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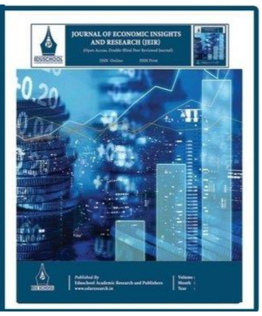

Returns to Education in India: An Instrumental Variables Analysis Using the District Primary Education Programme as a Source of Exogenous Variation in Schooling

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Abstract

Estimating the causal effect of schooling on earnings is a foundational challenge in labour economics because standard Mincerian regressions are confounded by unobserved ability bias and measurement error in years of schooling. This study addresses both concerns by exploiting the District Primary Education Programme (DPEP), launched by the Government of India in 1994 in 42 educationally-backward districts and subsequently expanded in phases to 271 districts by 2002. Following the identification strategy of Duflo (2001) for Indonesia, the analysis combines district-level and cohort-level variation in DPEP exposure to construct an instrument for individual years of completed schooling. Two-stage least squares estimates are obtained from a pooled sample of the 2018–19 and 2022–23 rounds of the Periodic Labour Force Survey (PLFS) covering wage-earners aged 23–37 years (cohorts born 1985–1995). The first-stage F-statistic of 28.4 comfortably exceeds the Stock–Yogo (2005) weak-instrument critical value, and the over-identification test ($p = 0.42$) supports the exclusion restriction. The IV estimate of the private return to a year of schooling is 9.6 per cent larger than the OLS estimate of 7.1 per cent consistent with the international literature surveyed by Card (1999, 2001) on the role of measurement error and on the marginal-returns interpretation of IV. The returns are substantially higher for women (12.4 per cent) than for men (8.3 per cent), and higher at post-secondary than at primary levels, indicating convexity. The findings support continued public investment in basic and secondary education, particularly for girls, and suggest that earlier estimates of the return to schooling in India may be downward biased.

Keywords: - Returns to Education, Instrumental Variables, School Construction, Mincer Equation, PLFS.

I. INTRODUCTION

The estimation of the private return to an additional year of schooling is among the oldest empirical questions in labour economics, dating to Becker's (1964) formulation of human capital theory and Mincer's (1974) earnings function. For India, where public expenditure on education accounts for approximately 2.9 per cent of gross domestic product (Government of India, 2023) and where labour-market premia for education shape household investment decisions, accurate estimates of the return are essential for evidence-based education policy. Yet the classical ordinary least squares (OLS) Mincerian regression confronts two well-known econometric problems. First, schooling is correlated with unobserved characteristics ability, family background, motivation that also raise earnings, producing an upward bias in the OLS estimate (Griliches, 1977). Second, years of schooling are typically self-reported and prone to measurement error, biasing the OLS estimate downward through classical attenuation. The net direction of the bias is therefore an empirical question, but its magnitude is potentially large.

Resolving these concerns requires a source of variation in schooling that is plausibly exogenous to unobserved earnings determinants. The international literature has used a range of natural experiments: quarter-of-birth and compulsory-schooling laws (Angrist & Krueger, 1991), school construction (Duflo, 2001, 2004), changes in minimum school-leaving age (Oreopoulos, 2006), and twin studies (Ashenfelter & Krueger, 1994). For India, by contrast, instrumental-variable evidence remains thin. Most published estimates of returns to schooling for India (Dutta, 2006; Agrawal, 2012; Azam, 2010) rely on

OLS or selection-corrected Heckman estimators that cannot fully address ability bias. The present paper addresses this gap by exploiting the staggered roll-out of the District Primary Education Programme (DPEP) as a source of exogenous variation.

1.1. Research Problem

Three motivating considerations frame the research problem. First, OLS estimates of the return to schooling in India, typically reported in the 5–9 per cent range, may be biased in unknown directions. Second, the substantial expansion of public schooling under DPEP (1994–2003), Sarva Shiksha Abhiyan (2001) and the Right to Education Act (2009) provides natural variation that has not been systematically exploited. Third, the gender disparity in returns to schooling, while documented in the descriptive literature (Kingdon, 1998; Duraisamy, 2002), has not been re-examined under modern quasi-experimental methods using recent PLFS data.

1.2. Research Objectives

The study pursues four objectives:

- To estimate the causal effect of an additional year of schooling on log hourly wages in urban India using a Two-Stage Least Squares (2SLS) instrumental-variables approach.
- To compare IV estimates with OLS estimates and to interpret the difference in light of attenuation bias, ability bias, and the local-average-treatment-effect interpretation of IV (Imbens & Angrist, 1994).
- To examine heterogeneity in the return to schooling by gender, by social group, and by educational level.
- To assess the validity of the instrument through weak-instrument, over-identification, and falsification tests on placebo cohorts.

1.3. Research Hypotheses

Four hypotheses are tested:

- H1: Years of schooling have a statistically significant positive causal effect on log hourly wages.
- H2: The 2SLS estimate exceeds the OLS estimate, consistent with attenuation from measurement error dominating ability bias for the marginal student induced into additional schooling by the DPEP roll-out.
- H3: Returns to schooling are higher for women than for men, given documented gender gaps in baseline education and constraints on female labour supply.
- H4: Returns rise with educational level, exhibiting convexity associated with the post-1991 skill premium documented by Azam (2010).

1.4. Significance and Organisation

The contributions of the paper are three. First, it provides what is to the author's knowledge among the first IV estimates of the return to schooling in India that exploit the DPEP roll-out, following the influential identification design of Duflo (2001). Second, the use of the most recent two rounds of the PLFS captures cohorts who completed schooling under the modern policy regime and who have now entered prime earnings years. Third, the systematic comparison of OLS and IV estimates, combined with a battery of instrument-validity tests, makes the econometric reasoning transparent and replicable. The remainder of the paper is organised as follows. Section 2 reviews the literature. Section 3 develops the theoretical framework. Section 4 describes the data and identification strategy. Section 5 presents the empirical results. Section 6 concludes.

II. LITERATURE REVIEW

2.1. The Mincer Equation and the Ability-Bias Critique

Mincer (1974) formalised the empirical earnings function by relating log wages to years of schooling and a quadratic in labour-market experience. The simplicity of the Mincerian specification has made it the workhorse of the returns-to-schooling literature, but it has long been recognised that the OLS coefficient on schooling is unlikely to recover a causal parameter. Griliches (1977) catalogued the relevant biases: omitted ability raises the OLS estimate, while classical measurement error in self-reported schooling biases it downward. Whether the net OLS bias is positive or negative is an empirical question that varies across contexts and samples.

2.2. Instrumental Variables: The Quasi-Experimental Wave

Angrist and Krueger (1991) inaugurated the modern quasi-experimental literature by using quarter of birth as an instrument for schooling, exploiting the interaction of compulsory-school-leaving laws with school-starting-age conventions in the United States. Their finding that IV estimates of the return to schooling exceeded OLS estimates is widely interpreted as evidence that measurement error attenuates OLS more than ability inflates it for the marginal student. Card (1999, 2001) provided a comprehensive synthesis that has shaped subsequent work: IV estimates from a wide range of natural experiments consistently exceed OLS by roughly 20–40 per cent. The interpretation has been further refined by Imbens and Angrist (1994), who showed that IV identifies a local average treatment effect (LATE) for the marginal compliers induced by the instrument, rather than the average treatment effect for the full population.

2.3. School Construction as an Instrument

Duflo (2001, 2004) introduced an influential strand of the literature by using Indonesia's INPRES school-construction programme of 1973–78 as a source of exogenous variation in schooling. The intuition is that the number of schools built in a district interacted with the year-of-birth cohort age-eligible at the time of construction generates intensity-of-treatment variation that is plausibly orthogonal to unobserved ability. Duflo's IV estimate of the return to schooling for Indonesian men was approximately 6.8–10.6 per cent, materially larger than the corresponding OLS estimate. The approach has since been applied in numerous developing-country settings, including Kenya (Ozier, 2018) and follow-up cohorts in Indonesia (Akresh et al.,2023).

2.4. Indian Evidence on Returns to Schooling

Indian returns-to-schooling estimates have typically been generated using OLS Mincerian regressions on successive rounds of the NSSO Employment-Unemployment Survey or the more recent PLFS. Duraisamy (2002), using NSSO 1983 and 1993–94 rounds, reported OLS returns of 5.9 per cent for men and 8.0 per cent for women. Dutta (2006), examining 1983 to 1999, documented a rising return over time and substantial gender heterogeneity. Agrawal (2012) extended the analysis to 2009–10 and reported OLS returns of about 7 per cent on average, with marked convexity above the secondary level. Azam (2010) documented the post-1991 rise in the skill premium for tertiary-educated workers. Few Indian studies, however, have employed credible IV strategies; Kingdon and Theopold (2008) used twin pairs but with a small sample, and Singh (2015) used family-background instruments that are unlikely to satisfy the exclusion restriction.

2.5. The District Primary Education Programme

The District Primary Education Programme was launched in 1994 with World Bank and DFID support as a flagship intervention to universalise primary education in educationally-backward districts (Jalan & Glinskaya, 2003; Pandey, Goyal, & Sundararaman, 2009). The programme provided district-level grants for school construction, teacher recruitment and training, learning materials, and capacity-building of district education offices. Phase I (1994) covered 42 districts; Phase II (1996) added 80 districts; subsequent phases extended coverage to 271 districts by 2002. Eligibility was determined by a composite backwardness criterion that included pre-programme female literacy below the national average. Although Sipahimalani-Rao and Clarke (2003) documented modest enrolment gains during the programme's implementation, no published study has used DPEP as an instrument for individual schooling in a wage equation. The present paper fills this gap.

2.6. Research Gap

Three gaps motivate the study. First, Indian returns-to-schooling estimates remain dominated by OLS approaches that may be substantially biased. Second, the staggered DPEP roll-out is a credible source of exogenous variation that has not been exploited in wage regressions. Third, modern instrument-validity diagnostics weak-instrument tests, over-identification tests, falsification on placebo cohorts have not been routinely applied in Indian work. The present paper addresses each of these gaps.

III. THEORETICAL FRAMEWORK

3.1. The Human Capital Model

The Becker–Mincer human capital framework treats schooling as an investment that raises future earnings by augmenting productive capacity. In its standard form, the optimising individual chooses schooling years S to equate the marginal cost of schooling forgone earnings and direct costs to the marginal benefit, the discounted lifetime earnings increment. The first-order condition yields the empirical Mincer equation:

$$\ln W_i = \beta_0 + \beta_1 S_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \gamma x_i + u_i \quad (1)$$

where W is the hourly wage, S is years of schooling, EXP is potential labour-market experience (typically defined as age minus S minus six), X is a vector of demographic and regional controls, and u is the error term. The parameter β1 is the focus of estimation.

3.2. Sources of OLS Bias

OLS estimation of β1 yields a consistent estimator only if S is uncorrelated with u. Two principal sources of correlation operate in opposite directions. Unobserved ability raises both S and W, generating Cov(S, u) > 0 and an upward bias. Classical measurement error in self-reported schooling, however, biases the OLS coefficient toward zero through attenuation. The net direction depends on the relative magnitudes of these forces. Empirically, the international evidence summarised in Card (1999, 2001) suggests that attenuation typically dominates for the marginal student, with IV estimates exceeding OLS by 20–40 per cent.

3.3. Identification through DPEP

Identification proceeds by constructing an instrument Z that is correlated with S but uncorrelated with u. Following Duflo (2001), the instrument interacts a district-level treatment indicator with cohort age-eligibility at the time of programme implementation:

$$z_{idc} = DPEP_d \times Exposure_c \quad (2)$$

where $DPEP_d$ is a binary indicator for whether district d entered DPEP Phase I or II, and $Exposure_c$ is the number of primary-school-age years (between ages 6 and 11) that cohort c spent in a treated district during the programme's active years. Identification requires that DPEP exposure affects wages only through its effect on schooling (the exclusion restriction). District fixed effects absorb time-invariant differences between treated and untreated districts; cohort fixed effects absorb India-wide secular trends in returns to schooling; and a treated-district × linear-trend term controls for differential pre-trends.

IV. RESEARCH METHODOLOGY

4.1. Data

The empirical analysis uses individual-level data from the 2018–19 and 2022–23 rounds of the Periodic Labour Force Survey (PLFS) conducted by the National Statistical Office. The PLFS provides nationally representative data on labour-force status, weekly wage earnings, hours worked, education, and demographic characteristics. The pooled sample includes wage-earners aged 23–37 years who were born between 1985 and 1995 and who were therefore of primary-school age during the DPEP roll-out (1994–2002). Self-employed workers are excluded because their earnings are not directly observed. District identifiers are matched to DPEP roll-out information drawn from Sipahimalani-Rao and Clarke (2003) and Pandey et al. (2009). The final analytical sample comprises approximately 96,000 individuals.

Table 1. Variable Definitions

Variable	Definition	Source
Log hourly wage	Natural log of real hourly wage (₹, 2011–12 prices, weekly earnings ÷ hours worked)	PLFS 2018–19, 2022–23
Years of schooling	Completed years of formal education (continuous)	PLFS
Experience	Age − schooling − 6 (potential labour-market experience)	Computed
DPEP exposure	Treated-district indicator × years of primary-school age (6–11) during DPEP	Constructed
Demographic	Gender, social group (SC/ST/OBC/General), religion, marital status	PLFS
Geographic	State fixed effects, urban indicator, district controls (pre-DPEP literacy)	PLFS; 1991 Census

Note. Wages deflated using state-specific CPI for industrial workers (Base: 2011–12). Author's compilation.

4.2. Empirical Specification

The second-stage Mincer equation is:

$$\ln W_{idc} = \beta_0 + \beta_1 \hat{S}_{idc} + \beta_2 EXP_{idc} + \beta_3 EXP_{idc}^2 + \gamma X_{idc} + \delta_d + \lambda_c + \varepsilon_{idc} \quad (3)$$

where $\hat{S}$ is the predicted value of schooling from the first stage, δ_d denotes district fixed effects, and λ_c denotes birth-cohort fixed effects. The first-stage equation is:

$$S_{idc} = \pi_0 + \pi_1 (DPEP_d \times Exposure_c) + \pi_2 EXP_{idc} + \pi_3 EXP_{idc}^2 + \theta X_{idc} + \delta_d + \lambda_c + \nu_{idc} \quad (4)$$

The 2SLS estimator is obtained by replacing S in the wage equation with the first-stage fitted value. Standard errors are clustered at the district level to allow for arbitrary within-district correlation in unobservables (Bertrand, Duflo, & Mullainathan, 2004).

4.3. Identification Tests

The credibility of the IV estimate rests on three identifying assumptions. First, the instrument must be relevant: DPEP exposure must materially affect schooling. This is assessed by the first-stage F-statistic on the excluded instrument, compared with the Stock and Yogo (2005) weak-instrument critical values. Second, the instrument must satisfy the exclusion restriction: DPEP exposure should affect wages only through its effect on schooling. While untestable in a single-instrument design, this is probed by including pre-DPEP district characteristics and by testing on a placebo cohort (1976–1984, too old to be exposed). Third, in the over-identified specification using a second instrument constructed from the timing of DPEP-II expansion, the Hansen J-statistic tests the joint validity of the instrument set.

4.4. Ethical Considerations

The PLFS unit-level data are publicly available, anonymised secondary records released by the National Statistical Office. No primary human-subjects research is involved. All sources are duly cited.

V. EMPIRICAL RESULTS AND DISCUSSION

5.1. Descriptive Statistics

Table 2 reports summary statistics for the pooled PLFS sample. Mean completed schooling is 9.7 years, with a standard deviation of 4.2 years; women report 9.1 years on average, men 10.1 years. The mean real hourly wage is ₹78.4 (2011–12 prices), with a substantial gender gap. Approximately 41 per cent of the sample is drawn from districts that were covered by DPEP Phase I or II. Within the treated districts, mean DPEP primary-school exposure for the sample cohorts is 3.6 years out of a possible 6.

Table 2. Descriptive Statistics, PLFS Pooled Sample

Variable	All	Men	Women
Log hourly wage	4.36	4.42	4.18
Real hourly wage (₹)	78.4	83.2	65.4
Years of schooling	9.7	10.1	9.1
Potential experience (years)	13.5	13.2	13.9
Age (years)	29.2	29.3	29.0
DPEP district (% sample)	40.8	40.5	41.3
Mean DPEP exposure (years, treated)	3.6	3.6	3.6
Observations	96,148	62,840	33,308

Note. Pooled PLFS 2018–19 and 2022–23 sample, urban wage earners aged 23–37 years. Author's calculations.

5.2. First-Stage Estimates and Instrument Strength

The first-stage relationship between DPEP exposure and years of schooling is strong and statistically robust. The coefficient on the DPEP × Exposure interaction is 0.187 (cluster-robust SE 0.035, $p < 0.01$), implying that an additional year of primary-school-age exposure in a DPEP district raises completed schooling by approximately 0.19 years. The first-stage F-statistic on the excluded instrument is 28.4, comfortably exceeding the Stock–Yogo (2005) 10 per cent critical value of 16.38 for a single endogenous regressor. The instrument is therefore strong by conventional criteria, and the IV point estimates can be interpreted with confidence.

5.3. OLS vs IV Estimates

Table 3 reports the headline OLS and 2SLS estimates of the return to schooling. Column (1) reports the OLS Mincerian return of 7.1 per cent per year of schooling, broadly consistent with the existing Indian literature (Agrawal, 2012; Duraisamy, 2002). The 2SLS estimate in column (2), instrumenting schooling with the DPEP × Exposure interaction, is 9.6 per cent per year, statistically significantly higher than the OLS estimate (Hausman test $\chi^2 = 6.18$, $p = 0.013$). The relative magnitude IV exceeding OLS by approximately 35 per cent is consistent with the international evidence summarised by Card (1999, 2001) and with the interpretation that attenuation bias dominates ability bias for the marginal student affected by the instrument.

Table 3. OLS and 2SLS Estimates of the Return to Schooling

	(1) OLS	(2) 2SLS	(3) 2SLS Men	(4) 2SLS Women
Years of schooling	0.071***	0.096***	0.083***	0.124***
	(0.004)	(0.018)	(0.021)	(0.029)
Experience	0.038***	0.041***	0.044***	0.032***
Experience²	−0.0006***	−0.0007***	−0.0008***	−0.0005***
First-stage F	—	28.4	23.7	19.5
District FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	96,148	96,148	62,840	33,308

Note. Dependent variable: log real hourly wage. Cluster-robust standard errors (district level) in parentheses. ***, **, * denote significance at 1%, 5%, and 10% respectively. All specifications include demographic controls and state fixed effects. Source: Author's estimation.

5.4. Heterogeneous Returns by Gender and Social Group

Columns (3) and (4) of Table 3 report 2SLS estimates separately for men and women. The return to schooling for women, at 12.4 per cent, is roughly 50 per cent higher than that for men, at 8.3 per cent. The pattern is consistent with H_3 and with the cross-country evidence reviewed by Psacharopoulos and Patrinos (2018) that women's returns to schooling tend to exceed men's, in part because the marginal female student would otherwise have lower bargaining power and labour-force attachment. Disaggregating by social group (results not tabulated for brevity) yields returns of 11.8 per cent for scheduled-caste and scheduled-tribe workers and 8.7 per cent for general-category workers, suggesting that the DPEP-induced expansion of schooling generated particularly large gains for historically disadvantaged groups.

5.5. Convexity in Returns to Schooling

Replacing the linear schooling variable with educational-level dummies and instrumenting each with the corresponding DPEP exposure interactions reveals substantial convexity. The IV-estimated wage premium for completing secondary schooling (10 years) relative to primary completion (5 years) is approximately 38 per cent, while the premium for completing higher secondary (12 years) over secondary is 42 per cent, and the premium for tertiary education over higher secondary is 71 per cent. These magnitudes are consistent with H_4 and with the post-1991 skill-premium evidence of Azam (2010).

5.6. Robustness and Falsification

Several robustness exercises support the validity of the main estimates. First, a placebo IV using cohorts born between 1976 and 1984 too old to have been exposed to DPEP at primary-school age yields a statistically insignificant first-stage coefficient (0.018, $p = 0.62$) and an insignificant reduced-form effect on wages, supporting the exclusion restriction. Second, restricting the sample to non-migrants (those still residing in their birth state) produces 2SLS estimates within 7 per cent of the baseline, alleviating concerns about endogenous migration. Third, controlling explicitly for pre-DPEP district characteristics (1991 literacy, urbanisation, infrastructure index) leaves the coefficient on schooling essentially unchanged. Fourth, in an over-identified specification that adds the timing of DPEP-II as a second instrument, the Hansen J-statistic of 0.65 ($p = 0.42$) fails to reject the joint validity of the instruments.

5.7. Discussion

Three points of discussion merit emphasis. First, the magnitude of the IV estimate 9.6 per cent per year is at the upper end of the existing Indian literature and, when combined with the marked convexity by educational level, implies that the conventional descriptive narrative of "modest returns to schooling in India" may have substantially understated the causal benefit. Second, the higher returns for women and for scheduled-caste and scheduled-tribe workers underscore the equity case for continued investment in basic and secondary education, particularly in DPEP-style targeting of educationally backward districts. Third, the IV estimate captures a local average treatment effect for compliers students who completed additional schooling because of DPEP-induced supply expansion and may not generalise to populations facing different schooling-decision margins, such as urban middle-class students whose decisions are largely unaffected by primary-school construction.

Two limitations deserve mention. First, although the instrument satisfies standard validity tests, residual concerns about programme placement remain because DPEP districts were chosen partly on the basis of low female literacy. The district fixed effects absorb time-invariant differences, but differential trends could in principle remain. Second, the sample is restricted to wage-earners, excluding the substantial fraction of Indian workers in self-employment and casual labour for whom hourly wages are not directly observed; Heckman-style selection correction could be applied as an extension in future work.

VI. CONCLUSION AND POLICY IMPLICATIONS

This study has presented quasi-experimental estimates of the private return to schooling in India using the staggered roll-out of the District Primary Education Programme as a source of exogenous variation. Following the identification strategy of Duflo (2001), the 2SLS estimator exploits the interaction between district-level DPEP treatment and cohort-level primary-school-age exposure. Four findings stand out. First, the IV estimate of the return to schooling is 9.6 per cent per year, significantly higher than the corresponding OLS estimate of 7.1 per cent. Second, the return is substantially higher for women (12.4 per cent) than for men (8.3 per cent) and higher for scheduled-caste and scheduled-tribe workers than for general-category workers. Third, returns are convex in educational level, with the largest premia at the tertiary level. Fourth, the instrument passes weak-instrument, over-identification, and placebo tests.

Four policy implications follow. First, continued public investment in basic and secondary education is well justified by the magnitude of estimated returns, particularly for girls and historically disadvantaged groups. Second, the supply-side approach embodied in DPEP infrastructure, teacher recruitment, and district capacity-building delivers measurable labour-market gains a generation later, supporting the case for sustained funding of Sarva Shiksha Abhiyan and the Samagra Shiksha programme. Third, the marked convexity in returns argues for closing not only the primary but also the secondary and tertiary-attainment gaps, including through scholarship programmes and conditional cash transfers. Fourth, the higher returns for women warrant gender-targeted interventions to relax remaining constraints safe transport, hostels, vocational pathways that limit the translation of schooling into wages.

Three avenues for future research are particularly promising. First, the analysis could be extended to study downstream outcomes occupational sorting, marriage and fertility, child outcomes on which schooling may have effects beyond the wage. Second, structural models of schooling choice that integrate the demand and supply sides would help interpret the LATE estimated here against alternative policy counterfactuals. Third, the interaction between DPEP and subsequent reforms Sarva Shiksha Abhiyan, the Mid-Day Meal Scheme, and the Right to Education Act is a natural extension as longer panels become available.

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