

# The Impact of Teacher Effectiveness on Student Learning in Africa

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# Teacher Quality

- ▶ Teacher quality is a key determinant of learning
- ▶ Two approaches:
  1. **Teacher Effectiveness Estimates (TVE)** and find that variations in TVE explain a substantial part of the variation in test scores (Chetty et al., 2014; Angrist et al., 2016; Azevedo & Krashinsky, 2018; Roth & Uno, 2017 and many others)
  2. **Program Efficacy Estimates (PEE)** involving teachers' adherence of the most effective (Glass & Murphy-Knauer, 2015; Krashinsky et al., 2017; Ganimian & Manning, 2014; McFadyen, 2014; Frang & Papan, 2014)
- ▶ This paper integrates these two approaches

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  2. **Program Evaluation:** Interventions involving teachers are some of the most effective. (Glewwe & Muralidharan, 2015; Kremer *et al.*, 2013; Ganimian & Murnane, 2014; McEvan, 2014; Evans & Popova, 2016)
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1. How effective are Ugandan teachers? Estimate TVA
  - Providing the first estimates of TVA in Africa
  - Both classroom and teacher effects
  - Student randomization to address sorting
2. What do good teachers do? Correlate teacher effectiveness with teacher characteristics and behaviour
3. What is the effect of teacher training? Measure the impact of a randomized intervention on TVA



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## Preview of Results

- ▶ A 1 SD increase in teacher effectiveness increases student learning by 0.14 - 0.19 standard deviations.
- ▶ Teacher effectiveness correlates with teacher behaviours such as observing performance, encouraging participation and lesson planning, but not characteristics.
- ▶ Teacher training and support increases the spread of the TVA distribution by making the good teachers better.



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- ▶ Four year longitudinal RCT (2013-2016). Random sample of children tested using EGRA and followed across years.
  - ▶ 2013 (38 schools): Grade 1.
  - ▶ 2014 (128 schools): Grade 1, Grade 2.
  - ▶ 2015 (128 schools): Grade 1, Grade 2, Grade 3.
  - ▶ 2016 (128 schools): Grade 1, Grade 2, Grade 3, Grade 4.
- ▶ We utilize two aspects of this program:
  1. In 2013 and 2016 randomized students to teachers (99% in 2013, 60% in 2016 with two classrooms).
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# Sample

**Table:** Samples Across Years and Grades

	Full Sample	Longitudinal Sample	Random Sample
<b>Panel A: All Schools</b>			
# Schools	128	125	128
# Teachers	714	275	501
# Children	30,094	18,342	14,920
Pupils/Teacher	28	32	29
<b>Panel B: Schools with more than one teacher</b>			
# Schools	127	98	127
# Teachers	688	248	496
# Children	27,111	12,939	14,379
Pupils/Teacher	27	30	28

## Classroom Effects

$$Y_{icgt} = \beta_0 + \beta_1 Y_{icgt-1} + \beta_2 X_{icgt} + \gamma_{cgt} + \zeta_g + \tau_t + \beta_3 Y_{ict-1} * \zeta_g + u_{icgt}$$

$Y_{icgt}$ : is end-of-year test scores

$Y_{icgt-1}$ : is beginning-of-year test scores

$\zeta_g$ : is a grade fixed effect

$\tau_t$ : is a year fixed effect

$\gamma_{cgt}$ : is classroom fixed effects and our coefficient of interest

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## Three Main Estimation Challenges

- ▶ **Separating classroom effects from school effects.**

We re-scale classroom effects to be relative to the school mean

- ▶ Getting a precise estimate of classroom effect.

We follow the approach suggested by Araujo (2016) and analytically adjust the estimated variance for measurement error.

- ▶ Sorting of students into classrooms.

We utilize the fact that we have random assignment of children to teachers in 2013 and 2016 to estimate effects and assess the degree of bias present.

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## Teacher Effects

Classroom effects are estimated for each teacher in each year. With multiple years of data it is possible to purge the year-to-year fluctuations and obtain teacher effects.

$$\hat{\gamma}_{cgst} = \hat{\alpha} + \hat{\delta}_{cgs} + \varphi_{cgst} \quad (1)$$

$\hat{\gamma}_{cgst}$ : is the demeaned classroom effects.

$\hat{\delta}_{cgs}$ : is a vector of teacher indicators.



## Teacher Effects

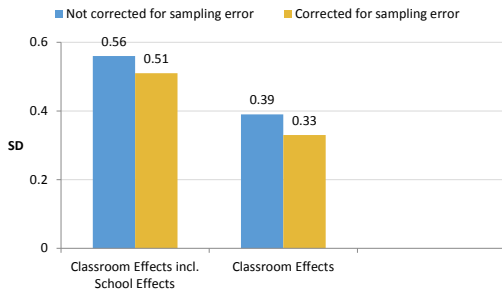
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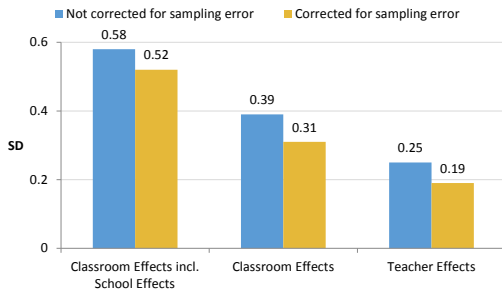
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## Results - Full Sample



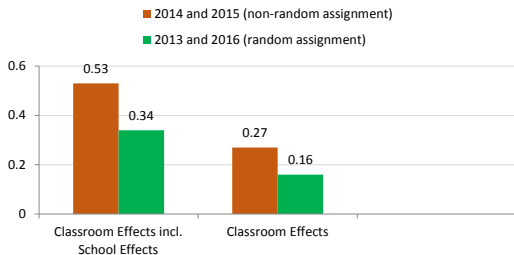
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## Results - Longitudinal Sample

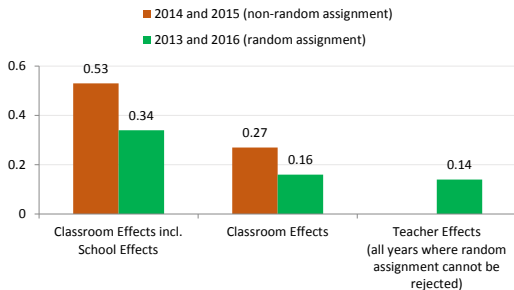


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## Results - Random Sample



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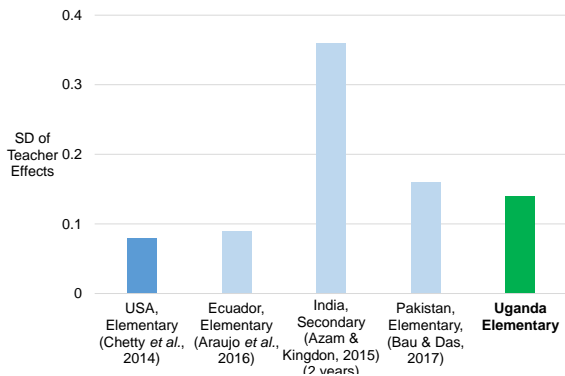
## What Do These Numbers Mean?

- ▶ Our most conservative estimates suggests that a 1 SD increase in teacher quality would increase student learning by 0.14 - 0.19 SDs
- ▶ Taking a *bad* teacher (10<sup>th</sup> percentile) to the level of a *good* teacher (90<sup>th</sup> percentile) would increase student learning by 0.35 SDs

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# Estimates of Teacher Effectiveness in Different Contexts





# Who are Good Teachers?

- ▶ Teacher characteristics
  - ▶ Surveys in 2013 and 2014

## Who are Good Teachers?

VARIABLES	TVA
Age	0.001 (0.002)
Years of schooling	0.002 (0.011)
Ravens score	0.012 (0.011)
Salary	0.198 (0.166)
Gender	-0.010 (0.030)
Observations	114
R-squared	0.029

# What do Good Teachers do?

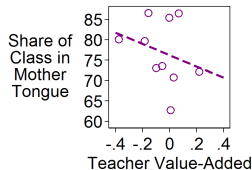
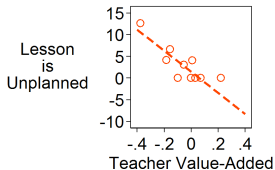
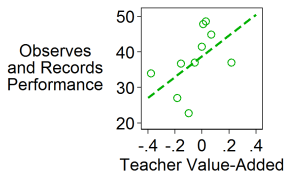
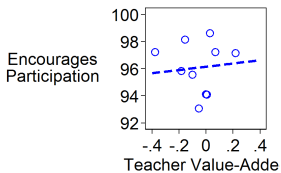
## ▶ Classroom Observations

- ▶ Available in 2013.
- ▶ Experienced observers visiting three times during the year.
- ▶ Observation windows were 10 minutes in a 30 minute lesson

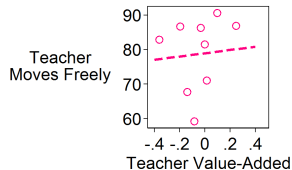
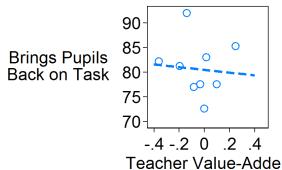
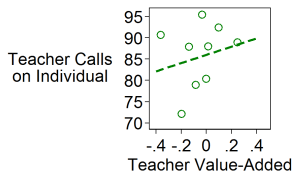
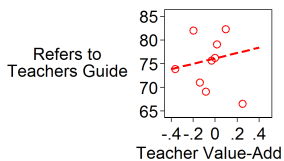
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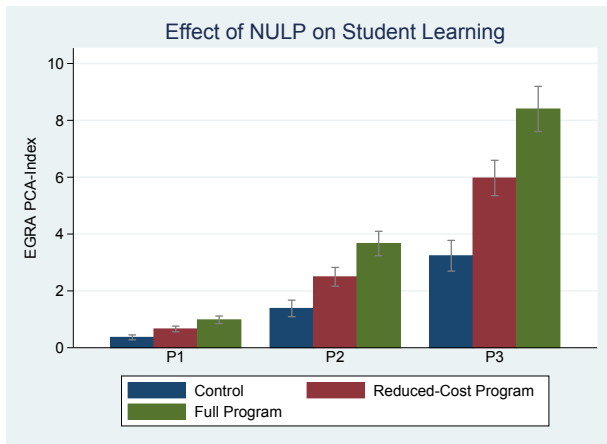
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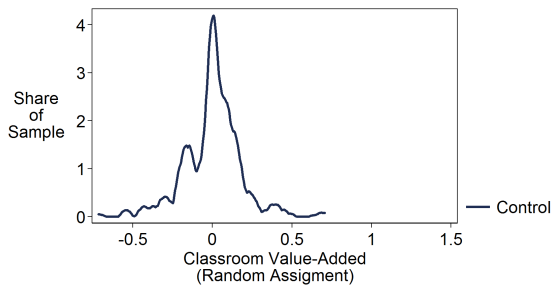
# What do Good Teachers do? cont'd



# Impact of the NULP on Student Learning

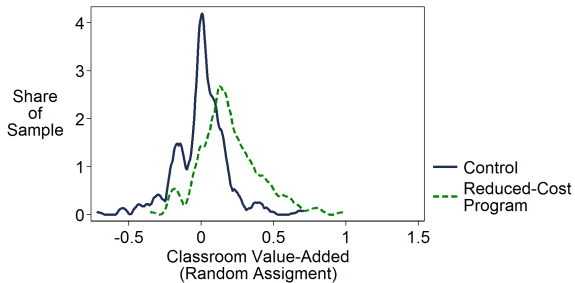


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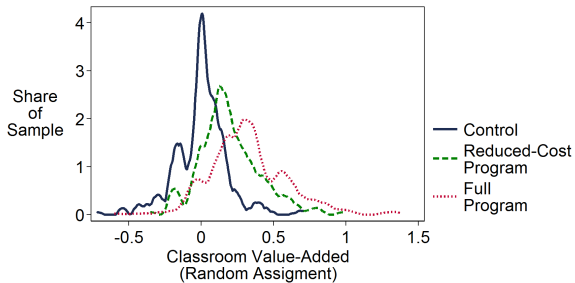




# Impact on Teacher Effectiveness



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# Take Aways

- ▶ We estimate teacher effectiveness in Africa.
  - ▶ Taking out school effects, estimation error and bias due to sorting still imply that a 1 SD increase in teacher effectiveness increase student learning by 0.14 to 0.19 SDs.
  - ▶ As previous literature we find that TVA correlates with teacher behaviour but not characteristics.
- ▶ Taking the literature further we shed light on what happens when we introduce a high impact teacher intervention.
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  - ▶ As previous literature we find that TVA correlates with teacher behaviour but not characteristics.
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  - ▶ Increases the spread of TVA, by making the good teachers relatively better than bad teachers.

## Future Directions

- ▶ Using video observations to figure out what the good teachers are doing?
- ▶ Who are the teachers that benefit the least/most from the program?