The Impact of Teacher Effectiveness on Student Learning in Africa

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University of Copenhagen

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Teacher Quality

- Teacher quality is a key determinant of learning
- Two approaches:
  1. Teacher Effectiveness: Estimate TVA and find that variation in TVA explain a substantial part of the variation in test scores. (Chetty et al., 2014; Araujo et al., 2016; Azam & Kingdon, 2015; Bau & Das, 2017 amongst others)
  2. Program Evaluation: Interventions involving teachers are some of the most effective. (Glewwe & Muralidharan, 2015; Kremer et al., 2013; Ganimian & Murnane, 2014; McEwan, 2014; Evans & Popova, 2016)
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   - 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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- 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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  - 2013 (38 schools): Grade 1.
  - 2014 (128 schools): Grade 1, Grade 2.
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  - 2016 (128 schools): Grade 1, Grade 2, Grade 3, Grade 4.

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Sample

Table: Samples Across Years and Grades

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Longitudinal Sample</th>
<th>Random Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: All Schools</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Schools</td>
<td>128</td>
<td>125</td>
<td>128</td>
</tr>
<tr>
<td># Teachers</td>
<td>714</td>
<td>275</td>
<td>501</td>
</tr>
<tr>
<td># Children</td>
<td>30,094</td>
<td>18,342</td>
<td>14,920</td>
</tr>
<tr>
<td>Pupils/Teacher</td>
<td>28</td>
<td>32</td>
<td>29</td>
</tr>
<tr>
<td><strong>Panel B: Schools with more than one teacher</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>127</td>
<td>98</td>
<td>127</td>
</tr>
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<td>248</td>
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</tr>
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\[ Y_{icgt} = \beta_0 + \beta_1 Y_{icgt-1} + \beta_2 X_{icgt} + \gamma_{cgt} + \zeta_g + \tau_t + \beta_3 Y_{ict-1} \ast \zeta_g + u_{icgt} \]

\( Y_{icgt} \): is end-of-year test scores
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- **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.

\[ \hat{\gamma}_{cgst} = \hat{\alpha} + \hat{\delta}_{cgs} + \varphi_{cgst} \]  

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Results - Full Sample

Motivation
Data
Methodology
Results
Concluding Remarks

Results - Full Sample

- Classroom Effects incl. School Effects
  - Not corrected for sampling error: 0.56
  - Corrected for sampling error: 0.51
- Classroom Effects
  - Not corrected for sampling error: 0.39
  - Corrected for sampling error: 0.33
Results - Longitudinal Sample

![Graph showing SD values for Classroom Effects incl. School Effects, Classroom Effects, and Teacher Effects, with and without sampling error correction.]

- Classroom Effects incl. School Effects: 0.58 (Not corrected), 0.52 (Corrected)
- Classroom Effects: 0.39 (Not corrected), 0.31 (Corrected)
- Teacher Effects: 0.25 (Not corrected), 0.19 (Corrected)
Results - Random Sample

- **Classroom Effects incl. School Effects**
  - 2014 and 2015 (non-random assignment): 0.53
  - 2013 and 2016 (random assignment): 0.34

- **Classroom Effects**
  - 2014 and 2015 (non-random assignment): 0.27
  - 2013 and 2016 (random assignment): 0.16
Results - Random Sample

<table>
<thead>
<tr>
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<tbody>
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<td>0.53</td>
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<td></td>
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<td>0.16</td>
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<tr>
<td>Teacher Effects</td>
<td>0.14</td>
<td></td>
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(all years where random assignment cannot be rejected)

Years:
- 2013 and 2016 (random assignment)
- 2014 and 2015 (non-random assignment)
What Do These Numbers Mean?

- Our most conservative estimates suggest that a 1 SD increase in teacher quality would increase student learning by 0.14 - 0.19 SDs.
- Taking a *bad* teacher (10\textsuperscript{th} percentile) to the level of a *good* teacher (90\textsuperscript{th} percentile) would increase student learning by 0.35 SDs.
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Estimates of Teacher Effectiveness in Different Contexts

- USA, Elementary (Chetty et al., 2014)
- Ecuador, Elementary (Araujo et al., 2016)
- India, Secondary (Azam & Kingdon, 2015) (12 years)
- Pakistan, Elementary (Bau & Das, 2017)
- Uganda, Elementary
Who are Good Teachers?

- Teacher characteristics
  - Surveys in 2013 and 2014
Who are Good Teachers?

<table>
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<th>TVA</th>
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<tbody>
<tr>
<td>Age</td>
<td>0.001</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>0.002</td>
</tr>
<tr>
<td>Ravens score</td>
<td>0.012</td>
</tr>
<tr>
<td>Salary</td>
<td>0.198</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.010</td>
</tr>
<tr>
<td>Observations</td>
<td>114</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.029</td>
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- Classroom Observations
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  - Experienced observers visiting three times during the year.
  - Observation windows were 10 minutes in a 30 minute lesson.
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What do Good Teachers do?

- **Encourages Participation**
  - Teacher Value-Added
  - Observed and Records Performance

- **Lesson is Unplanned**
  - Teacher Value-Added

- **Share of Class in Mother Tongue**
  - Teacher Value-Added
What do Good Teachers do? cont’d
Impact of the NULP on Student Learning

![Graph showing the effect of the NULP on student learning across different programs.](image)

The graph compares the EGRA PCA-Index for different programs:
- **P1**: Control Program
- **P2**: Reduced-Cost Program
- **P3**: Full Program

The results indicate a significant increase in the EGRA PCA-Index for the Full Program compared to the Control and Reduced-Cost Programs.
Impact on Teacher Effectiveness

![Graph showing impact on teacher effectiveness](image-url)
Impact on Teacher Effectiveness

![Graph showing the impact on teacher effectiveness](image)
Impact on Teacher Effectiveness

![Graph showing the impact on teacher effectiveness. The x-axis represents Classroom Value-Added (Random Assignment), and the y-axis represents Share of Sample. The graph compares the control group, reduced-cost program, and full program.]
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 increases 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.
  - Increases the spread of TVA, by making the good teachers relatively better than bad teachers.
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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?