Understanding Rural Private School Performance

Nick Eubank

November 7, 2012

Context

1. **Massive growth in rural private enrollment.**
   - Andrabi, Jishnu Das, and Khwaja, 2008; Pratham, 2005

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But *why* are private schools better?

Explanation 1: Teaching Quality

Possibility 1: Better Inputs

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Possibility 2: Better Induced Effort

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  - Chaudhury et al., 2006; Muralidharan and Kremer, 2008

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Possibility 2: Better Induced Effort

- Pay for performance, fire bad teachers.
- Clearly improvement over public schools.
  - Chaudhury et al., 2006; Muralidharan and Kremer, 2008
- Importance shown in US research.
  - Banerjee et al., 2007; Hanushek, 1997; Hanushek, 2003

Explanation 2: Sorting

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  - Selective admission

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If true, then private school superiority is illusory.

- Vouchers could result in massive mis-allocation of resources.

This Paper

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   - In fractionalized villages, school choice is based on caste politics.

Tells us that *at least* half of private school premium comes from selective sorting, not better teaching.

Outline

Methodology

Fractionalization and Performance

Teaching Quality

Selective Sorting

Summary

Data

Learning and Educational Attainment in Punjab Schools (LEAPS)

- 2003-2007 panel data with data from teachers, students, households, and owners.
- One four year panel (12,110 children)
- One two year panel (11,852 children)
- Includes: Child Test Scores, Teacher Test Scores, Parental Educational, HH Wealth
- Test scores are normalized using IRT – mean 0, standard deviation 1.
- 112 Villages in Three Districts


Kabul
ANISTAN
Islamabad
Rawalpindi
Gujranwala
Lahore
Faisalabad
Ludhiana
PAKISTAN
Meerut
Delhi
Agra
Jaipur
Kanpur
Hyderabad
Karachi
INDIA
Bhopal
Ahmadabad

Measuring Learning

Lagged-Value-Added Model:

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

Measuring Learning

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

- Flexible persistence parameter
- All past scores included to control of measurement error.

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- Flexible persistence parameter
- All past scores included to control of measurement error.
- Controls for differences in initial levels, but not differences in rates.

Measuring Learning

Village Level:

1. Run Lagged-Value Added regressions with village-school type dummies for each village j.

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

2. Extract dummies and calculate village public-private gap.
3. Analyze at level of village.

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

Measuring Learning

Teacher Level:

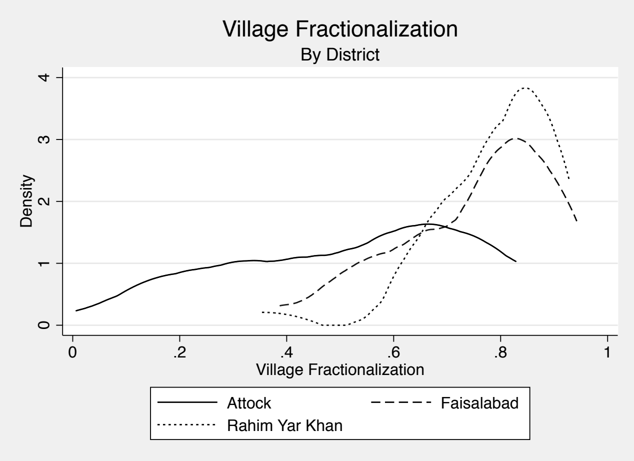
1. Run Lagged-Value Added regressions with teacher fixed effects dummies for each teacher k.

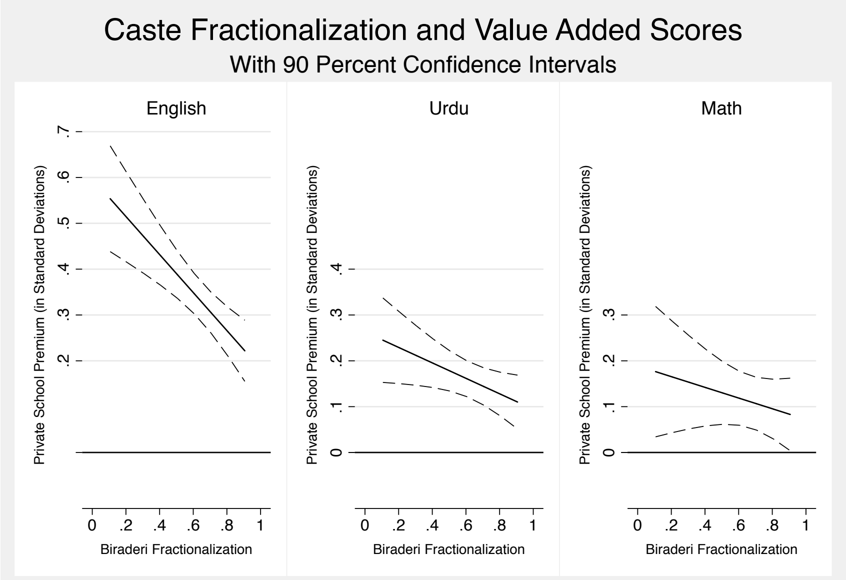
$$Y_{i,t} = X_{i,t}\alpha + Y_{i,t-1}\beta + \mathbb{I}_{i,k,t}\zeta_k + \epsilon_{i,t}$$

2. Extract fixed effect coefficients as estimates of teacher contributions
3. Analyze at level of teacher (weighted by number of students).

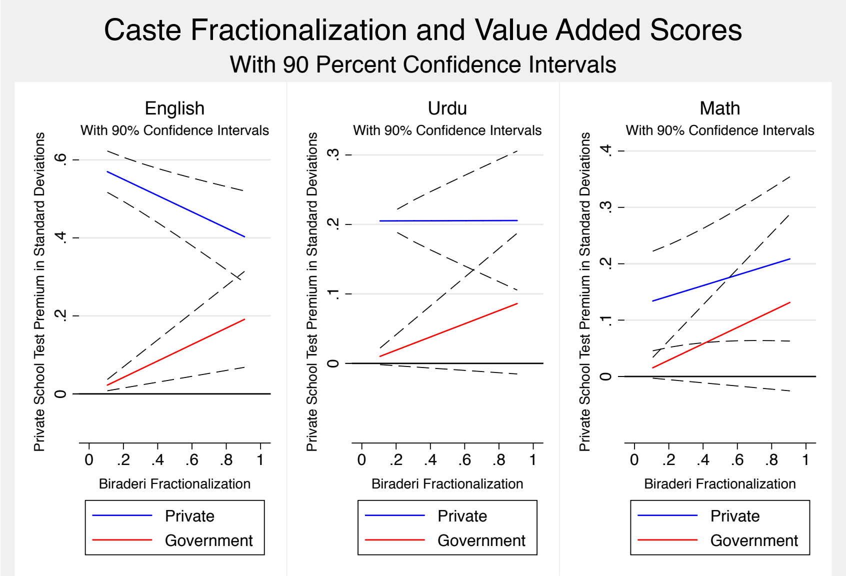
Outline

Caste in Punjab





Controls include village fixed effects, gender, age, age squared, child wealth and parental education



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Outline

No Difference in Inputs

Table 4: Private Teacher Characteristics and Village Fractionalization

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

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Table 5: Government Teacher Characteristics and Village Fractionalization

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

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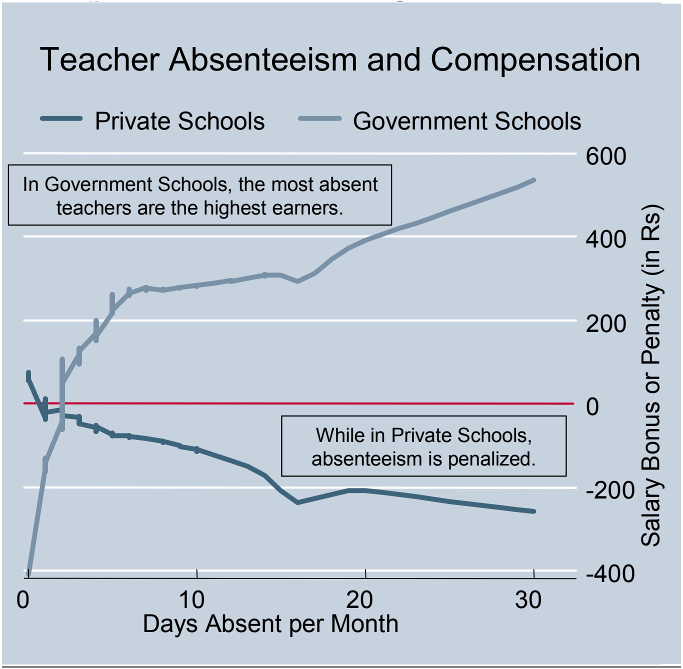
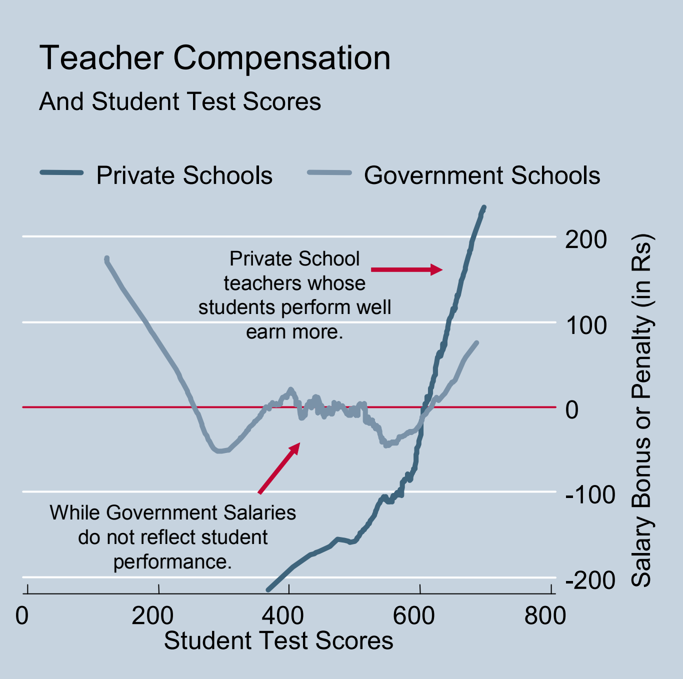

Teacher Absenteeism and Compensation
Private Schools
Government Schools
In Government Schools, the most absent teachers are the highest earners.
While in Private Schools, absenteeism is penalized.
600
400
200
0
-200
-400
Salary Bonus or Penalty (in Rs)
0
10
20
30
Days Absent per Month



Teacher Compensation
And Student Test Scores
Private Schools
Government Schools
Private School teachers whose students perform well earn more.
While Government Salaries do not reflect student performance.
200
100
0
-100
-200
Salary Bonus or Penalty (in Rs)
0
200
400
600
800
Student Test Scores

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**	-0.0068	0.0017	0.0041***
	(2.00)	(-0.85)	(0.40)	(2.79)
Biraderi Fractionalization	0.24	0.21	-0.085	-0.050
	(1.18)	(0.78)	(-1.47)	(-0.74)
Days Absent * Fractionalization	-0.063**		0.0050	
	(-2.05)		(0.77)	
Gender	-0.32***	-0.27**	-0.012	0.0095
	(-3.78)	(-2.17)	(-0.72)	(0.54)
Age of teacher	0.0053	0.023**	0.021***	0.018***
	(1.21)	(2.54)	(12.18)	(14.48)
Average Value Added Score		0.22		-0.033
		(0.48)		(-0.48)
Value-Added * Fractionalization		-0.47		-0.020
		(-0.67)		(-0.22)
Constant	7.07***	8.02***	7.51***	7.60***
	(29.09)	(20.15)	(47.83)	(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
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Outline

A Sorting Story

Homogenous Villages: Children sort on academic potential.

Fractionalized Villages: Children also sort by social status.

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Homogenous Villages: Children sort on academic potential.

Fractionalized Villages: Children also sort by social status.

1. Parents pick winners

Sorting

Table 7: Child Test Scores and Fractionalization

	English		Urdu		Math	
	(1)	(2)	(3)	(4)	(5)	(6)
Private School	0.31***	0.29***	0.14***	0.14***	0.11***	0.087**
	(10.98)	(10.42)	(5.74)	(5.65)	(3.17)	(2.58)
Biraderi Fractionalization	0.13*	0.096	0.085	0.069	0.13	0.13
	(1.70)	(1.33)	(1.26)	(1.08)	(1.34)	(1.46)

Sorting

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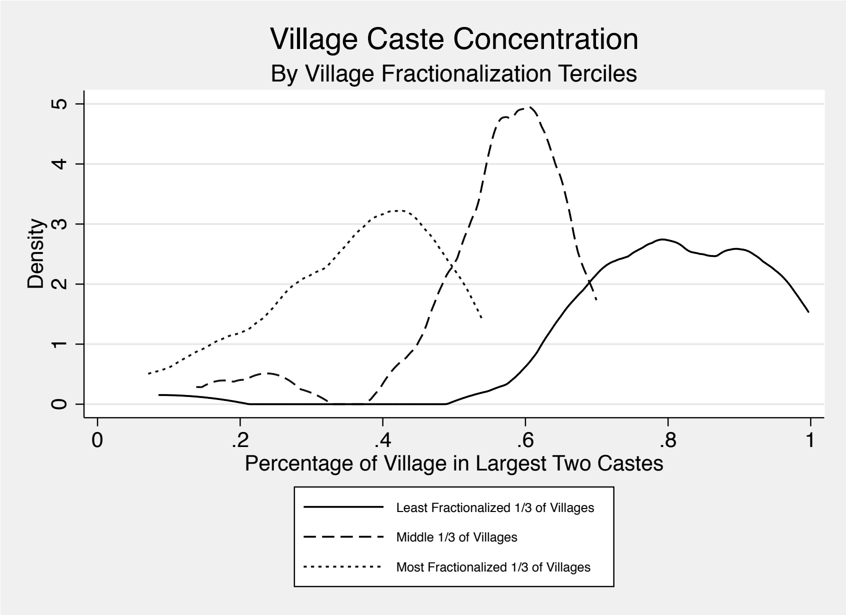
	(1.70)	(1.33)	(1.26)	(1.08)	(1.34)	(1.46)

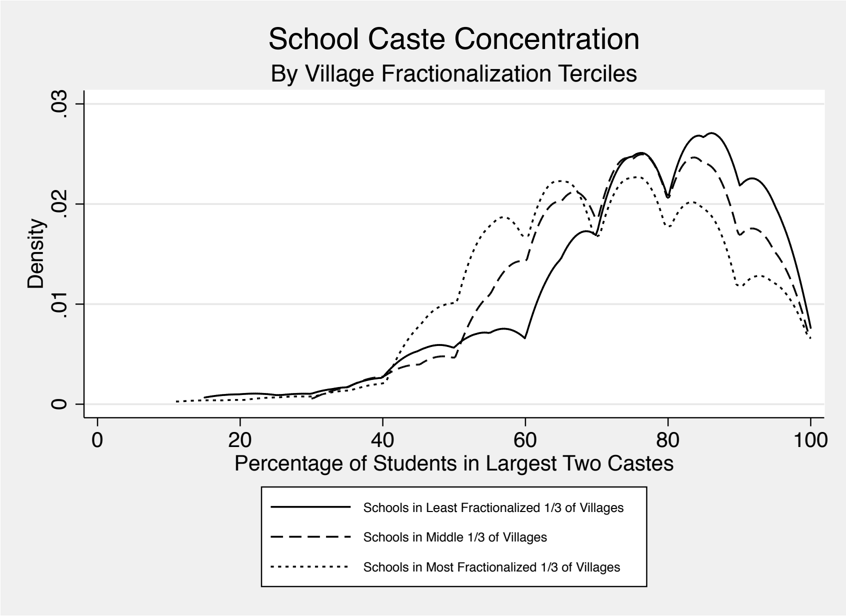
Table 9: School Choice and Child Intelligence

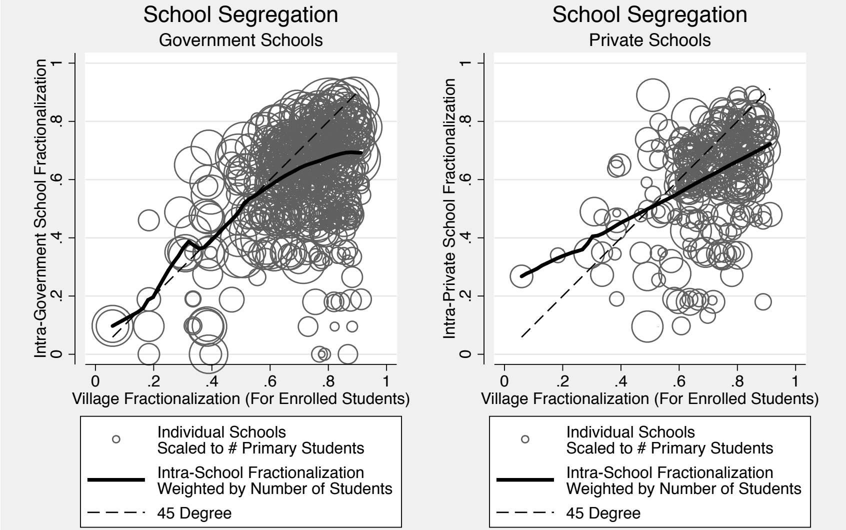
	(1)	(2)
Mom Reports Child Above Average Intelligence	0.058**	0.041*
	(2.82)	(1.99)
Mom Has Some Schooling	0.080	-0.032
	(1.51)	(-0.27)
Mom Has Some Schooling	0.084**	0.084
	(3.23)	(0.71)
Log Month Expenditure	0.043	-0.038
	(1.78)	(-1.05)
Age	-0.021***	-0.017**
	(-3.76)	(-3.26)
Age Squared	0.00025	0.00017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

t statistics in parentheses

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


Village Caste Concentration
By Village Fractionalization Terciles
Density
0
1
2
3
4
5
0
.2
.4
.6
.8
1
Percentage of Village in Largest Two Castes
Least Fractionalized 1/3 of Villages
Middle 1/3 of Villages
Most Fractionalized 1/3 of Villages


School Caste Concentration
By Village Fractionalization Terciles
Density
0
.01
.02
.03
0
20
40
60
80
100
Percentage of Students in Largest Two Castes
Schools in Least Fractionalized 1/3 of Villages
Schools in Middle 1/3 of Villages
Schools in Most Fractionalized 1/3 of Villages



Fractionalization is probability two randomly chosen students will be from different castes.

	(1) Pct of Students High Status	(2) Pct of Students High Status
Private School	-0.11**	-0.13**
	(-2.30)	(-2.13)
Biraderi Fractionalization	-0.047*	-0.19***
	(-1.85)	(-14.78)
Fractionalization * Private	0.18**	0.21**
	(2.34)	(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	1.00***
	(-0.10)	(83.16)
District Fixed Effects	Yes	No
Village Fixed Effects	No	Yes
Observations	782	782

t statistics in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

	(1) Pct of Students High Status	(2) Pct of Students High Status
Private School	-0.11**	-0.13**
	(-2.30)	(-2.13)
Biraderi Fractionalization	-0.047*	-0.19***
	(-1.85)	(-14.78)
Fractionalization * Private	0.18**	0.21**
	(2.34)	(2.15)
Median Village Expenditure	0.0000014	
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Fractionalization and Prices

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

t statistics in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

Inconsistencies

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)

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Sorting Paradox

Why pay more for the same education?

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Neighborhood Effects: Students performance is affected by peers

Sorting Paradox

Why pay more for the same education?

Neighborhood Effects: Students performance is affected by peers

Networking: About forming positive associations.

- In homogenous villages, most important association is intelligence.
- In fractionalized villages, caste matters too.

Outline

Conclusion

Take-aways:

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Things I would like from you:

- Alternative explanations for convergence?
- Alternative tests for this explanation?