# The Economic Returns to Foundational Literacy and Numeracy: Evidence from Indonesia

Lee Crawfurd

## Abstract

Despite rapid increases in access to school in low- and middle-income countries, learning outcomes remain extremely poor. This has led to calls for a new policy focus on ensuring foundational literacy and numeracy skills. Yet we have little direct, causal evidence on the long-term effects of investing in foundational skills in the early years of school. In this paper, we estimate the relationship between early-grade skills and adult earnings, using longitudinal data from the Indonesia Family Life Survey. Individuals are tested in foundational literacy and numeracy between the ages of 7 and 12 and then followed through multiple survey rounds to adulthood between the ages of 24 and 29. After adjusting for family background in childhood, a one standard deviation difference in foundational skills is associated with an 11 percent increase in adult earnings. This effect is mediated in part but not primarily by completed schooling. Those with higher foundational skills as children are less likely to have had children themselves by age 24 -29. We don't see correlations with other health outcomes. If the associated relationship can be interpreted as causal, this magnitude of returns implies a large positive benefit-cost ratio for investments in foundational skills.

WORKING PAPER 722 · JULY 2025

**The Economic Returns to Foundational Literacy and Numeracy: Evidence from Indonesia**

**Lee Crawfurd**
*Center for Global Development*

Lee Crawfurd. 2025. "The Economic Returns to Foundational Literacy and Numeracy: Evidence from Indonesia." CGD Working Paper 722. Washington, DC: Center for Global Development. https://www.cgdev.org/publication/economic-returns-foundational-literacy-and-numeracy-evidence-indonesia

I'm grateful for helpful comments to David Evans, Eeshani Kandpal, Jack Rossiter, Justin Sandefur, Kehinde Ajayi, Naureen Karachiwalla, and participants at the Centre for the Study of African Economies (CSAE) conference. All errors are my own.

**CENTER FOR GLOBAL DEVELOPMENT**
2055 L Street, NW Fifth Floor
Washington, DC 20036
202.416.4000

1 Abbey Gardens
Great College Street
London
SW1P 3SE

www.cgdev.org

# 1 Introduction

Are there long-term labour market returns to investments in foundational literacy and numeracy in low- and middle-income countries? While there is substantial evidence for labour market returns to *schooling*, even in low- and middle-income countries with low quality schooling, there is surprisingly little direct evidence on labour market returns to improved school quality outside of high-income countries. One recent study reviews 705 estimates of the "Mincerian" labour market returns to schooling (Psacharopoulos and Patrinos, 2018). By contrast we find just one prior estimate of the labour market returns to better childhood foundational skills (Glewwe et al., 2022). Research showing the importance of skills and not just schooling for economic outcomes (Hanushek and Woessmann, 2008) has been influential in moving policy focus from access to school to learning and quality.

In this paper, we provide new estimates of the relationship between foundational literacy and numeracy skills and adult earnings. We make use of several waves of the Indonesia Family Life Survey, to test the size of the correlation between skills measured age 6 - 12, and adult outcomes for those same individuals 17 years later, when they reach age 24 - 29.

We find that foundational literacy and numeracy test scores are associated with adult outcomes. After adjusting for a rich set of childhood controls, a one standard deviation difference in foundational skills is associated with an 11 percent increase in adult earnings. This is smaller than the correlation between adult skills and earnings, which is around 17 percent. The correlation between foundational skills and earnings is only partially mediated by completed schooling and adult skills. Holding completed schooling and adult skills constant only reduces the effect of foundational skills by around a third. We don't see statistically significant effects of foundational skills on employment, subjective wellbeing, early marriage, or health outcomes. We do see a small effect on lower fertility, of around 3 percentage points. Turning to heterogeneity, we see positive effects of foundational skills on employment for women, and negative effects for men.

One standard deviation higher foundational skills is associated with completing an additional 0.5 years of schooling. This translates to a 1.5 percentage point higher chance of completing primary school (from a very high base of 95 percent), a 5 percentage point higher chance of completing secondary, and a 3 percentage point higher chance of completing tertiary education. If these correlations can be interpreted as causal effects, they are significant in themselves, given widespread evidence on the value of schooling for a range of outcomes.

If these correlations can be interpreted as causal, the magnitude implies a large positive benefit-cost ratio for investments in improving foundational skills. Comparing earnings gains can also provide an 'exchange rate' for comparing studies that improve learning with those that increase schooling.

Human capital theory suggests that improvements in foundational literacy and numeracy should allow children to access more of the curriculum and learn higher-order skills, be less likely to drop out, more likely to complete school, and ultimately achieve higher productivity and earnings in the labour force (Evans and Hares, 2021). Different studies have tested different steps of this process.

First, several studies focus on the first step, from early grade foundational skills to later schooling attainment. This includes an earlier study using the first three waves of the Gansu Survey, finding that early grade test scores increase school completion (Glewwe et al., 2017). Using five rounds of the Young Lives survey and the LEAPS study from Punjab, Pakistan, Das et al. (2022) find that one standard deviation higher test scores age 12 is associated with 1-2 more years of completed schooling by age 22. Using data from the same survey as us, Suryadarma and Suryahadi (2011) find that a one standard deviation difference in primary school test scores is associated with a 7-9 percentage point increase in the probability of completing junior secondary school. Another study using data from the Young Lives project data looks at long-term effects of early foundational skills such as memory and self-control on educational attainment 8 years later, with mixed results (Lopez et al., 2024).

The second step in the causal chain is from later secondary school test scores and adult earnings. In the United States Murnane et al. (2000) find that one standard deviation in test scores is associated with a 10-15 percent increase in earnings. In the 'Young Lives' survey data from India, Ethiopia, Peru, and Vietnam, one standard deviation in skills at age 15 is associated with a 15-28 percent increase in earnings at age 26-27 (Perez-Alvarez et al., 2023).

Third, many more studies show *contemporaneous* correlations between adult skills and adult wages (Adhitya et al., 2019; Aslam et al., 2012; Boissiere et al., 1985; Campos-Vazquez, 2018; Danon et al., 2024; Hanushek and Woessmann, 2008; Hanushek et al., 2015; Jolliffe, 1998; Sun, 2019; Valerio et al., 2016). The pooled estimate for the effect of a standard deviation improvement in adult literacy skills on earnings across seven middle-income countries[1] is 15 percent (Valerio et al., 2016), and across 22 high-income countries is 18 percent (Chua, 2017).

Far fewer studies have used longitudinal data to directly examine the overall relationship between childhood test scores and later adult earnings. All of the estimates that do exist are from high-income or upper-middle-income countries. Estimates could differ in low- and middle-income country contexts, in which weak and informal labour markets could change the returns to early skills. In the United States, studies have used random assignment to kindergarten classrooms (Chetty et al., 2011) and exogenous variation in primary school teacher quality (Chetty et al., 2014) to show large long-run earnings gains from improved foundational skills. Similarly in Norway, a one standard deviation improvement in primary and lower secondary school quality (value-added) leads to 1.5 percent higher earnings around age 32 (Kirkebøen, 2021). In China, Glewwe et al. (2022) use four waves of the longitudinal 'Gansu Survey of Children and Families', finding that one standard deviation higher test scores at age 9–12 is associated with 13% higher wages at age 24 - 27 years old.

Our study adds to this literature by providing the first direct estimates of the correlation between foundational literacy and numeracy and adult earnings from a lower-middle-income

[1] Armenia, Bolivia, Colombia, Georgia, Kenya, Ukraine, and Vietnam.

(Indonesia), as well as adding new estimates on the intermediate step from foundational skills to schooling.

We also contribute to the broader literature on the long-term impacts of educational improvements. There has been an interesting pattern across many studies of short-term fade-out of effects on skills (see for example Andrabi et al. (2011); Jacob et al. (2010), followed by later re-emergence and persistence of effects on other outcomes (Bailey et al., 2020). One recent study on medium-term impacts finds sustained impacts on learning of an early grade reading intervention in South Africa, four years after the end of the intervention (Stern et al., 2023). A switch of language instruction policy in the Philippines led to lower completed schooling 8 years later for affected cohorts (Lloyd and Yang, 2024). We also know that other outcomes aside from test scores matter for long-term outcomes, such as teacher effects on non-cognitive skills (Jackson et al., 2020; Kraft, 2019).

The remainder of this paper proceeds as follows. We outline the data used in Section 2 and the empirical approach in Section 3. We then present our results in Section 4, and policy implications in Section 5.

# 2 Data

We use data from the Indonesia Family Life Survey (IFLS), one of the longest-running longitudinal panel surveys from a low- or middle-income country. This survey is ideal for our research question as it includes both a test of foundational skills in childhood, and follows the same individuals into adulthood to track long-run outcomes. We reviewed 21 other longitudinal panel surveys from low and middle-income income countries, none of which satisfy both of these two criteria.[2] Indonesia is the fourth largest country in the world, with over 50 million children in primary or secondary school. The survey we use is representative of 83 percent of Indonesia's population (Frankenberg et al., 2000). Our foundational skill assessments are drawn from Wave 2 of the survey conducted in 1997. At the time, the government of Indonesia spent around 1 percent of GDP on education, well below other countries. Despite this low recurrent spending, enrolment rates were relatively high thanks to large investments in infrastructure made in the 1970s (Duflo, 2001), and the introduction of compulsory primary schooling in 1984 (Beatty et al., 2021). This period predated increased spending on education in the 2000s (de Ree et al., 2018). The 1994 curriculum mandated 10 hours a week of math instruction for grades 1–3 and eight hours a week for grades 4–6 (Beatty et al., 2021).

For our analysis we restrict the sample to the 3,063 children aged between 7 and 12 in wave 2 (1997) who had cognitive test scores. 96 percent of these children were enrolled in primary school, with just 4 percent not enrolled. The median child was enrolled in grade 4, with a range from grade 1 to grade 8. Of these 3,063 children tested at baseline 2,192 (72 percent) were tracked through to wave 5 (2014), aged between 24 and 29.

## 2.1 Childhood Survey (IFLS Wave 2, 1997)

### Foundational Literacy and Numeracy Assessments

Children answered one of four different assessments designed for different age groups, covering mathematics and Bahasa Indonesia. The two mathematics assessments for 7-9 or 10-12 year olds both had 40 question items. The Bahasa test for 7-9 year olds is 35 questions long, and for 10-12 year olds is 40 questions long. The Bahasa assessments use primarily reading comprehension questions, plus some basic grammatical questions. The mathematics assessments use primarily arithmetic items, but also include some items on basic geometry, measurement, time, and fractions. All questions are multiple-choice and

[2] These are the Albania Panel Survey, 'Birth to 30', Cape Area Panel Study, and Kwazulu Natal Income Dynamics Survey in South Africa, Brazil Birth Cohort Study, Cebu Longitudinal Health and Nutrition Survey (Philippines), China Health and Nutrition Survey, Ecuador Longitudinal Survey of Child Health and Development, EGSF and INCAP in Guatemala, ICRISAT, Kagera Health and Development Survey (Tanzania), Kenya Life Panel Survey, Malawi MLFSH, Malaysia Family Life Survey, Matlab, Mexico Family Life Survey, Nang Rong, New Delhi Birth Cohort Study, Vietnam Life Survey, and Young Lives (up to round 6).

administered individually. The publicly available data only reports the total number of correct answers and not answers to individual question items. The level of difficulty of the assessments is similar to the United Nations standard for Global Minimum Proficiency at the end of lower primary, which forms the Sustainable Development Goal (SDG) indicator for foundational literacy and numeracy.[3] We standardize Bahasa and Mathematics test scores by age group.

**Other background variables**

Foundational literacy and numeracy skills are highly correlated with parental income and wealth, which may also have direct effects on outcomes for children. To capture this we construct an asset index. This index is based on ten household assets; a house, other buildings, farmland, livestock, vehicles, household appliances, savings, receivables, jewelry, and furniture. For each asset, we created a binary indicator of ownership. We also used the log of the total value of these assets as a continuous variable to capture the overall value. We then used principal component analysis to combine these variables into a single asset index, and standardised this index to have a mean of zero.

We also adjust for sex, age, grade, parent's education, and height-for-age. 50 percent of individuals are female. The median child was in grade 4 in the first wave, with a range from zero (not yet enrolled) through grade one to grade eight. 31 percent of children had a parent who had completed secondary education or higher. Height-for-Age Z-score (HAZ) is a well-established and widely used anthropometric indicator, serving as a robust summary proxy for chronic nutritional status. HAZ reflects linear growth and is sensitive to cumulative nutritional deficits and long-term health insults experienced during critical periods of growth (Grantham-McGregor et al., 2007), and predicts later life outcomes (Behrman et al., 2014). We use the WHO Child Growth Charts and WHO Reference 2007 Charts to standardise height measured in centimetres by age and sex.

## 2.2 Adult Outcome Survey (IFLS Wave 5, 2014)

In the final adult survey wave, 78 percent of individuals are employed (defined as working at least one hour in the previous week). The majority of the non-employed are engaged in housekeeping, with very few still in education, entirely unemployed, or economically inactive due to disability or other reasons. Mean salaries are 48 million Indonesian rupiah, or around $4,000 US dollars. For all those earning a wage, 7 percent work in a government job, and 45 percent work in a firm with 10 or more employees, which we use as a proxy for formal sector employment.

[3]The SDG indicator for foundational literacy and numeracy is SDG 4.1.1a. To be eligible for linking to the global minimum proficiency level, a maths assessment must include at a minimum 20 items and cover two of four constructs, and a reading assessment must also include 20 items covering both decoding and comprehension (UNESCO UIS, 2023).

95 percent have completed primary school, 77 percent completed secondary, and 18 percent completed tertiary education. 43 percent are "completely" or "very" satisfied with their life. Just 1 percent report being married before the age of 18, and the average respondent has 0.55 children. 84 percent report that they are "very" or "somewhat" healthy, and 13 percent accessed healthcare in the last month. The average respondent has 1.6 days sick in the last month from their primary activity (Table 1).

Table 1: Descriptive Statistics

| | Mean | SD | N |
|---|---|---|---|
| 1997 | | | |
| Female | 0.50 | 0.50 | 3,063 |
| Age | 9.69 | 1.65 | 3,063 |
| Grade | 3.74 | 1.74 | 3,063 |
| Household Assets (Index) | 0.00 | 1.00 | 3,063 |
| Parent completed secondary | 0.31 | 0.46 | 3,063 |
| Height-for-age (z) | 0.00 | 1.00 | 3,063 |
| 2014 | | | |
| Employed | 0.77 | 0.42 | 2,064 |
| Salary(Rp) | 47,782,798 | 619,326,208 | 1,957 |
| HH Income (Rp) | 62,904,832 | 620,745,789 | 2,064 |
| Education(Years) | 10.8 | 3.2 | 2,053 |
| Completed Primary | 0.95 | 0.22 | 2,053 |
| Completed Secondary | 0.77 | 0.42 | 2,053 |
| Completed Tertiary | 0.18 | 0.38 | 2,053 |
| Life satisfaction | 0.43 | 0.50 | 2,064 |
| Children(number) | 0.55 | 0.50 | 2,192 |
| Height(cm) | 158.17 | 8.32 | 1,978 |
| Healthy | 0.84 | 0.36 | 2,054 |
| Sick last month (days missed) | 1.64 | 3.58 | 2,054 |
| Accessed care last month | 0.13 | 0.34 | 2,192 |
| Not surveyed | 0.28 | 0.45 | 3,063 |

Note: This table presents descriptive statistics for our sample. All variables are binary indicators unless units are shown otherwise in parentheses. The asset index is the first principal component for 10 binary indicators of household assets and the log of the total value of these assets. More details are in section 2.1. Life satisfaction is a binary indicator for being "completely" or "very" satisfied with life. Children is the mean number of children.

# 3 Empirical Approach

Our goal is to estimate the effect of greater foundational literacy and numeracy skills on test scores. We rely on the conditional independence assumption, that conditional on our observable control variables, differences in foundational skills are assigned independently of later outcomes. This is a strong assumption but we do have detailed controls for student age, gender, grade, health, their parent's education, and their household wealth as a child. We can also estimate household fixed effects models, though sample size here is limited. We estimate the total effect of better foundational skills in childhood on later adult earnings, regressing earnings $Y_i$ (at age 24-27) on foundational test scores $FLN_i$ (at age 7-12), whilst adjusting for covariates including age, gender, and early household wealth $X_i$. We include district ("Kecamatan") fixed effects. To adjust for non-random attrition and selection into wage employment we use inverse probability weights and estimate a Heckman selection model (Heckman, 1979) with controls for the inverse Mills ratio.

We then estimate the indirect effect of foundational skills on earnings through their contribution to schooling attainment $S_i$. We do this by comparing the change in the coefficient on FLN before ($\beta_1$) and after ($\beta_2$) adjusting for schooling.

$$Y_i = \beta_1 FLN_i + \lambda_1 X_i + \varepsilon_i \tag{1}$$

While we use inverse probability weighting and a Heckman correction to adjust for non-random selection, these approaches rely on strong assumptions and cannot fully eliminate bias from unobservable factors. In particular, selection on unobserved ability or motivation may still bias the estimated returns. Therefore we also assess the robustness of our results to Oster-style bounds on unobservable confounders (Oster, 2019) and Kling et al. (2007)-style bounds on non-random attrition (Kling et al., 2007).

$$Y_i = \beta_2 FLN_i + \lambda_2 X_i + \theta S_i + \varepsilon_i \tag{2}$$

# 4 Results

## 4.1 Attrition

We first present results on the correlates of missing wage data. This comprises both attrition and those in the final dataset who are not earning a wage. Of 3,063 individuals in the baseline data, 2,192 are present in the endline data (an attrition rate of 28 percent), and 1,436 earn a wage in the endline data. Foundational skills do predict attrition in the data - those with higher early test scores are more likely to be absent from the data, perhaps through migration. This is a particular concern at the very high end - those with early test scores 1.5 standard deviations above the mean are much more likely to be missing. This likely biases our estimate of the effect of foundational skills on earnings downwards. Table 2 column 1 shows which variables correlate with remaining in the final survey round at all. Those with one standard deviation higher foundational skills are 3.2 percent less likely to be in the final sample and earning a wage. Column 2 shows correlates of remaining in the final sample and also earning a wage. The correlation between foundational skills and remaining in the final sample and also earning a wage is small and not statistically significant. Those who are female and who had a higher height-for-age at age 7-12 are less likely to be in the final sample and earning a wage. Those with higher family wealth in 1997 are more likely to remain in the sample. Column 3 in Table 2 adds contemporaneous factors to the selection equation. The results indicate that when controlling for these contemporaneous factors reduces the influence of factors measured age 7-12. The inclusion of these contemporaneous factors shows that being married is associated with a lower likelihood of wage employment and having children is associated with a higher likelihood. Though there is clearly non-random selection into our final sample, we do adjust for selection through the Heckman equation, and through inverse probability weighting.

Table 2: Correlates of missing wage data

| | (1) | (2) | (3) |
|---|---|---|---|
| Age 7-12 | | | |
| FLN | -0.032* | -0.015 | 0.005 |
| | (0.019) | (0.010) | (0.010) |
| HH Wealth | 0.021 | 0.034*** | 0.036*** |
| | (0.019) | (0.010) | (0.010) |
| Age in 1997 | -0.001 | -0.006 | -0.010 |
| | (0.017) | (0.009) | (0.009) |
| Female | 0.027 | -0.211*** | -0.018 |
| | (0.033) | (0.018) | (0.037) |
| Parent has secondary ed | -0.063 | -0.015 | -0.001 |
| | (0.042) | (0.022) | (0.022) |
| Grade in 1997 | -0.006 | 0.010 | 0.017* |
| | (0.016) | (0.009) | (0.009) |
| Height-for-age (z-score) | -0.054*** | -0.020** | -0.004 |
| | (0.019) | (0.010) | (0.010) |
| Age 24-27 | | | |
| Married | | | -0.659*** |
| | | | (0.040) |
| Children | | | 0.244*** |
| | | | (0.022) |
| Female x Married | | | 0.408*** |
| | | | (0.061) |
| Female x Children | | | -0.240*** |
| | | | (0.046) |
| District FE | Yes | Yes | Yes |
| Obs. | 3,063 | 3,063 | 2,192 |
| Non-missing obs | 2,192 | 1,436 | 1,436 |
| $R^2$ | 0.03 | 0.07 | 0.18 |

Note: The outcome variable is an indicator equal to 1 if wage data is present for that individual. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

## 4.2 Direct impacts

We next look at the total direct effect of early test scores on labour market outcomes. Table 3 column 1 shows the unconditional correlation - one standard deviation higher foundational literacy and numeracy (FLN) is associated with around 17 percent higher earnings. Adding extensive controls for family wealth, parental education, sex, age, school grade, and also early health measures, reduces the coefficient to around 10 percent (column 2). Further adjusting for selection with the inverse Mills ratio leads to just a small increase to 11 percent. Using a Heckman-selection approach and adjusting for the inverse Mills ratio again slightly increases the coefficient, to 12 percent. Alternatively, we estimate Kling et al. (2007)-style bounds - first splitting the sample by above or below median foundational skills, and then assuming that individuals with missing salary information are 0.1 standard deviations above or below the group mean. The most likely pattern of non-random attrition would be that those with high foundational skills are more likely to drop out of the sample and also be earning higher than average earnings. Assuming that missing high-FLN observations have above average earnings, and missing low-FLN observations have below average earnings, gives us an upper bound point estimate which is substantially higher, at 27 percent (column 5). Assuming the opposite, which seems less likely a priori, would give a much smaller point estimate of 4 percent (column 6).

For comparison we also estimate the return to a standard deviation of higher contemporaneous adult skills to be 17 percent (column 7), and to an additional year of schooling to be around 8 percent (column 8). This contemporaneous correlation is similar in magnitude to estimates from other countries that are in the range 15-18 percent (Chua, 2017; Valerio et al., 2016). Our estimates of the return to schooling are similar in magnitude to other observational estimates for Indonesia (Montenegro and Patrinos, 2021).

Though we have a rich set of control variables we cannot rule out confounding by unobserved variables. Our results are though robust to unobserved confounding proportional to confounding on observables through the coefficient stability method (Oster, 2019). With unobserved confounding proportional to observed confounding, the coefficient on foundational skills in our main estimate falls by around 25 percent. For the coefficient to be zero would require selection on unobservables to be over three times larger than selection on observables (all assuming the largest potential value of R-squared to be 1.3 times the observed R-squared in the fully controlled model).

Table 3: Foundational Skills (age 7-12) and Adult Earnings

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Unadj | Adj | IPW | Heckman | Upper Bound | Lower Bound | | | Occ FE |
| Age 7-12 | | | | | | | | | |
| FLN | 0.166*** | 0.105*** | 0.110*** | 0.119*** | 0.268*** | 0.036*** | | | 0.085** |
| | (0.037) | (0.036) | (0.036) | (0.035) | (0.004) | (0.001) | | | (0.036) |
| HH Wealth | | 0.148*** | 0.145*** | 0.146*** | 0.003 | 0.000 | 0.138*** | 0.093** | 0.141*** |
| | | (0.040) | (0.040) | (0.040) | (0.005) | (0.001) | (0.040) | (0.041) | (0.040) |
| Age 24-27 | | | | | | | | | |
| Mills' ratio | | | | -0.800*** | | | | | |
| | | | | (0.179) | | | | | |
| Test scores (2014) | | | | | | | 0.172*** | | |
| | | | | | | | (0.040) | | |
| Years of Education | | | | | | | | 0.077*** | |
| | | | | | | | | (0.013) | |
| Controls | | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation FE | | | | | | | | | Yes |
| Obs. | 1,428 | 1,428 | 1,428 | 1,428 | 2,049 | 2,049 | 1,428 | 1,428 | 1,428 |
| $R^2$ | 0.07 | 0.16 | 0.17 | 0.17 | 0.67 | 0.67 | 0.17 | 0.18 | 0.20 |

Note: The outcome variable is the log of monthly earnings. Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, height, and weight. The inverse Mills ratio is estimated with the Heckman selection model, with the interactions of sex, marital status, and having any children being used to predict missing wages. Standard errors clustered at the household level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Second, looking at other outcomes, we see similar coefficients for household income rather than individual earnings, but a negative correlation with household farm income. We see no correlation with subjective wellbeing, and a negative correlation with fertility - one standard deviation higher foundational skills as associated with being 2.9 percentage points less likely to have a child (Table 4). Parent's wealth and own school attainment have more consistent correlations with these outcomes. Girls who at age 7-12 with higher family wealth were less likely to have children and have married early. These effects are mediated in part (but not wholly) by their own completed schooling age 24-27. We also look at effects on health outcomes in Table A1. None of the correlations between adult health outcomes and foundational literacy and skills are statistically significant.

Table 4: Foundational skills (age 7-12) and Other Adult Outcomes

| | HH Income | | Farm Income | | SWB | | Children | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Age 7-12 | | | | | | | | |
| FLN | 0.106 | 0.058 | -0.352* | -0.327 | -0.013 | -0.017 | -0.029*** | -0.009 |
| | (0.103) | (0.103) | (0.196) | (0.202) | (0.012) | (0.012) | (0.011) | (0.011) |
| HH Wealth | 0.400*** | 0.286** | 0.231 | 0.229 | 0.028** | 0.018 | -0.014 | 0.006 |
| | (0.117) | (0.119) | (0.190) | (0.198) | (0.012) | (0.012) | (0.011) | (0.011) |
| Age 24-27 | | | | | | | | |
| Years of Education | | 0.148*** | | -0.020 | | 0.013*** | | -0.032*** |
| | | (0.041) | | (0.072) | | (0.004) | | (0.004) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Outcome mean | 16.7 | 16.7 | 4.0 | 4.0 | 0.4 | 0.4 | 0.6 | 0.6 |
| Obs. | 2,062 | 2,051 | 2,062 | 2,051 | 2,062 | 2,051 | 2,189 | 2,051 |
| $R^2$ | 0.04 | 0.04 | 0.05 | 0.05 | 0.04 | 0.04 | 0.18 | 0.21 |

Note: Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, height, and weight. The inverse Mills ratio is estimated with the Heckman selection model, with the interactions of sex, marital status, and having any children being used to predict missing wages. Standard errors clustered at the household level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

## 4.3 Indirect impacts and mechanisms

We can expect the effect of foundational skills on earnings to operate partially through an indirect effect through schooling. Foundational skills might both enable people to complete more schooling that is then rewarded in the labour market, and enable people to acquire other unmeasured skills that are also rewarded, independently of their schooling attainment.

First, we can decompose the indirect effect from the total effect, by adjusting for completed schooling and adult skills, as we do in Table 5 columns 1 and 2. Adjusting for completed schooling and adult skills reduces the coefficient on FLN by around one third. This therefore suggests that the economic return to foundational skills does not primarily come through increased schooling attainment, but through some other mechanism.

We can also estimate the effect of foundational skills on completed schooling and adult skills. Here we find that a standard deviation change in foundational skills is associated with 0.5 additional years of completed schooling. Valuing a year of schooling at an 8 percentage point increase in earnings, suggests that the indirect effect of early test scores through schooling is around 4 percentage points, similar to the change in the direct effect seen between columns 1 and 2. One standard deviation higher foundational skills is associated with a 1.5 percentage point higher chance of completing primary school, 5 percentage point higher chance of completing secondary, and 3 percentage point higher chance of completing tertiary education. The effect of foundational skills on primary school completion is small, as primary completion levels are so high to begin with (95 percent). Effects are larger for secondary and tertiary completion, where average levels of completion are lower - 77 percent have completed secondary school, and only 18 percent have completed tertiary education. The effects are in all cases smaller than a standard deviation increase in childhood family wealth. This is consistent with findings that family background matters more than ability for predicting schooling attainment and completion in other low- and middle-income countries (Das et al., 2022).

We also estimate the effects of foundational skills on adult skills. A one standard deviation change in foundational skills is associated with just a 0.09 standard deviation change in adult skills. This again implies that existing estimates of the returns to adult skills (such as Chua 2017; Valerio et al. 2016) are only weakly informative about the returns to foundational skills.

Table 5: Foundational skills (age 7-12) and Completed Schooling (age 24-27)

| | (1) Earnings | (2) Earnings | (3) School (Yrs) | (4) Primary | (5) Secondary | (6) Tertiary | (7) Adult skills |
|---|---|---|---|---|---|---|---|
| Age 7-12 | | | | | | | |
| FLN | 0.124*** | 0.0822** | 0.463*** | 0.0150*** | 0.0510*** | 0.0298*** | 0.0815*** |
| | (0.0351) | (0.0360) | (0.0640) | (0.00486) | (0.00936) | (0.00874) | (0.0236) |
| HH Wealth | 0.143*** | 0.0814** | 0.733*** | 0.0228*** | 0.0754*** | 0.0643*** | 0.100*** |
| | (0.0391) | (0.0397) | (0.0732) | (0.00537) | (0.0104) | (0.00916) | (0.0228) |
| Age 24-27 | | | | | | | |
| Years of Education | | 0.0636*** | | | | | |
| | | (0.0138) | | | | | |
| Test scores (2014) | | 0.0982** | | | | | |
| | | (0.0421) | | | | | |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Outcome Mean | | | 10.908 | 0.952 | 0.771 | 0.182 | 0.392 |
| Obs. | 1,434 | 1,428 | 2,051 | 2,051 | 2,051 | 2,051 | 2,150 |
| $R^2$ | 0.18 | 0.20 | 0.33 | 0.08 | 0.17 | 0.21 | 0.09 |

Note: Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, height, and weight. The inverse Mills ratio is estimated with the Heckman selection model, with the interactions of sex, marital status, and having any children being used to predict missing wages. Standard errors clustered at the household level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

A common concern is that the returns to education may be driven at least in part by access to rationed jobs in the formal public sector with rents (Duflo et al., 2021; Pritchett, 2001). We find no effect of foundational skills on the probability of obtaining a government job, and can rule out even a small effect (Table A2). Looking at work in the formal sector more broadly, we do see a small positive effect, which is mediated entirely via completed schooling. There is also no effect of either foundational skills or schooling on the likelihood of a household making any farm income (which is around 29 percent of households).

When we estimate heterogeneity in effects of foundational skills on earnings by sector, estimates are not statistically significant but we can't rule out large differences in effects on earnings for those in the government sector (Table 6). We don't see statistically significant differences in effects based on other individual characteristics such as parental education or wealth, or being located in the capital city Jakarta. We don't see differences between men and women in the effect of foundational skills on earnings or subjective wellbeing, but do see a small difference in the relationship with employment. Table A3 shows men with one standard deviation better foundational skills are around 2.5 percentage points less likely to be employed. This is not explained by higher educational enrolment, and is perhaps consistent with 'queueing' for the limited number of formal sector jobs. For women the correlation between skills and employment is positive but not statistically significantly different from zero.

Table 6: Heterogeneous effects on earnings

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| FLN | 0.079* | 0.109*** | 0.102*** | 0.098*** | 0.064 | 0.056 |
| | (0.043) | (0.035) | (0.036) | (0.038) | (0.051) | (0.082) |
| Parent has secondary=1 | 0.249*** | | | | | |
| | (0.083) | | | | | |
| Parent has secondary=1 × FLN | 0.093 | | | | | |
| | (0.074) | | | | | |
| FLN × HH Wealth | | 0.044 | | | | |
| | | (0.031) | | | | |
| Jakarta=1 | | | 0.365** | | | |
| | | | (0.150) | | | |
| Jakarta=1 × FLN | | | 0.215 | | | |
| | | | (0.172) | | | |
| Government=1 | | | | 0.405*** | | |
| | | | | (0.102) | | |
| Government=1 × FLN | | | | 0.082 | | |
| | | | | (0.084) | | |
| Formal=1 | | | | | 0.647*** | |
| | | | | | (0.070) | |
| Formal=1 × FLN | | | | | 0.033 | |
| | | | | | (0.067) | |
| Manufacturing | | | | | | 0.708*** |
| | | | | | | (0.127) |
| Services (Self-employed) | | | | | | 0.090 |
| | | | | | | (0.146) |
| Services (Government) | | | | | | 0.706*** |
| | | | | | | (0.144) |
| Services (Employee) | | | | | | 0.339*** |
| | | | | | | (0.114) |
| Manufacturing × FLN | | | | | | -0.008 |
| | | | | | | (0.107) |
| Services (Self-employed) × FLN | | | | | | 0.018 |
| | | | | | | (0.138) |
| Services (Government) × FLN | | | | | | 0.126 |
| | | | | | | (0.113) |
| Services (Employee) × FLN | | | | | | 0.055 |
| | | | | | | (0.098) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 1,434 | 1,434 | 1,434 | 1,434 | 1,403 | 1,434 |
| $R^2$ | 0.17 | 0.17 | 0.17 | 0.17 | 0.21 | 0.20 |

Note: The dependent variable is the log of adult earnings in 2014. Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, and height. Standard errors clustered at the household level are shown in parentheses. Note that linear combination of FLN and Female=1 x FLN is not statistically significantly different from zero. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

# 5 Discussion

## 5.1 Investment in foundational literacy and numeracy

What do the estimated monetary benefits to foundational skills imply for how much we should invest in improving these skills? To answer this question we calculate the benefit-cost ratio of a foundational skills program. We focus here entirely on the private labour market returns to improved foundational skills, ignoring any potential intergenerational or spatial spillovers, any non-monetary benefits, and any possible negative externalities through displacement or zero-sum competition for fixed jobs.

We start with the dataset collated by Sandefur et al. (2023) which covers all USAID early grade reading programs that have an evaluation (either randomized or non-randomized difference-in-difference) and a per student cost estimate. This leaves us with 29 programs from 19 countries. On average these interventions have an effect size of 0.3 standard deviations, which is relatively high compared to other interventions in international education, which have a median effect size of 0.1 standard deviations (Evans and Yuan, 2022). We combine this with data on median national income from the World Bank Poverty & Inequality Platform (PIP).

Our estimates from Table 3 are that one standard deviation in foundational skills is worth a 11% increase in earnings, so we multiply this parameter by average earnings in each country and by the program effect size for that country. We calculate the net present value of the total expected lifetime earnings gain from the program, assuming a 40 year working life and an annual discount rate of 5 percent:

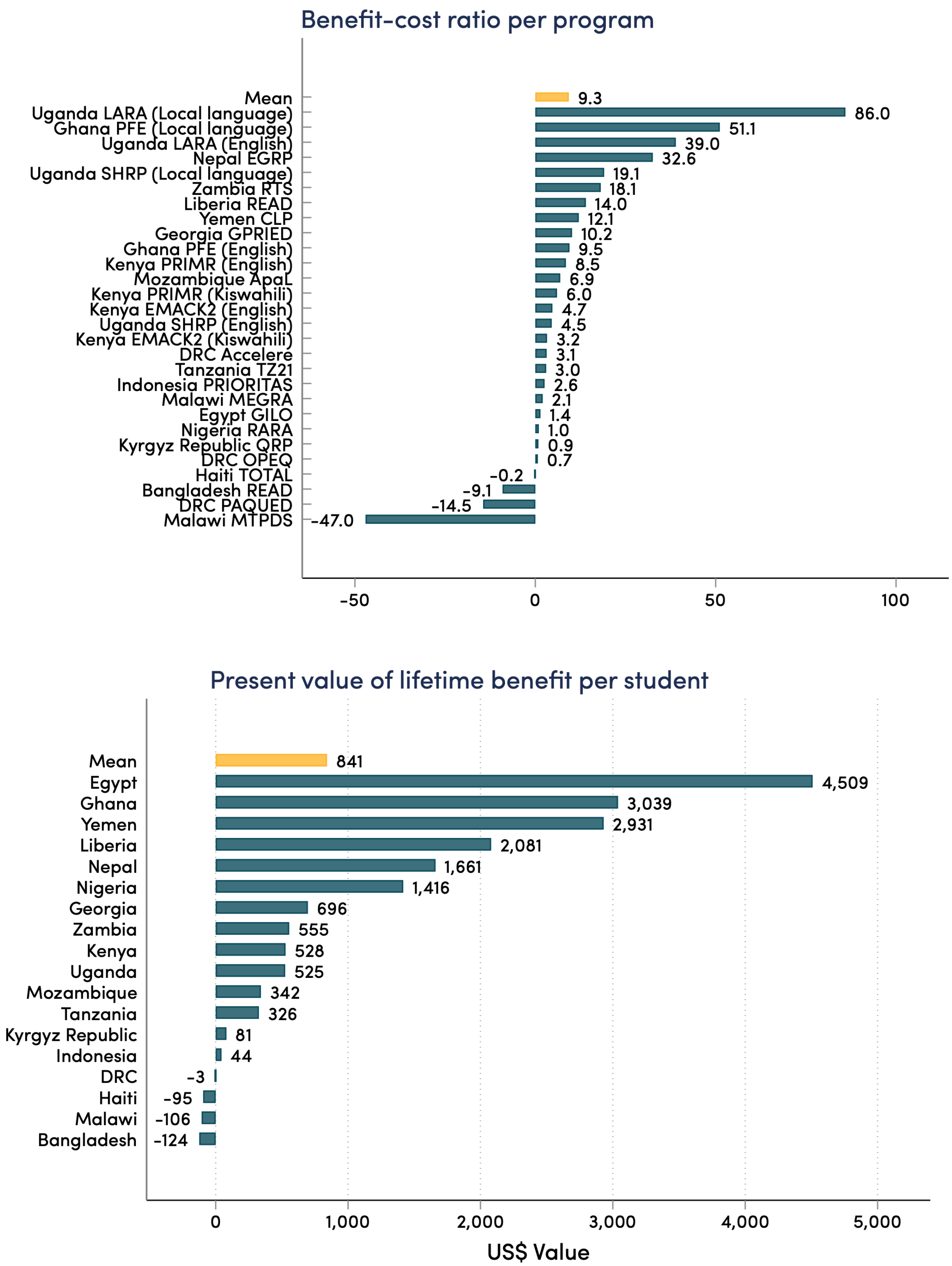
$$PV = E_0 \times \left[ \frac{1 - \left(\frac{1}{1+r}\right)^n}{r} \right] \tag{3}$$

Where:

$$\begin{aligned} E_0 &= \text{increase in initial earnings} \\ r &= \text{discount rate} = 5\% \\ n &= \text{number of years} = 40 \end{aligned}$$

We then simply compare the ratio of these per student benefits to per student program costs. On average, these programs have a benefit-cost ratio of 9.3, though this varies substantially, with seven programs having a ratio below one, implying the costs are greater than or equal to the benefits. The present value of lifetime benefits per student imply that it would be worth spending hundreds of dollars per student on average to achieve these gains (true program costs have a mean of \$256 and median of \$87 per pupil.

Figure 1: Simulated benefits of large foundational literacy programs




Note: This figure shows estimated benefit-cost ratios for USAID reading programs, using data on effect sizes and costs from Sandefur et al. (2023), combined with the estimate of the effect of learning on earning from Table 3, and data on average (median) earnings per country from the World Bank Poverty & Inequality Platform (PIP).

## 5.2 Comparing education interventions with different outcomes

A second implication of these findings is how we should think about comparing the value of increases in the quantity of schooling to improving its quality. There is an important policy demand to be able to compare the cost-effectiveness of interventions that target different outcomes, either schooling or learning. A leading approach has been to combine both into a single metric - 'Learning-adjusted years of schooling' (Angrist et al., 2025). In this approach impacts on schooling are adjusted for the quality of that schooling. Impacts on learning are converted into the equivalent years of quality-adjusted schooling, calculated as the ratio of learning impacts to the average learning gained from a year of high-quality schooling (concretely, high-quality benchmark is set as the 0.8 standard deviations learned in the highest performing school system, Singapore). One possible concern with this approach is that schooling might impart economically valuable skills (such as character or non-cognitive skills) that are not captured by cognitive tests of mathematics and literacy ability.

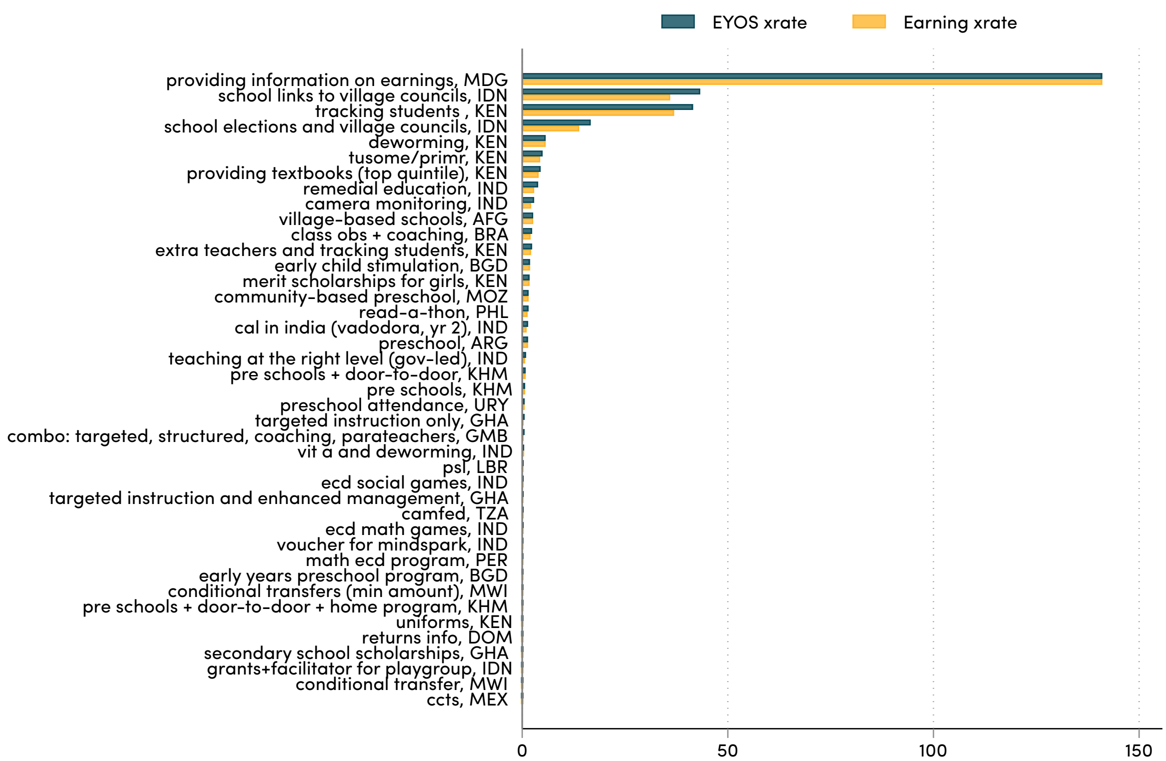
An alternative approach is to use the earnings metric as the exchange rate. To illustrate, consider a first intervention that increases schooling by one year in South Africa, and a second that increases learning by 0.25 standard deviations. Using the LAYS approach these would both be considered to be equivalent, as the average student learns 0.25 standard deviations per year in South Africa, and both interventions would be worth 0.31 LAYS.

If we instead use the earnings exchange rate, a year of schooling is worth a 10 percent increase in earnings, whilst a 0.25 standard deviation improvement in learning is worth just a 2.75 percent increase in earnings. Our result therefore values interventions that increase schooling relative to learning 4 times more than the LAYS approach.

Despite this large difference in the implied relative value of learning and schooling, this doesn't have a substantial effect in the ranking of interventions by "Learning-adjusted years of schooling". Angrist et al. (2025) review all experimental and quasi-experimental studies from low- and middle-income countries, covering over 200 studies, of which 41 have statistically significant outcomes on schooling or learning, as well as data on costs.

Applying our earnings exchange rate to their sample of studies, interventions that increase learning are reduced in their average estimated cost-effectiveness by 1.2 LAYS per $100, with schooling interventions remaining unchanged. This difference is small compared to the overall range in cost-effectiveness, which has a standard deviation of 23 LAYS, and compared to the order of magnitude difference in rankings between the most cost-effective interventions and average interventions (Figure 2).

Figure 2: Learning adjusted-years of school




Note: This figure is based on a review by Angrist et al. (2025) on the cost-effectiveness of education interventions. We compare here two alternative methods for putting learning and schooling on the same scale. First, the approach used by Angrist et al. (2025) converts from learning gains to 'Learning-adjusted years of school' (LAYS) by comparing to the learning gains during a typical year of school in a high-quality benchmark country. Second, we use the earnings gains from learning and schooling, as estimated in Table 3, as an alternative exchange rate.

# 6 Conclusion

This study investigates the long-term labor market returns to foundational literacy and numeracy, using longitudinal data from the Indonesia Family Life Survey. A one standard deviation improvement in foundational skills correlates with a 11 percent increase in adult earnings. If these correlations can be interpreted as causal, this implies significant economic value and a high benefit-cost ratio of investing in foundational education, with monetary returns outweighing program costs. Clearly foundational skills have value beyond their economic value. You can't read for pleasure if you're never taught how to read. Foundational skills are also associated with higher school attainment, which in turn has been shown to be associated with a range of other benefits including improvements to children's safety (Evans et al., 2023) and wider social benefits (Cui and Martins, 2021).

We should however be cautious around causal inference, due to potential unobserved confounders and attrition. We find some evidence consistent with positive-sum effects on productivity, but also some evidence consistent with zero-sum competition for the limited number of public-sector formal jobs. Future research should explore experimental or quasi-experimental designs to validate these relationships, extend the analysis to other low- and middle-income contexts, and unpack the nature of the returns to investment in education in the context of segmented and dual labour markets.

While foundational skills do increase schooling attainment, the mechanism driving economic returns appears to be additional to the increased years of schooling. These results have clear relevance for policy, suggesting that interventions prioritizing foundational skills can yield substantial benefits. By quantifying the economic returns to foundational skills, this work contributes to ongoing policy discussions on optimizing education spending for sustainable development.

# References


**Adhitya, Dhian, Tri Mulyaningsih, and Bhimo Rizky Samudro**, "The role of cognitive and non-cognitive skills on labour market outcomes in Indonesia," *Jurnal Ekonomi Malaysia*, 2019, *53* (1), 3–16. Number: 1 Publisher: Penerbit Universiti Kebangsaan Malaysia.

**Andrabi, Tahir, Jishnu Das, Asim Ijaz Khwaja, and Tristan Zajonc**, "Do Value-Added Estimates Add Value? Accounting for Learning Dynamics," *American Economic Journal: Applied Economics*, July 2011, *3* (3), 29–54.

**Angrist, Noam, David K. Evans, Deon Filmer, Rachel Glennerster, Halsey Rogers, and Shwetlena Sabarwal**, "How to improve education outcomes most efficiently? A review of the evidence using a unified metric," *Journal of Development Economics*, January 2025, *172*, 103382.

**Aslam, Monazza, Faisal Bari, and Geeta Kingdon**, "Returns to schooling, ability and cognitive skills in Pakistan," *Education Economics*, 2012, *20* (2), 139–173. Publisher: Taylor & Francis Journals.

**Bailey, Drew H., Greg J. Duncan, Flávio Cunha, Barbara R. Foorman, and David S. Yeager**, "Persistence and Fade-Out of Educational-Intervention Effects: Mechanisms and Potential Solutions," *Psychological science in the public interest : a journal of the American Psychological Society*, October 2020, *21* (2), 55–97.

**Beatty, Amanda, Emilie Berkhout, Luhur Bima, Menno Pradhan, and Daniel Suryadarma**, "Schooling progress, learning reversal: Indonesia's learning profiles between 2000 and 2014," *International Journal of Educational Development*, September 2021, *85*, 102436.

**Behrman, Jere R., John Hoddinott, John A. Maluccio, Erica Soler-Hampejsek, Emily L. Behrman, Reynaldo Martorell, Manuel Ramírez-Zea, and Aryeh D. Stein**, "What determines adult cognitive skills? Influences of pre-school, school, and post-school experiences in Guatemala," *Latin American Economic Review*, December 2014, *23* (1), 4.

**Boissiere, M, J B Knight, and R. H. Sabot**, "Earnings, schooling, ability, and cognitive skills," *American Economic Review*, 1985, *75* (5), 16.

**Campos-Vazquez, Raymundo M.**, "Returns to cognitive and non-cognitive skills: evidence for Mexico," *Applied Economics Letters*, September 2018, *25* (16), 1153–1156.

**Chetty, Raj, John N. Friedman, and Jonah E. Rockoff**, "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates," *American Economic Review*, 2014, *104* (9), 2593–2632.

_ , _ , **Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan**, "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star," *The Quarterly Journal of Economics*, November 2011, *126* (4), 1593–1660.

**Chua, Kenn**, "Skill achievement and returns in developing countries: Evidence from adult skills surveys," *European Journal of Education*, 2017.

**Cui, Ying and Pedro S. Martins**, "What drives social returns to education? A meta-analysis," *World Development*, December 2021, *148*, 105651.

**Danon, Alice, Jishnu Das, Andreas de Barros, and Deon Filmer**, "Cognitive and socioemotional skills in low-income countries: Measurement and associations with schooling and earnings," *Journal of Development Economics*, May 2024, *168*, 103132.

**Das, Jishnu, Abhijeet Singh, and Andres Yi Chang**, "Test scores and educational opportunities: Panel evidence from five low- and middle-income countries," *Journal of Public Economics*, February 2022, *206*, 104570.

**de Ree, Joppe, Karthik Muralidharan, Menno Pradhan, and Halsey Rogers**, "Double for Nothing? Experimental Evidence on an Unconditional Teacher Salary Increase in Indonesia," *The Quarterly Journal of Economics*, May 2018, *133* (2), 993–1039.

**Duflo, Esther**, "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment," *American Economic Review*, September 2001, *91* (4), 795–813.

_ **, Pascaline Dupas, and Michael Kremer**, "The Impact of Free Secondary Education: Experimental Evidence from Ghana," June 2021.

**Evans, David and Susannah Hares**, "Should Governments and Donors Prioritize Investments in Foundational Literacy and Numeracy?," Center for Global Development Working Paper May 2021.

**Evans, David K. and Fei Yuan**, "How Big Are Effect Sizes in International Education Studies?," *Educational Evaluation and Policy Analysis*, September 2022, *44* (3), 532–540.

_ **, Hares Susannah, Holland Peter A., , and Amina Mendez Acosta**, "Adolescent Girls' Safety In and Out of School: Evidence on Physical and Sexual Violence from Across Sub-Saharan Africa," *The Journal of Development Studies*, May 2023, *59* (5), 739–757. Publisher: Routledge _eprint: https://doi.org/10.1080/00220388.2023.2172333.

**Frankenberg, E, P Hamilton, S Polich, W Suriastini, and D Thomas**, "User's Guide for the Indonesia Family Life Survey, Wave 2," Technical Report, RAND 2000.

**Glewwe, Paul, Qiuqiong Huang, and Albert Park**, "Cognitive skills, noncognitive skills, and school-to-work transitions in rural China," *Journal of Economic Behavior & Organization*, February 2017, *134*, 141–164.

**_ , Yang Song, and Xianqiang Zou**, "Labor market outcomes, cognitive skills, and noncognitive skills in rural China," *Journal of Economic Behavior & Organization*, January 2022, *193*, 294–311.

**Grantham-McGregor, Sally, Yin Bun Cheung, Santiago Cueto, Paul Glewwe, Linda Richter, and Barbara Strupp**, "Developmental potential in the first 5 years for children in developing countries," *The Lancet*, January 2007, *369* (9555), 60–70. Publisher: Elsevier.

**Hanushek, Eric A. and Ludger Woessmann**, "The Role of Cognitive Skills in Economic Development," *Journal of Economic Literature*, September 2008, *46* (3), 607–668.

**_ , Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann**, "Returns to skills around the world: Evidence from PIAAC," *European Economic Review*, 2015, *73* (C), 103–130.

**Heckman, James J.**, "Sample Selection Bias as a Specification Error," *Econometrica*, 1979, *47* (1), 153–161. Publisher: [Wiley, Econometric Society].

**Jackson, C. Kirabo, Shanette C. Porter, John Q. Easton, Alyssa Blanchard, and Sebastián Kiguel**, "School Effects on Socioemotional Development, School-Based Arrests, and Educational Attainment," *American Economic Review: Insights*, December 2020, *2* (4), 491–508.

**Jacob, Brian A., Lars Lefgren, and David P. Sims**, "The Persistence of Teacher-Induced Learning," *Journal of Human Resources*, October 2010, *45* (4), 915–943. Publisher: University of Wisconsin Press Section: Articles.

**Jolliffe, Dean**, "Skills, Schooling, and Household Income in Ghana," *The World Bank Economic Review*, January 1998, *12* (1), 81–104.

**Kirkebøen, Lars J**, "School value-added and long-term student outcomes," Technical Report 2021.

**Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz**, "Experimental Analysis of Neighborhood Effects," *Econometrica*, January 2007, *75* (1), 83–119. Publisher: John Wiley & Sons, Ltd.

**Kraft, Matthew A.**, "Teacher Effects on Complex Cognitive Skills and Social-Emotional Competencies," *Journal of Human Resources*, January 2019, *54* (1), 1–36.

**Lloyd, Thomas and Dean Yang**, "The Long Shadow of Early Education: Evidence from a Natural Experiment in the Philippines," Technical Report 2024.

**Lopez, Jennifer, Jere Behrman, Santiago Cueto, Marta Favara, and Alan Sánchez**, "Late-childhood foundational cognitive skills predict educational outcomes through adolescence and into young adulthood: Evidence from Ethiopia and Peru," *Economics of Education Review*, June 2024, *100*, 102543.

**Montenegro, Claudio E. and Harry Anthony Patrinos**, "A data set of comparable estimates of the private rate of return to schooling in the world, 1970–2014," *International Journal of Manpower*, January 2021, *ahead-of-print* (ahead-of-print).

**Murnane, Richard J., John B. Willett, Yves Duhaldeborde, and John H. Tyler**, "How important are the cognitive skills of teenagers in predicting subsequent earnings?," *Journal of Policy Analysis and Management*, 2000, *19* (4), 547–568.

**Oster, Emily**, "Unobservable Selection and Coefficient Stability: Theory and Validation," *Journal of Business & Economic Statistics*, 2019, *37(2), 187-204.*

**Perez-Alvarez, Marcello, Catherine Porter, and Anvita Ramachandran**, "Does Human Capital Influence the Gender Gap in Earnings? Evidence from Four Developing Countries," Technical Report 2023.

**Pritchett, Lant**, "Where Has All the Education Gone?," *The World Bank Economic Review*, October 2001, *15* (3), 367–391.

**Psacharopoulos, George and Harry Anthony Patrinos**, "Returns to investment in education: a decennial review of the global literature," *Education Economics*, September 2018, *26* (5), 445–458.

**Sandefur, Justin, Thomaz Alvares de Azevedo, Xiaomin Ju, and Thi Le**, "Phonics and Foreign Aid: Can America Teach the World to Read?," Technical Report November 2023.

**Stern, Jonathan M B, Matthew C H Jukes, Jacobus Cilliers, Brahm Fleisch, Stephen Taylor, and Nompumelelo Mohohlwane**, "Long-Term Impacts of an Effective Early Grade Reading Intervention in South Africa," Technical Report, CGD Working Paper 672 2023.

**Sun, Qian**, "Estimating the earnings returns to exam-measured unobserved ability in China's urban labor market: Evidence for 2002–2013," *China Economic Review*, February 2019, *53*, 180–190.

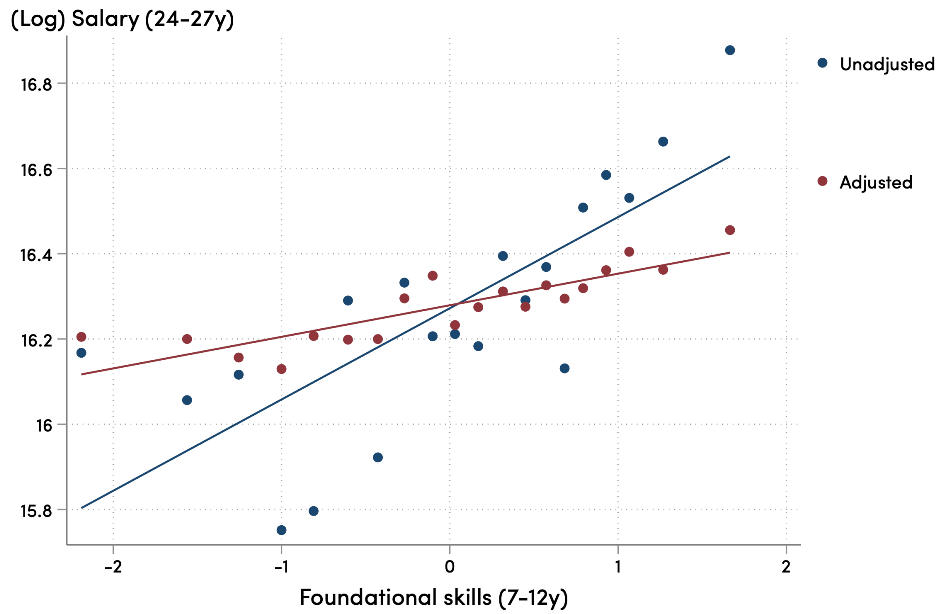
**Suryadarma, Daniel and Asep Suryahadi**, "Determinants of Education Attainment in Developing Countries: Can Higher Skills Compensate for Poverty?," Technical Report 2011.

**UNESCO UIS**, "Policy Linking for Measuring Global Learning Outcomes Toolkit," Technical Report 2023.

**Valerio, Alexandria, Sanchez Puerta, Maria Laura, Sebastian Monroy Taborda, and Namrata Raman Tognatta**, "Are there skills payoffs in low- and middle-income countries ? empirical evidence using STEP data," Technical Report WPS7879, The World Bank November 2016.

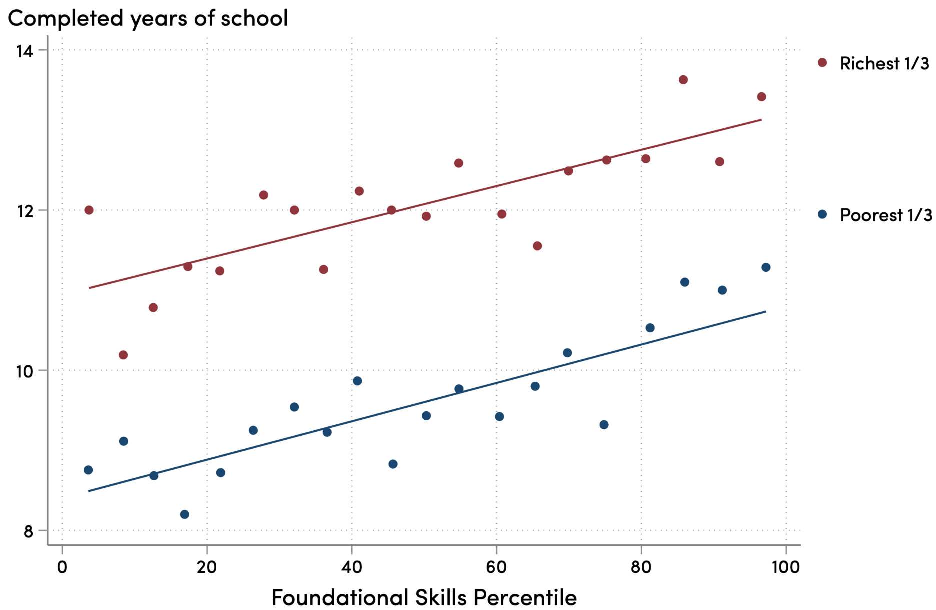
# A Appendix Tables and Figures

Figure A1: Foundational skills and adult earnings




Note: This figure shows a binned scatterplot of foundational skills on the x-axis and log salary on the y-axis. Blue dots and fitted line show the raw unadjusted data, the red dots and fitted line show log income after adjusting for family background, age, gender, location, and with adjustments for selection.

Figure A2: Inequality of opportunity




Note: This figure shows a binned scatterplot with percentiles of foundational skills on the x-axis and completed years of schooling on the y-axis, split by the richest and poorest thirds of households.

Table A1: Foundational skills (age 7-12) and Health Outcomes

| | Height | | Healthy | | Sick last month | | Accessed care | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Age 7-12 | | | | | | | | |
| FLN | 0.219 | 0.134 | 0.011 | 0.007 | 0.117 | 0.119 | 0.001 | 0.003 |
| | (0.144) | (0.146) | (0.009) | (0.009) | (0.097) | (0.101) | (0.008) | (0.008) |
| HH Wealth | 0.479*** | 0.373** | 0.009 | 0.003 | 0.106 | 0.117 | 0.011 | 0.013 |
| | (0.152) | (0.154) | (0.010) | (0.010) | (0.084) | (0.085) | (0.008) | (0.008) |
| Age 24-27 | | | | | | | | |
| Years of Education | | 0.157*** | | 0.010*** | | -0.016 | | -0.001 |
| | | (0.048) | | (0.003) | | (0.029) | | (0.003) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Outcome mean | 158.2 | 158.2 | 0.8 | 0.8 | 1.6 | 1.6 | 0.1 | 0.1 |
| Obs. | 1,976 | 1,961 | 2,052 | 2,040 | 2,052 | 2,040 | 2,189 | 2,051 |
| $R^2$ | 0.56 | 0.56 | 0.03 | 0.03 | 0.03 | 0.03 | 0.05 | 0.05 |

Note: Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, height, and weight. The inverse Mills ratio is estimated with the Heckman selection model, with the interactions of sex, marital status, and having any children being used to predict missing wages. Standard errors clustered at the household level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table A2: Foundational skills and Type of Work (age 24-27)

| | Government | | Formal | | Any Farm | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Age 7-12 | | | | | | |
| FLN | 0.00109 | -0.00409 | 0.0266* | 0.0170 | -0.0165 | -0.0176 |
| | (0.00910) | (0.00887) | (0.0159) | (0.0159) | (0.0126) | (0.0127) |
| HH Wealth | 0.0218** | 0.0103 | 0.0682*** | 0.0488*** | -0.000145 | -0.00187 |
| | (0.00939) | (0.00926) | (0.0152) | (0.0157) | (0.0124) | (0.0130) |
| Age 24-27 | | | | | | |
| Primary | | -0.00988 | | -0.126* | | -0.111* |
| | | (0.0201) | | (0.0743) | | (0.0675) |
| Secondary | | 0.0304** | | 0.0964** | | 0.0502 |
| | | (0.0122) | | (0.0399) | | (0.0316) |
| Tertiary | | 0.136*** | | 0.241*** | | -0.00840 |
| | | (0.0280) | | (0.0406) | | (0.0316) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Outcome mean | 0.073 | 0.073 | 0.453 | 0.453 | 0.286 | 0.286 |
| Obs. | 1,251 | 1,247 | 1,220 | 1,216 | 1,643 | 1,634 |
| $R^2$ | 0.06 | 0.09 | 0.09 | 0.13 | 0.09 | 0.09 |

Note: Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, and height. Standard errors clustered at the household level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table A3: Foundational skills and heterogeneity by gender

| | Earnings | | Employed | | Subjective Wellbeing | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| FLN | 0.082** | 0.049 | -0.020** | -0.023** | -0.009 | -0.022 |
| | (0.040) | (0.040) | (0.009) | (0.009) | (0.031) | (0.031) |
| Female=1 | -0.689*** | -0.710*** | -0.310*** | -0.312*** | 0.264*** | 0.260*** |
| | (0.076) | (0.076) | (0.017) | (0.018) | (0.040) | (0.040) |
| Female=1 × FLN | 0.074 | 0.067 | 0.044** | 0.044** | -0.042 | -0.041 |
| | (0.071) | (0.071) | (0.018) | (0.018) | (0.040) | (0.040) |
| Years of Education | | 0.072*** | | 0.006* | | 0.032*** |
| | | (0.013) | | (0.003) | | (0.007) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Outcome mean | 16.27 | 16.27 | 0.77 | 0.77 | 2.28 | 2.28 |
| Obs. | 1,434 | 1,430 | 2,062 | 2,051 | 2,062 | 2,051 |
| $R^2$ | 0.17 | 0.18 | 0.15 | 0.15 | 0.06 | 0.06 |

Note: Controls are all measured at age 7-12, and include sex, age, parental education, school grade, household wealth, and height. The inverse Mills ratio is estimated with the Heckman selection model, with the interactions of sex, marital status, and having any children being used to predict missing wages. Standard errors clustered at the household level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.