a *biraderi*.”(Gazdar and Mohmand, 2007, p. 29).

*Biraderi* is correlated with wealth, land holdings, and education, but it is not synonymous with economic class. As a related report observes, “while economic power is required to reinforce *biraderi*-based dominance, membership of a dominant *biraderi* can help mitigate some of the effects of being economically poor. As one respondent put it, ‘the poorest Jatt is still better off than the richest kammi.’” (Gazdar and Mohmand, 2007, p. 13)

While the centrality of caste politics is relatively universal across villages in Punjab, however, there is significant variation in village *biraderi* composition. Figure 1 below shows the density plot of villages of different levels of ethnic fractionalization, as measured using a simple herfindahl index.<sup>3</sup> As the figure shows, there is significant variation in the degree of fractionalization both within and across the three districts of the LEAPS survey.

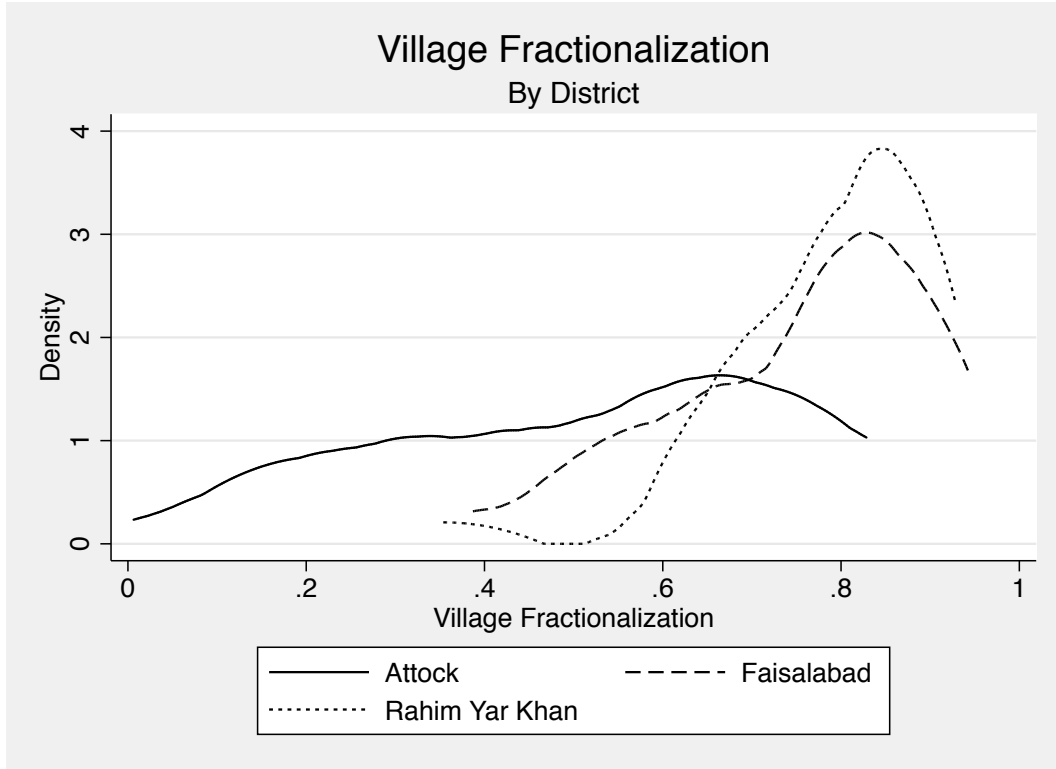
Interestingly, segregation is not clearly related to village wealth, land inequality, or adult education, as shown below in Table 1. There is some relationship to primary school enrollment rates and village size, but on the whole fractionalization appears to be relatively independent of other compositional characteristics of villages.

---

<sup>3</sup>The herfindahl is a common measure of fractionalization equal to the probability that any two randomly selected individuals belong to the same group. Village fractionalization is computed using data from a village census conducted in 2002 to facilitate household sampling for the LEAPS survey which includes data on the *biraderi* of all households in LEAPS villages.



Figure 1:



### 3.2 Caste Fractionalization and Private School Dominance

Having provided some background on the nature of caste in Punjab, the main empirical regularity of the paper can be presented. Table 2 presents lagged-valued-added estimates of learning as a function of various demographic controls and village fractionalization. It shows that the effect of caste fractionalization on the government-private test score gap is negative and significant for English and Urdu, and negative (albeit insignificant) for math. Further, as shown in columns (2), (5), and (8) of Table 2, the inclusion of various

Table 1: Village Characteristics and Fractionalization

	(1) Median Wealth	(2) Adult Literacy	(3) Land Gini	(4) Enrollment Pct	(5) Schools per HH	(6) Log Num HH
Fractionalization	-262.5 (-0.44)	-7.64 (-1.36)	0.073 (1.35)	-16.0** (-2.43)	-0.0017 (-0.18)	0.68** (2.09)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112	112	112	112	112	112

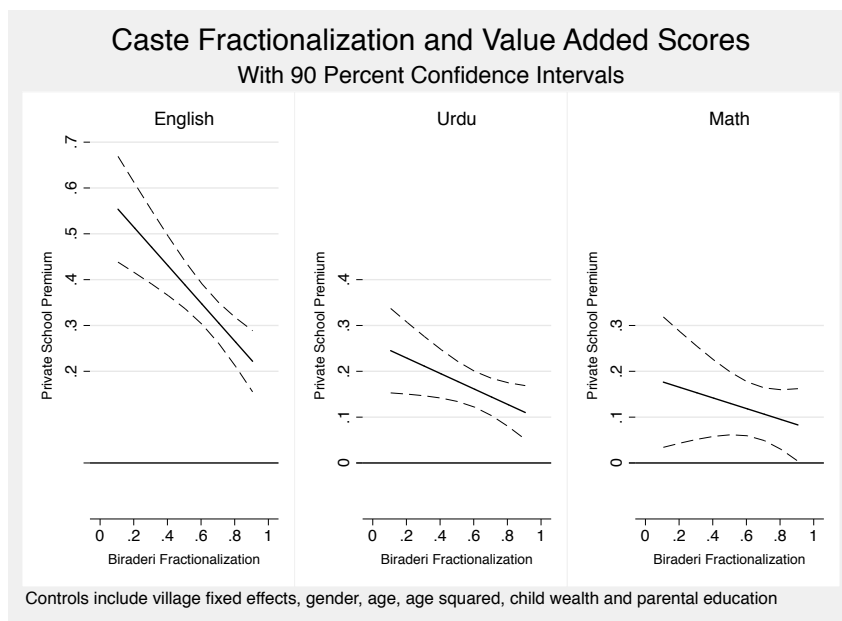
*t* statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

demographic controls such as a child wealth index and dummies for parental education along with the village fixed effects has no significant effect on the results.

Given the difficulty associated with interpreting interaction terms, Figure 2 plots the private-public test score gap as a function of caste fractionalization (these plots correspond to columns (2), (5), and (8) respectively). In all three cases, the rise in fractionalization is associated with a near 50% decline in the private school premium, although this is by far most striking in the case of English, which is considered the path to upward mobility, and is the speciality of private schools in Punjab.

Figure 2: Private School Test Score Premium with Lagged Scores



Note that the decline in the government-private test score gaps is not coming just from improvement in government schools or a decline in private schools, but rather a combination of the two. This is shown in Column 3 of Table 2, where village fixed effects are replaced with district fixed effects, allowing for a comparison of test scores levels (rather than just the government-private gap) across villages. In the case of English the convergence appears to be driven in equal parts by improvements in government schools and a decline in private schools.

Consistent results can also be obtained when this analysis is conducted at the level of the village using Specification 3, as shown in Table 3. As discussed in methodology, the dependent variable in these regressions is the village gap in government-private “value-added” scores after controlling for all available observable student demographics. This adjusted-gap is then regressed on a number of village characteristics. While the results are not quite as strong as when estimated at the level of the child, all three regressions

Table 2: Child Test Scores

	English			Urdu			Math		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Private School	0.63*** (8.35)	0.60*** (7.28)	0.59*** (7.31)	0.27*** (4.16)	0.26*** (4.01)	0.20*** (2.93)	0.19* (1.67)	0.19* (1.88)	0.12 (1.25)
Fractionalization * Private	-0.43*** (-3.77)	-0.41*** (-3.46)	-0.42*** (-3.68)	-0.17* (-1.71)	-0.17* (-1.74)	-0.094 (-0.98)	-0.082 (-0.53)	-0.12 (-0.83)	-0.052 (-0.39)
Lagged English Scores	0.37*** (21.16)	0.36*** (20.03)	0.39*** (20.61)	0.15*** (13.05)	0.14*** (11.37)	0.14*** (11.69)	0.16*** (10.78)	0.15*** (10.06)	0.16*** (9.86)
Lagged Math Scores	0.069*** (8.55)	0.072*** (8.91)	0.071*** (8.49)	0.12*** (14.10)	0.12*** (13.51)	0.12*** (13.96)	0.37*** (29.56)	0.38*** (27.37)	0.40*** (28.76)
Lagged Urdu Scores	0.15*** (14.04)	0.15*** (13.28)	0.15*** (12.71)	0.38*** (34.36)	0.38*** (32.65)	0.40*** (31.74)	0.23*** (17.67)	0.22*** (17.01)	0.22*** (16.84)
Child's Wealth Index		0.017*** (5.19)	0.015*** (4.29)		0.0073** (2.46)	0.0068** (2.28)		0.014*** (3.52)	0.016*** (3.73)
Educated Parent		0.058*** (4.75)	0.053*** (4.07)		0.052*** (4.77)	0.049*** (4.40)		0.046*** (3.35)	0.043*** (3.08)
Biraderi Fractionalization			0.21** (2.56)			0.095 (1.40)			0.14 (1.38)
Village: Pct Adults Literate			0.00017 (0.18)			-0.00054 (-0.62)			0.00036 (0.27)
Log Village Size			0.019 (1.47)			0.014 (1.01)			0.0088 (0.50)
Village Land Gini			0.053 (0.47)			0.061 (0.63)			-0.25* (-1.88)
Constant	0.25 (0.99)	0.40* (1.78)	0.57** (2.28)	0.56** (2.58)	0.69*** (2.78)	0.78*** (2.80)	0.12 (0.37)	0.31 (0.99)	0.60* (1.74)
Village Fixed Effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
District Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	37147	26141	26141	37147	26141	26141	37147	26141	26141

Controls for age, age squared, gender, and class omitted from table. Standard errors clustered at village level.

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

show declines in the government-private gap associated with increasing fractionalization, especially for English.

Table 3: Village Level Government-Private Gap

	(1) English	(2) Urdu	(3) Math
Biraderi Fractionalization	-0.36* (-1.80)	-0.18 (-1.02)	-0.28 (-1.03)
Median Village Wealth	-0.000010 (-0.32)	0.0000096 (0.34)	-0.000043 (-0.97)
Log Village Size	0.0016 (0.03)	-0.033 (-0.63)	0.019 (0.23)
Pct of Adults Literate	-0.00021 (-0.06)	0.0019 (0.64)	0.0047 (1.00)
Land Gini	0.35 (1.01)	-0.084 (-0.27)	0.32 (0.66)
District Fixed Effects	Yes	Yes	Yes
Observations	109	109	109

*t* statistics in parentheses

\* p<sub>i</sub>0.10, \*\* p<sub>i</sub>0.05, \*\*\* p<sub>i</sub>0.01

## 4 School Superiority

This section address the question of whether the convergence in public and private test scores in fractionalized villages is compatible with changes in the actual quality of teaching, either in government or private schools. This is addressed by first examining whether there are any differences in educational “inputs” (school facilities, teacher training and education, etc.) between homogenous and fractionalized villages. Then it examines the more difficult question of whether the way schools operate changes across villages.

### 4.1 Inputs

The most obvious way in which schools might differ across villages is in the quality of their teachers or facilities. The LEAPS survey collected extensive data on these questions, making this question readily answerable.

Table 4 regresses a number of school- and teacher-quality dependent variables against village fractionalization and a number of controls. The table shows that there is little or

no evidence that – at least in terms of visible inputs – differences in inputs can explain the decline in private school performance in fractionalized villages. If anything, private school teachers appear to be slightly *better* educated in fractionalized villages.

Table 5 repeats this exercise for government schools. It should be noted that government schools in Pakistan are administered at the state level, and are thus relatively insulated from village politics, making any such differences unlikely. Nevertheless, results are presented for thoroughness. These results show no difference in school inputs across villages.

## 4.2 Teacher Incentives

Having shown there is no difference in teachers or school facilities that can explain private-public test score convergence in fractionalized villages, attention is now turned to the question of teacher incentive systems.

In 2003 the World Bank, Harvard University, and Pomona College, in conjunction with the Government of Punjab, mounted a massive four year survey of schools, students, teachers, and households in 112 villages in rural Punjab. The aim of the project – the Learning and Educational Attainment in Punjab Schools (LEAPS) survey (on which this author was a research assistant) and on whose data this analysis is based – was to study the inner workings of government and private schools in the hopes of better understanding how private schools were able to do so much with so little.

The conclusion of the LEAPS authors is that private schools are able to deliver better educational outcomes despite hiring local women with only secondary educations and no training and paying relatively low wages is that where government schools focus on inputs, private schools are output-oriented. Government schools pay their teachers well, but their pay is unrelated to the performance of their students. Private school teachers, by contrast, are paid more when their students do better. As a result, government school teachers exert less effort. As shown in Figure 3 from the report, while frequently absent private school teachers are paid less, absent government school teachers are actually paid *more*, and where private school teachers with high score students are paid more, no such relationship exists for government teachers. This leads the authors to conclude that:

Teacher and institutional attributes can be broadly separated into three categories: hard to observe teacher characteristics such as motivation, which can emerge only over time, easy to observe characteristics such as educational qualifications, experience and training and, the institutional framework

Table 4: Private Teacher Characteristics and Village Fractionalization

	(1)	(2)	(3)	(4)	(5)	(6)
	Days Absent	Female	From Village	Teacher English Exam Score	More than Grade School Education	Basic School Facility Index
Biraderi Fractionalization	-0.91 (-1.32)	-0.052 (-0.60)	0.31* (1.71)	0.19 (1.06)	0.20* (1.68)	-0.023 (-0.07)
Median Village Expenditures	0.000054 (0.64)	0.0000057 (0.46)	0.0000030 (0.12)	0.000016 (0.50)	0.000013 (0.68)	0.000049 (1.13)
Log Number of Households	-0.29 (-1.47)	-0.030* (-1.67)	-0.036 (-0.74)	0.045 (0.86)	0.0072 (0.29)	-0.13 (-1.43)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1494	1494	1494	768	1494	493

All results clustered at the village level.

All regressions weighted by number of students.

Robust t-statistics presented in parenthesis.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

Table 5: Government Teacher Characteristics and Village Fractionalization

	(1)	(2)	(3)	(4)	(5)	(6)
	Days Absent	Female	From Village	Teacher English Exam Score	More than Grade School Education	Basic School Facility Index
Biraderi Fractionalization	-0.33 (-0.34)	0.099 (0.72)	0.26 (1.20)	0.093 (0.36)	-0.10 (-0.84)	0.32 (0.63)
Median Village Expenditures	-0.00018 (-0.99)	0.000026 (0.99)	-0.0000068 (-0.23)	0.000052* (1.75)	0.000021 (1.23)	0.000033 (0.53)
Log Number of Households	-0.33 (-1.41)	-0.040* (-1.80)	-0.040 (-0.59)	0.034 (0.71)	0.000076 (0.00)	-0.094 (-0.85)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	988	988	988	477	988	291

All results clustered at the village level.

All regressions weighted by number of students.

Robust t-statistics presented in parenthesis.

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

embodied in incentives such as the teacher salaries and bonuses. Research in the United States has tried to separate the influence of the first two types of characteristics (motivation and qualification); given that most of this research is for public school teachers, it has made less progress on the impact of incentives. This research finds that characteristics like motivation and a love of teaching are far more important in explaining the variation in student learning compared to educational qualifications, experience, and training. Experience for instance, matters only in the first year. In short, in systems with the same set of incentives, teachers appear to be born, not made. (Andrabi et al., 2007, p. 78)

Figure 3:

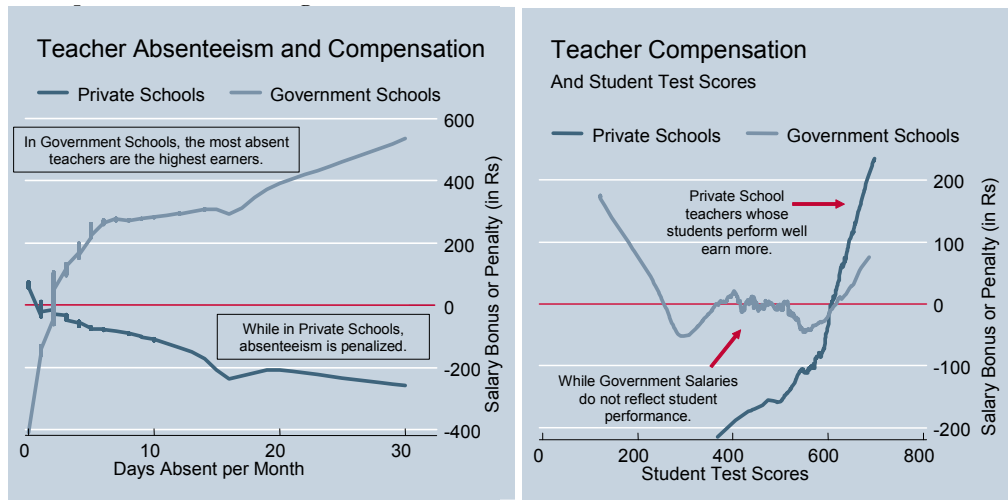


Table 6 below recreates the analyses underlying two figures with two adjustments. First, rather than measuring performance using average test scores (in levels), more rigorous teacher “value-added” scores (Specification 3) are employed to measure teacher contributions to learning. Second, a village fractionalization measure is included in all regressions as an interaction term. If it is the case that differences in incentive schemes are driving test score convergence, then we should see (a) the private-school salary penalty for absenteeism decline in fractionalization, and (b) the compensation bonus for performance decline. As shown in the table, however, the absenteeism penalty actually *increases* in fractionalization (which under the incentive story should result in *increased* private school scores), and no relationship exists between performance and compensation.

And as expected, there is no relationship between fractionalization and how government teachers are compensated.



Table 6: Village Fractionalization and Teacher Compensation

	Private Teachers		Government Teachers	
	(1) Log Salary	(2) Log Salary	(3) Log Salary	(4) Log Salary
Days Absent Last Month	0.041** (2.00)	-0.0068 (-0.85)	0.0017 (0.40)	0.0041*** (2.79)
Biraderi Fractionalization	0.24 (1.18)	0.21 (0.78)	-0.085 (-1.47)	-0.050 (-0.74)
Days Absent * Fractionalization	-0.063** (-2.05)		0.0050 (0.77)	
Gender	-0.32*** (-3.78)	-0.27** (-2.17)	-0.012 (-0.72)	0.0095 (0.54)
Age of teacher	0.0053 (1.21)	0.023** (2.54)	0.021*** (12.18)	0.018*** (14.48)
Average Value Added Score		0.22 (0.48)		-0.033 (-0.48)
Value-Added * Fractionalization		-0.47 (-0.67)		-0.020 (-0.22)
Constant	7.07*** (29.09)	8.02*** (20.15)	7.51*** (47.83)	7.60*** (61.24)
District Fixed Effects	Yes	Yes	Yes	Yes
Observations	619	154	1302	618

Controls for Experience and Teacher Education excluded from table.

Robust t-statistics clustered at the village level in parenthesis

\* p<sub>i</sub>0.10, \*\* p<sub>i</sub>0.05, \*\*\* p<sub>i</sub>0.01

## 5 Sorting

The preceding section showed the incompatibility of the “incentive” story with the convergence of public and private test scores, suggesting that this phenomenon may instead be the result of changes in how students “sort” across schools.

The evidence appears to support this conclusion. If it were the case that convergence were driven by government school improvement or private school decline, one would expect that to be reflected in some change in overall scores. But as shown in Table 7, this is not the case. Overall test scores are essentially flat across villages – English scores are slightly higher in more fractionalized villages in Column 1, but the magnitude of this difference is relatively small, and once more demographic controls are added in Column 2 this effect disappears. No relationship exists for other subjects. Public scores increase and private scores decline with fractionalization, but those changes are almost perfectly offsetting.

The most obvious explanation for this pattern is that intelligent children are more likely to attend private schools in homogenous villages than they are in fractionalized villages. But why?

This section presents evidence that in all villages, children who are perceived to be more intelligent are more likely to be sent to private schools (presumably because the education of a gifted child is perceived to be a better investment by parents). But in more heterogenous villages, school choice is also influenced by a desire to send children to “caste appropriate” schools where they will be surrounded by children of a similar status. As a result, “high status” families are more likely to send their children to private schools *regardless of their academic potential*. Thus high-status but low-achieving children who would be left in a government school in a homogenous village end up in private schools, dragging down test scores, and vice-versa for low status children (who are either driven out by social pressure or higher prices). This weakens the degree to which children are sorting on academic potential, leading to convergence of public and private schools.

Note that this argument is dependent upon some basic assumptions about the distribution of talent across castes. In particular, it requires that residual talent – talent that cannot be explained by things like parental education and wealth – be either relatively equally distributed across the different social strata, or be distributed slightly in favor of lower status *biraderis*. If not, and even the least talented “high status” students were more talented than the most talented “low status” students, then this type of sorting could result in *divergence*, rather than *convergence*, of test scores. As shown in Table 8, however, there is no evidence that those from higher social status *biraderis* have higher residual talent than those from low status *biraderis*.

Table 7: Child Test Scores and Fractionalization

	English		Urdu		Math	
	(1)	(2)	(3)	(4)	(5)	(6)
Private School	0.31*** (10.98)	0.29*** (10.42)	0.14*** (5.74)	0.14*** (5.65)	0.11*** (3.17)	0.087** (2.58)
Biraderi Fractionalization	0.13* (1.70)	0.096 (1.33)	0.085 (1.26)	0.069 (1.08)	0.13 (1.34)	0.13 (1.46)
Lagged English Scores	0.40*** (22.32)	0.39*** (21.10)	0.16*** (13.39)	0.14*** (11.90)	0.17*** (10.27)	0.16*** (9.92)
Lagged Math Scores	0.067*** (8.18)	0.070*** (8.37)	0.12*** (14.51)	0.12*** (14.00)	0.39*** (30.92)	0.40*** (28.87)
Lagged Urdu Scores	0.15*** (13.26)	0.15*** (12.80)	0.39*** (34.01)	0.40*** (31.76)	0.23*** (17.96)	0.22*** (16.87)
Village: Pct Adults Literate	0.00067 (0.68)	0.00022 (0.23)	-0.00018 (-0.21)	-0.00053 (-0.61)	0.00043 (0.31)	0.00036 (0.27)
Log Village Size	0.017 (1.33)	0.019 (1.39)	0.011 (0.73)	0.014 (1.01)	0.0070 (0.35)	0.0087 (0.50)
Village Land Gini	0.0097 (0.08)	0.045 (0.39)	0.013 (0.13)	0.059 (0.61)	-0.28** (-2.22)	-0.25* (-1.90)
Child's Wealth Index		0.015*** (4.22)		0.0068** (2.27)		0.016*** (3.73)
Educated Parent		0.053*** (4.13)		0.049*** (4.42)		0.043*** (3.08)
Constant	0.44 (1.57)	0.63** (2.52)	0.67*** (2.65)	0.80*** (2.83)	0.32 (0.87)	0.61* (1.76)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37147	26141	37147	26141	37147	26141

Controls for age, age squared, gender, and class omitted from table. Standard errors clustered at village level.

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table 8: Child Social Status and Residual Talent

	English			Urdu			Math		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Status Biraderi	-0.035 (-0.79)	-0.062 (-0.93)	-0.11** (-2.41)	-0.044 (-0.75)	-0.11 (-1.55)	-0.081 (-1.61)	0.0056 (0.09)	-0.019 (-0.22)	0.034 (0.50)
Private School	0.30** (2.53)	0.20 (1.50)	0.18 (1.46)	0.22* (1.92)	0.18 (1.37)	0.026 (0.21)	-0.10 (-0.96)	-0.13 (-0.96)	-0.24 (-1.55)
Fractionalization * Private	0.0010 (0.01)	0.12 (0.60)	0.100 (0.54)	-0.097 (-0.60)	-0.057 (-0.29)	0.11 (0.63)	0.35** (2.02)	0.42* (1.97)	0.47** (2.13)
Lagged English Scores	0.32*** (7.79)	0.31*** (6.95)	0.40*** (10.37)	0.15*** (4.80)	0.15*** (4.19)	0.15*** (5.12)	0.17*** (3.81)	0.17*** (3.74)	0.16*** (3.93)
Lagged Math Scores	0.066** (2.21)	0.061* (1.68)	0.050 (1.51)	0.12*** (3.04)	0.094** (2.23)	0.10** (2.57)	0.31*** (6.38)	0.29*** (5.93)	0.38*** (8.33)
Lagged Urdu Scores	0.17*** (4.72)	0.18*** (4.11)	0.16*** (4.04)	0.34*** (8.85)	0.35*** (7.57)	0.40*** (8.74)	0.25*** (5.51)	0.25*** (4.96)	0.25*** (4.94)
Child's Wealth Index		-0.0055 (-0.43)	-0.0080 (-0.69)		0.0060 (0.57)	0.0046 (0.52)		-0.0094 (-0.57)	-0.0062 (-0.44)
Educated Parent		0.12*** (2.95)	0.13*** (3.52)		0.14*** (3.25)	0.14*** (4.01)		0.15*** (2.85)	0.17*** (3.68)
Biraderi Fractionalization			-0.0096 (-0.09)			-0.076 (-0.70)		-0.024 (-0.16)	
Village: Pct Adults Literate			0.00000016 (0.00)			-0.0030** (-2.03)		-0.0022 (-0.84)	
Log Village Size			0.011 (0.33)			0.016 (0.52)		0.026 (0.44)	
Village Land Gini			-0.031 (-0.17)			0.054 (0.28)		-0.11 (-0.37)	
Constant	-0.62 (-1.25)	0.20 (0.29)	1.00* (1.71)	-0.15 (-0.26)	2.16*** (3.07)	2.28*** (3.46)	-0.71 (-1.07)	2.98*** (3.44)	2.59*** (2.90)
Village Fixed Effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
District Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1859	1381	1381	1859	1381	1381	1859	1381	1381

Controls for age, age squared, gender, and class omitted from table. Standard errors clustered at village level.

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

## 5.1 Investing in Winners...

As shown in Table 9 below, which regresses the choice to send a child to a private school on a number of characteristics, parental perceptions of child intelligence are an extremely strong predictor of whether a parent will send their child to a private school. Most notably in this table, this pattern holds even *within individual households*. As shown in Column 2, which includes household fixed effects, many parents send the child they perceive to be more intelligent to private school and the child they perceive to be less intelligent to government schools.

Table 9: School Choice and Child Intelligence

	(1)	(2)
Mom Reports Child Above Average Intelligence	0.058** (2.82)	0.041* (1.99)
Mom Has Some Schooling	0.080 (1.51)	-0.032 (-0.27)
Mom Has Some Schooling	0.084** (3.23)	0.084 (0.71)
Log Month Expenditure	0.043 (1.78)	-0.038 (-1.05)
Age	-0.021*** (-3.76)	-0.017** (-3.26)
Age Squared	0.00025 (1.78)	0.00017 (1.64)
Female	0.029 (1.27)	-0.0012 (-0.04)
Constant	-0.24 (-1.13)	0.35 (1.85)
Village Fixed Effects	Yes	No
Household Fixed Effects	No	Yes
Observations	3426	3426

*t* statistics in parentheses

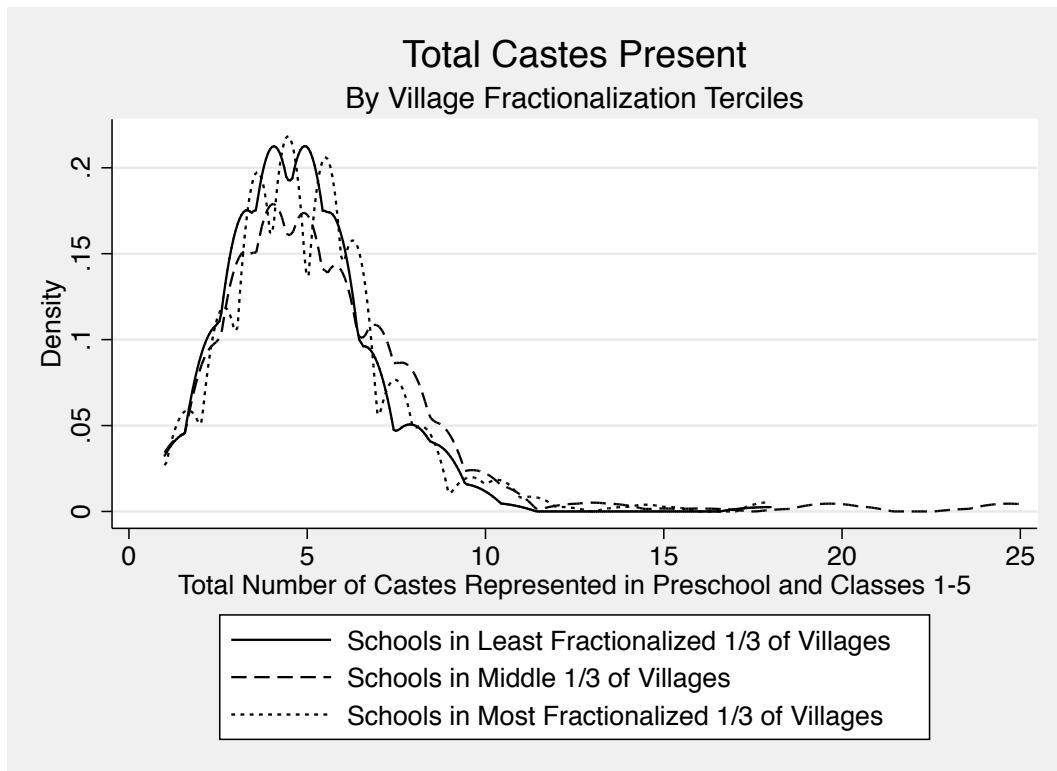
\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## 5.2 ...But Preserving Status

In more fractionalized villages, however, the social composition of schools becomes salient and this “sorting on intelligence” breaks down. Instead, children from “high status” *biraderis* begin to concentrate in private schools and children from “low status” *biraderis* become concentrated in government schools.

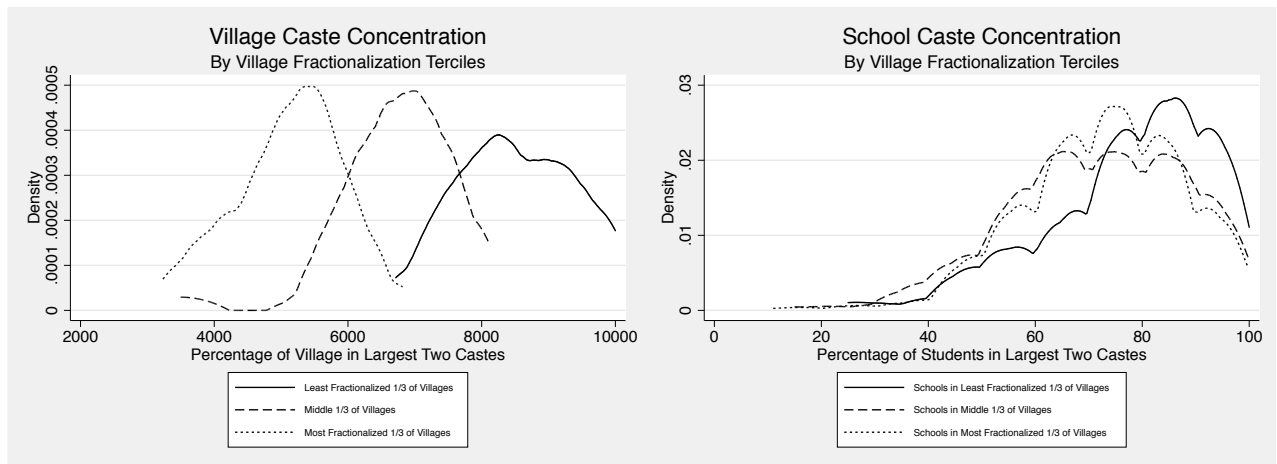
This segregation of schools can be seen in a number of ways. Figure 4 below plots the number of biraderis represented in each school for high, medium, and low fractionalized villages. As the figure shows, despite large differences in the fractionalization of the villages in which these schools operate, a remarkably similar numbers biraderis a present among their student bodies.

Figure 4:



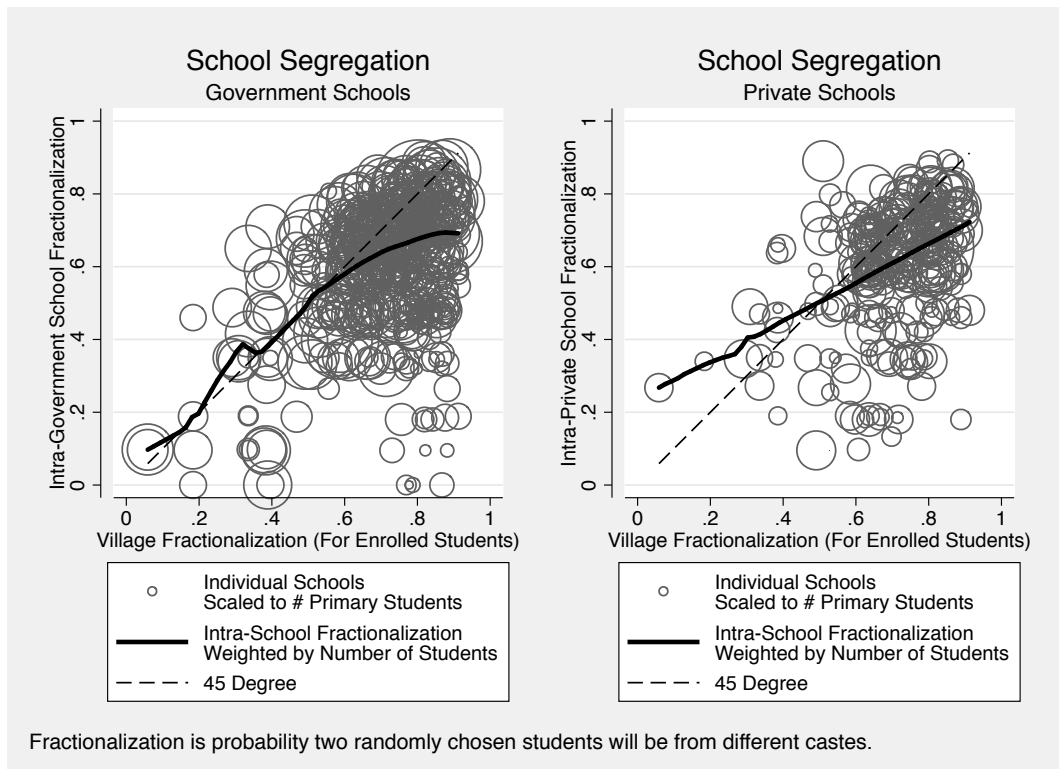
This figure is easily interpreted, but does not take into account the relative size of the population of each *biraderi* within the student body. Figure 5 plots the population share of the two largest biraderis among students in the village at large and in each school level respectively. Again, this figure shows that while in more fractionalized villages the share of students from the top two castes in the average school is indeed slightly lower, it does not come close to keeping pace with changes in village demographics.

Figure 5: Village and School Fractionalization



And finally, if schools were unsegregated, then we would expect herfindahl indices computed within each school to track closely with herfindahl indices computed at the village level. Yet as shown in Figure 6, this is far from the case. Almost all schools are below the 45 degree line that would indicate school and village diversity moving one for one, and many are well below.

Figure 6:



This data shows a clear pattern of segregation, but it does not provide an entirely clear

picture of which groups are attending which schools. Grouping *biraderis* into “high” and “low” social status groupings allows for a better understanding of segregation patterns. The crudeness of these categorizations is unfortunate, but necessary – although *biraderis* are associated with strict hierarchies within villages, there does not exist an explicit global hierarchy of *biraderis* in Pakistan as in India. As a result, these hierarchies may vary somewhat from village to village, and as noted previously, this variation may not perfectly follow economic position. Fortunately, interviews with numerous Pakistanis has provided evidence that these categorizations are sufficient consistent at this level of generality and in the region of the LEAPS survey for these rankings to be useful.<sup>4</sup>

As shown in Table 10, these categorizations make it possible to show that in villages with higher caste fractionalization, a larger share of private school students come from higher status *biraderis* and a larger share of government school students come from low *biraderis*.

Also consistent with this story is the fact that the price of private schools increases dramatically with *biraderi* fractionalization, despite the fact private schools appear to be delivering worse educational outcomes. As shown in Table 11 below, moving from a perfectly non-fractionalized village to a perfectly fractionalized village is associated with a 600 Rupees increase in annual school fees. Given that the average annual fee for all private schools in the LEAPS survey is 1191 Rupees, this is a very significant amount.<sup>5</sup>

Further, as shown in Table 12, none of these changes are driven by a change in the share of students in private schools. The percentage of students in private schools in almost perfectly stable, even when controlling for numerous village characteristics.

### 5.3 Limitations of Sorting Evidence

Some of the results predicted by the sorting story do not appear in the data, however. For example, this story suggests that the importance of perceived intelligence in school choice should decline with village fractionalization. Table 13 below employs the same specification used in Table 9 to show that parents are more likely to send children they perceive as intelligent to private school, but with the addition of an interaction term on

---

<sup>4</sup>Some interviewees have also provided threefold divisions, which generate consistent results with those presented here. If this work is extended, I would like to replace these rankings with more precise categories on the basis of systematic interviews, but that was not possible at this time. A further robustness check would be to replicate a methodology used by Jacoby and Mansuri (2011), where castes are ranked on the basis of their land holding. I elected to not use this methodology at this time as numerous Pakistanis cautioned me that social standing and land holding are not equivalent in many cases.

<sup>5</sup>Fees above the 95th percentile – 1900 Rupees – were adjusted down to 1900 Rupees. Without this adjustment, the coefficient on village fractionalization is approximately 950 Rupees with a t-stat of 2.09



Table 10: Student Social Status by School Type

	(1) Pct of Students High Status	(2) Pct of Students High Status
Private School	-0.11** (-2.30)	-0.13** (-2.13)
Biraderi Fractionalization	-0.047* (-1.85)	-0.19*** (-14.78)
Fractionalization * Private	0.18** (2.34)	0.21** (2.15)
Median Village Expenditure	0.0000014 (0.87)	
Village: Pct Adults Literate	0.00022 (1.22)	
Log Village Size	0.00074 (0.16)	
Village: Pct High Status	1.01*** (62.12)	
Constant	-0.0039 (-0.10)	1.00*** (83.16)
District Fixed Effects	Yes	No
Village Fixed Effects	No	Yes
Observations	782	782

*t* statistics in parentheses

\* p<sub>i</sub>0.10, \*\* p<sub>i</sub>0.05, \*\*\* p<sub>i</sub>0.01

Table 11: Annual Private School Fees

	(1) Weighted by School	(2) Weighted by School	(3) Weighted by Primary Students
Biraderi	504.7**	527.9**	608.6**
Fractionalization	(2.33)	(2.50)	(2.37)
Village: Median		61.6	20.8
Expenditures		(1.25)	(0.44)
Expenditure Gini		-49.9 (-0.24)	45.5 (0.20)
District Fixed Effects	Yes	Yes	Yes
Observations	287	287	285

*t* statistics in parentheses

\* p<sub>i</sub>0.10, \*\* p<sub>i</sub>0.05, \*\*\* p<sub>i</sub>0.01

Table 12: Share of Enrolled Students in Private Schools

	(1) Pct Class 3 in Private	(2) Pct Class 3 in Private
Biraderi Fractionalization	0.056 (0.63)	0.063 (0.70)
Median Village Expenditure		0.000029** (1.99)
Village Land Gini		0.033 (0.21)
Village: Pct Adults Literate		0.0019 (1.27)
Log Village Size		0.019 (0.71)
District Fixed Effects	Yes	Yes
Observations	112	112

*t* statistics in parentheses

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

child intelligence. As shown in the table, there is no evidence of a change in the coefficient on perceived intelligence with village fractionalization for either high or low status families.

Interpreting this result is made somewhat difficult by the structure of the LEAPS data. Ideally, these regressions would be run for the full 30,000 children surveyed, but household data is only available for 4,212 of these children (who come from, at most, 16 households per village). As such, there is reason to believe that this “non-result” may reflect the limited quality of the data rather than the accuracy of the sorting story. Nevertheless, the lack of a finding in this setting must be considered when weighing the strength of the evidence here.

## 5.4 The Sorting Paradox

One question that strikes any reader of this literature is why, if private schools do not provide a better education than government schools, do parents continue to pay for private educations?

There are a number of possible explanations for this. The first is that there is some evidence for neighborhood effects in education, whereby a student’s success is shaped by the attitudes and aspirations of his or her classmates (Goddard, 2003; Pong, 1998; Roscigno, 2000; Jencks and Mayer, 1990). Given that fact, private schools may in fact deliver a su-

Table 13: School Choice and Child Intelligence

	All		High Status		Low Status	
	(1)	(2)	(3)	(4)	(5)	(6)
Mom: Child Above Avg Intelligence	0.056	0.063	0.15	0.085	0.075	0.28
	(0.66)	(1.01)	(1.53)	(1.22)	(0.41)	(1.25)
Biraderi Fractionalization	-0.022	0.19	0.90***	0.18		0.45**
	(-0.55)	(1.00)	(22.83)	(0.76)		(2.64)
Child Above Avg * Fractionalization	0.0029	-0.031	-0.14	-0.067	-0.067	-0.35
	(0.02)	(-0.35)	(-0.96)	(-0.64)	(-0.26)	(-1.19)
Mom Has Some Schooling	0.081	-0.033	0.088	-0.013	0.12	-0.100
	(1.51)	(-0.28)	(1.40)	(-0.08)	(1.05)	(-1.08)
Mom Has Some Schooling	0.084***	0.083	0.094***	0.023	-0.094	0.22***
	(3.23)	(0.71)	(2.78)	(0.13)	(-1.09)	(2.80)
Log Month Expenditure	0.043*	-0.010	0.036	0.39***	0.11	-0.058**
	(1.79)	(-1.19)	(1.25)	(15.17)	(1.48)	(-2.18)
Age	-0.021***	-0.017***	-0.022***	-0.019***	-0.097	-0.058
	(-3.76)	(-3.26)	(-4.68)	(-3.20)	(-1.11)	(-0.53)
Age Squared	0.00025*	0.00017	0.00025*	0.00022**	0.0035	0.0023
	(1.78)	(1.62)	(1.93)	(2.01)	(0.77)	(0.40)
Female	0.029	-0.0013	-0.017	-0.010	0.14*	0.090
	(1.27)	(-0.05)	(-0.77)	(-0.41)	(1.81)	(0.92)
Constant	-0.23	0.087	-0.38	-3.12***	-0.40	0.40
	(-1.13)	(0.94)	(-1.62)	(-13.72)	(-0.50)	(0.69)
Village Fixed Effects	Yes	No	Yes	No	Yes	No
Household Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	3426	3426	2212	2212	440	440

*t* statistics in parentheses

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01

perior education *simply because they collect the most talented students*. This would make the decision of parents to send their children to private schools entirely rational, but the reason these schools are better has nothing to do with the school itself.

This possibility is particularly worrisome because of its implications for the students left in government schools. In the absence of “neighborhood” effects, the existence of private schools that are no better or worse than government schools has little social impact. If private schools are siphoning off talented students, however, and this has negative second-order effects on the students left behind, then the growth of private schools may be socially deleterious.

Basu (2009) offers a similar explanation:

Suppose that one important consideration in choosing a school is to form associations and networks that can help later in life. I am suggesting the kind of consideration that often prompts students in American campuses to join fraternities and sororities. [...] What the children or their parents will be paying for is partly the quality of education, but more importantly, for the quality of associates that students are likely to find in this school.

Either way, these considerations would rationalize the desire of parents to send their children to private schools even if private schools themselves are not directly delivering a superior education.

## **6 Discussion and Policy Implications**

The results presented here do not show conclusively that private schools are no better than government schools. Even in the most heterogeneous villages, private schools still outperform government schools (just by dramatically less than in homogenous villages). But these results do suggest at least two major reasons for caution on the part of policy-makers thinking about the implications of private school growth, and whether recent calls for the widespread distribution of private school vouchers (e.g. Chakrabarti and Peterson (2008), Kelkar (2006), and Panagariya (2008)) are good policy.

First, this analysis shows that even with a lagged-value-added specification, parental education and wealth controls, and panel data, it is still easy to vastly over-estimate the contributions of private schools to learning using observational data. As such, this study illustrates the need for researchers and policy-makers to maintain a healthy degree of skepticism when reading observational studies that claim to separate sorting from school qual-

ity.

Second, while this analysis only shows that 50% of the private school premium can be explained by sorting, it is important to remember that this represents a lower-bound. The difference between homogenous and heterogenous villages is not “sorting on intelligence” and “no sorting on intelligence,” but rather “sorting on intelligence” and “*less* sorting on intelligence.” As such, sorting is still likely contributing to the private school premium in heterogenous villages. Indeed, as shown in Table 13, perceived intelligence remains an important determinant of school choice even in highly fractionalized villages.

In light of persistent poor performance among government schools, the hope that private schools will reform the South Asian education sector is understandable, and may yet prove to be well founded. But as shown here the superiority of private school is not self-evident, and the government would do well to gather more evidence before embracing private schools as a substitute for public education.

## References

- Alderman, H., Kim, J., and Orazem, P. F. (2003). Design, Evaluation, and Sustainability of Private Schools for the Poor: The Pakistan Urban and Rural Fellowship School Experiments. *Economics of Education Review*, 22(3):265–74.
- Alderman, H., Orazem, P. F., and Paterno, E. M. (2001). School Quality, School Cost, and the Public/Private School Choices of Low-Income Households in Pakistan. *The Journal of Human Resources*, 36(2):304–326.
- Andrabi, T., Das, J., Ijaz Khwaja, A., and Zajonc, T. (2011). Do Value-Added Estimates Add Value? Accounting for Learning Dynamics. *American Economic Journal: Applied Economics*, 3(3):29–54.
- Andrabi, T., Das, J., Khwaja, A., Vishwanath, T., and Zajonc, T. (2007). *Pakistan: Learnings and Educational Achievements in Punjab Schools*. The World Bank.
- Angrist, J., Bettinger, E., Bloom, E., King, E., and Kremer, M. (2002). Vouchers for Private Schooling in Colombia: Evidence from a Randomized Natural Experiment. *The American Economic Review*, 92(5):1535–1558.
- Banerjee, A. (2009). Published Comments and Discussion for "The Rise of Private Schooling in India". *India Policy Forum*, 5:45–51.
- Banerjee, A. V., Cole, S., Duflo, E., and Linden, L. (2007). Remedying Education: Evidence from Two Randomized Experiments in India. *The Quarterly Journal of Economics*, 122(3):1235–1264.
- Basu, K. (2009). Published Comments and Discussion for "The Rise of Private Schooling in India". *India Policy Forum*, 5:39–45.
- Bellei, C. (2008). The Private-Public School Controversy: The Case of Chile. In Chakrabarti, R. and Peterson, P. E., editors, *School Choice International: Exploring Public-Private Partnerships*, page 272. The MIT Press, Cambridge, Massachusetts.
- Chakrabarti, R. and Peterson, P. E. (2008). *School Choice International: Exploring Public-Private Partnerships*. MIT Press, Cambridge, Massachusetts.
- Chaudhury, N., Hammer, J., Kremer, M., Muralidharan, K., and Rogers, F. H. (2006). Missing in Action: Teacher and Health Worker Absence in Developing Countries. *The Journal of Economic Perspectives*, 20(1):91–116.

- Chay, K. Y., McEwan, P. J., and Urquiola, M. (2005). The Central Role of Noise in Evaluating Interventions That Use Test Scores to Rank Schools. *The American Economic Review*, 95(4):1237–1258.
- Currie, J. and Thomas, D. (1995). Does Head Start Make a Difference? *The American Economic Review*, 85(3):341–364.
- Desai, S., Dubey, A., Vanneman, R., and Banerji, R. (2009). Private schooling in india: A new educational landscape. *India Policy Forum*.
- Fuller, B., editor (2002). *Inside Charter Schools: The Paradox of Radical Decentralization*. Harvard University Press.
- Gazdar, H. and Mohmand, S. K. (2007). Social Structure in Rural Pakistan.
- Glewwe, P., Ilias, N., and Kremer, M. (2010). Teacher Incentives. *American Economic Journal: Applied Economics*, 2(3):205–227.
- Goddard, R. D. (2003). Relational Networks, Social Trust, and Norms: A Social Capital Perspective on Students’ Chances of Academic Success. *Educational evaluation and policy analysis*, 25(1):59–74.
- Gordon, R., Kane, T. J., and Staiger, D. O. (2006). Identifying Effective Teachers Using Performance on the Job. The Hamilton Project Policy Brief No. 2006-01. *Brookings Institution*.
- Hanushek, E. A. (1997). Assessing the effects of school resources on student performance: An update. *Educational evaluation and policy analysis*, 19(2):141–164.
- Hanushek, E. A. (2003). The Failure of Input-based Schooling Policies. *The Economic Journal*, 113(485):F64–F98.
- Jacoby, H. and Mansuri, G. (2011). Crossing boundaries: gender, caste and schooling in rural Pakistan. *World Bank Policy Research Working Paper No. 5710*.
- Jencks, C. and Mayer, S. (1990). The Social Consequences of Growing Up in a Poor Neighborhood. In Lynn, L. E. J. and McGahey, M., editors, *Inner-City Poverty in the United States*, pages 111–186. National Academies Press, Washington, DC.
- Jimenez, E. and Lockheed, M. E. (1995). Public and Private Secondary Education in Developing Countries: A Comparative Study. *World Bank Discussion Papers*.

- Jimenez, E., Lockheed, M. E., and Paqueo, V. (1991). The Relative Efficiency of Private and Public Schools in Developing Countries. *The World Bank Research Observer*, 6(2):205–218.
- Kane, T. J. and Staiger, D. O. (2002). The Promise and Pitfalls of Using Imprecise School Accountability Measures. *The Journal of Economic Perspectives*, 16(4):91–114.
- Kelkar, V. (2006). Let Every Parent be a Consumer. *India Today*.
- McCaffrey, D. F., Lockwood, J. R., Koretz, D., and Hamilton, L. (2003). *Evaluating value-added models for teacher accountability*. Rand Corp.
- Muralidharan, K. and Kremer, M. (2008). Public and Private Schools in Rural India. In Chakrabarti, R. and Peterson, P. E., editors, *School Choice International: Exploring Public-Private Partnerships*. MIT Press.
- Panagariya, A. (2008). *India: The Mergeing Giant*. Oxford University Press, New York.
- Pong, S.-I. (1998). The School Compositional Effect of Single Parenthood on 10th-Grade Achievement. *Sociology of Education*, 71(1):23–42.
- Pratham (2005). *Annual Status of Education Report*. Pratham Documentation Center, New Delhi.
- Roscigno, V. J. (2000). Family/School Inequality and African-American/Hispanic Achievement. *Social Problems*, 47(2):266–290.
- Rothstein, J. (2010). Teacher Quality in Educational Production: Tracking, Decay, and Student Achievement. *The Quarterly Journal of Economics*, 125(1):175–214.
- Tooley, J. and Dixon, P. (2003). *Private schools for the poor: A case study from India*. Centre for British Teachers, Reading, UK.