Evaluating the Effect of the Primary Literacy Project on Literacy and Academic Achievement

Analysis Plan

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Note: *In late 2013 we submitted an analysis plan for the one-year pilot RCT that was conducted during the 2013 school year.[1] This document expands and revises that analysis plan to include our plans for the analysis of the full, four-year RCT, which now runs from 2013 to 2016. We are submitting it on January 16, 2015, prior to the entry of any outcome data for the 2014 school year.*

Our two main research questions are:

1) What is the educational benefit of receiving the full PLP program on pupils?
2) What is the educational benefit of receiving the partial PLP program on pupils?

To answer question 1, we will compare the differences in outcomes in the full Treatment group A and Control group C classrooms. To answer question 2, we compare differences in outcomes between Partial Treatment (Group B) classrooms to the Control (Group C) classrooms. This compares pupils in classrooms where only the teaching learning material is provided to pupils in schools with no PLP program. We will use additional data from teacher, parent, and pupil surveys to insure balanced randomization as well as to use control variables to help with the precision of our estimates. Figure 3, below, illustrates the three study arms and the comparisons between them.

In addition to these two main research questions, we are interested in heterogeneous treatment effects, as well as measuring spillover effects on to teachers, parents, siblings, and students in other grades. We are also interested in measuring the mechanisms through which there are learning effects with a second randomization of inputs (wall clocks and slates) and with classroom observations using video recording.

[1] That document remains available on the AEA trial registry site. The details for it are as follows:
"PLP Evaluation Analysis Plan 20131118.doc
MD5: 43fe4e6024912858a9ea06e2888108bd
SHA1: ce357b4bfb21c2055b42a71753b11258ce95122c
Uploaded At: November 20, 2013"

Outcome Variables

Our major outcome variables of interest are measures of academic achievement and performance, but we will also look at subsidiary outcomes such as attitudes toward school and time use.

<u>Major outcome measures include but are not limited to:</u>
Lango reading comprehension (EGRA) scores
Lango writing ability (EGWA) scores
Oral English comprehension scores
English reading comprehension (EGRA) scores
Classroom marks
Attendance
Classroom observations

<u>Subsidiary outcome measures include but are not limited to:</u>
Parent & teacher attitudes and investment toward education
Parent & teacher attitudes toward the PLP
Teacher time use
Teacher expectations for students
Pupil time use and effort
Parent perceptions of pupil performance
Parent expectations for students

Spillovers and Ancillary Benefits

In addition to measuring impacts on the pupils, teachers, and parents directly included in the PLP, we will also look at spillover measures in two ways: within schools and within households. To do this, we take advantage of the fact that in the Treatment A and Treatment B schools the PLP program was rolled out only in P1, so students in higher levels would benefit only through spillovers. Our specific plan is to conduct additional endline exams for two groups of students: 1) siblings of P1 pupils from schools in the experiment who are enrolled in higher grade levels; and 2) other pupils in higher grade levels from schools in the experiment. This will allow us to measure the general within-school spillovers of the PLP to higher-level students, as well as the spillovers specifically within the same household. Taking the difference gives us an estimate of the additional program spillovers that occur due to having a sibling in the program.

The exam data for the siblings will be supplemented with information from the endline parent surveys, which ask parents about the behavior and perceived performance of all children in the household, not just the pupils included in the main sample. This will give us an expanded set of outcome measures for those pupils, to look at a wider range of outcomes.

Statistical Methods

To conduct the analyses outlined above, we will employ a set of regressions comparing outcomes in the different study arms. Because the assignment of schools to study arms was random, this will allow us to measure the causal effect of the PLP (and also the half program). In our secondary specifications we will control for other baseline factors such as class size and teacher experience. While the random experiment guarantees that such factors will be evenly distributed across study arms on average, it is possible that the arms will differ on some measure simply through random chance. Our secondary specifications will therefore ensure that any potential imbalance is not driving our results. Our preferred specifications will use the entire sample possible, but attrition throughout the study is likely.

To enhance the precision of our estimates, all our regressions will control for the stratification cells (lottery groups) used in the randomization of schools to study arms, following Bruhn and McKenzie (2009).

Our analysis will utilize the data at several different levels. First, we will run student-level analyses, where each observation represents a single student. We will also run similar analyses at the household level, using survey data on the parents of our student sample.

Our preferred regression specification for the student- and parent-level analyses will be:

$$EndlineOutcome_{is}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

Here i indexes students (or households) and s indexes schools. $EndlineOutcome_{is}$ is the endline value of the outcome variable in question – an exam score or a survey question. $\boldsymbol{LotteryGroup_s}$ is a vector of dummy variables for the different lottery groups used in the randomization of schools to study arms. $MTSchool_s$ and $CCTSchool_s$ are indicators for a school being in the MT Program or CCT Program respectively, so estimates of β_1 and β_2 will represent the effect of being in either variant of the program.

In addition to the individual-level regressions described about, some of our analyses will be conducted at the classroom or teacher level instead – for example, our analyses of the data from the classroom observations. In this case we will estimate

$$EndlineOutcome_{cs}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{cs}$$

with c indexing teachers or classroom. We may also conduct school-level analyses, in which case the regression equation would be

$$EndlineOutcome_{s}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{s}$$

Alternative Specifications

As secondary analyses, we will also explore regressions that include exogenous controls captured at baseline, such as baseline values of the outcome variable, class size, and teacher experience. While the random experiment guarantees that such factors will be evenly distributed across study arms on average, it is possible that the arms will differ on some measure simply through random chance. Not all controls will be available for all outcomes: for example, none of the pupils could read English at baseline, so no baseline English exams were conducted. For variables where baseline data is available for some but not all of the sample, we will use imputation methods to fill in the missing baseline values. In particular, we will use imputing the simple mean as our preferred approach, but will explore multiple imputation approaches as well. For the individual-level analyses, these alternative regressions will take the form

$$EndlineOutcome_{is}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+\boldsymbol{\gamma LotteryGroup_s}+\boldsymbol{\eta Controls_{is}}+\varepsilon_{is}$$

where $\boldsymbol{Controls_{is}}$ is a set of exogenous controls; the regression equations for classroom/teacher and school-level analyses would be formed similarly. The main control we will rely on is baseline values of the outcome, following Chetty et al. (2014) who find that controlling baseline exam scores corrects almost all of the omitted variable bias in a non-randomized evaluation of the effects of teacher quality.

We may also look at change in the outcome variable from baseline to endline as left-hand-side variable in a regression. These regressions will take the form

$$ChangeInOutcome_{is}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+\boldsymbol{\gamma LotteryGroup_s}+\boldsymbol{\eta Controls_{is}}+\varepsilon_{is}$$

where $ChangeInOutcome_{is} = EndlineOutcome_{is} - BaselineOutcome_{is}$ and $\boldsymbol{Controls_{is}}$ includes other potential controls aside from baseline values of the outcome. As for the first set of alternative analyses, the above equation is for the individual-level analyses, and the classroom/teacher-level and school-level regression equations would be formed similarly.

Panel Regressions

Once we have data for the same student, or teacher/classroom, over multiple years, we also plan to exploit the panel nature of our data. This would involve running regressions of the following form:

$$EndlineOutcome_{ist}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+\boldsymbol{\gamma LotteryGroup_s}+\delta \boldsymbol{Year_t}+\varepsilon_{ist}$$

In this case t indexes the year of the observation and $\boldsymbol{Year_t}$ is a vector of dummy variables for the year of the observation.

Combined Outcome Indices

Many of our outcomes of interest come from exams with multiple components. We will analyze these exams in two ways. First, we will analyze each component separately. Second, we will construct combined outcome indices using principal components analysis. Specifically, we will begin by normalizing each component to the control group (subtracting the control mean and dividing by the control standard deviation). Then, using the control group data alone, we will find the factor loadings for the first principal component of the matrix of the data. We will then construct a weighted average of all the exam components, where the weights are the factor loadings described above. This follows Black and Smith (2006) in assuming there is a single underlying factor driving all the components for a given exam. As an alternative weighting scheme, we will follow Kling, Liebman, and Katz (2007) in taking the simple, unweighted average of the normalized exam components.

Slate and Wall Clock Analysis

In addition to measuring the effect of the two program variants on student performance we are also interested in disentangling the effects of the materials provided by the NULP from the other aspects of the program. To do this we plan to run the following regression:

$$EndlineOutcome_{is}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+ \beta_3 Clocks_s+ \beta_4 Slates_s+ \beta_5 ClocksAndSlates_s+\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

$Clocks_s$ is a dummy variable indicating that a school received wall clocks, $Slates_s$ is an indicator for receiving slates, and $ClocksAndSlates_s$ is an indicator for receiving both. The coefficients on these dummies estimate the effects of each type of materials. We are also interested in whether the effect of these materials varies between control and CCT program schools, so we will estimate:

$$EndlineOutcome_{is}=\beta_0+\beta_1 MTSchool_s+\beta_2 CCTSchool_s+ \beta_3 Clocks_s+ \beta_4 Slates_s+ \beta_5 ClocksAndSlates_s+ \beta_6 CCTSchool_s*Clocks_s+\beta_7 CCTSchool_s*Slates_s+\beta_8 *CCTSchool_s*ClocksAndSlates_s+\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

β_6, β_7, and β_8 estimate the extent to which the effects of each combination of materials differ between the CCT program schools and the control schools.

We may augment this specification by varying the controls used, or by using the change in the outcome as the outcome variable, or by running panel regressions instead, as described above.

Our primary approach will be to include the data for the MT Program schools in the analytic sample, and include an indicator for membership in the MT Program in our regression specification, as described above. We will also explore an alternate approach, which is to drop the MT program schools from the sample and omit the $\beta_1 MTSchool_s$ term from the regression specification.

Report Card and Information Treatment Analysis

We will also study the effect of parents receiving different kinds of report cards, and different information on the returns to investment in schooling, on the outcomes we measure. Parents will be randomly assigned to receive different kinds of information on

Our analysis of the effects of the report cards will involve estimating

$$EndlineOutcome_{is}=\beta_0+\beta_1 NULPReportCard_s +\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

where $NULPReportCard_{is}$ is a dummy for a household receiving the NULP report card instead of the standard report card. β_1 estimates the effects of receiving the NULP report card.

We will also study the effect of receiving information about the returns to education, using the following specification:

$$EndlineOutcome_{is}=\beta_0+\ \beta_1 Information_{is}+\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

Here $Information_{is}$ is a dummy for a household receiving additional information about the returns to schooling and β_1 estimates the effects of receiving the information on the outcome.

We are additionally interested in the combined effect of report cards plus the information treatment, which we can estimate as follows:

$$EndlineOutcome_{is}=\beta_0+\beta_1 NULPReportCard_s+\beta_2 Information_{is}+ \\ \beta_3 NULPReportCard_{is*}Information_{is}\ +\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

In this specification, β_1, β_2, and β_3 respectively estimate the effects of receiving the NULP report card, the information about returns, and the additional effect of getting both together, on the outcome in question.

For all three of these analyses, we also plan to explore whether the effects are different by study arm, which we can do by interacting indicators for the different study arms with $NULPReportCard_s$, $\beta_2 Information_{is}$, or $\beta_3 NULPReportCard_{is*}Information_{is}$. For our analysis of differences in the effect of the report cards across study arms, this regression will take the form:

$$EndlineOutcome_{is}=\beta_0+\ \beta_1\ NULPReportCard_{is}\ +\ \beta_2 MTSchool_s+\beta_3 CCTSchool_s\ + \\ \beta_4 MTSchool_s*NULPReportCard_{is}\ +\beta_5 CCTSchool_s*NULPReportCard_{is}\ +\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

Here β_1 is the effect of the report cards for the control schools, and β_4 and β_5 are the differences in the effect for the MT program and CCT program schools respectively.

For our analysis of differences in the effect of the information treatment across study arms, this regression will take the form:

$$EndlineOutcome_{is}=\beta_0+\ \beta_1 Information_{is}+\ \beta_2 MTSchool_s+\beta_3 CCTSchool_s\ +\beta_4 MTSchool_s* \\ Information_{is}\ +\beta_5 CCTSchool_s\ *\ Information_{is}\ +\boldsymbol{\gamma LotteryGroup_s}+\varepsilon_{is}$$

Here β_1 is the effect of the information treatment for the control schools, and β_4 and β_5 are the differences in the effect for the MT program and CCT program schools respectively.

For our analysis of differences across study arms in the combined effect of the information treatment and the report cards, this regression will take the form:

$$EndlineOutcome_{is} = \beta_0 + \beta_1 NULPReportCard_{is} + \beta_2 Information_{is} + \beta_3 NULPReportCard_{is} * Information_{is} + \beta_4 MTSchool_s + \beta_5 CCTSchool_s + \beta_6 MTSchool_s * NULPReportCard_{is} + \beta_7 CCTSchool_s * NULPReportCard_{is} + \beta_8 MTSchool_s * Information_{is} + \beta_9 CCTSchool_s * Information_{is} + \beta_{10} MTSchool_s * Information_{is} * NULPReportCard_{is} + \beta_{11} CCTSchool_s * Information_{is} * NULPReportCard_{is} + \boldsymbol{\gamma LotteryGroup}_s + \varepsilon_{is}$$

Here β_3 is the additional effect receiving both the report cards and the information treatment for the control schools, and β_{10} and β_{11} are the differences in the effect for the MT program and CCT program schools respectively.

As with the clocks and slates we may explore alternative analyses here, and we plan to exploit the panel nature of the dataset, with modified specifications that mirror those laid out above for our main comparisons of the three study arms.

Figure 3: Treatment Arms and Analyses

Figure 3a: Phase 1, 2013

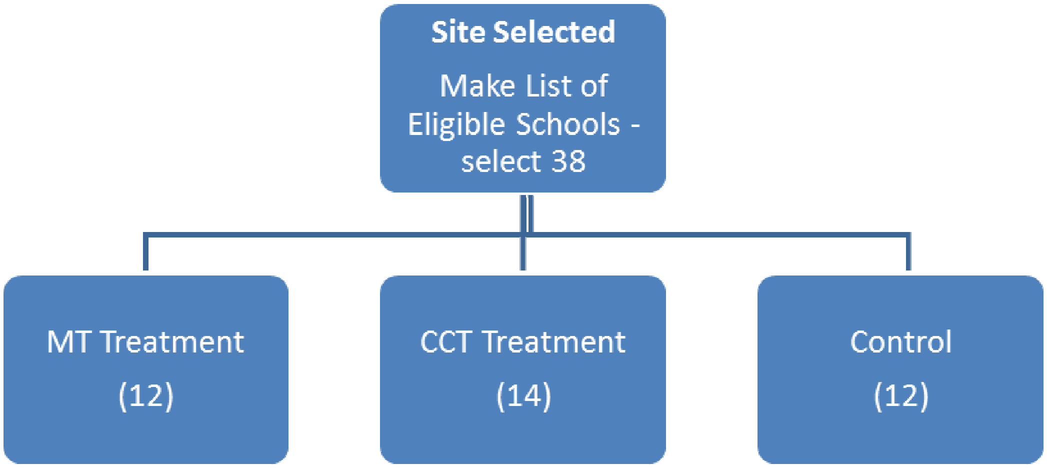
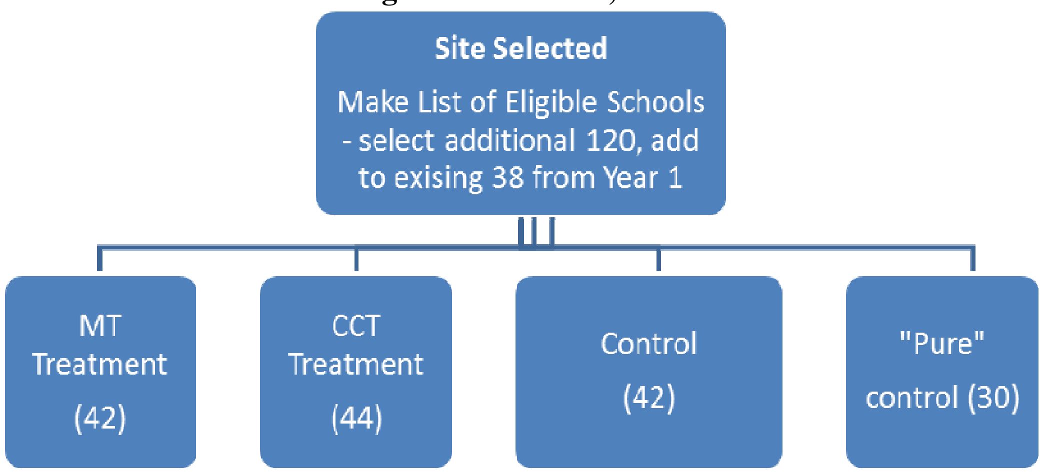
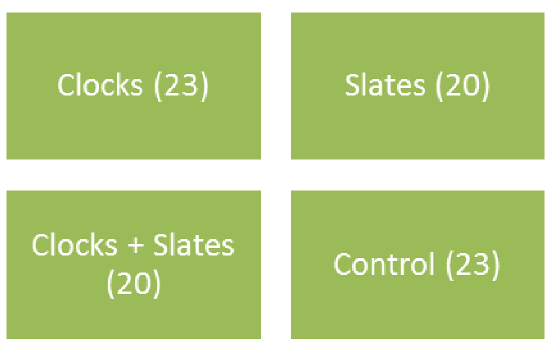


Figure 3b: Phase 2, 2014



Clock and Slate Randomization – CCT and Control Arms



Data collection

We will measure the differences between each of the treatment groups and the control group based on Lëblaŋo language reading and writing skills, other subject scores, as well as non-academic benefits. We will draw on a number of data sources: baseline and endline surveys for all participants and baseline and endline EGRA and EGWA exams for pupils. We will also make use of school administrative data on pupils, teachers, head teachers and CCTs, and classroom observations of teachers and pupils by Mango Tree field officers and CCTs.

Surveys of participating pupils' parents will have questions about the entire household, in order to look at factors that might affect the efficacy of the PLP, and also to explore potential spillover benefits to other children in the household. These will be conducted at a mass meeting of all the parents at each school, with any parents who don't attend being found through a visit to the household. Parent meetings will happen both at the beginning and end of the school year.

The table below presents the intended data collection methods and which groups will be covered by each data source:

Participant Group	**Baseline Survey**	**Baseline EGRA Exam**	**Classroom Observations**	**School Administrative Data**	**Endline Survey**	**Endline EGRA Exam**
Pupils	X	X	X	X	X	X
Pupils' Siblings				X	X	X
Teachers	X		X	X	X	
Head Teachers	X			X	X	
PTA SMC Representatives	X				X	
CCTs	X			X	X	
Parents	X				X	

The following is a list of the kinds of questions included on each data source:

- Examinations
    - Initial scores (baseline)
    - Test scores at the end of each year of the study (endline)
    - Official school data of pupil marks at the end of each term
- Teacher, Head teacher and CCT surveys
    - Teaching experience
    - Educational background
    - Family background
    - Opinions on PLP, school and local language instruction in general
    - Own ratings of pupils and marks
    - Own rating of personal performance
    - Attendance
- Parent surveys
    - Opinions on PLP, school in general and local language instruction in general
    - Family background
    - Educational background

- Literacy rates/languages spoken at home
    - Avail. of books at home/other reading materials/radio
    - Pupil's time spent on homework
    - Involvement in pupil's education
- Pupil surveys
    - Opinions on PLP, school in general and local language instruction in general
    - Self-reported enrichment activities, e.g. taking a book home, talking about the material outside the class
    - Nursery school attendance
- Classroom observations
    - Engagement of pupils
    - Compliance with PLP guidelines
- School administrative data
    - Attendance of the teachers including the head teachers
    - Attendance of pupils
    - Behavioral issues
    - Pupils' in-school marks

Sample Size

Please see the separate Power Calculations document under Supporting Documents & Materials.

References

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