The Misallocation of Pay and Productivity in the Public Sector: Evidence From the Labor Market for Teachers

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Motivation

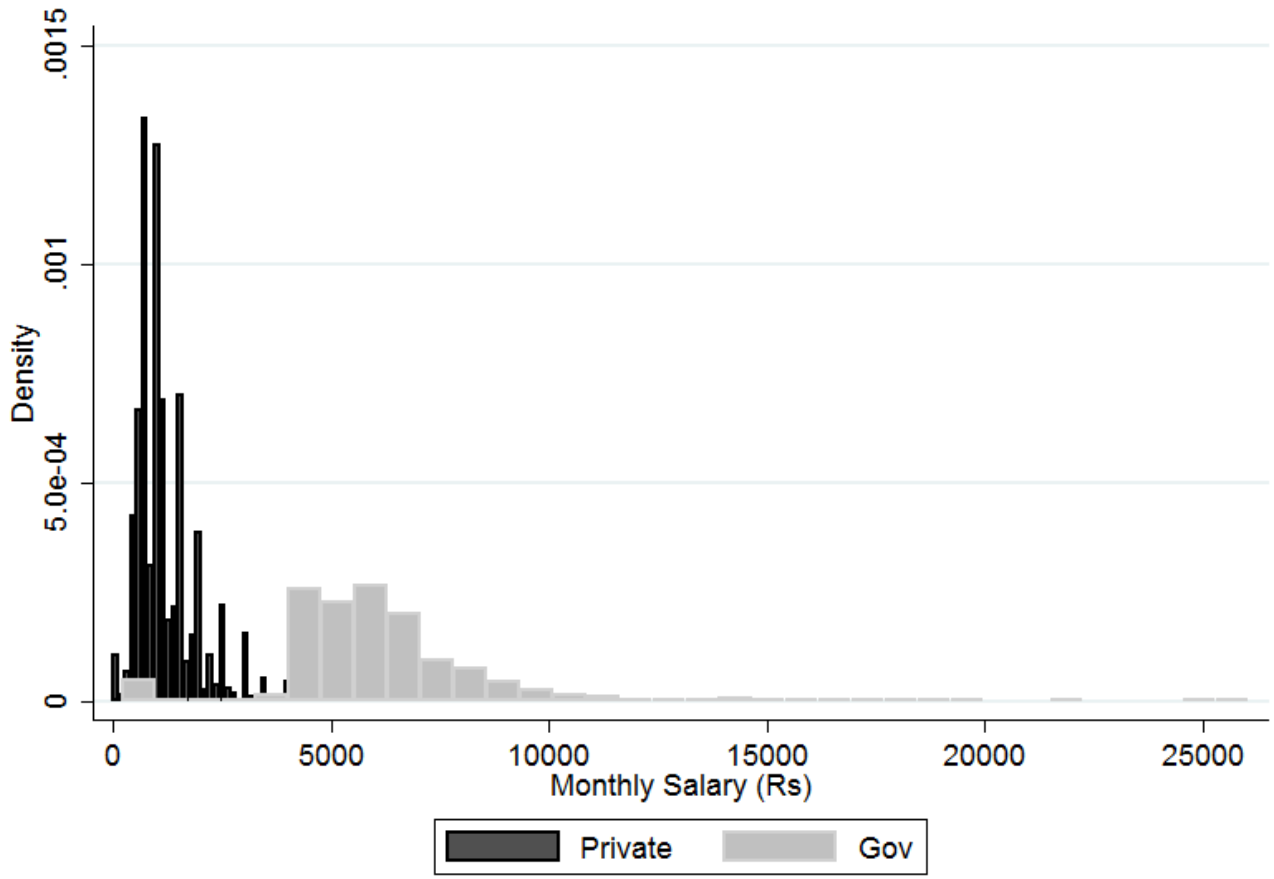
- Important and contentious policy question: how to recruit and retain high quality teachers.
  - Typical solution: higher salaries.
  - But others argue that that public school teachers are overpaid (Biggs and Richwine, 2011).
- Particularly important for low-income countries: teacher salaries account for 80 percent of educational expenditures.
- In light of this debate, we need to know:
  - What teacher characteristics are associated with teacher effectiveness and whether teachers are rewarded for them.
  - Would average teacher quality fall if baseline salaries declined?

LEAPS Data

Two key surveys in 112 villages of Punjab Province, Pakistan, each conducted every year from 2003-2007:

- Geo-coded survey of the universe of schools.
  - 574 sex-segregated public schools and 1,533 public school teachers in 112 villages.
  - Data on school and teacher characteristics.
- Surveys of children in the schools, including low-stakes test scores in math, Urdu, and English.
  - 22,857 children in public schools.

Teacher Salaries in 2004



TVA Estimation

Estimate:

$$y_{ijt} = \beta_0 + \sum_a \beta_a y_{ij,t-1} I(grade = a) + \gamma_j + \alpha_t + \mu_g + \epsilon_{ijt}.$$

- i denotes a student, j denotes a teacher, and t denotes a school.
- y_{ijt} is student i's test score in year t.
- γ_j is the teacher fixed effect or the teacher value-added.
- α_t is the round fixed effect.
- μ_g is the grade fixed effect.

Key assumption: $\epsilon_{i,t} \perp \gamma_j$.

TVA Robustness

- **Omitted variable bias test # 1**: Including controls for class-size, peer quality, and socioeconomic characteristics has little effect on the estimates.
- **Omitted variable bias test # 2**: The TVA of school-changers' future teachers does not predict current TVA.
- **Specification test**: TVAs are highly predictive of school-changers' test score gains.

How Important is Teacher Quality?

- The variance of the TVAs also tells us about the importance of teacher quality in low income countries.
- With a sampling error correction, a 1 SD better teacher will increase mean student test scores by 0.16 sd.

▸ Sampling Error Calculation

- Higher end of still substantial variance in teacher quality in the U.S. (Rothstein, 2004; Chetty et al., 2014).

Association Between Teacher Characteristics and TVA

	(1) Mean TVA	(2) Mean TVA	(3) Mean TVA	(4) Mean TVA	(5) Mean TVA
Female	0.070***	-0.036	0.080***	0.207	
	(0.026)	(0.134)	(0.026)	(0.225)	
Local	0.025	0.008	0.024	-0.004	
	(0.025)	(0.031)	(0.028)	(0.049)	
Some Teacher Training	-0.023	-0.101	-0.093	-0.213*	
	(0.055)	(0.072)	(0.075)	(0.126)	
Has BA or Better	0.054**	0.043	0.012	0.010	
	(0.025)	(0.031)	(0.033)	(0.059)	
Had $>$ 3 *Years of Exp in* 2007	0.060	0.076	0.037	0.163*	
	(0.038)	(0.052)	(0.047)	(0.097)	
Temporary Contract	-0.003	0.049	-0.020	0.051	
	(0.036)	(0.048)	(0.043)	(0.083)	
Mean English Test Score			0.032**	0.015	
			(0.015)	(0.022)	
Mean Urdu Test Score			0.034	0.013	
			(0.023)	(0.037)	
Mean Math Test Score			0.023	-0.013	
			(0.022)	(0.034)	
Have 0 *or* 1 *Years Exp.*					-0.305**
					(0.135)
Lagged Mean Score					0.717***
					(0.013)
Fixed Effects	District	School	District	School	Teacher
Number of Observations	1,383	1,383	919	919	27,089
Adjusted R Squared	0.224	0.450	0.228	0.415	0.721
Clusters	471	471	469	469	583
F	2.031	1.194	2.533	0.602	

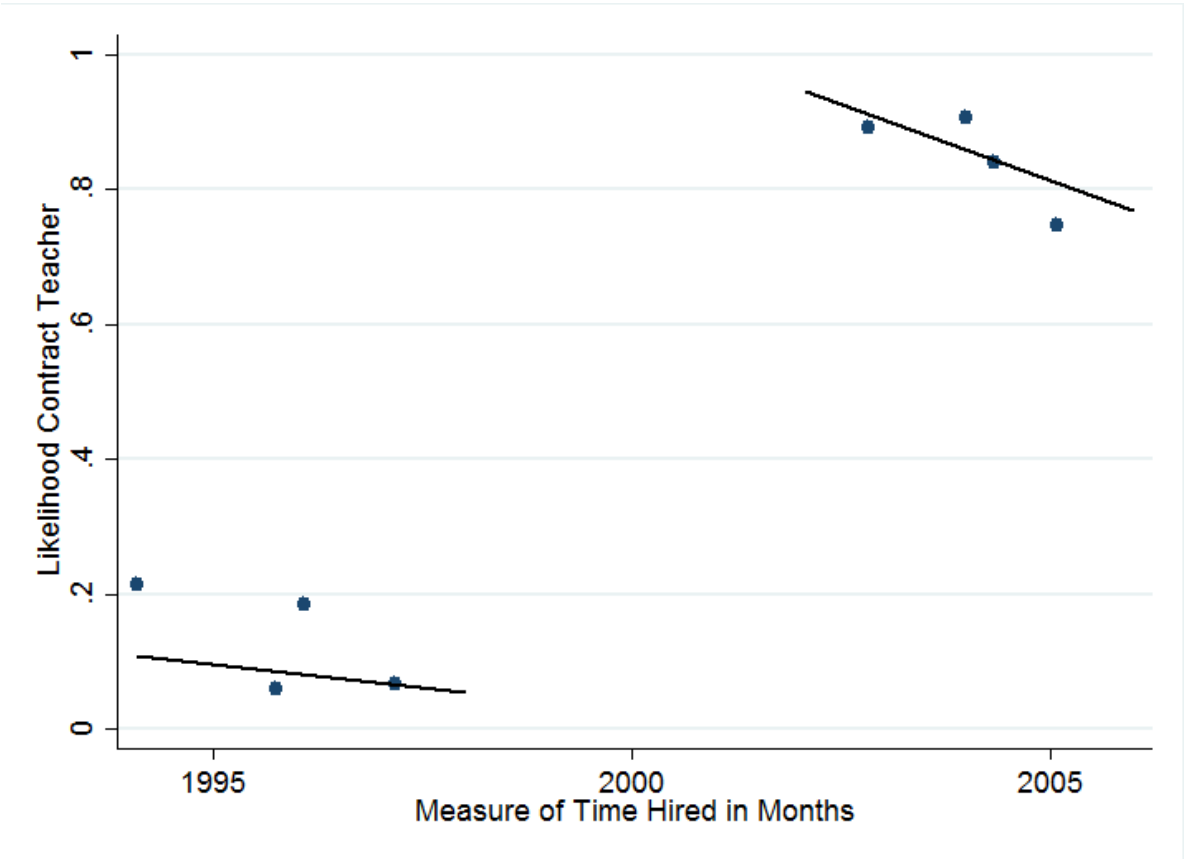
Effect of TVA on Teacher Salaries

	(1) Log Salary Public	(2) Log Salary Public	(3) Log Salary Public	(4) Log Salary Public	(5) Log Salary Private
Mean TVA		-0.007	-0.028	-0.044	0.111**
		(0.014)	(0.025)	(0.036)	(0.046)
Female	-0.036***	-0.035***	0.154**	0.054	-0.413***
	(0.013)	(0.013)	(0.070)	(0.094)	(0.043)
Local	-0.052***	-0.051***	-0.049	-0.019	-0.178***
	(0.019)	(0.019)	(0.032)	(0.043)	(0.029)
Some Teacher Training	0.518***	0.518***	0.392***	0.837***	0.165***
	(0.141)	(0.141)	(0.140)	(0.316)	(0.045)
Has BA or Better	0.255***	0.255***	0.263***	0.211***	0.334***
	(0.019)	(0.019)	(0.028)	(0.042)	(0.045)
Had $>$ 3 *Years of Exp in* 2007	0.063	0.064	0.120*	0.122	0.020
	(0.042)	(0.042)	(0.064)	(0.101)	(0.029)
Temporary Contract	-0.354***	-0.355***	-0.327***	-0.308***	
	(0.032)	(0.032)	(0.059)	(0.092)	
Age	0.058***	0.058***	0.063***	0.039	0.016**
	(0.015)	(0.015)	(0.020)	(0.029)	(0.007)
Age^2	-0.000***	-0.000***	-0.001**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean English Score				0.016	
				(0.017)	
Mean Urdu Score				-0.006	
				(0.029)	
Mean Math Score				0.020	
				(0.025)	
Fixed Effects	District	District	School	School	District
Adjusted R Squared	0.616	0.615	0.662	0.707	0.459
Number of observations	1,383	1,383	1,383	919	807
F	108.304	96.471	35.025	12.496	38.522
Clusters	471	471	471	469	294

How Elastic is the Teacher Labor Supply?

- Our TVA results suggest that there is little link between teacher salaries and teacher quality.
- Raises an important policy question: How would lowering teacher salaries affect the quality of teachers?
- A regime change following Pakistan's unexpected nuclear tests in 1998 allows us to look at the joint effect of a salary decrease combined with greater accountability.

Effect of the Regime Change on Teacher Contracts



Estimation Strategy

- First stage:

$$TemporaryContract_j = \delta_0 + \delta_1 Post_j + \delta_2 month\_hired_j + \delta_3 month\_hired_j \times Post_j + \alpha_d + \mu_j,$$

where $Post_j$ is an indicator variable equal to 1 if a teacher is hired after 1998 and 0 otherwise and α_d is a district fixed effect.

- Second stage:

$$TVA_j = \beta_0 + \beta_1 TemporaryContract_j + \beta_2 month\_hired_j + \beta_3 month\_hired_j \times Post_j + \alpha_d + \epsilon_j.$$

Effect on TVA

	(1) Mean TVA	(2) SE	(3) N	(4) Within School Mean TVA	(5) SE	(6) N
OLS (Full Sample)	-0.004*	0.042	1,337.000	0.024*	0.026	1,278
RD (Full Sample)	-0.004	0.052	1,337.000	0.056	0.041	1,278
RD (2 Year)	0.840	0.550	227.000	0.360	0.322	201
RD (3 Year)	0.219	0.241	376.000	0.254**	0.123	336
RD (4 Year)	0.350	0.234	393.000	0.193*	0.097	350

Effects of Contract Status on Sorting

- **Individuals to teaching**: No discontinuous change in teacher characteristics.
- **Teachers to schools**: Contract teachers assigned to smaller schools with fewer teachers and less facilities.
- **Students to teachers**: Some evidence that contract teachers' students' have less educated fathers.

Is the Quality of Contract Teachers Declining Over Time?

Estimate:

$$y_{ijt} = \beta_0 + \beta_1 month\_hired_j + \beta_2 Post_j + \beta_3 Post_j * month\_hired_j + \sum_g \beta_g y_{i,t-1} I(grade = g) + \alpha_t + \epsilon_{ijt}.$$

- Sample: teacher-year observations where contract teachers have 0 or 1 years of experience and all permanent teachers.
- Include permanent teachers to identify round fixed effects in case student test scores are increasing over time.
- Coefficient of interest: β_3 captures the effect of being hired later after the policy change.

Is the Quality of Contract Teachers Declining Over Time?

	(1) Mean Test Scores
Month Hired	0.002**
	(0.001)
Month Hired $\times$ *I*(*Year Hired* $>$ 2001)	-0.007
	(0.024)
I(*Year Hired* $>$ 2001)	Y
Round FE	Y
District FE	Y
Grade by Lagged Test Score Interactions	Y
Number of Observations	21,788
Adjusted R Squared	0.660
Clusters	450

No evidence that contract teacher quality is decreasing over time.

Conclusion

- Teacher quality is important in low-income countries.
- As in the United States, besides experience, most observable teacher characteristics do not predict quality.
- Teacher salaries are not related to teacher quality.
- A regime change shows that the teacher supply is highly inelastic at current wages.
- Students of teachers hired on 35 percent lower salaries perform as well or better than students of permanent teachers.

LEAPS Testing Structure

	(1) Number of Teachers	(2) Number of Students	(3) Teachers in Schools With >1 Teacher With Tested Students	(4) Students in Schools With >1 Teachers With Tested Students
Round 1	487	8,341	7	171
Round 2	592	9,309	219	3,350
Round 3	1,007	16,904	879	15,249
Round 4	1,085	15,239	875	13,110

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Public School Students Used in TVA Estimation

	Rounds Student-Years		
Grade	2	3	4
1	1	1	0
2	3	1	5
3	347	34	364
4	6,676	1,135	6,449
5	6	6,373	865
6	0	5	4,653
7	0	0	8

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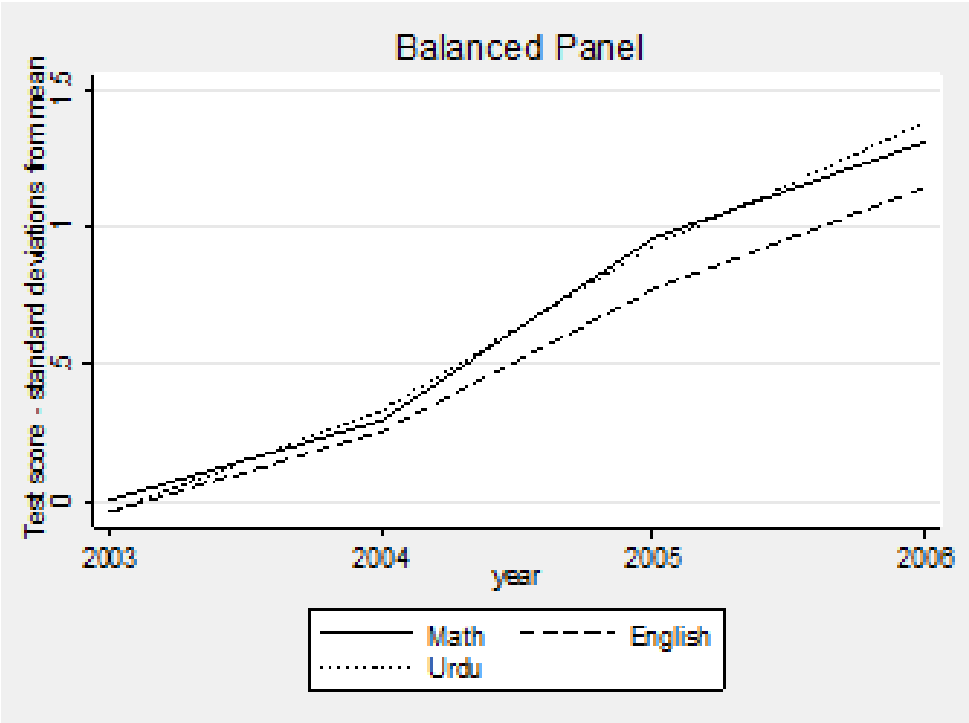
Learning Over Time



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What Does a Test Score Mean?

	Year 1 Prop correct	Year 2 Prop correct	Year 3 Prop correct	Year 4 Prop correct
Total kids	6,038	6,038	6,038	6,038
English				
Eng 12: Match picture with word, Banana	0.631	0.75	0.834	0.873
Eng 18: Fill missing letter for picture, Cat	0.68	0.743	0.817	0.853
Eng 19: Fill missing letter for picture, Flag	0.287	0.299	0.478	0.554
Eng 30: Fill missing word in sentence	0.276	0.332	0.441	0.535
Eng 43: Construct sentence with word 'deep'	0.01	0.014	0.037	0.108
Eng 44: Construct sentence with word 'play'	0.024	0.027	0.113	0.218
	0.318	0.361	0.453	0.524
Math				
Math 1: Count number of moons, write number	0.622	0.687	0.797	0.749
Math 9: Add 3 + 4	0.903	0.91	0.951	0.94
Math 12: Multiply 4 x 5	0.603	0.641	0.759	0.811
Math 24: Add 36 + 61	0.855	0.878	0.922	0.93
Math 25: Add 678 + 923	0.561	0.595	0.712	0.745
Math 27: Subtract 98 - 55	0.698	0.756	0.826	0.856
Math 30: Multiply 32 x 4	0.522	0.569	0.703	0.756
Math 32: Divide 384 / 6	0.193	0.245	0.456	0.541
Math 34: Cost of necklace, simple algebra	0.092	0.148	0.257	0.278
Math 39: Convert 7/3 into mixed fractions	0.014	0.046	0.07	0.145
	0.5063	0.5475	0.6453	0.6751
Urdu				
Urdu 3: Match picture with word, Book	0.739	0.822	0.916	0.946
Urdu 4: Match picture with word, Banana	0.736	0.824	0.906	0.945
Urdu 5: Match picture with word, House	0.538	0.601	0.679	0.755
Urdu 10: Combine letters into word	0.737	0.792	0.861	0.897
Urdu 12: Combine letters into word	0.372	0.45	0.537	0.627
Urdu 19: Antonyms, Chouta	0.44	0.502	0.688	0.792
Urdu 20: Antonyms, Khushk	0.368	0.493	0.623	0.693
Urdu 36: Complete passage for grammar	0.293	0.391	0.563	0.678

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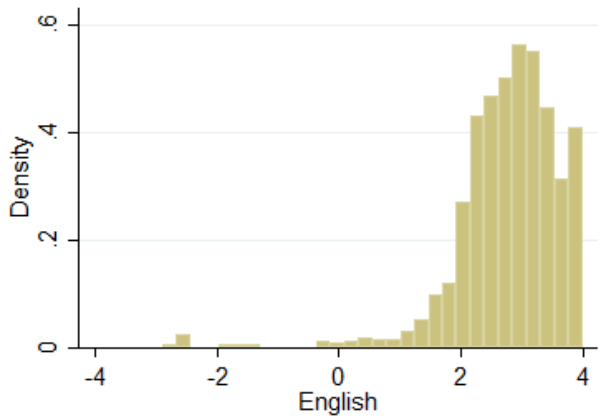
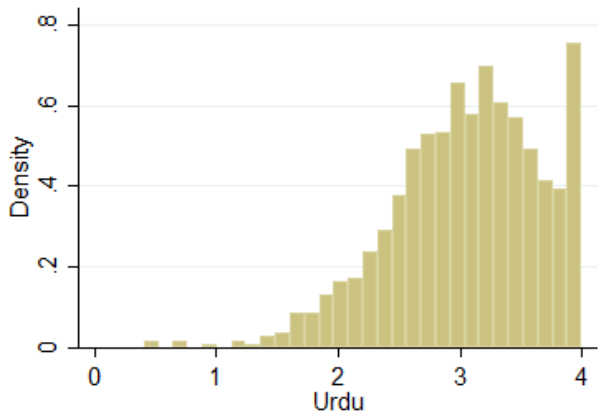
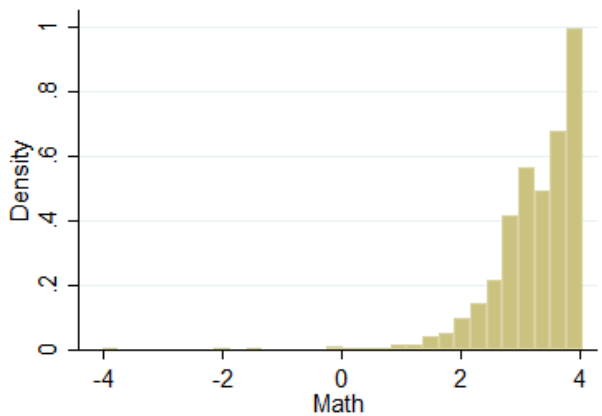
Teacher Knowledge







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Alternative Methods I: Empirical Bayes (Chetty et al., 2004; Kane and Staiger, 2008)

- Multiply noisy estimate of TVA (such as TVA generated by our method) by an estimate of its reliability.
- Estimate reliability as ratio of signal (TVA) variance to signal plus noise (student and year variance).
- Within classroom variance gives student variance.
- Covariance between average residual in teacher's class in t and $t-1$ gives teacher variance.
- Variance of classroom component is the remainder of the residual's variance.

Alternative Methods I: Empirical Bayes (Chetty et al., 2004; Kane and Staiger, 2008)

Problems:

- Estimating teacher variance this way requires that a teacher's quality is time-invariant.
- To satisfy this assumption, authors include experience fixed effects.
- We cannot control for experience without subsuming the contract effect.
- Instead, teacher fixed effects capture mean teacher quality over the surveyed period, including mean experience effects.

Alternative Methods II: Child Fixed Effects (Rockoff, 2004)

- Method:
  - Include child fixed effects in the TVA estimating equation to further control for selection.
- Problem:
  - Relies on children switching teachers.
  - In Pakistan, teachers teach multiple grades, so this reduces the effective sample by 54 percent.
  - Mis-entered teacher ids may dominant the new sample, biasing estimates.

Alternative Methods II: Child Fixed Effects (Rockoff, 2004)

For example, assume:

- Students are identical and TVA is randomly distributed.
- A student has a probability $p = 0.1$ of changing teachers each year.
- An ID has a probability $e = 0.01$ of being incorrectly entered.

Then, there are three cases where a change appears to take place:

- Id was incorrectly entered and no change occurs: probability $= 0.01 \times 0.9 = 0.009$
- Id is correctly entered and a change happens: probability $= 0.99 \times 0.1 = .099$
- Id is incorrectly entered and a change occured: probability $= 0.1 \times 0.01 = 0.001$

So, the probability a teacher id is mis-attributed in the effective sample is $\frac{0.01}{(0.009+0.099+0.001)} = 0.09$

Alternative Methods II: Child Fixed Effects (Rockoff, 2004)

More generally, assume:

- Students are identical and TVA is randomly distributed.
- A student has a probability p of changing teachers each year.
- An ID has a probability e of being incorrectly entered.

Then,

$$E(\widehat{TVA_j}) = \frac{p}{e(1-p)+p(1-e)+ep} TVA_j + \frac{e}{e(1-p)+p(1-e)+ep} \overline{TVA_j}.$$

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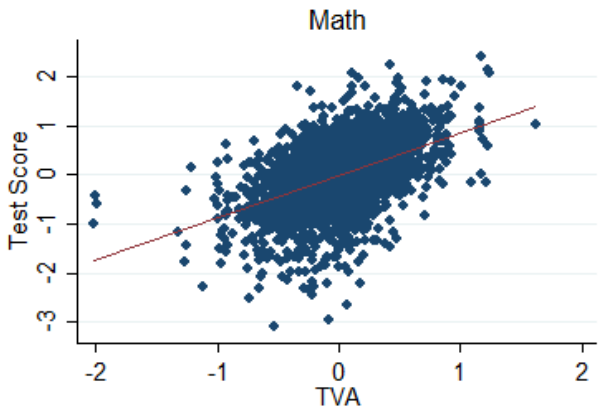
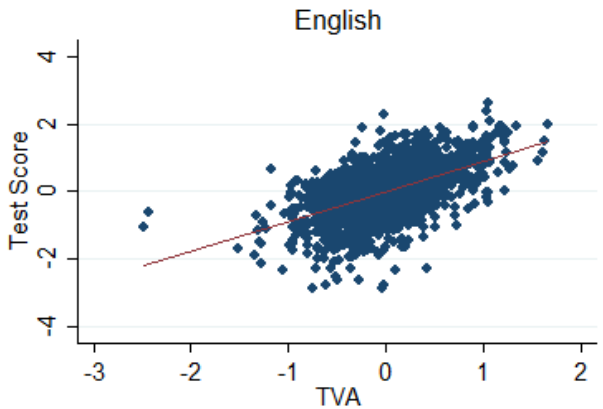
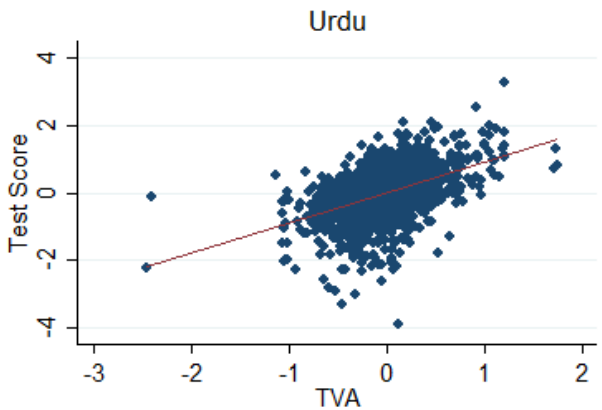
Graphical Results







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Sampling Error

$$\phi = E(\widehat{\phi}) - \frac{1}{M}\sum_{js}\left(\frac{\sigma^2}{N_{js}}\left(1-\frac{1}{T_s}\right)+\frac{1}{T_s^2}\sum_{d=1}^{T_s}\frac{\sigma^2}{N_{ds}}\right).$$

- ϕ is the variance of the true TVAs.
- M is the number of teachers.
- N_{js} is the number of students of a teacher j in a school s.
- σ^2 is the variance of idiosyncratic shocks at the student-level.
- T_s is the number of teachers in a school s.

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