

**Digital Divide In Economic Literacy:
How Unequal Access To Technology Shapes Student Outcomes**

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Abstract

The digital divide—the systematic inequality in access to information and communication technology (ICT) across socioeconomic, geographic, and gender dimensions—is widely hypothesized to exacerbate educational inequality in developing countries. Yet rigorous causal evidence on the magnitude and mechanisms of this effect, particularly for economics learning outcomes in low- and middle-income country (LMIC) contexts, remains sparse. This paper addresses that gap using a uniquely constructed five-wave panel dataset of 18,640 secondary and higher-secondary students across 186 schools in four Pakistani provinces, collected between 2020 and 2025. Exploiting quasi-random variation in district-level ICT infrastructure roll-out generated by the Pakistan Tehreek-e-Insaf government's Digital Pakistan initiative as an instrumental variable, we estimate the causal effect of technology access on a newly developed and psychometrically validated Economic Literacy Index (ELI). Our two-stage least squares (2SLS) estimates indicate that moving from the bottom to the top quartile of the district-level Digital Access Index (DAI)—a composite measure of device ownership, broadband availability, electricity reliability, and digital skill—is associated with a 0.74 standard deviation (SD) improvement in the ELI ($p < 0.001$). The effect is substantially larger for female students (0.88 SD), students in the lowest household wealth quintile (0.97 SD), and students in rural government schools (0.82 SD), confirming that the digital divide amplifies pre-existing educational inequalities rather than operating uniformly across the student population. Structural equation modelling (SEM) reveals that approximately 41 percent of the total effect operates through the channel of access to digital learning resources, 28 percent through teacher digital pedagogy quality, and 31 percent through student self-directed study time. A counterfactual simulation suggests that eliminating the observed inter-district digital access gap in Pakistan would reduce the

ELI variance attributable to socioeconomic background by 34 percent. These findings have direct and urgent implications for Pakistan's educational technology policy, ICT infrastructure investment strategy, and the design of digital inclusion programmes targeting the most educationally marginalised populations.

JEL Classification: I24, I26, O15, O33, C33, D63

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Introduction

The digital divide is not a new concept. Since Norris's (2001) foundational taxonomy of global, democratic, and social divides, scholars have documented with increasing granularity the ways in which unequal ICT access stratifies life opportunities across nations, communities, and households. What has changed in the two decades since that foundational work is not the existence of the divide but its stakes. In an educational environment in which digital fluency is increasingly a precondition for accessing quality learning resources from adaptive tutoring platforms to open-access academic content, from digital examination preparation to collaborative online problem-solving the ICT access gap has metastasised from a secondary disadvantage into a primary driver of learning outcome inequality.

Nowhere is this dynamic more consequential than in Pakistan. With a population of approximately 245 million, a school-age cohort of nearly 60 million, and an economy in chronic need of the human capital upgrade that quality education can provide, Pakistan represents one of the most important test cases in the world for understanding what the digital divide does to educational outcomes. Yet the empirical literature on this question, at least with respect to economics education specifically a domain with particular relevance to financial literacy, democratic economic accountability, and labour market productivity is strikingly thin. The studies that exist are predominantly cross-sectional, suffer from severe endogeneity in their treatment of ICT access (wealthier students have more access and also receive better education for many non-technology-related reasons), and rarely distinguish between the distinct channels through which technology access might affect learning.

This paper makes four distinct contributions to the literature. First, it constructs and validates a novel Economic Literacy Index (ELI) calibrated to Pakistan's secondary and higher-secondary economics curriculum, with demonstrated psychometric properties ($\alpha = 0.91$, IRT-confirmed item fit) that make it a credible instrument for outcome measurement in this context. Second, it assembles a five-wave panel dataset to our knowledge the largest longitudinal dataset on economics learning outcomes in Pakistan spanning 18,640 students across 186 schools in all four major provinces over five years. Third, it addresses the endogeneity of ICT access using an instrumental variables strategy that exploits the quasi-random timing of Digital

Pakistan initiative infrastructure roll-out across districts, thereby recovering estimates that have a plausible causal interpretation. Fourth, it deploys structural equation modelling to decompose the total effect of digital access into its constituent causal channels, providing a richer mechanistic account than the single-equation approach that dominates this literature.

The remainder of the paper proceeds as follows. Section 2 reviews the theoretical and empirical literature. Section 3 describes the data sources, the Economic Literacy Index, and the Digital Access Index construction. Section 4 presents the identification strategy and econometric specifications. Section 5 reports the primary results. Section 6 analyses heterogeneity across student subgroups. Section 7 presents the structural equation model and mechanism analysis. Section 8 reports robustness checks. Section 9 discusses counterfactual simulations. Section 10 discusses policy implications. Section 11 concludes.

Theoretical Framework and Literature Review

Conceptualising the Digital Divide in Educational Contexts

The theoretical literature on the digital divide has evolved through three generations of conceptualisation (van Dijk, 2006; Hargittai & Hinnant, 2008; Ragnedda & Muschert, 2013). The first-generation concept was binary: one either had access to a computer and internet connection or did not. The second generation recognised that access is multidimensional, distinguishing between physical access (device and connectivity), motivational access (desire and perceived utility of use), skills access (technical and informational competencies), and usage access (variety and quality of applications). The third generation extended this to examine the differential outcomes of differential usage not merely whether one is connected but what one does when connected and what this means for life outcomes.

Applied to educational contexts in developing countries, this third-generation framework suggests that the effect of ICT access on learning outcomes operates through multiple pathways. The most direct is the resource channel: students with better ICT access can access digital educational content practice problems, explanatory videos, adaptive platforms, past examination papers that supplement and in many cases substantially exceed the quality of what is available through conventional school-based instruction. This resource-supplementation effect can be very big in economics classrooms in Pakistan where the quality of textbooks is proven to be poor and the subject-expertise of teachers is often unsatisfactory (Pakistan Institute of Education, 2024). The other, less extensively examined channel is the pedagogical quality channel. Educators who have greater access to ICT and are more digitally literate can provide the highest quality education using data visualisations, real-world economic news and simulation-based demonstrations that can bring economic concepts alive in the ways that is impossible under chalk-and-blackboard teaching. There is no strict causality, but the relationship between the ICT infrastructure at school level and the quality of teaching that teachers give is well-reported in South Asian schools. (Muralidharan et al., 2019; Bold et al., 2021).

A third pathway is the autonomy and self-efficacy channel.. When students have good access to ICT, they acquire self-directed digital inquiry habits by the ability to seek explanations, check comprehension and curiosity about learning that goes beyond the walls of formal instruction which is linked with increased academic success and enhanced learning motivation (Deci and Ryan, 2000; Bandura, 2001).). In the case of economics in particular, the learning activity of consulting real-world economic information, after financial news, and economic analysis as a living practice (as opposed to a fixed curriculum) is a habitual activity that ICT access alone makes possible.

Empirical Evidence: What We Know and What We Do Not

Existing empirical data on ICT access and learning outcomes are vast and heterogeneous in terms of methods. The systematic review conducted by Escueta et al. (2020) found 126 studies examining the connection between technology access and academic achievement in developing countries, of which only 31 involved experimental or quasi-experimental designs, which could be used to draw a causal conclusion, and only 8 studies specifically focused on outcomes in the social sciences or economics. The estimated effect sizes in the papers of the causal-inference-grade studies were -0.03 SD (one of the null results in one of the Peruvian laptop programme assessments by Cristia et al., 2017) to $+0.64$ SD (one of the high-quality tablet-based intervention studies in Kenya by Jukes et al., 2022), and the pooled effect estimate of about $+$

The most directly relevant prior work is Muralidharan et al.'s (2019) evaluation of the Mindspark computer-aided instruction program in Delhi, which found an effect of $+0.37$ SD on standardised academic achievement after 4.5 months. Comparable work in Pakistan is sparse; the most credible existing estimates come from Beg et al. (2022), who report a $+0.22$ SD effect of a tablet-based mathematics learning program in rural Punjab. Neither study examines economics learning specifically, and neither addresses the heterogeneous effects of the digital divide across the student population with the granularity this paper provides.

The literature on gender and the digital divide in educational contexts specifically is relevant to our heterogeneity analysis. Duflo et al. (2021) and Bharadwaj et al. (2020) document that female students in South Asian educational environments tend to show larger learning gains from technology-assisted instruction relative to conventional instruction, hypothesising that the private, self-paced, non-judgmental character of digital learning environments lowers the social barriers to analytical engagement that female students disproportionately face in mixed or male-dominated classrooms. Our results are directly interpretable within this framework.

Pakistan-Specific Context: The Digital Access Landscape

The digital future of Pakistan in 2025 is an unequal but fast technological transformation. There is more than 84 percent of mobile phones among adults above 18 and 4G has reached about 72 percent of the population (Pakistan Telecommunication Authority, 2025). However, these headline statistics conceal deep

inter-district inequality. The average 4G download speed in the Gulberg district of Lahore is 22 Mbps, and the prevalence of household devices (with smartphones that can be used to run educational applications) is 91 percent. Meaningful broadband access does not exist in the Dera Bugti district of Balochistan, ownership of household devices is less than 18 percent, and power is less than 8 hours a day. This digital access heterogeneity overlay near-perfectly onto pre-existing patterns of socioeconomic disparity, linguistic marginalisation and educational disadvantage that constitutes a compound deprivation where students with the poorest traditional educational backgrounds are also the ones with the poorest access to the digital resources which may replace those poor backgrounds.. This is where we are structurally studying the impact of the digital divide on economic literacy.

Data, Measurement, and Sample

Survey Design and Panel Construction

This paper is empirically based on the Pakistan Digital Education and Literacy Panel (PDEL), a five-wave panel survey that will be conducted in association with the Pakistan Centre of Economic Research in Pakistan (CERP) with the Lahore University of Management Sciences in 2020-2025. The survey is of stratified random sample of 186 schools 113 public and 73 private based on 62 districts in Punjab (28 districts), Sindh (14 districts), Khyber Pakhtunkhwa (12 districts), and Balochistan (8 districts).). In sampled schools, all students in economics at the SSC (Classes 9-10) and HSSC (Classes 11-12) levels were eligible to the study, which provided a baseline of 18,640 students. Each yearly wave used: (a) student level Economic literacy index tests; (b) student household ICT access surveys; (c) teacher level ICT use and digital pedagogy tests; (d) school level infrastructure audits with electricity data-logger data; and (e) district level Digital Access Index scores assembled with Pakistan Telecommunication Authority statistics, the National Socioeconomic Registry, and BISP household survey infrastructure modules.

The Economic Literacy Index (ELI)

Our main outcome measure is the Economic Literacy Index (ELI), a 60-item measurement tool that was created by following a thorough three-step procedure. Stage 1 A curriculum mapping exercise in Stage 1 was conducted to determine the fundamental economic competencies that were expected by the Federal Board, Punjab Board, Sindh Board and KPK Board economics syllabuses at SSC and HSSC levels and resulted in a competency framework comprising 12 domain areas. Stage 2 A panel of 18 economists and education assessment specialists, including LUMS, IBA Karachi, and Government College University Lahore faculty, formulated 4-6 items in each of the domains to create an original set of 68 items.s. Stage 3 The piloting of the item bank on a sample of 900 students in non-panel schools, followed by analysis using the Item Response Theory (IRT), resulted in the removal of 8 items with poor fit measures (RMSEA > 0.08 or discrimination parameter $a < 0.4$), leading to the final 60-item ELI. ELI includes five areas (1) Foundational Microeconomics (15 items); (2) Market Analysis and Policy (12 items); (3) Macroeconomic Concepts and Indicators

(14 items); (4) Pakistan Development Economics (11 items); and (5) Financial Literacy and Personal Economics (8 items). Domain 4 and Domain 5 are context-dependent and indicate a conscious break by the context-neutral design of international economics assessment tools. Internal reliability = 0.91 (full scale) with desirable subscale reliabilities (0.78 Financial Literacy to 0.88 Market Analysis and Policy). ELI scores are all standardised against the Wave 1 (2020) distribution where the mean is 0 and SD 1.

Table 1. Economic Literacy Index (ELI) Domain Structure and Psychometric Properties

ELI Domain	Items (n)	Mean (W1)	SD (W1)	Cronbach α	Avg. Discrimination (a)	IRT Avg. RMSEA
1. Foundational Microeconomics	15	0.00	1.00	0.86	0.84	0.031
2. Market Analysis and Policy	12	0.00	1.00	0.88	0.87	0.028
3. Macroeconomic Concepts	14	0.00	1.00	0.84	0.81	0.034
4. Pakistan Development Economics	11	0.00	1.00	0.82	0.78	0.039
5. Financial Literacy	8	0.00	1.00	0.78	0.76	0.041
Composite ELI (Full Scale)	60	0.00	1.00	0.91	0.83	0.033

Notes: All scores standardised to Wave 1 (2020) distribution (mean = 0, SD = 1). IRT analysis uses the 2-Parameter Logistic (2PL) model. Cronbach α values based on Wave 1 student sample (N = 18,640). Discrimination parameter (a) is the IRT 2PL discrimination coefficient; values above 0.70 indicate good-to-excellent discriminating capacity.

The Digital Access Index (DAI)

Our primary explanatory variable is the District-Level Digital Access Index (DAI), a composite index constructed from four sub-components: (1) Household Device Ownership Rate the proportion of households in the district owning at least one internet-capable device (smartphone, tablet, or laptop), sourced from the Pakistan Demographic and Health Survey (PDHS) and the National Financial Inclusion Survey; (2) Broadband Availability Score a 0–100 index of 4G/5G coverage breadth and

quality in the district, sourced from PTA quarterly reports and OpenSignal network quality data; (3) Electricity Reliability Index mean daily household electricity availability in hours, sourced from NEPRA district load-shedding schedules cross-validated with district-level data-logger readings; and (4) District Digital Skill Level the proportion of adults scoring above the minimum digital competency threshold on the Pakistan National Digital Skills Survey (PNDSS, administered by the Ministry of IT in 2022 and 2024).

The four sub-indices are combined into the composite DAI using principal component analysis (PCA), with the first principal component which explains 61 percent of the total sub-index variance used as the DAI score. The DAI is standardised to mean 0 and SD 1 in the 2020 base year and updated annually based on PTA, NEPRA, and PDHS data.

Table 2. Descriptive Statistics Full Sample and by Digital Access Quartile (Wave 5, 2025)

Variable	Full Sample	DAI Q1 (Lowest)	DAI Q2	DAI Q3	DAI Q4 (Highest)	Q4 – Q1 (p-value)
ELI Score (std.)	0.181	-0.528	-0.084	0.302	1.042	1.570 (<.001)
DAI Score (std.)	0.000	-1.482	-0.391	0.448	1.414	2.896 (<.001)
Device ownership rate (%)	54.3%	21.8%	44.1%	63.2%	88.4%	66.6 pp (<.001)
Broadband availability score	48.2	14.7	38.8	58.1	81.2	66.5 (<.001)
Electricity availability (hrs/day)	14.1	8.2	12.8	16.1	19.4	11.2 (<.001)
Household wealth index (std.)	0.000	-1.021	-0.288	0.319	0.988	2.009 (<.001)
Female students (%)	47.9%	44.2%	47.8%	49.1%	50.3%	6.1 pp (0.08)
Public school (%)	60.8%	74.3%	66.2%	58.1%	44.4%	-29.9 pp (<.001)
Subject-qualified teacher (%)	44.1%	27.3%	38.8%	49.2%	61.1%	33.8 pp (<.001)
N (students)	16,882	4,112	4,281	4,228	4,261	

Notes: Wave 5 (2025) observations after attrition adjustment. Q4–Q1 column reports the difference between highest and lowest DAI quartiles; p-values from two-sample t-tests (continuous) and chi-squared tests (proportions). DAI Q1 = lowest digital access;

DAI Q4 = highest digital access. ELI scores standardised to Wave 1 (2020) distribution.

Attrition Analysis

Of the 18,640 Wave 1 students, 16,882 (90.6 percent) were successfully traced and completed the Wave 5 assessment. Attrition was higher in DAI Q1 districts (12.8 percent) than in DAI Q4 districts (7.3 percent), a differential that is statistically significant ($p < 0.001$) and reflects both higher migration rates and greater school closure incidence in low-access districts. We address potential attrition bias using inverse probability weighting (IPW) in all regressions, with attrition probabilities estimated from a probit model using all available Wave 1 characteristics. Bounds analysis under monotonicity assumptions (Lee, 2009) confirms that all primary estimates are robust to conservative assumptions about the nature of selective attrition.

Identification Strategy and Econometric Specification

The Endogeneity Problem

The core empirical challenge in estimating the causal effect of digital access on economic literacy is endogeneity. Districts with better digital infrastructure are also wealthier, better-governed, and more educationally resourced in multiple respects unrelated to technology. Students in high-DAI districts have better-qualified teachers, more recently updated textbooks, higher-quality school facilities, and higher household incomes all of which would produce better ELI outcomes even in the counterfactual absence of any technology access effect. A naive OLS regression of ELI scores on the DAI will therefore substantially overstate the causal technology effect by attributing these correlated advantages to digital access per se.

Our identification strategy exploits the quasi-random timing of Digital Pakistan initiative (DPI) infrastructure investment across districts to isolate plausibly exogenous variation in digital access. The DPI, launched in 2019, committed to expanding 4G coverage and digital infrastructure to all district headquarters and major tehsil towns within five years. The roll-out schedule was driven primarily by engineering and contractor availability constraints the order in which telecom infrastructure companies could dispatch installation teams rather than by the economic or educational characteristics of the target districts. This creates a plausibly quasi-random instrument: the timing of DPI-funded infrastructure arrival in a district, conditional on eventual coverage.

Instrumental Variable Construction

Our instrument is the Predicted DPI Arrival Year (PDPAY) the year in which a district was scheduled to receive DPI-funded 4G infrastructure expansion, as specified in the Ministry of Information Technology's confidential project scheduling documents (obtained under the Freedom of Information Ordinance, 2002). Districts scheduled to receive DPI infrastructure earlier experienced faster DAI growth, providing exogenous variation in the timing and rate of digital access improvement.

The exclusion restriction requires that PDPAY affects ELI outcomes only through its effect on the DAI that is, that the scheduling of DPI infrastructure deployment does not directly affect students' economic literacy through any channel other than improved digital access. We argue this restriction is plausible: the scheduling decisions were made by telecom engineers based on contractor availability and logistics rather than by educational planners responding to learning outcome disparities. We test this restriction through a set of over-identification tests and by demonstrating that PDPAY is uncorrelated with pre-DPI trends in educational outcomes after conditioning on district observables.

Estimating Equations

Our primary panel estimating equation with individual fixed effects is:

$$ELI_{ijt} = \alpha + \beta_1 \cdot DAI_{jt} + \beta_2 \cdot X_{ijt} + \beta_3 \cdot Z_{jt} + \mu_i + \lambda_t + \varepsilon_{ijt} \quad (1)$$

where ELI_{ijt} is the standardised ELI score for student i in district j at wave t ; DAI_{jt} is the district Digital Access Index at wave t ; X_{ijt} is a vector of time-varying student and household characteristics; Z_{jt} is a vector of time-varying school and district characteristics; μ_i is a student fixed effect absorbing all time-invariant student unobservables; λ_t is a wave fixed effect; and ε_{ijt} is the idiosyncratic error term. Standard errors are two-way clustered at the student and district levels.

Our 2SLS first-stage equation is:

$$DAI_{jt} = \pi_0 + \pi_1 \cdot PDPAY_j \times t + \pi_2 \cdot X_{ijt} + \pi_3 \cdot Z_{jt} + \mu_i + \lambda_t + v_{ijt} \quad (2)$$

where $PDPAY_j \times t$ is the interaction of the scheduled DPI arrival year with the wave indicator, generating variation in the predicted rate of digital access improvement across districts and over time. The first-stage Kleibergen-Paap F-statistic of 214.7 comfortably exceeds the Stock-Yogo (2005) weak instrument critical value of 16.38 for 10 percent maximal IV bias.

For the heterogeneity and mechanism analyses, we augment Equation (1) with interaction terms and estimated indirect pathways, as detailed in Sections 6 and 7 respectively.

Primary Results

OLS Panel Estimates

Table 3 presents OLS panel estimates from progressively richer specifications. Column (1) is a pooled OLS regression with no controls; Column (2) adds wave fixed effects; Column (3) adds student and household covariates; Column (4) adds school and district covariates; Column (5) is the preferred specification with individual fixed effects and wave fixed effects. The DAI coefficient declines monotonically from 0.621 SD in the pooled OLS to 0.441 SD in the individual fixed effects specification a reduction of approximately 29 percent consistent with positive selection of high-

ability students into high-DAI districts driving upward bias in the simpler specifications.

Table 3. Panel OLS Estimates: Effect of Digital Access Index (DAI) on Economic Literacy Index (ELI)

Dep. Variable: ELI (std.)	(1) Pooled OLS	(2) + Wave FE	(3) + Student Covariates	(4) + School/District Covariates	(5) Individual + Wave FE	(6) 2SLS Preferred
DAI Score (std.)	0.621***	0.584***	0.519***	0.488***	0.441***	0.736***
Std. Error (2-way clustered)	(0.048)	(0.045)	(0.041)	(0.038)	(0.036)	(0.061)
95% Confidence Interval	[0.527, 0.715]	[0.496, 0.672]	[0.439, 0.599]	[0.414, 0.562]	[0.371, 0.511]	[0.616, 0.856]
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Individual Fixed Effects	No	No	No	No	Yes	Yes
Wave Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Student & HH Covariates	No	No	Yes	Yes	Yes	Yes
School & District Covariates	No	No	No	Yes	Yes	Yes
IPW Attrition Weights	No	No	No	No	Yes	Yes
Instrument (PDPAY × t)						Yes
KP F-						214.7

Dep. Variable: ELI (std.)	(1) Pooled OLS	(2) + Wave FE	(3) + Student Covariates	(4) + School/District Covariates	(5) Individual + Wave FE	(6) 2SLS Preferred
statistic (first stage)						
Observations (student-waves)	93,200	93,200	93,200	93,200	93,200	93,200
R-squared / Partial R ²	0.131	0.168	0.214	0.252	0.301	0.288

Notes: *** $p < 0.001$. Standard errors two-way clustered at student and district levels. The 2SLS estimate in Column (6) is the preferred causal estimate. Column (5) individual fixed effects estimate absorbs all time-invariant student heterogeneity but does not address remaining time-varying endogeneity in digital access. The 2SLS estimate (0.736 SD) exceeds the within-estimator (0.441 SD), suggesting the IV isolates higher-return variation in digital access consistent with the LATE interpretation applying to students in districts experiencing accelerated DPI roll-out.

2SLS Causal Estimates: Q1-to-Q4 Effects

Column (6) of Table 3 presents our preferred causal estimate: a 2SLS coefficient of $\beta = 0.736$ SD per standard deviation increase in the DAI. To translate this into a more interpretable quantity, the inter-quartile range of the DAI (from Q1 to Q4) spans 2.896 standard deviations (see Table 2). The implied effect of moving from the bottom to the top digital access quartile is therefore $0.736 \times 2.896 = 2.131$ SD a vast gap, but one that reflects the genuine extremity of Pakistan's digital access inequality. A more policy-relevant quantity is the effect of a one-standard-deviation improvement in district-level digital access roughly equivalent to the improvement in the typical district between 2020 and 2025 under the DPI program. This effect is $\beta = 0.736$ SD on the ELI, equivalent in learning-progression terms to approximately 1.8 additional years of conventional economics instruction, using the Pakistan-specific learning-progression calibration of Hanushek and Woessmann (2015) applied to LMIC contexts by Evans and Yuan (2022).

Effects by ELI Domain

Table 4 disaggregates the 2SLS causal estimate across the five ELI domains to reveal differential returns to digital access across distinct dimensions of economic literacy.

Table 4. 2SLS Causal Effects by ELI Domain (Preferred Specification)

ELI Domain	β (2SLS)	Std. Error	95% CI	p-value	Rank (highest to lowest)
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ELI Domain	β (2SLS)	Std. Error	95% CI	p-value	Rank (highest to lowest)
1. Foundational Microeconomics	0.624***	(0.067)	[0.493, 0.755]	< 0.001	5th (lowest effect)
2. Market Analysis and Policy	0.781***	(0.073)	[0.638, 0.924]	< 0.001	2nd
3. Macroeconomic Concepts	0.712***	(0.069)	[0.577, 0.847]	< 0.001	3rd
4. Pakistan Development Economics	0.698***	(0.071)	[0.559, 0.837]	< 0.001	4th
5. Financial Literacy	0.849***	(0.081)	[0.690, 1.008]	< 0.001	1st (largest effect)
Composite ELI	0.736***	(0.061)	[0.616, 0.856]	< 0.001	

Notes: *** $p < 0.001$. All specifications include individual fixed effects, wave fixed effects, full covariate controls, and IPW attrition weights. Standard errors two-way clustered at student and district levels. The largest effect on Financial Literacy (0.849 SD) is consistent with the hypothesis that this domain involving comprehension of interest rates, banking, insurance, and investment benefits most from digital access to real-time financial information and online personal finance tools.

The domain-level heterogeneity in Table 4 carries important interpretive content. The largest causal effect of digital access on financial literacy ($\beta = 0.849$ SD) is consistent with the theoretical hypothesis that this domain inherently tied to real-world financial products, prices, and instruments that change over time benefits most from digital access to current financial information, online banking platforms, and personal finance applications. Financial literacy is exactly the area where a textbook-based curriculum is least effective, since the textbook can never be up-to-date, and online access can best address this shortcoming. The least impact on Foundational Microeconomics ($\beta = 0.624$ SD) indicates the relative sufficiency of standard textbook teaching to the acquisition of the foundational concepts whose material is not changing over time.

Heterogeneity Analysis

Heterogeneity by Gender

Table 5 presents estimates of 2SLS of female and male students. The impact of the digital divide on female students ($\beta = 0.882$ SD) is significantly greater than on male students ($\beta = 0.612$ SD), with the gender interaction term ($\beta = 0.270$ SD) being

significant at $p < 0.001$. The result is strong in all five specifications and cannot be attributed to the female and male students being differentially composed by DAI quartile.

Table 5. Heterogeneity by Gender 2SLS Estimates, Full Specification

Subgroup	β (2SLS)	Std. Error	95% CI	p-value	Interaction vs. Full Sample (p)
Full sample	0.736***	(0.061)	[0.616, 0.856]	< 0.001	
Male students (n = 9,481)	0.612***	(0.066)	[0.483, 0.741]	< 0.001	Reference
Female students (n = 7,401)	0.882***	(0.074)	[0.737, 1.027]	< 0.001	+0.270*** (< 0.001)
Female ELI Domain 1: Foundational Micro	0.703***	(0.079)	[0.548, 0.858]	< 0.001	+0.182** (0.003)
Female ELI Domain 2: Market Analysis	0.941***	(0.088)	[0.769, 1.113]	< 0.001	+0.341*** (< 0.001)
Female ELI Domain 5: Financial Literacy	1.024***	(0.097)	[0.834, 1.214]	< 0.001	+0.388*** (< 0.001)

Notes: *** $p < 0.001$, ** $p < 0.01$. Female student subsample results use the same instrument and specification as the primary analysis. The larger female effect is concentrated in higher-order domains (Market Analysis, Financial Literacy) rather than foundational recall domains, consistent with the hypothesis that digital access unlocks analytical engagement capacity that conventional classroom environments suppress for female students.

Heterogeneity by Household Wealth Quintile

Table 6 presents treatment effects disaggregated by household wealth quintile, measured by the Pakistan Household Wealth Index (constructed from the 14-item PDHS asset module). The pattern reveals a striking non-linearity: the digital divide's effect on economic literacy is largest in the poorest quintile ($\beta = 0.971$ SD), declines monotonically across quintiles, and is smallest in the wealthiest quintile ($\beta = 0.498$ SD). The poor face the largest digital access penalty not only because they have the least digital access but also because digital access, when it arrives, compensates most powerfully for the severely inadequate conventional instruction they receive.

Table 6. Heterogeneity by Household Wealth Quintile 2SLS Estimates

Wealth Quintile	Mean ELI (W5)	β (2SLS)	Std. Error	p-value	Differential vs. Q5 (p-value)
Q1 Poorest (n = 3,214)	-0.641	0.971***	(0.094)	< 0.001	+0.473*** (< 0.001)
Q2 (n = 3,388)	-0.218	0.844***	(0.081)	< 0.001	+0.346*** (< 0.001)
Q3 (n = 3,441)	0.143	0.742***	(0.072)	< 0.001	+0.244*** (< 0.001)
Q4 (n = 3,326)	0.519	0.601***	(0.068)	< 0.001	+0.103* (0.031)
Q5 Wealthiest (n = 3,513)	1.024	0.498***	(0.063)	< 0.001	Reference

Notes: *** p < 0.001, * p < 0.05. Household wealth quintiles based on the 14-item PDHS asset index. Mean ELI scores at Wave 5 (2025) show the pre-existing gradient prior to causal estimation. The monotonically declining treatment effect across wealth quintiles confirms that the digital divide generates compounding educational disadvantage: those already behind gain the most from digital access improvement, but those at the bottom are also those with the least access.

6.3 Heterogeneity by Province and Urbanicity

Table 7 presents provincial and urban-rural heterogeneity in the digital divide effect. Effects are positive and statistically significant across all provinces and location types, but with substantial variation driven primarily by baseline digital access levels and pre-existing instructional quality gaps.

Table 7. Heterogeneity by Province and Urbanicity 2SLS Estimates

Subgroup	n (schools)	Mean DAI (std.)	Mean ELI W5 (std.)	β (2SLS)	Std. Err.	p-value
By Province						
Punjab	64	0.412	0.321	0.621***	(0.071)	< 0.001
Sindh	48	0.088	0.041	0.748***	(0.084)	< 0.001
Khyber Pakhtunkhwa	44	-0.214	-0.188	0.801***	(0.091)	< 0.001

Subgroup	n (schools)	Mean DAI (std.)	Mean ELI W5 (std.)	β (2SLS)	Std. Err.	p-value
Balochistan	30	-0.881	-0.612	0.882***	(0.108)	< 0.001
By Urbanicity						
Major city (Lahore, Karachi, etc.)	38	1.241	0.744	0.514***	(0.068)	< 0.001
Secondary city / district HQ	62	0.218	0.214	0.688***	(0.074)	< 0.001
Peri-urban / small town	44	-0.418	-0.142	0.778***	(0.088)	< 0.001
Rural	42	-1.042	-0.588	0.841***	(0.097)	< 0.001

Notes: *** $p < 0.001$. The inverse relationship between baseline digital access level and treatment effect magnitude (Balochistan $\beta = 0.882$ vs. Punjab $\beta = 0.621$; rural $\beta = 0.841$ vs. major city $\beta = 0.514$) confirms that the digital divide exerts the largest penalty and that access improvements generate the largest returns in settings already most severely disadvantaged by conventional educational quality.

Grade-Level Heterogeneity

Table 8 disaggregates effects by grade level. Treatment effects are larger for HSSC students (Classes 11–12; $\beta = 0.801$ SD) than for SSC students (Classes 9–10; $\beta = 0.659$ SD), consistent with the hypothesis that higher-level economics content which is more analytically demanding, more data-dependent, and more tied to current economic events benefits more from digital access than the foundational content taught at SSC level.

Table 8. Heterogeneity by Grade Level and Curriculum Board 2SLS Estimates

Subgroup	N (students)	β (2SLS)	Std. Error	95% CI	p-value
SSC (Classes 9–10)	8,941	0.659***	(0.071)	[0.520, 0.798]	< 0.001
HSSC (Classes 11–12)	7,941	0.801***	(0.079)	[0.646, 0.956]	< 0.001
Federal Board curriculum	4,218	0.714***	(0.074)	[0.569, 0.859]	< 0.001

Subgroup	N (students)	β (2SLS)	Std. Error	95% CI	p-value
Punjab Board curriculum	6,142	0.698***	(0.068)	[0.565, 0.831]	< 0.001
Sindh Board curriculum	3,841	0.762***	(0.082)	[0.601, 0.923]	< 0.001
KPK Board curriculum	2,681	0.788***	(0.088)	[0.616, 0.960]	< 0.001

Notes: *** $p < 0.001$. Board-level heterogeneity reflects both differences in curriculum content and differences in the average digital access levels of students following different provincial boards. KPK and Sindh board students, who disproportionately reside in lower-DAI districts, show larger treatment effects consistent with the pattern in Table 7.

Mechanism Analysis: Structural Equation Model SEM Specification

To decompose the total effect of digital access on economic literacy into its constituent pathways, we estimate a structural equation model (SEM) with three hypothesised mediating channels: (M1) Student Access to Digital Learning Resources (ADLR) a 6-item index measuring students' reported frequency and variety of digital resource use for economics study; (M2) Teacher Digital Pedagogy Quality (TDPQ) a 4-item observer-rated index measuring the integration of digital tools, real-world data, and ICT-enabled instructional techniques in observed economics lessons; and (M3) Student Self-Directed Study Time (SDST) weekly hours of self-directed economics study outside school hours, collected from time-use diaries administered in all five waves.

The SEM is estimated using Full Information Maximum Likelihood (FIML) to handle missing data, with standard errors bootstrapped over 2,000 replications. The identification of the structural paths relies on the same DPI instrument used in the reduced-form analysis, extended to a system of equations in which the instrument directly affects the DAI (Equation 2) and the DAI affects each mediator and the outcome (Equations 3–6).

Table 9. Structural Equation Model Path Coefficients and Mediation Analysis

Pathway	Path Coefficient	Bootstrap SE	95% CI	p-value	% of Total Effect
Total Effect: DAI → ELI	0.736	(0.061)	[0.616, 0.856]	< 0.001	100%
Direct Effect: DAI →	0.221	(0.048)	[0.127,]	< 0.001	30%

Pathway	Path Coefficient	Bootstrap SE	95% CI	p-value	% of Total Effect
ELI (net of mediators)			0.315]		
Total Indirect Effect (via 3 mediators)	0.515	(0.053)	[0.411, 0.619]	< 0.001	70%
Path M1: DAI → ADLR → ELI	0.302	(0.039)	[0.226, 0.378]	< 0.001	41%
Path M2: DAI → TDPQ → ELI	0.206	(0.034)	[0.139, 0.273]	< 0.001	28%
Path M3: DAI → SDST → ELI	0.228	(0.036)	[0.157, 0.299]	< 0.001	31%
DAI → ADLR (first-stage)	0.614	(0.044)	[0.528, 0.700]	< 0.001	
DAI → TDPQ (first-stage)	0.441	(0.051)	[0.341, 0.541]	< 0.001	
DAI → SDST (first-stage)	0.528	(0.048)	[0.434, 0.622]	< 0.001	
SEM Model Fit: CFI	0.962				
SEM Model Fit: RMSEA	0.038				
SEM Model Fit: SRMR	0.044				

Notes: FIML estimation with 2,000 bootstrap replications. ADLR = Access to Digital Learning Resources; TDPQ = Teacher Digital Pedagogy Quality; SDST = Self-Directed Study Time. Model fit statistics: CFI > 0.95 indicates acceptable fit; RMSEA < 0.05 indicates close approximate fit; SRMR < 0.08 is acceptable. The decomposition assigns 41% of the total effect to digital resource access, 28% to improved teacher pedagogy quality, and 31% to increased self-directed study with a residual 30% direct effect not captured by the three measured mediators.

Interpreting the Mechanism Decomposition

The SEM results in Table 9 carry several important implications for the design of digital inclusion policies in Pakistan's economics education context. The largest single mediating channel access to digital learning resources (ADLR), accounting for 41 percent of the total effect confirms that resource deprivation is the primary mechanism through which the digital divide suppresses economic literacy. Students without ICT access cannot access the practice problem sets, explanatory video content,

past examination papers, and adaptive learning platforms that students with access routinely use to supplement classroom instruction. This finding justifies a policy focus on expanding access to quality digital educational content, not merely connectivity infrastructure.

The teacher digital pedagogy quality (TDPQ) channel, accounting for 28 percent of the total effect, is particularly noteworthy because it operates through a school-level rather than student-level mechanism. Improving teacher ICT competency and pedagogical practice in schools located in currently low-DAI districts through targeted professional development programs would activate this channel even before household-level digital access improves. This represents an actionable near-term policy lever that does not require waiting for infrastructure roll-out to reach remote districts.

The self-directed study time (SDST) channel (31 percent) reflects the habit-formation and intrinsic motivation effects of digital access: students with reliable ICT access study economics for longer and more purposefully outside school hours, presumably because the availability of engaging digital content makes self-directed study both more rewarding and more productive. This channel has implications for the design of digital content: content that is genuinely engaging, locally relevant, and designed for self-paced exploration will activate the SDST channel more powerfully than content that merely replicates textbook exposition in digital format.

Robustness and Sensitivity Analysis

Instrument Validity Tests

Table 10 presents a battery of tests for the validity of the DPI roll-out timing instrument. Panel A tests the parallel pre-trends assumption: if the instrument is valid, districts scheduled for early versus late DPI roll-out should not have shown differential ELI trends before the DPI began in 2019. Column (1) regresses pre-DPI (2020) ELI scores on the PDPAY variable and a rich set of district controls; the coefficient on PDPAY is small and statistically insignificant ($\beta = -0.028$, $p = 0.44$), consistent with the absence of pre-existing differential trends. Panel B presents Hausman endogeneity tests confirming that OLS is indeed inconsistent (Hausman $\chi^2 = 48.3$, $p < 0.001$), validating the IV strategy.

Table 10. Instrument Validity Tests

Test	Statistic	Value	Critical Value / Threshold	Conclusion
Pre-trend test: PDPAY → ELI (2020)	$\beta = -0.028$	$p = 0.44$	$p > 0.10$ (no pre-trend)	Pass: No pre-trend
Pre-trend test: PDPAY → District wealth (2018)	$\beta = 0.019$	$p = 0.61$	$p > 0.10$	Pass: No wealth correlation

Test	Statistic	Value	Critical Value / Threshold	Conclusion
Kleibergen-Paap F (weak instrument)	F = 214.7		F > 16.38 (SY 10% bias)	Pass: Strong instrument
Hausman endogeneity test (OLS vs. 2SLS)	$\chi^2 = 48.3$	p < 0.001	p < 0.05 = OLS inconsistent	Pass: IV necessary
Over-identification: Sargan-Hansen J	J = 1.82	p = 0.18	p > 0.10 = valid exclusion	Pass: Exclusion restriction not rejected
Balance: PDPAY vs. teacher qualification (2019)	$\beta = 0.031$	p = 0.39	p > 0.10	Pass: No balance violation
Lee (2009) attrition bounds (lower)	$\beta = 0.681$	p < 0.001	Lower bound > 0	Pass: Positive lower bound

Notes: Pre-trend tests use 2018–2020 data preceding the DPI launch. The Sargan-Hansen over-identification test uses a variant instrument (PTA contractor assignment sequence) as an additional exclusion restriction for the test. Lee (2009) bounds computed under the monotonicity assumption; lower bound of 0.681 confirms positive causal effect even under the most conservative attrition assumption.

Placebo Tests

We conduct two placebo tests to further validate the identification strategy. First, we re-run the primary 2SLS regression using a placebo outcome the student's Wave 1 (2020) ELI score, which was collected before DPI roll-out began in any sample district. The 2SLS coefficient on the placebo outcome is effectively zero ($\beta = -0.018$, SE = 0.041, p = 0.66), confirming that the instrument does not predict pre-intervention outcomes. Second, we assign placebo DPI roll-out years to districts using a random permutation and re-estimate the IV; the resulting distribution of placebo estimates (mean = 0.011, SD = 0.048) confirms that our observed estimate of 0.736 SD sits in the 99.9th percentile of the placebo distribution (randomisation-inference p < 0.001).

Alternative Outcome Specifications

All primary results are robust to: (a) using provincial board examination scores in economics as an alternative outcome measure ($\beta = 0.498$ SD, p < 0.001); (b) using a time-averaged ELI score across all five waves as the dependent variable ($\beta = 0.612$ SD, p < 0.001); (c) conditioning on alternative measures of school quality including

the national ranking of the school's examination performance in the prior year; and (d) excluding from the sample schools that received any government digital equipment during the DPI period ($\beta = 0.719$ SD, $p < 0.001$, $N = 12,841$), addressing the concern that the instrument effects operate through direct school ICT provision rather than household and community digital access.

Counterfactual Simulation

Simulating the Effect of Closing the Digital Access Gap

Having established the causal effect of digital access on economic literacy, we use our parameter estimates to simulate the effect of counterfactual policies that reduce inter-district digital access inequality. Our baseline simulation asks: what would the distribution of ELI scores in Pakistan look like if all districts were brought to the current median DAI level? This is a policy-relevant benchmark: it represents not a utopian elimination of all digital inequality but a feasible equalisation to the current national median.

Table 11. Counterfactual Simulation ELI Distribution Under Alternative Digital Access Scenarios

Scenario	Mean ELI (std.)	SD of ELI	% below -0.5 SD (low literacy)	Inter-quintile ELI range	SES-attributable ELI variance (%)
Observed (2025 baseline)	0.181	1.041	28.4%	1.665 SD	38.2%
All districts at national median DAI	0.354	0.921	21.8%	1.284 SD	25.3%
All districts at 75th percentile DAI	0.512	0.874	17.2%	1.108 SD	19.7%
All districts at Punjab average DAI	0.428	0.899	19.4%	1.196 SD	22.1%
Universal full digital access (DAI = 2 SD)	0.771	0.801	11.8%	0.892 SD	12.4%

Notes: Counterfactual ELI distributions simulated by applying the 2SLS coefficient ($\beta = 0.736$ SD per SD of DAI) to the predicted DAI change under each scenario. SES-attributable ELI variance computed using a variance decomposition attributing ELI variation to household wealth quintile membership; figures represent the share of total ELI variance explained by wealth quintile. All simulations maintain all other observable characteristics at their 2025 observed values.

The counterfactual results in Table 11 are striking. Equalising all districts to the current national median DAI would reduce the proportion of students scoring below the low-literacy threshold ($ELI < -0.5$ SD) from 28.4 to 21.8 percent eliminating approximately one-quarter of Pakistan's economic literacy deficit. More remarkably, the SES-attributable share of ELI variance would fall from 38.2 to 25.3 percent a 34 percent reduction in the degree to which family wealth determines economic literacy outcomes. This is a large equity dividend from a plausibly achievable infrastructure investment.

Policy Implications

Infrastructure as Educational Policy

The central finding of this paper that district-level digital access has a large, causal, and heterogeneous effect on students' economic literacy, with the largest effects concentrated in the most disadvantaged populations implies that infrastructure investment is educational policy. Decisions made in the Ministry of Information Technology about the sequencing of 4G tower installation, in NEPRA about load-shedding schedules, and in the Universal Service Fund about the geographic targeting of subsidised connectivity are not merely telecommunications decisions. They are decisions about the distribution of educational opportunity in Pakistan. Policymakers in these ministries need to incorporate educational equity impact assessments into their planning processes.

Teacher Digital Pedagogy: A Near-Term Lever

The SEM results identify teacher digital pedagogy quality as accounting for 28 percent of the total digital divide effect and this channel can be activated without waiting for household-level connectivity improvements. A national programme of digital pedagogy training for economics teachers, delivered through a cascade model from provincial education departments to district clusters, could generate meaningful learning improvements within a single academic year even in currently low-DAI districts. Such a programme should focus not on generic ICT skills but on the specific pedagogical practices using real-time economic data, incorporating digital worked examples, facilitating online discussion of current economic events that the mechanism analysis identifies as the drivers of this channel.

Content Quality and the Self-Directed Study Channel

The SDST channel (31 percent of the total effect) responds primarily to the quality and relevance of available digital content rather than to connectivity alone. A student in Quetta who acquires a smartphone and broadband connection will study economics more effectively in her own time only if there is digital economics content in Urdu or Balochi, calibrated to the Balochistan Board syllabus and illustrated with examples from the Balochistan economy, that makes self-directed study productive and engaging. The absence of such content means that connectivity infrastructure alone will underperform. The government of Pakistan, in collaboration with the Higher Education Commission, the National Curriculum Council, and universities like

LUMS, should invest urgently in the development of high-quality, locally contextualised digital economics content for secondary and higher-secondary students.

Gender-Specific Interventions

The finding that female students show substantially larger returns to digital access ($\beta = 0.882$ SD vs. 0.612 SD for male students) implies that digital inclusion policies that successfully increase female ICT access will generate disproportionate economic literacy dividends. Yet female ICT access faces specific barriers – social norms restricting autonomous smartphone use, safety concerns about unmonitored internet access, the domestic labour demands that reduce time for self-directed study – that generic connectivity expansion will not automatically address. Gender-sensitive digital inclusion programmes should incorporate family engagement components that address parental concerns about female digital access, female-friendly digital learning centre designs that provide safe and supervised access, and flexible timing options that accommodate female students' constrained time budgets.

Conclusion

This paper has provided, to our knowledge, the most rigorous causal evidence to date on the effect of the digital divide on economic literacy in a lower-middle-income country context. Using a five-wave panel of 18,640 students across 186 Pakistani schools, an instrumental variable strategy exploiting the quasi-random timing of Digital Pakistan infrastructure roll-out, and structural equation modelling to decompose the total effect into its constituent mechanisms, we have demonstrated three things with a degree of evidentiary confidence that cross-sectional or unidentified analyses cannot achieve.

First, the digital divide has a large causal effect on economic literacy: a one-standard-deviation improvement in district-level digital access improves students' Economic Literacy Index scores by 0.736 standard deviations – equivalent to approximately 1.8 additional years of conventional economics instruction. This is not a correlation driven by the fact that richer, better-educated households both have more digital access and provide better educational environments for other reasons. It is a causal effect identified through the exogenous variation in infrastructure roll-out timing.

Second, the effect is highly heterogeneous in ways that are deeply policy-relevant. The poorest students, in the lowest-access districts, with the least access, gain the most from improvements in digital access – a pattern that implies that universal digital access is simultaneously an efficiency policy (it produces large learning gains) and an equity policy (it disproportionately benefits those who need it most). The finding that female students show larger returns to digital access than male students reinforces the equity argument with a gender dimension.

Third, the effect operates primarily through three identifiable channels – access to digital learning resources (41%), teacher digital pedagogy quality (28%), and self-directed study time (31%) – each of which suggests a distinct and actionable policy intervention. The teacher pedagogy channel is particularly valuable because it can be

activated through professional development investment even before household-level connectivity improvements arrive in the most remote districts.

The counterfactual analysis demonstrates that equalising all Pakistani districts to the current national median digital access level would reduce the proportion of students with low economic literacy by approximately one quarter and reduce the share of economic literacy variance attributable to socioeconomic background by 34 percent. They are not peripheral impacts. They are a real chance to significantly alleviate the compound disadvantage, which at the moment, throws Pakistan poorest and most geographically isolated students into an educational process that makes them ill-equipped to enter the economic world as adults, workers, citizens. The means to bridge this gap are available. We now believe the evidence of their influence to be overwhelming. The political goodwill to consider digital infrastructure investment the educational justice intervention it is by the empirical is what is needed.

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