The Causal Effects of Multidimensional School and Household Poverty on Student Achievement: An IV-Latent Class Analysis

Danny Turkson[1], Samiratu Wahab[2], Frederick Richmond Yorke[3], and Sarah Akyena[4]

[1]University of North Carolina, Chapel Hill
[2]University of Birmingham
[3]University of Ghana
[4]Georgia State University

Abstract

This paper estimates the causal effects of multidimensional school and household poverty on student achievement in Mathematics and English. Using data from the 2016/17 Young Lives school survey covering seventh- and eighth-grade students across 30 public schools in Ethiopia, we construct poverty indices at both levels using the Alkire-Foster framework and estimate value-added models combining instrumental variables with latent class analysis (IV+LCA), exploiting cross-subject scores as an instrument and recovering five discrete student ability types. Achievement is highly persistent across grades, but much of this persistence reflects stable differences in latent ability rather than genuine state dependence. The preferred IV+LCA estimates reveal an asymmetry between the two poverty dimensions: household poverty carries a robust negative effect on English achievement, while its Mathematics effect is not statistically significant, and school poverty loses significance once student composition is properly accounted for. This points to household-level constraints (limited assets, poor health, and disrupted schooling) as the primary barrier to learning, even after conditioning on school quality and prior achievement. Heterogeneous effects show that school poverty in Mathematics matters most for average-ability students and is significantly larger for girls than for boys, pointing to a gendered dimension of disadvantage that aggregate estimates obscure. Policy simulations indicate that eliminating school infrastructure deprivation yields a predicted Mathematics gain of around 0.46 points, equivalent to 6 percent of a standard deviation, while household interventions targeting asset poverty and health generate English gains of up to 0.13 points, equivalent to 1.8 percent of a standard deviation. The findings make a case for redirecting education policy attention toward household deprivations and demonstrate that multidimensional poverty measurement reveals levers that income-based measures would miss.

Keywords: multidimensional poverty; value added model; latent class analysis; Ethiopia

JEL Codes: I21; I25; O15; O18

1 Introduction

Globally, quality education is crucial for both individual growth and social development (Idris et al., 2025). School enables individuals to attain emotional intelligence and cognitive development. It also promotes civic engagement, effective communication, and active participation in lifelong learning (Mutala, 2023; Rasheed et al., 2024; Mahmood and Zafar, 2025). An efficient school community and strong systems are therefore essential for high-quality teaching and high learning outcomes. One of the means through which researchers and policymakers assess the effectiveness of education is through the academic performance of students. High academic performance indicates quality teaching practices, a conducive academic atmosphere, and adequate resources, whereas poor academic performance emphasizes challenges such as poor teaching quality and lack of resources Suleiman et al. (2024). Learning outcomes affect several aspects of an individual's life, including academic pursuits, career paths, and earning potentials (Tilbe and Biru, 2026). Researchers have also linked high academic performance to better health outcomes and improved social mobility (Gamage et al., 2021; Tilbe and Biru, 2026). Academic achievement is therefore beneficial to individuals and society, both in the short run and long run (Kelly and Donaldson, 2016).

In recent decades, researchers have revealed that, school physical environment is among the factors that influence school performance. In Africa, studies have suggested that schools with infrastructural facilities produce higher academic achievers than schools with inadequate academic facilities (Mohammed and Abera, 2022; Tilbe and Biru, 2026). In emphasizing the essential role of infrastructure in educational outcomes, UNESCO (2008) explained that all stakeholders must be involved to ensure well-equipped libraries, laboratories, and efficient classroom conditions to achieve effective teaching and learning outcomes. An efficient, inclusive, and enabling school environment promotes collaborations and student engagement, supports learning, and increases school attendance, whereas poor infrastructural facilities increase absenteeism, dropout rates, and behavioral issues (Mahmood and Zafar, 2025) and can have negative impacts on learning outcomes (Assoumpta and Andala, 2020). In addition to the infrastructural facilities, factors such as teacher-student ratio and teaching quality contribute to learning outcomes (Wiswall, 2013; Chetty et al., 2014; Waita et al., 2016; Wang and Du, 2024). Many developing countries face infrastructural challenges and staff inadequacy, especially at the primary and secondary education levels, which tend to impact the learning outcomes of students. In Ethiopia, the decline in academic performance among primary students has been associated with low teaching quality, low student-teacher ratio, overcrowded classrooms, inadequate facilities, and poor leadership (Abitew, 2019; Tilbe and Biru, 2026).

Studies have also linked academic performance with household socioeconomic status and facilities like internet and electricity (see for instance, Wang and Du, 2024; Tilbe and Biru, 2026). Lack of access to the internet and electricity poses challenges to students in their academic work, which often leads to poor learning outcomes. Children who belong to poor homes also face energy challenges in their academic pursuits resulting in low learning outcomes (Jamil et al., 2018; Adigun, 2023; Wang and Du, 2024). In addition, studies have suggested that parental or household income enhances the school performance of children (see for instance, Dahl and Lochner (2005); Duncan et al. (2011); Breger (2017)). Wealthy parents can provide the educational needs of their children and are in the position to enroll them in supplemental educational programs, such as private tuition, to increase their school performance and academic achievements. According to Cooper and Miralay (2022), children from low-income countries face delays in cognitive development and poor learning outcomes due to poverty. Cooper and Miralay (2022) explained that in low-income countries, poverty makes it difficult for parents to afford books and other educational materials needed by children to achieve higher learning outcomes. In Ethiopia, poor school performance is also associated with malnutrition (Dessie et al., 2025), which is also associated with poverty (Van Malderen et al., 2019).

In this study, we examine the impact of school poverty and household poverty on student academic performance in Ethiopia. We construct school poverty and household poverty indices using the Alkire and Foster (2011) multidimensional poverty index (MPI). Student performance measured by English and Maths testscore is constructed as a function of school poverty, household poverty and lagged achievement. To address potential endogeneity that may arise from lagged achievement and unobserved heterogeneity in learning ability, we estimate value-added models combining instrumental variables with latent class analysis (IV+LCA). We exploit cross-subject performance or achievement as an instrument for lagged achievement and consider five discrete student ability types from the joint distribution of test scores. We use data from the 2016-2017 Young Lives school survey in Ethiopia which collects data on children, their school and teachers, and their household conditions.

Our estimates evolve from using an OLS model to an IV only model, an LCA only model and then to a combined IV+LCA model. In our OLS specifications, both school poverty has a negative effect on English and Maths scores. When the instruments are considered in our IV only estimates, the coefficients are still negative but with reduced gaps. The LCA only specification dissolves the school poverty effects and they become insignificant while household poverty retains a significant negative effect for English but loses significance for Mathematics. In our preferred IV+LCA specifications we find that school poverty leads to a statistically significant increase in Maths scores (0.85). Although the coefficient for school poverty is also positive under our English specification, it is not significant (0.60). Household poverty on the other hand results in a negative and statistically significant effect on English scores (0.45), while the effect on Maths scores (0.20) is no longer statistically significant. These results suggest the compositional nature of the channels through which school poverty operates compared to household poverty, that could cause learning damages in ways that school quality alone cannot offset. Additionally, while student achievement is highly persistent across grades, it is highly driven by stable differences in latent ability rather than by genuine state dependence.

Our study contributes to the extant literature that have examined various factors affecting school performance in developing countries (see for instance, Yangambi, 2023; Wanke et al., 2024; Mahmood and Zafar, 2025). The outcomes of these studies underscore the crucial role of various factors, including household income, school infrastructure, energy sources, student-teacher ratio, and teacher quality, in determining the school performance of students. Although our findings complement these studies, our paper differs in several ways. First, we focus on both school poverty and household poverty, presenting their joint effects on student achievement. Most studies have either focused on household poverty or school poverty separately to capture distinct dimensions of poverty. Second, we construct both school and household poverty from a multidimensional framework, providing a more accurate capture of deprivations compared to single-indicator measures like household income or school infrastructure. Understanding how multidimensional school and household poverty affect the school performance of children will provide targeted insights for policymakers to design policies to enhance academic performance and human capital development. Moreover, we utilize latent class analysis, and consider five discrete student ability types to capture unobserved heterogeneity across students that would have otherwise been unaccounted for. Apart from improving our model specification, this approach also provides additional insights into how much heterogeneity lies beneath average achievement figures for policy purposes.

The rest of the paper proceeds as follows. Section 2 reviews the relevant literature. Sections 3 and 4 lay out the theoretical motivation and empirical framework. Section 5 describes the data and measurement approach. Section 6 presents the main estimation results alongside heterogeneous effects by student ability type and gender. Section 7 discusses the findings in relation to the broader literature. Section 8 presents policy simulations based on the estimated parameters. Section 9 concludes.

2 Literature Review

The effect of school poverty on school performance has been explored in both developed and developing countries. In many developing countries, poor academic performance among students is attributed to poor physical facilities. For instance, in Congo, Yangambi (2023) examine the effect of school infrastructure on academic performance and finds that poor school facilities negatively affect student learning and academic performance. Similar outcome was found by Mokaya (2013) in Kenya, Assoumpta and Andala (2020) in Rwanda, Jamil et al. (2018) and Jamshaid et al. (2024) in Pakistan, and Murillo and Román (2011) in Latin America, which suggest that school infrastructures play a significant role in school performance and academic performance of students. Facilities such as adequate science laboratories, adequate libraries, adequate and well-spaced classrooms, and adequate water and sanitation facilities are essential for academic performance of students (Mokaya, 2013).

In Brazil, Wanke et al. (2024) employed a quantile regression model to examine 35,490 schools in urban and rural Brazil. The outcome of the study shows that facilities such as school libraries, projectors, computer facilities and televisions play a significant role in the academic performance of primary school students. School infrastructures are a major factor in the provision of quality education. Physical facilities provide students with a conducive atmosphere for academic work, which contributes immensely to their academic performance (Shami and Hussain, 2005). In the United Kingdom, Teixeira et al. (2017) find that school infrastructural facilities enhance students' academic performance and explain about 16% of the changes in school achievement among primary school students.

Studies have also explored student-teacher ratio and school performance. For instance, Reeves (2003) employed 2-level hierarchical linear modelling to examine student poverty and school performance among Kentucky public schools. The outcome of the study shows that student poverty has a negative effect on school performance. Specifically, high student/teacher ratio negatively influences school improvement. Hence, Reeves (2003) suggests the need to reduce student/teacher ratio in low-performing schools, especially for early grade students, to improve school performance. A similar outcome was found by Waita et al. (2016) in Kenya. Their study involved 78 public schools. The outcome of the study shows that a high student/teacher ratio is associated with poor academic performance in national examinations.

Beyond physical infrastructure and staffing, a related strand of the literature draws attention to energy poverty as a distinct channel through which school-level disadvantage shapes learning outcomes. Studies have also examined energy poverty and child academic performance. Generally, energy poverty is negatively associated with education. Lack of reliable and affordable energy directly affects the quality of education. For instance, without internet and electricity, students often face challenges in pursuing their academic work. Additionally, schools that have no electricity access, no or poor internet access, poor heating or cooling systems often face low attendance rates and teacher retention problems, which contribute to poor academic performance among school children (Nsenkyire et al., 2023; Katoch et al., 2024).

Employing Ordinary Least Squares (OLS) and Ordered Logit regressions, Wang and Du (2024) used data from the 2012-2018 Chinese Family Panel Studies (CFPS) and found that energy poverty has a negative impact on the academic performance of school-age children in Chinese households. A similar outcome was found by Martirosyan (2023). The study showed that winter heating in schools positively influence the academic performance of school children. Similarly, Jamil et al. (2018) found that access to electricity and gas positively influence academic performance, especially among students in rural schools. Zhang et al. (2021) also found that energy poverty negatively affects mathematics subject performance, Chinese subject performance, and children's subjective wellbeing. Energy is a basic need of modern society, and adequate energy is required to pursue needs such as learning and self-actualization (Xiao et al., 2021), hence lack of access to facilities such as internet and electricity has a detrimental effect on the academic performance of students.

While the school-based literature focuses on the supply side of education, a parallel body of work examines how conditions in the home shape children's academic trajectories. Household poverty matters not only because it limits what parents can provide in terms of books, nutrition, and study space, but also because it constrains the time and cognitive bandwidth children can devote to learning. Understanding the effects of family poverty on children's achievements in school is essential for policy design and implementation, as household resource disparities may translate into persistent learning disparities. Evidence exists of a strong relationship between student outcomes and family or household poverty or income (see, for instance, Duncan et al. (2011); Breger (2017); Dahl and Lochner (2005)). Duncan et al. (2011) utilised data from a combination of 16 welfare and antipoverty programs and sites[1], and the instrumental variables approach to study the impact of family income on child achievement. Using the interaction between program treatment group assignments and site as an instrument to obtain exogenous variations in family income, the study finds an important positive impact of family income on pre-school children's school achievement. Family incomes for younger children were boosted by between due to the earnings supplement programs, raising children's achievements by between 5% and 12% standard deviations, suggesting that by raising family income, there is a proportionally larger impact on children.

Dahl and Lochner (2005) use a fixed effects instrumental variables approach to deal with identification problem, such as unobserved child or household characteristics that may correlate with both family income and child performance outcomes [2]. They examine the causal impact of family income on children's mathematics and reading performance using panel data from the National Longitudinal Survey of Youth (NLSY) and a sample of more than 6000 children. The results reveal that children from families with higher family income experience a rise in both math and reading performances, although the performance in reading is larger. When comparing children from parents with different characteristics, they find that most disadvantaged children who are most affected by the large changes in the Earned Income Tax Credit (EITC), such as black or Hispanic, not married, less educated and parents with two or more children, experience larger effects. In a most recent

[1] These programs and sites include Florida's Family Transition Program, the National Evaluation of Welfare-to-Work Strategies in Georgia, Michigan and California, the New Hope Project, the Los Angeles Jobs-First Greater Avenues for Independence Evaluation, the Minnesota Family Investment Program in rural and urban counties, Connecticut's Jobs First, and the Canadian Self-Sufficiency Project in British Columbia and New Brunswick.

[2] They use Earned Income Tax Credit (EITC) as an instrument for family income measured by pre-tax/transfer family income in their FEIV strategy.

study by Breger (2017), such biases addressed by Dahl and Lochner (2005) and Duncan et al. (2011) were not considered. Breger (2017) studies the impact of both family poverty and school poverty on achievement levels in Chicago Public Schools. Their results can be interpreted as a correlation. Thus, test scores measured by the percentage of students that passed mathematics, science and reading in ISAT exams are found to be lower for poor schools and poor families.

Alongside poverty-focused research is a substantial literature on teacher quality, which identifies the classroom as another critical node in the education production function. The reason this matters for our study is that teacher quality and school poverty are not independent: as the descriptive evidence in Section 5 shows, more deprived schools systematically attract less experienced and less credentialed teachers, meaning that the staffing channel compounds the infrastructure channel in shaping outcomes for disadvantaged students. Teachers are an important school-based input in the education production function. Variation in teacher quality, as typically measured by their contribution to student test scores (value added), has been shown to explain some of the differences in achievements across students. For example, Rockoff (2004) uses linked student-teacher data to examine the effect of student exposure to high-quality on test scores. Results from his analysis show that increases in teacher quality are associated with an increase in student performance on math and reading standardized tests. Consistent with these results, Rivkin et al. (2005) also found that variation in teacher quality reveals that teachers have predictive power on students' reading and mathematics achievements. A recent study by Chetty et al. (2014) shows that increases in teacher value added raise students' test scores, consistent with Rockoff (2004) and Rivkin et al. (2005), and improve outcomes in adulthood.

A natural question that emerges in the discussion of teacher quality is what characteristics of teachers are more predictive of their quality or value added? Evidence in the literature shows that teachers' experience significantly improves student scores, especially on reading tests (see Wiswall (2013)). Wiswall finds that the experience effect is much larger for student math achievements and persists over time. Similarly, Rivkin et al. (2005) find that teacher experience impacts test scores, but other However, Aaronson et al. (2007) find that teacher characteristics, such as advanced degrees and certification, have less predictive power on teacher quality. In our paper, we isolate the effect of teacher value added on students' test scores using their experience. We also include additional controls, such as teacher credentials and certification. The literature reviewed points toward a picture of educational disadvantage that is multidimensional and mutually reinforcing: poor schools lack infrastructure and energy access, attract weaker teachers, and draw students from households already constrained by income poverty. Disentangling these channels, and quantifying each one separately, is precisely what motivates the empirical strategy developed in the next two sections.

3 Theoretical Motivation

We examine how two distinct dimensions of poverty: school poverty P_{it}^S and household poverty P_{it}^H; shape students' academic achievements in Mathematics ($k = m$) and English ($k = e$). A central feature of our framework is the recognition that students differ in time-invariant latent learning ability θ_i, which captures unobserved cognitive endowments, early childhood investments, and other permanent factors that influence how productively students convert inputs into achievement. For student i attending school s at time t, subject-specific achievement is denoted y_{it}^k.

3.1 Household Optimization and the Role of Household Poverty

We motivate the household poverty channel through a standard intertemporal household maximization problem. Parents derive utility from own consumption C_{it} and from their children's academic achievements in Mathematics and English:

$$U = \sum_t \rho^t \Big(u(C_{it}) + \lambda\,\mathbb{E}\big[Y_{it}^m + Y_{it}^e\big] \Big), \tag{1}$$

where $\rho \in (0,1)$ is the discount factor and $\lambda > 0$ governs the weight placed on children's achievement relative to consumption. Parents choose consumption and home learning inputs h_{it} (study time, educational materials, nutritional support, health investments) subject to a budget constraint:

$$C_{it} + p_h\, h_{it} \;\le\; w_{it} + T_{it}, \qquad h_{it} \ge 0, \tag{2}$$

where p_h is the unit price of home learning inputs, w_{it} is household income, and T_{it} denotes any external transfers.

Household poverty operates through two reinforcing channels in this framework. First, it reduces the resources available to invest in children by lowering effective income:

$$w_{it} = w_{it}\Big(P_{it}^H\Big), \quad \frac{\partial w_{it}}{\partial P_{it}^H} < 0.$$

Second, poverty raises the effective price of learning inputs, through limited market access, poor health, or asset deprivation, thereby distorting the input mix:

$$p_h = p_h\Big(P_{it}^H\Big), \quad \frac{\partial p_h}{\partial P_{it}^H} > 0.$$

Jointly, these channels reduce the optimal level of home inputs h_{it}^* and compress their productivity.

We represent this as:

$$\text{Effective home learning} = \phi\left(P_{it}^{H}\right) \cdot h_{it}, \qquad \phi'(\cdot) < 0, \tag{3}$$

so that a household facing greater multidimensional deprivation in assets, water access, health, and educational continuity is doubly penalized: it supplies fewer inputs and each unit of input is less productive.

3.2 School Poverty and the Supply of School Inputs

Schools supply instructional inputs q_{it} such as teacher effectiveness, laboratory and ICT access, adequate sanitation, and reliable electricity. These inputs are constrained by school poverty:

$$q_{it} = \bar{q} - \kappa\, P_{it}^{S}, \qquad \kappa > 0, \tag{4}$$

where $\bar{q}$ denotes the input level achievable under no deprivation and κ captures the sensitivity of school inputs to poverty. The multidimensional school poverty index P_{it}^{S} aggregates deprivations across three dimensions: standard of living (sanitation, water), lighting (electricity), and infrastructure (computers, internet, laboratories, library, radio). Each of which reduces specific inputs: electricity deprivation constrains ICT usage and after-hours study; inadequate laboratories limit science instruction; poor sanitation increases absenteeism; weak infrastructure hampers teacher retention and printing. The linear specification in equation (4) provides a tractable first-order approximation to these mechanisms.

3.3 Latent Student Ability and Achievement Production Function

A key feature of the framework is the explicit modelling of time-invariant student heterogeneity. Let θ_i denote a student's latent learning ability, capturing permanent endowments that determine how productively inputs are converted into achievement across all subjects. This includes unobserved factors such as early childhood development, innate cognitive capacity, and persistent home learning environments that are not fully captured by observed household or school characteristics. We assume θ_i is time-invariant: it shapes the level and growth of achievement in every period but does not itself change as a result of schooling during the window under study. Critically, because θ_i influences performance in all subjects simultaneously, it induces a positive correlation across subject-specific test scores. This cross-subject correlation is the foundation of our instrumental variable strategy: lagged achievement in one subject serves as an instrument for lagged achievement in another, since both are driven by the same underlying ability type while subject-specific shocks remain largely orthogonal across subjects.

Given household inputs, school inputs, and latent ability, the subject-specific achievement production function follows the cumulative skill model of Todd and Wolpin (2007):

$$y_{it}^{k} = A_k(\theta_i)\Bigg[\underbrace{\eta_k\big(y_{i,t-1}^{k}\big)}_{\text{dynamic complementarity}} + \underbrace{g_k(h_{it})}_{\text{home inputs}} + \underbrace{r_k(q_{it})}_{\text{school inputs}}\Bigg] + \varepsilon_{it}^{k}, \tag{5}$$

where $A_k(\theta_i) > 0$ is an ability-specific productivity multiplier that scales the returns to all inputs, and ε_{it}^{k} is an idiosyncratic shock. The term $\eta_k(y_{i,t-1}^{k})$ captures dynamic complementarity: prior achievement raises the marginal productivity of current inputs, consistent with the developmental literature. The functions g_k and r_k translate home and school inputs, respectively, into subject-specific learning gains.

Assuming linearity and substituting the expressions for effective home learning (3) and school inputs (4), the production function reduces to the estimating equation:

$$y_{it}^{k} = \alpha_k + \gamma_k\, y_{i,t-1}^{k} + \beta_k^{H}\, P_{it}^{H} + \beta_k^{S}\, P_{it}^{S} + \mathbf{X}_{it}'\,\delta_k + \theta_i + \varepsilon_{it}^{k}, \qquad k \in \{m, e\}, \tag{6}$$

where γ_k captures the degree of dynamic persistence in achievement, β_k^{H} and β_k^{S} are the causal effects of household and school poverty on subject k, $\mathbf{X}_{it}'$ contains observed student, teacher, and household controls, and θ_i is the time-invariant student-level unobservable that would be estimated via latent class analysis. The econometric challenges of estimating equation (6) are endogeneity of the lagged dependent variable and unobserved heterogeneity in θ_i, which are addressed in Section 4.

4 Empirical Framework

4.1 Specification

The student achievement production function follows the standard value-added approach of Andrabi et al. (2011). Let $\mathbf{x}_{it}$ denote the vector of all observed student, household, and school inputs for student i at grade (time) t, and let y_{it}^{k} denote the test score in subject $k \in \{m, e\}$. The general achievement function is:

$$y_{it}^{k} = f\Big(y_{i,t-1}^{k},\, \mathbf{x}_{it},\, e_{it}^{k}\Big), \tag{7}$$

where e_{it}^{k} collects all unobservables. Assuming linearity and suppressing the subject superscript for brevity, equation (7) becomes:

$$y_{it} = \gamma\, y_{i,t-1} + \boldsymbol{\beta}'\mathbf{x}_{it} + e_{it}. \tag{8}$$

The parameter γ captures dynamic persistence, which is the degree to which past achievement carries over into current performance, while $\boldsymbol{\beta}$ is the vector of input coefficients. The inclusion of lagged achievement $y_{i,t-1}$ ensures that $\boldsymbol{\beta}$ identifies the value added by current inputs, net of all accumulated prior learning.

The error term e_{it} contains two components that must be separated. First, students differ in time-invariant latent learning ability θ_i, introduced in Section 3 as the permanent endowment that determines how productively inputs are converted into achievement across all subjects. This encompasses unobserved factors such as innate cognitive capacity, early childhood investments, and persistent home learning environments that are not captured by the observed controls in $\mathbf{x}_{it}$. Second, u_{it} is a mean-zero idiosyncratic shock, independent across students and time periods. Decomposing $e_{it} = \theta_i + u_{it}$ yields:

$$y_{it} = \gamma\, y_{i,t-1} + \boldsymbol{\beta}'\mathbf{x}_{it} + \theta_i + u_{it}. \tag{9}$$

Equation (9) contains two sources of endogeneity that would bias OLS estimates. First, θ_i is correlated with $y_{i,t-1}$ by construction: students with higher permanent ability achieve more in every period, inducing upward bias in $\hat{\gamma}$. Second, $y_{i,t-1}$ may be correlated with u_{it} because past achievement embeds earlier realisations of transitory shocks that persist through time. We address each problem in turn: the endogeneity of $y_{i,t-1}$ through instrumental variables (Section 4.1.1), and heterogeneity in θ_i through latent class analysis (Section 4.1.2). Section 4.1.3 presents the combined IV+LCA estimator.

We note that school-level heterogeneity is not addressed through school fixed effects. Instead, systematic differences across schools are captured by the multidimensional school poverty index P^S_{it} which aggregates deprivations in infrastructure, lighting, and standard of living, together with regional and urban/rural location controls included in $\mathbf{x}_{it}$. This approach reflects the structure of the data and estimation, and is consistent with the theoretical framework in which P^S_{it} is the primary channel through which school-level disadvantage operates.

4.1.1 Instrumental Variables: Addressing Lagged Achievement Endogeneity

To address the endogeneity of $y_{i,t-1}$, we instrument it using the student's lagged achievement in the *other* subject. For the Mathematics equation we use lagged English score as the instrument, and for the English equation we use lagged Mathematics score. Denote the instrument as $Z^k_{i,t-1}$, where for subject $k = m$, $Z^m_{i,t-1} = y^e_{i,t-1}$, and vice versa. The first-stage equation is:

$$y^k_{i,t-1} = \pi^k Z^k_{i,t-1} + \boldsymbol{\mu}'\mathbf{x}_{it} + \nu^k_{it}, \tag{10}$$

where ν_{it}^k is the first-stage residual. The predicted value $\widehat{y}_{i,t-1}^k$ from equation (10) then replaces $y_{i,t-1}^k$ in the second stage:

$$y_{it}^k = \gamma^k \,\widehat{y}_{i,t-1}^k + \boldsymbol{\beta}'\mathbf{x}_{it} + \theta_i + u_{it}^k. \tag{11}$$

A valid instrument must satisfy the relevance and exclusion restriction assumptions. Regarding relevance, lagged English achievement must be a strong predictor of lagged Mathematics achievement, and vice versa. This condition is credible because both subjects load on the same underlying latent ability θ_i: a student with higher permanent learning capacity performs better across all subjects in every period.[3] Regarding the exclusion restriction, the instrument must affect current achievement in subject k only through its effect on lagged achievement in the same subject, that is, $\mathbb{E}(u_{it}^k \mid Z_{i,t-1}^k) = \mathbb{E}(u_{it}^k)$. The key identifying assumption is that, conditional on observed controls $\mathbf{x}_{it}$ and latent ability θ_i, subject-specific contemporaneous shocks are orthogonal across subjects. For example, a student's current Mathematics performance may be affected by the quality of their Mathematics teacher in grade t, but this teacher-specific shock should not directly influence their prior English score from grade $t-1$. While both subjects share the general ability channel (absorbed by θ_i in the LCA step), curriculum-specific inputs, teacher assignments, and subject-specific effort allocation generate variation that is plausibly orthogonal across subjects within the same student and time period. The exclusion restriction would be violated if, for instance, students who received remedial English support in grade $t-1$ experienced direct spillovers into their Mathematics performance in grade t through channels unrelated to general ability. We consider this unlikely in the Ethiopian context, where subject-specific instruction is largely independent across classrooms.

4.1.2 Latent Class Analysis: Addressing Unobserved Heterogeneity

Even after instrumenting for $y_{i,t-1}^k$, the student-specific effect θ_i in equation (11) remains unobserved. Standard fixed-effects approaches cannot be applied here because we observe each student at only two time points, making within-student differencing infeasible without eliminating all time-invariant regressors of interest, including the poverty indices themselves. Instead, we model θ_i as a discrete latent variable using latent class analysis (LCA).

Let $C_i \in \{1, 2, \ldots, K\}$ denote the latent class membership of student i, where each class corresponds to a distinct ability type. The class membership probabilities are determined by class-specific

[3] We verify relevance empirically by reporting the first-stage F-statistic, with the conventional threshold of $F > 10$ as a benchmark for instrument strength.

intercepts:

$$\Pr(C_i = \ell) = \frac{\exp(\alpha_\ell)}{\sum_{h=1}^{K} \exp(\alpha_h)}, \qquad \ell = 1, 2, \ldots, K. \tag{12}$$

Within each class, student test scores across the $J = 3$ subjects (Mathematics, English, and Amharic) are assumed to be conditionally independent and normally distributed:

$$y_{ji} \mid (C_i = \ell) \sim \mathcal{N}\left(\mu_{j\ell}, \sigma_j^2\right), \qquad j = 1, 2, \ldots, J, \tag{13}$$

where $\mu_{j\ell}$ is the class-specific mean score on subject j and σ_j^2 is a subject-specific variance assumed common across classes. The local independence assumption (that is conditional on class membership, test scores across subjects are uncorrelated) is central to the LCA framework. It implies that once a student's latent ability type is known, the remaining variation in scores across subjects is pure noise. Any residual cross-subject correlation in the data is therefore attributed to heterogeneity in θ_i rather than to direct subject-to-subject spillovers.

The marginal distribution of observed scores follows a finite mixture of Gaussians:

$$f(y_{1i}, \ldots, y_{Ji}) = \sum_{k=1}^{K} \Pr(C_i = \ell) \prod_{j=1}^{J} \phi\left(y_{ji}; \mu_{j\ell}, \sigma_j^2\right), \tag{14}$$

where $\phi(\cdot; \mu, \sigma^2)$ is the Gaussian density. The optimal number of classes K is selected by minimising the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), subject to model convergence.

Once class membership probabilities are estimated, each student is assigned a posterior ability type, and a set of $K - 1$ student-type indicators $\mathbf{d}_i$ relative to the reference class, enters the estimating equation as additional regressors. This parameterises θ_i as one of K discrete values, effectively controlling for the primary source of unobserved heterogeneity in the value-added model.

4.1.3 Combined IV+LCA Estimator

Our preferred specification combines both corrections in three steps. In the first step, LCA is estimated on the joint distribution of Mathematics, English, and Amharic scores to recover posterior class membership probabilities and student-type indicators $\mathbf{d}_i$. In the second step, the first-stage regression (10) is re-estimated augmented with $\mathbf{d}_i$, so that the instrument $Z_{i,t-1}^k$ captures variation in lagged achievement that is orthogonal to both observed controls and latent ability. In the third step, the predicted value $\widehat{y}_{i,t-1}^k$ from the augmented first stage enters the following second-stage equation:

$$y_{it}^{k} = \gamma^{k}\,\widehat{y}_{i,t-1}^{k} + \beta_{H}^{k}\,P_{it}^{H} + \beta_{S}^{k}\,P_{it}^{S} + \mathbf{X}_{it}'\,\boldsymbol{\delta}^{k} + \underbrace{\boldsymbol{\psi}'\mathbf{d}_i}_{\theta_i} + u_{it}^{k}, \qquad k \in \{m, e\}, \tag{15}$$

where P_{it}^{H} is the household poverty index, P_{it}^{S} is the school poverty index, $\mathbf{X}_{it}$ contains observed student, teacher, household, regional, and location controls, and $\mathbf{d}_i$ is the vector of student-type indicators from the LCA. The coefficients of primary interest are β_H^k and β_S^k, which capture the causal effects of household and school poverty on subject k achievement, respectively, conditional on dynamic persistence, latent ability, and all observed controls.

To provide a transparent account of how successive modelling choices affect the estimates, we report four specifications for each subject: (i) OLS, which estimates equation (9) directly, treating θ_i as part of the composite error; (ii) IV alone, which instruments $y_{i,t-1}^{k}$ but leaves θ_i unmodelled; (iii) LCA alone, which controls for discrete ability types via $\mathbf{d}_i$ but does not instrument $y_{i,t-1}^{k}$; and (iv) the combined IV+LCA specification in equation (15), which is our preferred estimator.

5 Data

5.1 Data source

The data employed in this study is obtained from the 2016-2017 school survey collected in Ethiopia. The survey was conducted by Young Lives, an international body that conducts study on childhood poverty in developing countries such as Ethiopia, Peru, India and Vietnam. In addition to data on nutrition, health, education and livelihood, the survey provides information or data on children, their school and teachers, as well as the conditions in their households. The survey thus helps in deepening the knowledge on educational experience and the impact, causes and effect of childhood poverty. The first school survey conducted by Young Lives in Ethiopia was in 2009/10, whiles the second survey was conducted in 2012/13. These collect data on all Young Lives children and peers in Grade 4 and 5 in the 20 survey sites of Young Lives (located in Oromia, SNNP, Tigray, Amhara and Addis Ababa) in addition to other 10 sites located in Afar and Somali. The third and the most recent survey was conducted in 2016/17. This survey samples all schools within the 30 Young Lives school survey sites, irrespective of their ownership. The survey provides information on all school directors, all Grade 7 and 8 students who were taking the student tests for the first time, and all English and Mathematics teachers to these students. The survey thus captures all the student participant in the 2012/13 survey as well as any Young Lives younger cohort who have reached Grade 7 or 8. Our final analysis sample was 7,631 students after dropping students who did not take the test.

5.2 Measure

5.2.1 School and Household poverty

Poverty has been identified as a complex phenomena comprising simultaneous deprivations in multiple indicators. As such, different methodological approaches have been propounded to measure poverty as a composite index from different dimensions (indicators) including Atkinson (2003) and most recently, Alkire and Foster (2011) measure. In this study, we employ the Alkire and Foster (2011) multidimensional poverty index (MPI) which has been extensively applied in the literature (see for instance Agyire-Tettey et al. (2021); Osei and Turkson (2022), on child poverty in Ghana; Abbas et al. (2020), on energy poverty in South Asia; Sadath and Acharya (2017) on energy poverty in India). The Alkire and Foster (2011) MPI is a robust and reliable framework that captures different dimensions (indicators) of poverty that may simultaneously affect an individual. It allows us to obtain poverty scores for each individual using two distinct poverty cutoffs and also to capture both incidence and severity of poverty through aggregation.

In this paper, our MPI captures 6 indicators of school poverty carefully grouped into 2 dimensions and 4 indicators of household poverty grouped into 3 dimensions. Table 1 shows the details of dimensions, indicators and cutoffs below which one is considered as deprived in all indicators. School deprivation depicted in Panel A is measured using basic school needs including the following indicators: electricity, internet access, laboratories, libraries, radio and computer access and grouped into the following dimensions: lighting and school infrastructure. On the other hand, indicators for household poverty shown in Panel B include assets, access to water, diseases and school gap grouped into dimension: Standard of living, health and education.

The MPI involves two steps: identification and aggregation. Identification firstly identifies who is deprived in each indicator and secondly identifies who is multidimensionally deprived when each person's score is compared to a certain deprivation score cutoff. Aggregation collates the deprivation profiles of different members and computes the deprivation indices.

We start by presenting an $n * d$ matrix Z. Z contains the achievements of each individual i ($i = 1 \dots n$) in each indicator j ($j = 1 \dots d$), hence z_{ij} represents the achievement of individual i on indicator j. If the child does not meet the cutoff, v_j, for an indicator, say $z_{ij} < v_j$, the child is said to be deprived on that indicator and given a value of 1 in the deprivation matrix, g^0. Further, we assign a weight, w, to each indicator. Electricity, computer, radio, internet, laboratories, library, assets and water have weights 0.167 each while diseases and school gap have weights 0.333 each. There is an equal dimensional weighting for household poverty, and equal indicator weighting for school poverty. In addition, the sum of weights under each poverty type is equal to 100 percent or 1 (i.e. $\sum_{j=1}^{d} w_j = 1$). A column vector, c_i, of weighted deprivation score is then collected, where $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$.

A second cutoff, k, which defines who is multidimensionally poor is then introduced. In this paper, $k = 0.5$, meaning a child is found poor if their weighted deprivation score c_i is greater than k (i.e. $c_i \geq k$). We use the weighted deprivation score of each individual as our main independent variable in our estimates. This is taken from a censored multidimensional deprivation matrix $(g^0(k))$, where 1 is assigned to individuals who are multidimensionally deprived ($c_i \geq k$) and 0 otherwise ($c_i < k$).

Finally, we can obtain the MPI as the product of Poverty headcount, H and intensity or intensity of poverty S (i.e. $MPI = H * A$). Headcount H is therefore computed as:

$$H = \frac{q}{n} \tag{16}$$

Where q represents the number of children who are multidimensionally poor and n represents the total number of children in the sample. Intensity (severity) of poverty A, which measures average level of poverty or average deprivation score among poor children is given as:

$$A = \frac{\sum_{i=1}^{q} c_i(k)}{q} \tag{17}$$

5.2.2 Child Academic Performance

Student performance was measured by the English and Math testscore. To track the annual academic gains and the contribution of teachers to the student performance, the test was administered at the beginning and the end of the school year. The tests were on the scale of 0 – 40 points. The student English and Math testscore is generally the overall measurement of academic performance since these two subjects form the foundation of other subjects and test administered were standardized and tailored to basic concepts students in Grade 7 or 8 needed to understand. These tests are a standard tool which can be used to measure students' performance irrespective of the field of study they choose to major in.

Table 1: Dimensions, indicators, and weights for multidimensional school and household poverty

Panel A: School Poverty		
Dimension	**Indicators (baseline weights)**	**Deprivation cutoff**
• Lighting (0.167)	Electricity (0.167)	A child is deprived if there is no access to electricity in the school compound
• Infrastructure (0.8333)	Computer (0.167)	A child is deprived if the school has less than 20 working computers
	Radio (0.167)	A child is deprived if the school has no working radio that is used for teaching and learning
	Internet (0.167)	A child is deprived if the school has no connected and working internet access
	Laboratories (0.167)	A child is deprived if the school has only one or no laboratories
	Library (0.167)	A child is deprived if the school has no libraries

Panel B: Household Poverty		
Dimension	**Indicators (baseline weights)**	**Deprivation cutoff**
• Standard of living (0.333)	Assets (0.167)	A child is deprived if the child's home does not have a table, chair, bed, radio, telephone, television, fridge, Bicycle
	Water (0.167)	A child is deprived if it takes more than 30 minutes to get access to water at home
• Health (0.333)	Diseases (0.333)	A child is deprived if they have any health problem that regularly affects them in school.
• Education (0.333)	School gap (0.333)	A child is deprived if they have repeated any of grades 1 to 8.

5.3 Descriptive Statistics

Figures 1 and 2 plot kernel density distributions of end-of-year Math and English scores by school and household poverty status. In both subjects, students from non-poor schools and non-poor households sit noticeably to the right of their disadvantaged peers, pointing to systematically higher achievement. The gaps are most visible in Math: students in non-poor schools outscore those in poor schools by around 2.5 points on average, while the household poverty gap runs to about 1.4 points. English distributions show smaller but still meaningful differences, with more overlap between groups which is consistent with language achievement being somewhat more evenly spread than Mathematics. In all cases the distributions overlap considerably, which matters: high-achieving students exist across every group, and mean differences alone do not capture the full picture. This heterogeneity is precisely what motivates an empirical strategy that goes beyond simple comparisons of group averages.

Figure 1: Density distribution of Test Score over School Poverty Status

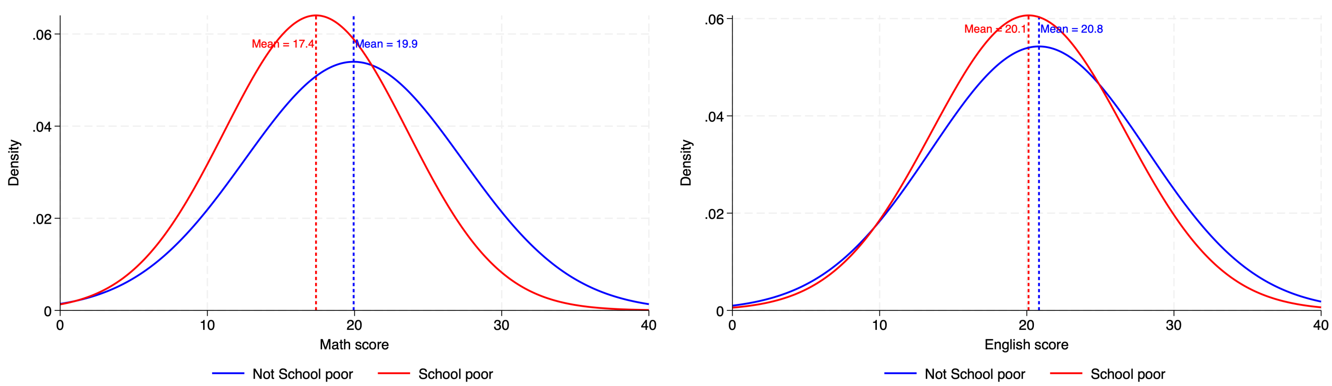


Figure 2: Density distribution of Test Score over Household Poverty Status

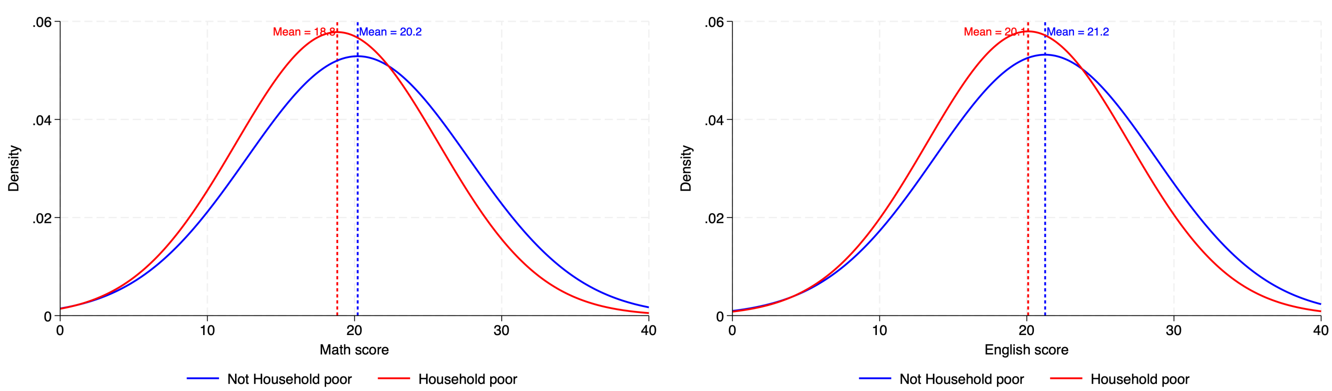


Table 2 reports descriptive statistics for the full sample and by poverty status. Of the 7,631 students, 6,615 attend non-poor schools and 1,016 attend poor schools; 4,197 come from non-poor households and 3,434 from poor ones. Mean Math scores rise from 17.1 at $t-1$ to 19.6 at t, while English scores move from 19.8 to 20.7, suggesting modest but positive learning gains over the year. School characteristics diverge sharply across groups. The school poverty index averages 0.49 in non-poor schools and 0.89 in poor ones, and passing rates follow the same gradient, 88 percent in non-poor schools against just under 68 percent in poor schools. School size is broadly similar across groups, so the performance differences are unlikely to reflect scale alone. There is also notable clustering: the household poverty index is higher among students attending poor schools (0.40 versus 0.37 overall), suggesting that school and home disadvantage often go together.

Teacher quality tells a consistent story. Math and English teachers in poor schools have somewhat less experience, lower certification rates, and fewer years of formal education than their counterparts in better-resourced schools. These are not trivial gaps, but they point to systematic difficulties in attracting and keeping qualified staff in the most deprived settings. On student inputs, aspirations are high across the board (average expectation of 0.82), but study time diverges: students in poor schools put in around 1.55 hours per day compared to 1.80 in non-poor schools, while differences by household poverty are smaller. Rural students are substantially overrepresented in poor schools (37 percent versus 23 percent), underscoring how geographic and socioeconomic disadvantage intersect.

Parental education gradients are steep. More than half of students in poor schools have mothers with no formal education, against 37 percent in non-poor schools, and similar gaps hold for fathers. Taken together, the descriptive picture is one of compounding disadvantage: poorer schools draw students who already face harder circumstances at home, with less educated parents and fewer resources to fall back on. Unpicking the independent contribution of each layer requires the empirical framework we turn to next.

Table 2: Descriptive Statistics by School and Household Poverty Status (Means)

	Full Sample	**School Poverty Status**		**Household Poverty Status**	
		Not Poor	Poor	Not Poor	Poor
Student Achievement					
Math Score (t)	19.589	19.931	17.362	20.214	18.826
Math Score ($t-1$)	17.114	17.369	15.454	17.600	16.520
English Score (t)	20.728	20.824	20.100	21.248	20.093
English Score ($t-1$)	19.782	19.841	19.395	20.332	19.109
School Characteristics					
School Poverty Index	0.547	0.494	0.891	0.549	0.544
School Passing Rate	85.337	88.006	67.960	85.788	84.785
School Size	1,482	1,477	1,509	1,437	1,536
Household Characteristics					
Household Poverty Index	0.369	0.365	0.396	0.184	0.595
Student Inputs					
Student Expectation	0.819	0.818	0.831	0.832	0.803
Study Time	1.762	1.795	1.547	1.736	1.794
Math Teacher Characteristics					
Teaching Experience	5.762	5.795	5.545	5.717	5.817
Certified Teacher	0.939	0.974	0.711	0.935	0.943
Years of Education	0.175	0.187	0.095	0.177	0.172
English Teacher Characteristics					
Teaching Experience	6.116	5.837	7.935	5.844	6.450
Certified Teacher	0.939	0.944	0.905	0.941	0.935
Years of Education	0.249	0.233	0.355	0.261	0.235
Student Demographics					
Girl	0.533	0.547	0.442	0.507	0.565
Age	14.191	14.133	14.573	14.047	14.367
Mother's Education					
No Education	0.390	0.370	0.520	0.377	0.405
Basic	0.447	0.463	0.342	0.431	0.466
Secondary	0.102	0.108	0.062	0.118	0.082
College	0.061	0.059	0.077	0.073	0.047
Father's Education					
No Education	0.345	0.336	0.404	0.332	0.360
Basic	0.384	0.396	0.302	0.372	0.398
Secondary	0.150	0.155	0.116	0.161	0.136
College	0.122	0.113	0.178	0.135	0.106
Location					
Rural	0.248	0.230	0.369	0.265	0.228
Observations	7,631	6,615	1,016	4,197	3,434

6 Results

6.1 Student-Level Unobserved Heterogeneity

We determine the number of latent classes by estimating models starting from two types and stepping up one class at a time. As Appendix Table A.9 shows, both AIC and BIC fall consistently as we move from two to five classes, with the five-class model recording the lowest values. A natural next question is whether adding a sixth class improves fit further. It does, marginally but the six-class model failed to converge, making those estimates unreliable. We therefore settle on five classes as the preferred solution.

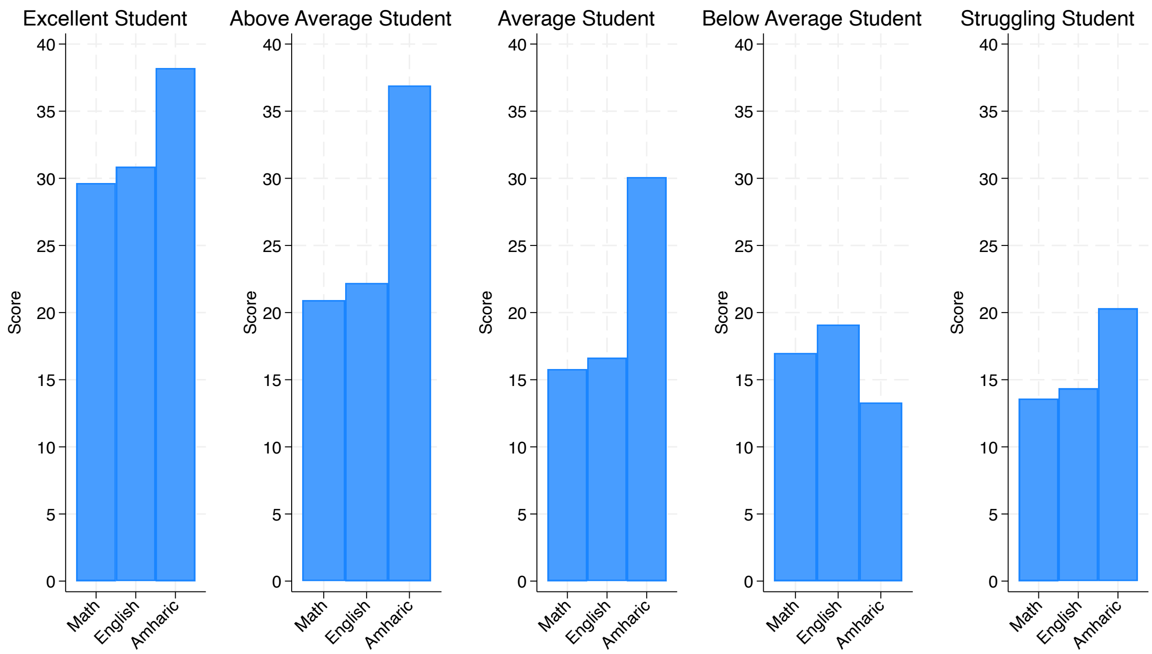
Figure 3 plots the average score profiles across Mathematics, English, and Amharic for each of the five types. The gradient is clean and monotonic. Excellent students score consistently high across all three subjects, with a particular strength in Amharic that suggests well-rounded foundational skills. Above-average students track a similar but slightly lower profile. Average students hold their own in language but lag more noticeably in Math, hinting at subject-specific gaps in quantitative skills. Below-average students show a broader decline, and struggling students score low across the board and their difficulties appear general rather than confined to any one subject.

Table 3 breaks the type distribution down by poverty status. Non-poor schools and households concentrate more students in the upper ability types, while poor schools have nearly nine times the share of below-average students compared to non-poor schools (10.5 versus 1.2 percent). Struggling students are also overrepresented among disadvantaged groups. This tells us that poverty is not just associated with lower average scores which is associated with a fundamentally different distribution of learning capacity, which has real consequences for how policy should be designed and targeted.

Table 3: Distribution of Student-level Unobserved Heterogeneity (θ_i)

	Full Sample	**School Poverty Status**		**Household Poverty Status**	
		Not Poor	Poor	Not Poor	Poor
Student Type (LCA)					
Excellent	0.169	0.180	0.100	0.205	0.125
Above Average	0.389	0.392	0.372	0.378	0.403
Average	0.168	0.171	0.144	0.159	0.178
Below Average	0.024	0.012	0.105	0.023	0.026
Struggling	0.250	0.245	0.279	0.234	0.268
Observations	7,631	6,615	1,016	4,197	3,434

Figure 3: Latent Class Profile for Student Type (θ_i)



6.2 Estimation Results

Tables 4 and 5 report estimates for Mathematics and English achievement across four specifications: OLS, IV, LCA, and IV+LCA. Each successive specification addresses an additional source of bias, and tracing how estimates shift across them is itself informative.

We begin with the first-stage results, which validate the instrument. The Test of Relevance yields F-statistics of 165.3 for Mathematics and 295.1 for English, both with p-values of 0.001, exceeding the conventional threshold of $F > 10$ for instrument strength. The first-stage coefficients on the cross-subject instrument are 0.556 (English predicting lagged Math) and 0.562 (Math predicting lagged English), both significant at the 1 percent level. The Test of Endogeneity is also strongly rejected for Mathematics, confirming that OLS estimates of the persistence parameter are indeed biased and that instrumentation is warranted. For English the endogeneity test statistic is 3.76, providing weaker but still shows evidence of endogeneity at the 10 percent level.

Lagged achievement is a strong predictor of current performance in every specification. OLS yields persistence coefficients of 0.676 for Math and 0.534 for English. Once the lagged score is instrumented, these rise to 0.965 and 0.817, respectively, an upward shift consistent with attenuation bias in OLS arising from measurement error and transitory shock correlation. When latent student types enter in the LCA specification, the persistence coefficients fall sharply to 0.312 (Math) and 0.178 (English), revealing that much of what OLS and IV attribute to state dependence is in fact unobserved ability. The preferred IV+LCA estimates confirm this; instrumented lagged achievement retains positive and significant effects, but at more modest magnitudes of 0.259 and 0.101, once both endogeneity and heterogeneity are jointly addressed.

Turning to the main variables of interest, poverty effects are large in simpler specifications but attenuate meaningfully as the model becomes more demanding. Under OLS, attending a poor school is associated with 1.59 fewer Math points and 2.37 fewer English points, while household poverty is associated with reductions of 1.22 and 1.13 points, respectively. IV correction reduces these gaps, particularly for household poverty, whose coefficient becomes insignificant for English, suggesting that part of the raw association reflects sorting on prior achievement rather than a direct causal effect. The LCA specification further dissolves the school poverty effect, which loses significance in both subjects once students are compared within ability types. Household poverty, however, retains a negative and significant coefficient for English, indicating that home-level constraints bite independently of a child's underlying ability.

The preferred IV+LCA estimates tell the clearest story. School poverty yields a positive and significant coefficient for Math (0.85), likely reflecting within-school sorting that the model is now absorbing, but remains insignificant for English (0.60). Household poverty is negative and significant for English, with an effect size of -0.45, while the Math coefficient (-0.20) is negative but falls short of statistical significance. These estimates are conservative by design, and the English household poverty effect is consistent with our interpretation that home-level deprivation in assets, health, and educational continuity constrains language learning in ways that school quality cannot offset.

Finally, the latent class results underscore how much heterogeneity lies beneath average achievement figures. Struggling students score roughly 15 points below excellent students in both subjects, even after controlling for poverty and observed background characteristics. Several covariates that appear significant under OLS lose their significance once ability types are included, suggesting they were partly proxying for latent capacity rather than operating through independent channels.

Table 4: Estimation Results for Mathematics

	(1) OLS $MATH_t$	(2) First Stage $Math_{t-1}$	(3) IV $MATH_t$	(4) LCA $MATH_t$	(5) IV+LCA $MATH_t$
$Math_{t-1}$	0.676***			0.312***	
	(0.011)			(0.011)	
$\widehat{Math}_{t-1}$			0.965***		0.259***
			(0.022)		(0.019)
$English_{t-1}$		0.556***			
		(0.010)			
School Poor	-1.591***	-1.628***	-1.164**	0.585	0.853**
	(0.534)	(0.480)	(0.583)	(0.399)	(0.423)
Household Poor	-1.215***	-0.634***	-0.597**	-0.308	-0.201
	(0.263)	(0.234)	(0.288)	(0.199)	(0.210)
Sch Passing Rate	-0.000	0.016***	-0.013*	-0.009*	-0.010**
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)
Sch Enrollment	-0.001***	-0.001***	-0.001***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Student Expectation	0.705***	0.878***	0.151	0.074	0.013
	(0.162)	(0.138)	(0.175)	(0.122)	(0.128)
Hours Homework	0.161**	0.174***	0.119	0.159***	0.161***
	(0.071)	(0.064)	(0.078)	(0.053)	(0.057)
Math Teacher Characteristics					
Teaching Experience	-0.012	-0.000	-0.010	-0.011	-0.011
	(0.014)	(0.012)	(0.015)	(0.010)	(0.011)
Certified Teacher	0.119	0.882***	-0.091	-0.384	-0.448*
	(0.279)	(0.261)	(0.304)	(0.238)	(0.252)
Years Education	-0.259	0.291*	-0.121	0.318**	0.390***
	(0.171)	(0.162)	(0.193)	(0.128)	(0.136)
English Teacher Characteristics					
Teaching Experience	-0.057***	0.021*	-0.059***	-0.027***	-0.024**
	(0.011)	(0.011)	(0.013)	(0.009)	(0.009)
Certified Teacher	0.498	-0.299	0.605*	0.529**	0.540**
	(0.309)	(0.286)	(0.334)	(0.236)	(0.249)
Years Education	-0.079	0.309	-0.350	-0.393**	-0.415**
	(0.221)	(0.192)	(0.232)	(0.168)	(0.175)
Female	-0.521***	-1.043***	-0.146	-0.498***	-0.505***
	(0.121)	(0.109)	(0.135)	(0.091)	(0.098)
Age	-0.131***	0.135***	-0.166***	-0.047	-0.034
	(0.043)	(0.040)	(0.048)	(0.033)	(0.035)
Student Type (LCA; ref: excellent)					
Above Average				-7.022***	-8.005***
				(0.151)	(0.158)
Average				-11.186***	-12.746***
				(0.192)	(0.191)
Below Average				-8.901***	-10.193***
				(0.512)	(0.531)
Struggling				-13.996***	-15.737***
				(0.202)	(0.194)
Observations	7,631	7,631	7,631	7,631	7,631
Test of Relevance		165.3			
		[0.001]			
Test of Endogeneity		326.52			
		[0.001]			

Columns (1) and (4) report OLS and LCA estimates respectively, treating lagged achievement as observed. Columns (3) and (5) instrument lagged Math (English) score with lagged English (Math) score. The LCA recovers five discrete student ability types from the joint distribution of Mathematics, English, and Amharic scores; student-type indicators enter as additional regressors with Excellent students as the reference category. In each estimation, we additionally control for student section, parental education, region, and location (rural/urban). Robust standard errors in parentheses. P-values in brackets.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Estimation Results for English

	(1) OLS $ENGLISH_t$	(2) First Stage $English_{t-1}$	(3) IV $ENGLISH_t$	(4) LCA $ENGLISH_t$	(5) IV+LCA $ENGLISH_t$
$English_{t-1}$	0.534***			0.178***	
	(0.011)			(0.010)	
$\widehat{English}_{t-1}$			0.817***		0.101***
			(0.020)		(0.017)
$Math_{t-1}$		0.562***			
		(0.010)			
School Poor	-2.367***	1.098**	-2.442***	0.381	0.596
	(0.528)	(0.503)	(0.554)	(0.368)	(0.377)
Household Poor	-1.125***	-1.508***	-0.357	-0.385**	-0.447**
	(0.257)	(0.239)	(0.272)	(0.184)	(0.190)
Sch Passing Rate	-0.003	0.022***	-0.016***	-0.008*	-0.006
	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)
Sch Enrollment	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Student Expectation	0.842***	0.844***	0.303*	0.152	0.195*
	(0.152)	(0.143)	(0.160)	(0.109)	(0.113)
Hours Homework	0.023	-0.148**	0.039	-0.055	-0.061
	(0.070)	(0.065)	(0.073)	(0.050)	(0.051)
Female	-0.063	0.271**	0.076	0.269***	0.278***
	(0.118)	(0.109)	(0.124)	(0.084)	(0.087)
Age	-0.086**	-0.100**	-0.075*	-0.058*	-0.055*
	(0.041)	(0.040)	(0.044)	(0.031)	(0.032)
Math Teacher Characteristics					
Teaching Experience	-0.014	-0.010	-0.010	-0.014	-0.013
	(0.012)	(0.013)	(0.013)	(0.009)	(0.009)
Certified Teacher	0.144	-0.688***	0.222	-0.664***	-0.721***
	(0.271)	(0.261)	(0.283)	(0.211)	(0.217)
Years Education	-0.769***	-1.116***	-0.378**	-0.459***	-0.484***
	(0.164)	(0.159)	(0.172)	(0.118)	(0.122)
English Teacher Characteristics					
Teaching Experience	-0.015	-0.028***	-0.008	0.005	0.005
	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)
Certified Teacher	-0.132	0.077	-0.094	-0.030	-0.027
	(0.284)	(0.277)	(0.291)	(0.201)	(0.204)
Years Education	0.210	0.606***	-0.110	-0.076	-0.038
	(0.201)	(0.201)	(0.212)	(0.146)	(0.149)
Student Type (LCA; ref: excellent)					
Above Average				-6.903***	-7.638***
				(0.141)	(0.142)
Average				-11.355***	-12.438***
				(0.181)	(0.177)
Below Average				-7.681***	-8.076***
				(0.557)	(0.579)
Struggling				-14.214***	-15.404***
				(0.195)	(0.188)
Observations	7,631	7,631	7,631	7,631	7,631
Test of Relevance		295.1			
		[0.001]			
Test of Endogeneity		3.762			
		[0.053]			

Columns (1) and (4) report OLS and LCA estimates respectively, treating lagged achievement as observed. Columns (3) and (5) instrument lagged Math (English) score with lagged English (Math) score. The LCA recovers five discrete student ability types from the joint distribution of Mathematics, English, and Amharic scores; student-type indicators enter as additional regressors with Excellent students as the reference category. In each estimation, we additionally control for student section, parental education, region, and location (rural/urban). Robust standard errors in parentheses. P-values in brackets.

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

6.3 Heterogeneous Effects Across Student Types and Gender

The pooled estimates in Section 6.2 offer a useful summary but inevitably conceal variation that matters for how policy should be designed. We therefore re-run the IV+LCA specification separately within each of the five latent ability classes and, in a separate exercise, by gender. Tables 6 and 7 report the school and household poverty coefficients from these within-group regressions.

The within-type results in Table 6 complicate the picture in interesting ways. In Mathematics (Panel A), the school poverty coefficient is positive and significant for average and above-average groups. The large positive effect among average-ability students does not fit the simple story that poor schools uniformly harm students, rather those attending more deprived schools do not appear worse off in Mathematics. The average-ability students who end up in the most deprived schools may come from communities where other unobserved compensating factors such as parental engagement, peer effects, and motivated teachers offset the material deficits that the poverty index captures. The English results (Panel B) are structured differently. Here, school poverty is positive and significant only among excellent students, consistent with the idea that high-ability learners draw more from the broader school environment regardless of its material conditions. The large negative and significant coefficient for below-average students suggest that these students may be set back quite noticeably by school deprivation in English, probably because building language skills is more dependent on consistent classroom instruction and resources than Mathematics, leaving below-average students with fewer ways to compensate when school conditions are poor. Household poverty effects across the ability types tell a nuanced story. In Mathematics, the coefficient reaches significance for two groups: it is negative and significant for above-average students (-0.594^*), and positive and significant for average students (0.791^*), suggesting that household deprivation interacts differently with ability levels rather than operating as a uniform drag.

The results in Table 7 reveal a gender asymmetry that the pooled estimates quietly absorb. For school poverty in Mathematics, the female coefficient is 1.562 and highly significant. Improvements in school conditions translate into real Mathematics gains for girls but not for boys. Girls in Ethiopia face school-specific barriers that boys largely do not: inadequate or unsafe toilet facilities, poor lighting, and long walk times that make attending a poorly resourced school a qualitatively different experience. When those conditions improve, girls come more regularly, stay longer, and learn more. For English, both genders show positive and similar school poverty coefficients that fall short of significance, so the gender gap here is less about direction and more about the absence of any strong effect for either group. Household poverty effects in Mathematics are insignificant for both genders, with coefficients of -0.162 for males and -0.287 for females. In English, the female coefficient (-0.488) is negative and significant at the 10 percent level, while the male coefficient (-0.440) is of similar magnitude but falls just short of conventional significance. This suggests that girls bear the more clearly identified household poverty burden in English, even if boys are

Table 6: Heterogeneous Effects by Student Type: Mathematics and English

	(1) Excellent	(2) Above Average	(3) Average	(4) Below Average	(5) Struggling
Panel A: Mathematics ($MATH_t$)					
School Poor	−1.518	1.220*	3.321***	−0.930	−1.045
	(0.943)	(0.688)	(1.166)	(3.850)	(1.040)
Household Poor	−0.446	−0.594*	0.791*	−0.675	0.270
	(0.551)	(0.345)	(0.445)	(1.654)	(0.368)
Observations	1,291	2,970	1,280	185	1,905
Panel B: English (ENG_t)					
School Poor	1.758**	0.266	0.350	−5.786*	0.570
	(0.872)	(0.594)	(1.077)	(3.265)	(0.931)
Household Poor	0.016	−0.252	−0.496	0.226	−0.358
	(0.481)	(0.303)	(0.381)	(1.162)	(0.338)
Observations	1,291	2,970	1,280	185	1,905

Notes: Each panel reports IV estimates from separate regressions run within each student ability type. Lagged Math (English) score is instrumented with lagged English (Math) score. Student ability types are recovered from the LCA on the joint distribution of Mathematics, English, and Amharic scores. In each estimation, we additionally control for school passing rate, school enrollment, student expectations, study time, Math and English teacher characteristics (experience, certification, years of education), student demographics (gender, age), parental education, region, location (rural/urban), and student section fixed effects. Robust standard errors in parentheses.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Heterogeneous Effects by Gender: Mathematics and English

	(1) Male MATH_t	(2) Female MATH_t	(3) Male ENG_t	(4) Female ENG_t
School Poor	−0.031	1.562***	0.611	0.621
	(0.631)	(0.573)	(0.555)	(0.519)
Household Poor	−0.162	−0.287	−0.440	−0.488*
	(0.318)	(0.277)	(0.282)	(0.257)
Student Type (LCA; ref: excellent)				
Above Average	−8.022***	−8.012***	−7.652***	−7.600***
	(0.230)	(0.217)	(0.209)	(0.194)
Average	−12.556***	−12.936***	−12.280***	−12.554***
	(0.281)	(0.264)	(0.260)	(0.242)
Below Average	−8.539***	−12.463***	−7.179***	−9.249***
	(0.703)	(0.756)	(0.702)	(0.958)
Struggling	−15.863***	−15.668***	−15.273***	−15.465***
	(0.286)	(0.268)	(0.280)	(0.254)
Observations	3,564	4,067	3,564	4,067

Notes: In each estimation, we control for lagged achievement (instrumented), school passing rate, school enrollment, student expectations, study time, Math and English teacher characteristics (experience, certification, years of education), age, parental education, region, location (rural/urban), and student section fixed effects. Robust standard errors in parentheses.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

directionally affected in a similar way. The greater sensitivity of girls to household poverty in Mathematics is plausible given that domestic and caregiving responsibilities in poor households tend to fall more heavily on girls, leaving less time for study.

7 Discussion

The central finding of this paper is an asymmetry between the two dimensions of poverty we study. Household poverty exerts a robust negative effect on English achievement that survives every layer of econometric scrutiny, that is, instrumentation, latent class adjustment, and the combination of both, while its effect on Mathematics is statistically insignificant. School poverty, by contrast, is strongly correlated with lower scores in simpler models, but this association largely dissolves once we account for the kinds of students who attend poor schools. The implication is that school-level disadvantage operates primarily through compositional channels rather than through direct causal mechanisms, whereas the constraints imposed by a poor home environment damage learning in ways that school quality alone cannot offset. A second finding worth emphasizing concerns persistence. Achievement is highly path-dependent, but much of this path dependence reflects stable differences in latent ability rather than genuine state dependence. Early disadvantage, particularly household poverty, therefore casts a long shadow. By the time students reach grades 7 and 8, much of the gap has already formed, and school-based interventions applied at this stage face an uphill task.

The heterogeneous effects analysis adds important texture to these average results. Running the IV+LCA regressions separately within ability types shows that school poverty is not as uniformly inert as the pooled estimates suggest: its effects on Mathematics are concentrated among average-ability students, and its effects on English fall most heavily on the below-average group. This points to school quality operating as a compensating resource, and this matters most for students who are neither so capable that they can work around poor conditions nor so far behind that even good conditions would not easily help them. The gender results reinforce a related point that girls appear to be considerably more sensitive to school-level deprivation in Mathematics than boys, which is consistent with the role of basic infrastructure in shaping female attendance and engagement in Ethiopian schools. Also on household poverty, girls carry the more precisely identified household poverty burden for language learning. All of this argues against treating poverty effects as homogeneous. The population of affected students is not a single group with a common vulnerability, and policies designed as if it were one will miss a good deal of the action.

These patterns have direct implications for resource allocation. Where budgets are constrained, the evidence points toward household-targeted interventions as the higher-return investment. Conditional cash transfers linked to attendance, school feeding programmes, subsidies for learning materials at home, and support for families facing the most acute deprivation all operate through channels that remain relevant even after controlling for school quality. Our multidimensional poverty framework helps sharpen this further: the relevant question for policymakers is not simply who is poor, but how they are poor. Deprivations in health, assets, and educational continuity each carry distinct implications for the type of support that will be most effective. This is not an argument for neglecting schools. Rather, it suggests that school investments are most productive when designed to serve students whose home environments are already a disadvantage; smaller classes for struggling learners, stronger remedial instruction, and better support for teachers in the most deprived communities. The within-type and gender results give some indication of where those investments would do the most good, such as schools serving large numbers of girls and those attended predominantly by average-ability students appear to be the settings where improvements in basic conditions translate most reliably into learning gains. School and household policies should complement each other, not compete for the same budget.

8 Policy Experiment

The causal estimates from the IV+LCA specification allow us to translate the empirical findings into concrete predictions about what specific government interventions might deliver in terms of student learning. We simulate six policies, three targeting school-level deprivation and three targeting household-level deprivation, using the estimated coefficients from the preferred specification. This partial equilibrium experiment design, asks how much achievement would change if a specific dimension of poverty were eliminated while everything else remained fixed. The error term averages to zero across students, so the predicted gain for policy p and subject k is simply:

$$\overline{\Delta\hat{y}}_p^k = \hat{\beta}^k \cdot \overline{\Delta c}_p$$

where $\hat{\beta}^k$ is the relevant estimated coefficient and $\overline{\Delta c}_p$ is the average reduction in the poverty index under policy p.

8.1 School and Household Investment Policies

The school poverty index built from two indicators: lighting (electricity) and infrastructure (computers, internet, radio, laboratories, and library) carrying weights of 0.167 and 0.833 are used in simulating three school policies. In Policy 1, government provides electricity to all schools currently lacking it, reducing the index by 0.167. Policy 2: government provides the infrastructure (computers, internet, radio, laboratories, and library) across all deprived schools. Policy 1+2 combines both. The delta for each student is the sum of weights on the indicators they are currently deprived of that the policy addresses.

Suppose now the government wants to target eradicating household poverty by improving standard of living and healthcare. The household poverty index is built from four indicators: standard of living ($w = 0.333$), disease burden ($w = 0.333$), and school gap ($w = 0.333$). We simulate three household policies. Policy 3 represents a cash transfer programme that is generous enough to lift households out of asset and water deprivation. Policy 4 represents universal free healthcare for children, eliminating health-related deprivation. Policy 3+4 combines both. School gap deprivation, grade repetition, is not targeted in any of these policies, as it reflects past educational disruptions that a current transfer or healthcare programme cannot undo.

8.2 Policy Results

Table 8 reports the predicted average gains across all six policies for Mathematics and English. On the school side, the contrast between Policies 1 and 2 is stark. Providing electricity (Policy 1) yields essentially no achievement gain (0.01 points in Mathematics and a similarly negligible figure in English) because only 7.5 percent of students attend schools currently lacking power, and the mean reduction in the poverty index is just 0.013. The problem, in other words, is already largely solved. Infrastructure investment (Policy 2) is a different story entirely. The mean index reduction is 0.534, yielding a predicted Mathematics gain of 0.46 points (equivalent to 6.25 percent of a standard deviation). The combined Policy 1+2 adds only marginally to Policy 2 alone (0.47 versus 0.46), confirming that electricity is not the binding school constraint. The English coefficient is insignificant in the main results hence these predicted gains should therefore be interpreted with caution.

On the household side, Policy 3, a cash transfer addressing asset and water deprivation, delivers a predicted English gain of 0.08 points (1.07 percent of a standard deviation). Policy 4, universal healthcare eliminating disease deprivation yields a predicted English gain of 0.05 points. The combined Policy 3+4 reaches further into both dimensions and delivers a predicted English gain of 0.13 points (1.82 percent of a standard deviation). Mathematics gains from household policies are near zero and should not be interpreted as real effects given the insignificant beta.

Stepping back, the simulations point to a clear hierarchy. Infrastructure investment in schools has the largest single predicted effect on Mathematics achievement, roughly 6 percent of a standard deviation, and electricity investment adds almost nothing incremental given near-universal coverage in this sample. For English, household interventions targeting assets and health generate modest but genuine predicted gains, consistent with the significant household poverty coefficient. None of the policies produces large predicted gains in absolute terms, which is not surprising: these are the effects of eliminating one dimension of poverty at a time, and deprivation in the data is multifaceted. A package combining school infrastructure investment with household transfers and health support would stack these gains rather than substitute among them.

Table 8: Policy Simulation Results: Predicted Achievement Gains

	Mathematics		English	
Policy	**Gain (pts)**	**% of SD**	**Gain (pts)**	**% of SD**
Panel A: School Investment Policies ($\hat{\beta}_m^S = 0.853^{**}$; $\hat{\beta}_e^S = 0.596$)				
Policy 1: Electricity only	0.011	0.15%	$0.008^{\dagger}$	0.10%
Policy 2: Infrastructure only	0.456	6.25%	$0.319^{\dagger}$	4.39%
Policy 1+2: Full school investment	0.467	6.40%	$0.326^{\dagger}$	4.50%
Panel B: Household Investment Policies ($\hat{\beta}_m^H = -0.201$; $\hat{\beta}_e^H = -0.447^{**}$)				
Policy 3: Cash transfer (assets + water)	$0.035^{\ddagger}$	0.48%	0.078	1.07%
Policy 4: Universal healthcare (diseases)	$0.024^{\ddagger}$	0.33%	0.054	0.74%
Policy 3+4: Full household intervention	$0.059^{\ddagger}$	0.81%	0.132	1.82%

Predicted gains are computed as $\hat{\beta}^k \cdot \overline{\Delta c_p}$ for school policies and $-\hat{\beta}^k \cdot \overline{\Delta c_p}$ for household policies (where $\hat{\beta}^H < 0$, so eliminating deprivation raises scores). Parameters are drawn from the IV+LCA estimates on the analysis sample of 7,631 students. All other regressors are held at observed values. Mean delta for school policies: Policy 1 = 0.013, Policy 2 = 0.534, Policy 1+2 = 0.547. Mean delta for household policies: Policy 3 = 0.174, Policy 4 = 0.120, Policy 3+4 = 0.295. $\hat{\beta}_e^S$ is statistically insignificant ($p = 0.113$); gains marked † should be interpreted with caution. $\hat{\beta}_m^H$ is statistically insignificant ($p = 0.338$); gains marked ‡ should be interpreted with caution. **, * denote significance at the 5% and 10% levels, respectively.

9 Conclusion

This paper examines the causal effects of multidimensional school and household poverty on student achievement in Mathematics and English, using data from the 2016/17 Young Lives school survey in Ethiopia. We construct poverty indices at both the school and household levels using the Alkire-Foster framework, and estimate value-added achievement models that combine instrumental variables with latent class analysis to address dynamic endogeneity and unobserved heterogeneity in learning ability simultaneously.

The results draw a clear distinction between the two poverty dimensions. Household poverty exerts a persistent negative effect on English test scores that holds up after accounting for prior achievement, latent student ability, and school characteristics, while its effect on Mathematics attenuates to insignificance. School poverty, while strongly correlated with lower scores in naive specifications, loses explanatory power once student composition is properly controlled for. Much of the apparent school poverty effect reflects who attends poor schools rather than what those schools do to learning. Achievement is highly persistent across grades, but this persistence is driven more by stable differences in latent ability than by genuine state dependence; a finding with important implications for when and how interventions are likely to be effective.

Going beyond the average effects, the heterogeneous analysis brings out variation that is consequential for targeting. School poverty effects on Mathematics are most pronounced among average-ability students, a group that is neither at the top of the distribution nor so far behind that school quality cannot make a difference. Below-average students bear the largest school poverty costs in English. On the gender side, girls are the ones whose Mathematics scores respond most to school-level conditions, while in English household poverty carries a clearly identified negative effect for girls but a less precisely estimated one for boys, pointing to a gendered dimension of language learning disadvantage that the aggregate results smooth over. These findings suggest that Ethiopia's educational disadvantage has a gendered dimension that material deprivation alone does not fully capture, and that any serious effort to close learning gaps needs to account for the specific ways in which poverty interacts with who students are and what constraints they face outside the classroom.

From a policy standpoint, the evidence makes a case for directing resources toward household-level deprivation, particularly in health, assets, and educational continuity, rather than relying solely on school infrastructure investment. At the same time, the large achievement gaps between latent student types suggest that universal school improvements will do little for the most disadvantaged learners without complementary household support. The heterogeneous results point toward where resources might go, that is schools with high female enrollment stand to benefit most from investments in basic infrastructure, while students in the middle of the ability distribution, the large above-average and average groups, appear to be the ones whose Mathematics learning is most responsive to school conditions. More broadly, the analysis demonstrates the value of measuring poverty in multiple dimensions, which is a richer picture of deprivation enables more precise targeting and a more honest account of why some children fall behind.

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A1 Appendix

Table A.9: Model Fit Statistics

Model (# of k)	Log Likelihood	AIC	BIC
2	-60957.17	121946.3	122057.5
3	-60078.81	120203.6	120363.4
4	-59802.71	119665.4	119873.8
5	-59440.32	118954.6	119211.6