13 May 2019

Southern New Hampshire University (SNHU)/Scalabrini – IDinsight Pre-analysis Plan

1. Rounds of Data Collection

As indicated in section IV. Methodology, learning outcomes will be measured through two types of instruments: 1) written, academic-style tests and 2) online skills-based tests that measure students' critical thinking ability and computer literacy. Professional (non-cognitive) skills outcomes will be measured at endline through an adapted version of the Anchored Big Five Inventory (ABFI) questionnaire. Sample ABFI questions are given in Appendix G.

Note that not all tests were administered at each time period. The following table documents which tests were administered at which periods. The treatment and comparison groups are respectively highlighted in blue and yellow:

	Treatment			Control		
	May-June 2018 baseline	**November 2018 midline**	**November 2019 endline**	**February 2019 baseline**	**July 2019 midline**	**July 2020 endline**
Demographic Survey	✓			✓		
English IELTS Reading	✓		✓	✓		✓
English IELTS Writing	✓	✓	✓	✓	✓	✓
Logical Reasoning	✓		✓	✓		✓
Critical thinking (Watson Glaser)	✓		✓	✓		✓
Computer Literacy	✓	✓	✓	✓	✓	✓
Professional Skills (Anchored Big Five Inventory)			✓			✓

2. Analytical Approach

Objective 1: Student Learning Outcomes

Examine the academic returns to the SNHU Cape Town program, as compared to a local university/college education.

Sample and subgroups

This analysis will compare the SNHU students with comparison students from local universities. Additionally, the following subgroups will be analyzed (subject to sufficient sample size):

- Gender
    - Male: N=146
    - Female: N=138
- Birth country
    - Anglophone (N=80)
    - Luso/Francophone (N=189)
- Household wealth
    - Below-median (N=142)
    - Equal to or above median (N=142)

For the subgroup, an indicator for the subgroup as well as an interaction term of the treatment indicator * subgroup indicator will be used to conduct subgroup analysis.

Primary indicators

For all of indicators, effect sizes will be reported in terms of standard deviations and percentage point change.

Indicators for student learning outcomes include the following test results:

- IELTS reading:
    - Number of questions answered correctly divided by the total number of questions.
    - Reading test scores can also be assessed as being above or below the threshold of 7.27. This is the average IELTS reading score of South African test-takers in 2017.[1]
- IELTS writing:
    - Aggregate score across the four grading categories (Task Response, Coherence and Cohesion, Lexical Resource, and Grammatical Range and Accuracy) divided by the total possible score.
    - Writing tests scores can also be assessed as performing above or below the threshold score of 7.0. This is the average IELTS writing score of South African test-takers in 2017.[1]
- Watson-Glaser critical thinking:
    - Number of questions answered correctly divided by the total number of questions.
- Logical reasoning:
    - For each of three sections (math, logic, English grammar), number of questions answered correctly divided by the total number of questions.
- Computer literacy (typing speed, web research, web credibility, Microsoft Word, Microsoft Excel, and email):
    - Scores for each section will be normalized by dividing by the total number of points possible, and then added together and divided by six such that the aggregate score has a maximum score of 1. For the purpose of normalization, the maximum words per minute for the typing speed test will be taken as 50 wpm.

Analytical model

The difference-in-difference model will be used.

For each i^{th} student, we regress

$$\Delta Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_{i,baseline} + \varepsilon_i$$

[1] https://www.ielts.org/teaching-and-research/test-taker-performance

where ΔY_i (represents change in outcomes over time) = $Y_{i,\text{endline}} - Y_{i,\text{baseline}}$. D_i is the treatment indicator (=1 if a Scalabrini student, 0 otherwise), X_i is a vector of covariates (as specified above), and ε_i is a random error term.

The parameter of interest is β_1, which represents the relative increase in score over time for Scalabrini students, compared to the comparison students.

For students who are missing baseline observations, we will use a missing indicator and replace missing observation values with 0. For inference, we will use heteroscedasticity-robust standard errors.

The following covariates (measured in baseline) will be included:

- *Gender:* Culturally imposed gender expectations, such as being less dominant or vocal for females, may affect learning outcomes.
- *Birth country:* Students from Francophone countries may have different levels of English fluency, compared to students from Anglophone countries, thereby affecting learning outcomes.
- *Age:* Age may affect cognitive ability and maturity, which would affect how much a student can gain from university education. The age at which a student enters university may also reflect the student's educational background (e.g. if they spent a few years out of school at some point, or if they went through primary and secondary school with no delays).
- *Previous level of education:* Prior educational qualifications may affect the pace at which students obtain learning gains from the program.
- *Household wealth:* The household wealth index is calculated following Anderson (2008)[2], which creates a standardized, weighted average of the following nine household variables: number of people in the household; number of rooms; roof material; floor material; toilet type; light source; cooking apparatus; television ownership; bicycle ownership. The resulting number is interpreted as a single, summary measure of household wealth.
- *Number of children:* Students with children may experience time and/or budget constraints that affect their learning outcomes.

Correction for Multiple Hypotheses Testing

To account for multiple hypothesis testing, we will adjust p-values using the Holm–Bonferroni method[3], within two families of hypotheses, one comprising the full-sample regressions for the different test scores and the other comprising the sub-group regressions.

Attrition

To address attrition, we plan to conduct robustness check using Lee bounds.[4] Alternatively, if possible, we can allocate some data collection funds towards tracking down a subset of attriters, and then use sampling weights too account for others.

[2] Anderson, M.L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association*, *103*(484), pp.1481-1495.

[3] Holm, S. (1979). "A simple sequentially rejective multiple test procedure". Scandinavian Journal of Statistics. 6 (2): 65–70.

[4] Lee, David S.. "Training , Wages , and Sample Selection : Estimating Sharp Bounds on Treatment Effects *." (2005).