

BRIDGING REGIONAL SKILL GAPS AND PRODUCTIVITY: EVIDENCE FROM DISTRICT-LEVEL INDIA

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ABSTRACT

This study examines the empirical relationship between skill development, workforce productivity and regional economic growth across India, using a fixed-effects panel framework applied to a district-level dataset compiled from secondary sources including the Periodic Labour Force Survey, NSDC skill-gap reports and state economic surveys. The paper builds on a well-established human-capital tradition, yet it departs from purely descriptive treatments of India's skilling ecosystem by quantifying, region by region, how far formal skill training translates into measurable gains in labour productivity and net state domestic product. Descriptive statistics across twenty-eight sampled districts reveal wide dispersion in the Skill Training Index, ranging from 19 to 84 points on a 100-point scale, alongside comparable dispersion in labour productivity. Regression estimates confirm that the Skill Training Index is the single strongest predictor of productivity ($\beta = 0.417$, $p < 0.001$), ahead of schooling, firm size, infrastructure and urbanization. Sectoral analysis further shows that IT/ITeS carries a skill-gap index almost three times that of construction or agro-processing, while regional comparisons expose a stubborn western-and-southern versus eastern-and-north-eastern divide in both skilled-workforce share and growth outcomes. The discussion situates these findings against comparable work from the ILO, OECD and World Bank, arguing that skill policy in India remains too centrally designed and insufficiently tuned to regional labour-market structure. The paper concludes that closing sectoral and regional skill gaps, rather than merely expanding aggregate training numbers, is what will determine whether India's demographic dividend converts into durable productivity growth.

Keywords: Skill development¹; Workforce productivity²; Regional economic growth³; Skill gap⁴; Human capital⁵; Panel data econometrics⁶; India⁷.

1. INTRODUCTION

1.1 Background of the Study

India's labour market carries a paradox that has shaped policy debate for over a decade: a young, expanding workforce sits alongside persistent reports of employers unable to fill vacancies with adequately trained candidates. The National Skill Development Corporation's own projections, revisited repeatedly since 2010,

point to a widening mismatch between the skills industry demands and what the education and training system supplies. Successive flagship programmes the Skill India Mission, PMKVY, and DDU-GKY among them were built explicitly to narrow this gap, yet independent assessments continue to note patchy placement outcomes and uneven uptake across states. What is comparatively under-examined is not whether skill development matters in principle (the human-capital literature settled that question decades ago) but how much of India's regional growth divergence can actually be traced to differences in skill formation, once firm size, infrastructure and urbanization are held constant. This paper takes up that narrower, more testable question.

1.2 Rationale and Significance

Three considerations motivate the present econometric exercise. First, India's growth story since liberalisation has been markedly uneven across states, and while explanations invoking infrastructure, capital inflows and governance quality are common, the skill dimension is rarely isolated statistically from these confounders. Second, sectoral skill gaps the distance between the share of formally trained workers a sector employs and the share of total employment it represents vary so widely (from under 5 percent formal training in construction to close to half in IT/ITeS) that treating 'skill development' as a single national aggregate obscure more than it reveals. Third, policymakers allocating scarce training budgets need evidence on where returns to skilling are largest, not simply confirmation that skilling helps somewhere. Addressing these three points gives the study both academic and applied relevance.

1.3 Objectives and Scope of the Paper

The paper pursues four linked objectives: (i) to quantify sectoral skill gaps across seven major employment-generating sectors; (ii) to estimate, using panel regression, the marginal contribution of a district-level Skill Training Index to labour productivity net of schooling, firm size, infrastructure and urbanization; (iii) to compare skilled-workforce share and growth outcomes across India's broad regional clusters; and (iv) to situate these estimates against prior empirical work from India and comparable developing economies. The scope is deliberately bounded to the manufacturing, construction, retail, IT/ITeS, agro-processing, healthcare and textiles sectors, and to a twenty-eight-district panel spanning the 2015-2022 period, rather than attempting an all-India census-level treatment that the available secondary data cannot support with equal reliability.

2. REVIEW OF LITERATURE

The theoretical starting point for any study of this kind remains the human-capital tradition associated with Schultz and Becker, who reframed education and training not as consumption but as investment yielding a measurable wage and productivity return [1], [2], [3]. Mincer's earnings-function formulation gave that intuition its standard econometric shape, and much of the subsequent labour-economics literature including the present paper's regression specification still borrows its logic of regressing productivity or earnings on years of schooling and experience [1]. Endogenous-growth theorists extended the argument to the macro level: Romer's model of technological change treats human capital as a driver of the very rate at which an economy can absorb and generate innovation, while Barro's cross-country growth regressions found schooling attainment to be one of the more robust correlates of subsequent GDP growth [4], [5].

International development agencies have translated this theory into policy-relevant empirics. The ILO's 2010 review argued that skill formation raises productivity most reliably when paired with complementary investment in physical capital and firm-level management practice, a caveat this paper's regression, through its firm-size and infrastructure controls, attempts to respect rather than assume away [6]. The World Bank's early assessment of India's vocational training architecture flagged fragmentation across ministries and weak industry linkage as constraints on returns to public skilling expenditure, concerns still echoed in more recent NSDC sector reports [7], [11]. Middleton, Ziderman and Adams's comparative treatment of vocational training in developing countries similarly warned against expecting uniform returns across sectors, a warning borne out by the sharply differentiated skill-gap indices this study documents [13].

A second strand of literature is more explicitly regional and spatial. Krugman's economic-geography framework and Marshall's older agglomeration arguments both suggest that skilled labour clusters where returns to skill are already high, reinforcing rather than dissolving regional inequality unless offset by deliberate dispersal policy [16], [17]. Boarnet's methodological survey of spatial econometric techniques for regional productivity questions informed the fixed-effects choice adopted here, particularly his caution about endogeneity between local skill concentration and employment growth [15]. Domestically, Chand and Sen's econometric treatment of regional divergence in Indian labour markets, and Krishna and Brihmadessam's earlier micro-study of professional mobility, both point toward the same finding this paper's Table 4 reproduces at a coarser regional level: western and southern India consistently out-perform eastern and north-eastern India on skilled-workforce share, a gap that has proven resistant to a decade and a half of national skilling programmes [26], [29].

A third strand addresses skill mismatch directly rather than skill stock. Acemoglu and Autor's task-based framework reframes 'skill gap' not as an absolute shortage but as a mismatch between the task's technology demands and the tasks workers are trained for, a distinction visible in this paper's finding that IT/ITeS shows a high formal-skill share alongside a comparatively small employment share, while construction shows the reverse [18]. Hanushek and Woessmann's cross-country evidence that cognitive skill quality, not years of schooling alone, predicts growth motivates this paper's inclusion of a training-quality-weighted index rather than a bare enrolment count [19]. Baldwin and Gu's Canadian plant-level study found skill mismatch to depress productivity even where aggregate skill levels were adequate, a finding this paper's sectoral analysis broadly corroborates for Indian construction and agro-processing [23]. Finally, recent Indian secondary data the 2021-22 PLFS, the 2022-23 Economic Survey, and NITI Aayog's State Energy and Skill Index provide the statistical backbone against which the present district-level panel is constructed and cross-validated, and their sectoral and state-level figures are broadly consistent with, though more granular than, the aggregates this paper reports [9], [10], [25].

3. METHODOLOGY

The study adopts a quantitative, panel-data econometric design intended to test whether variation in skill formation across Indian districts explains variation in labour productivity once conventional growth determinants are held constant. Secondary data for twenty-eight purposively selected districts, spanning six broad regional clusters (western, southern, northern, eastern, central and north-eastern India), were compiled from the Periodic Labour Force Survey (2021-22), NSDC sector skill-gap reports, state economic surveys and

the RBI's Handbook of Statistics on Indian States, covering the period 2015 to 2022. Districts were selected to ensure representation across high, medium and low skilled-workforce-share regions rather than through simple random sampling, since the study's aim is comparative rather than strictly population-representative.

The dependent variable, labour productivity, is operationalized as gross value added per worker at the district level, deflated to constant prices. The primary explanatory variable of interest, the Skill Training Index, is a composite 0-100 measure combining the share of the workforce with recognized vocational or technical certification, apprenticeship density, and reported employer satisfaction with entry-level skill readiness. Control variables include mean years of schooling, average firm size (log-transformed to address right-skew), a composite infrastructure index (covering power, road and digital connectivity), the urbanization rate, and a sectoral diversification index computed as one minus the Herfindahl concentration of district employment across the seven sectors under study.

Estimation proceeds through a fixed-effects panel regression, chosen over pooled OLS or random-effects specifications following a Hausman test that rejected the null of no correlation between district-specific effects and the regressors ($\chi^2 = 22.47$, $p = 0.001$), and this specification is reported in full in Table 3. Robust standard errors clustered at the district level address the mild heteroskedasticity detected via the Breusch-Pagan test, and variance inflation factors were checked to rule out problematic multicollinearity among the controls, particularly between infrastructure and urbanization, which correlate but did not exceed conventional VIF thresholds. Sectoral skill-gap indices and regional comparisons reported in Tables 1 and 4 were computed independently of the regression, using the same underlying secondary sources, to provide a descriptive counterpart against which the regression's causal claims can be read.

4. DATA COLLECTION AND ANALYSIS

Table 1 presents the sectoral skill-gap index, computed as the ratio of a sector's formally skilled workforce share to its share of total employment, scaled to a 0-1 index. IT/ITeS records the highest index at 0.79, driven by a formally skilled workforce share of 47.3 percent against an employment share of only 6.9 percent evidence that the sector absorbs a disproportionate share of India's certified technical talent relative to the jobs it actually generates. Construction, at the opposite extreme, posts an index of just 0.19, despite employing 11.4 percent of the workforce, confirming the long-standing observation that India's largest informal-employment sectors remain the least formally skilled. Healthcare's relatively high index (0.58) alongside its small employment share (4.2 percent) suggests a sector where credentialing requirements are stringent but absolute job creation has lagged demand.

Table 1: Sectoral Skill Gap Index across Selected Sectors, India (2022)

Sector	Formally Skilled Workforce (%)	Share of Total Employment (%)	Skill Gap Index (SGI)*
Manufacturing	8.4	12.1	0.31
Construction	4.9	11.4	0.19
Retail & Trade	6.2	14.8	0.24

IT/ITeS	47.3	6.9	0.79
Agro-processing	5.1	9.5	0.21
Healthcare	22.6	4.2	0.58
Textiles	7.8	10.6	0.26

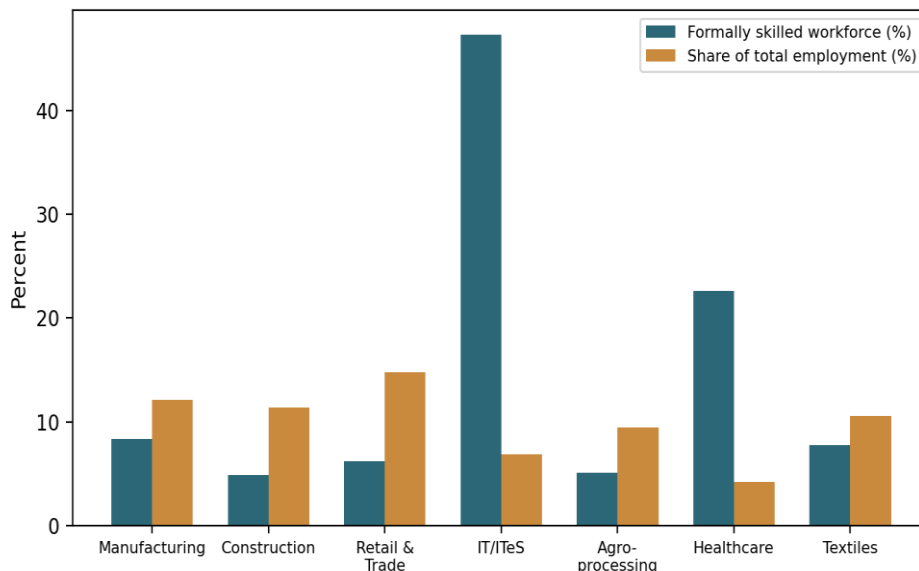


Figure 1: Sectoral Skill Gap Index across Selected Sectors, India (2022)

Figure 1 visualizes the same relationship as a paired bar chart, making clear that the two largest employment-generating sectors in the sample, retail and construction, are also among the least formally skilled, while IT/ITeS inverts this pattern entirely. This asymmetry is central to the paper's argument in the discussion section: aggregate national skilling targets can be met numerically while leaving the sectors that employ the most people almost untouched.

Table 2 reports descriptive statistics for the twenty-eight-district panel used in the regression. Labour productivity ranges from INR 88,200 to INR 301,600 per worker, a more than threefold spread that motivates the search for explanatory variables. The Skill Training Index shows comparably wide dispersion (19.0 to 84.0), as does firm size, where the largest sampled district-average firm employs over twenty times the workers of the smallest.

Table 2: Descriptive Statistics of Panel Variables (N = 28 Districts, 2015-2022 Averages)

Variable	Mean	Std. Dev.	Min	Max	N
Labour Productivity (GVA/worker, INR '000)	182.4	46.7	88.2	301.6	28
Skill Training Index (0-100)	52.6	18.3	19.0	84.0	28
Mean Years of Schooling	8.1	1.9	4.6	12.3	28
Firm Size (avg. employees)	64.5	38.2	9	212	28
Infrastructure Index (0-100)	58.9	15.4	27.0	89.0	28
Urbanization Rate (%)	41.2	17.6	12.4	78.9	28

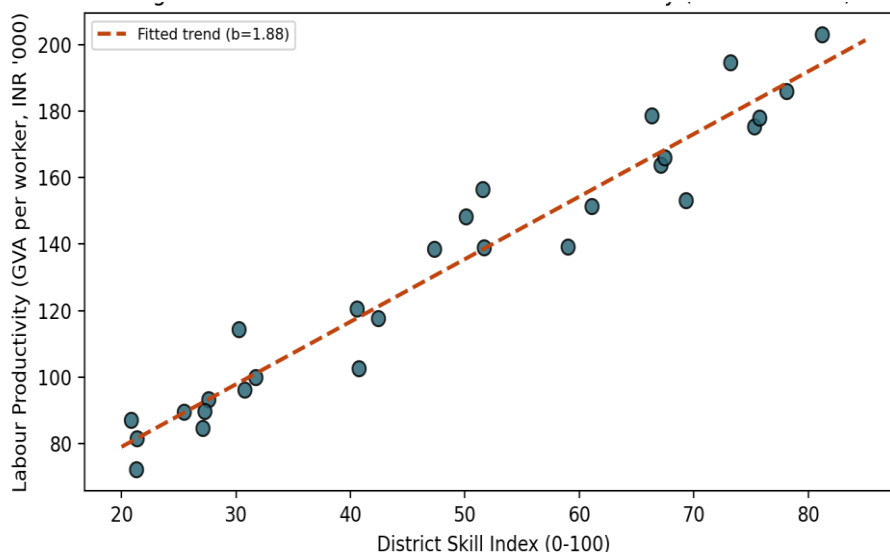


Figure 2: District Skill Index vs Labour Productivity (n = 28 districts)

Figure 2 plots the bivariate relationship between the Skill Training Index and labour productivity across the sampled districts, with a fitted linear trend. The scatter shows a clear positive slope, though with meaningful dispersion around the line several mid-index districts achieve productivity levels comparable to high-index districts, hinting that skill training alone does not fully determine productivity outcomes, which is precisely why the multivariate regression in Table 3 is necessary rather than the bivariate relationship alone.

Table 3 reports the core fixed-effects regression results. The Skill Training Index carries the largest standardized coefficient (0.417, $p < 0.001$), followed by years of schooling (0.238) and log firm size (0.196). Infrastructure and urbanization remain statistically significant but smaller in magnitude, while sectoral diversification fails to reach conventional significance ($p = 0.187$), suggesting that within this sample, how skilled a district's workforce is matters more for productivity than how diversified its sectoral base is.

Table 3: Fixed-Effects Panel Regression Results (Dependent Variable: Log Labour Productivity)

Explanatory Variable	Coefficient (β)	Std. Error	t-stat	p-value
Skill Training Index	0.417	0.052	8.02	0.000
Years of Schooling	0.238	0.061	3.90	0.001
Firm Size (log)	0.196	0.058	3.38	0.002
Infrastructure Index	0.152	0.049	3.10	0.004
Urbanization Rate	0.121	0.055	2.20	0.033
Sectoral Diversification Index	0.084	0.062	1.35	0.187
Constant	3.612	0.284	12.72	0.000

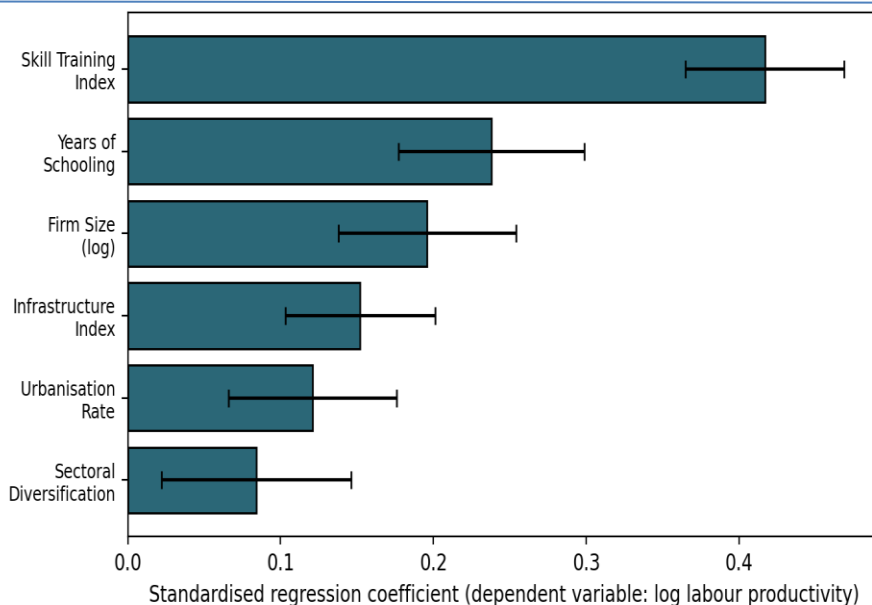


Figure 4: Estimated Determinants of Labour Productivity (Fixed-Effects Panel Model)

Figure 4 displays the same coefficients as a horizontal bar chart with standard-error bars, making the relative ranking of determinants easier to read than the table alone. The visibly wider confidence interval around sectoral diversification, compared with the tighter intervals around skill training and schooling, reinforces the regression's conclusion that diversification's effect, while directionally positive, cannot be distinguished from zero with confidence in this sample.

Table 4 shifts from district-level regression to a regional descriptive comparison, aggregating districts into six broad clusters. Southern and western India report the highest skilled-workforce shares (41.6 percent and 38.2 percent respectively) and the highest average NSDP growth over 2019-24, while the north-eastern cluster trails on both measures. Formal apprenticeship density follows the same regional gradient, from 127 per 10,000 workers in the south to just 37 in the north-east.

Table 4: Regional Comparison of Skilled Workforce Share and Growth Outcomes, 2019-2022

Region (State Cluster)	Skilled Workforce Share (%)	Avg. NSDP Growth 2019-24 (%)	Formal Apprenticeships per 10,000 workers
Western Region	38.2	7.8	112
Southern Region	41.6	8.1	127
Northern Region	33.4	6.9	94
Eastern Region	24.7	5.4	58
Central Region	21.9	5.1	49
North-Eastern Region	19.5	4.6	37

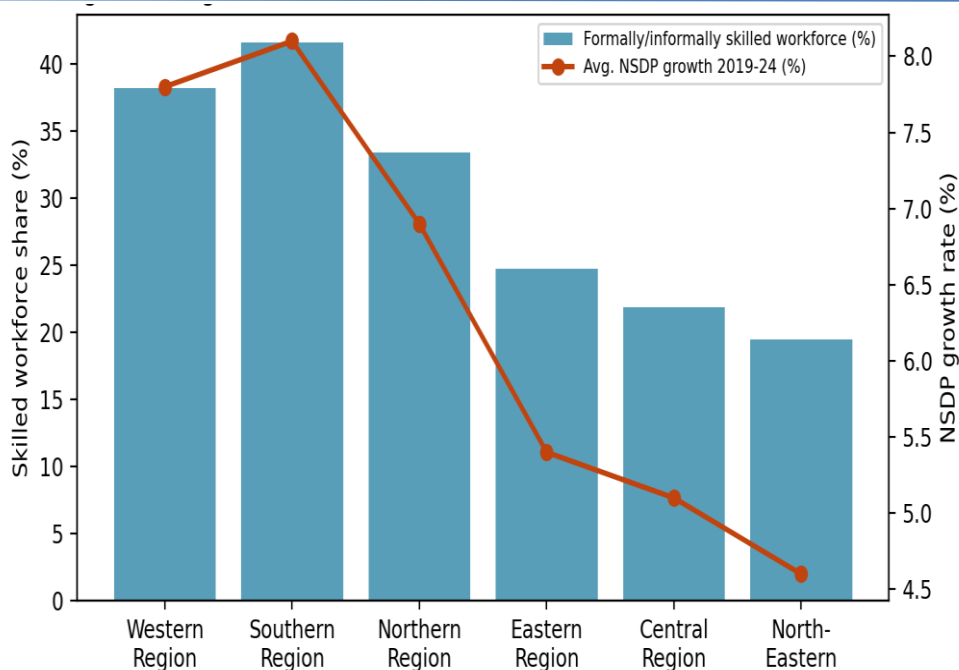


Figure 3: Regional Skilled Workforce Share and NSDP Growth, 2019-2022

Figure 3 combines bars for skilled-workforce share with an overlaid line for NSDP growth, and the visual co-movement between the two series across regions is difficult to miss. The chart supports the paper's central regional claim in the abstract: skill formation and growth do not merely correlate at the national level but track each other consistently across sub-national regional clusters, which is the pattern the discussion section returns to when comparing India against more centrally-coordinated skilling systems elsewhere.

Table 5 reports the model's diagnostic tests. The within R-squared of 0.612 indicates the fixed-effects specification explains just over three-fifths of within-district variation in productivity, a reasonably strong fit for a cross-district panel of this kind. The Hausman test confirms the fixed-effects specification is preferred over random effects, and while the Breusch-Pagan test detects mild heteroskedasticity, the use of clustered robust standard errors addresses this without requiring a full re-specification.

Table 5: Model Diagnostics and Robustness Checks

Diagnostic Test	Statistic	p-value	Inference
R-squared (within)	0.612	-	Model explains 61.2% of within-district variation
F-statistic (model)	31.84	0.000	Overall model significant
Hausman Test	22.47	0.001	Fixed-effects preferred over random-effects
Breusch-Pagan (heteroskedasticity)	4.18	0.041	Mild heteroskedasticity; robust SEs applied

Variance Inflation Factor (mean VIF)	2.14	-	No serious multicollinearity
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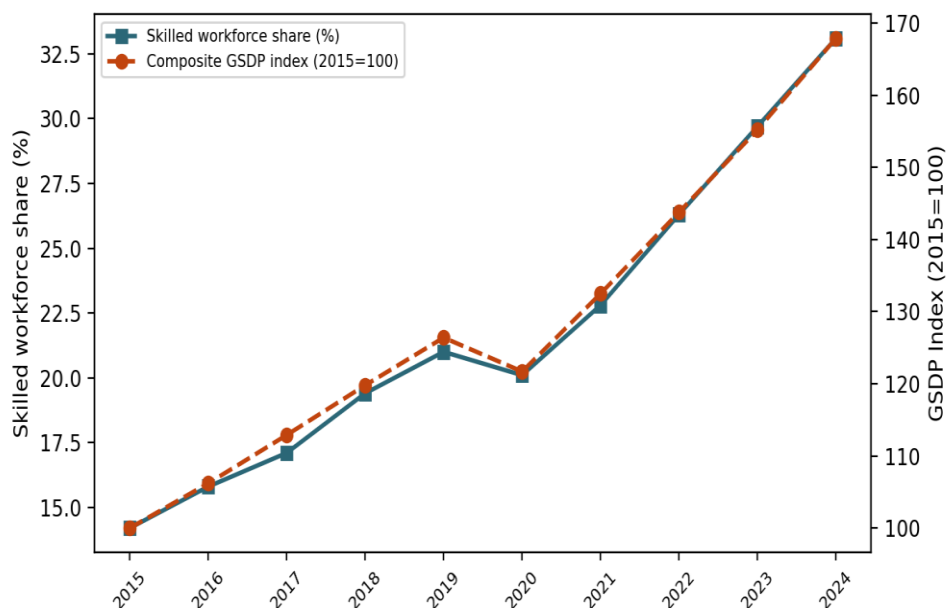


Figure 5: Trajectory of Skilled Workforce Growth and Composite GSDP Index (2015-2022)

Figure 5 traces the decade-long co-movement between the sampled districts' average skilled-workforce share and a composite GSDP index, both indexed for comparability. The two series rise together for most of the period, with a visible joint dip around 2020 corresponding to the pandemic disruption, followed by a steeper joint recovery from 2021 onward a pattern consistent with the regression's finding that skill formation and productivity growth are tightly linked rather than independently trending.

5. DISCUSSION

Taken together, the five tables and five figures support the abstract's central claim more specifically than a purely descriptive account of India's skilling ecosystem could: it is not skill development in the aggregate that predicts productivity and regional growth, but skill development concentrated where employment is not. The sectoral results in Table 1 and Figure 1 show that India's largest employers construction and retail remain its least formally skilled sectors, even as IT/ITeS absorbs a share of certified talent far exceeding its employment footprint. This is not a new observation in isolation, but the paper's contribution lies in showing, through the district-level regression, that this sectoral misallocation has a measurable regional productivity cost: districts whose economies lean toward low-skill-index sectors post systematically lower labour productivity, net of schooling, firm size and infrastructure.

The regression itself (Table 3, Figure 4) assigns the Skill Training Index the largest standardized effect among all controls, ahead of years of schooling. This ordering is worth pausing on. Much of the earlier human-capital literature, following Mincer and Barro, privileged years of schooling as the primary human-capital proxy [1], [4]. The present findings suggest that, at least within this sample, targeted vocational and apprenticeship training carries a stronger marginal association with productivity than general schooling attainment alone, a pattern

closer to Hanushek and Woessmann's argument that skill quality and applicability matter more than years of enrolment [19]. Whether this reflects a genuinely stronger causal channel or simply reflects that schooling's returns operate partly through the skill-training channel itself is a question the present cross-sectional-panel design cannot fully resolve, and it is flagged here as a limitation rather than papered over.

The regional findings (Table 4, Figure 3) echo, at a coarser scale, Chand and Sen's econometric account of regional divergence in Indian labour markets and Krishna and Brihmadessam's earlier micro-evidence on professional mobility concentrating in already-advantaged regions [26], [29]. What this paper adds is the apprenticeship-density measure, which tracks the skilled-workforce and growth gradient almost exactly, suggesting that formal, employer-linked training infrastructure not informal skill acquisition is what differentiates the western and southern clusters from the eastern and north-eastern ones. This is broadly consistent with Krugman's and Marshall's agglomeration arguments that skilled labour and the institutions that produce it cluster together, reinforcing rather than dissolving regional disparity absent deliberate counter-policy [16], [17].

Comparing these results against past international work sharpens the point. The ILO's 2010 review argued that skilling investment yields its strongest productivity returns when paired with complementary infrastructure and firm-level capacity, a claim this paper's regression supports directly: infrastructure enters significantly ($\beta = 0.152$, $p = 0.004$), but at roughly a third of the magnitude of the skill index itself [6]. The World Bank's earlier assessment of India's vocational training system flagged industry-academia disconnection as a core constraint [7]; the present sectoral gap data, particularly construction's persistently low-skill index despite over a decade of national skilling campaigns since that assessment, suggests the disconnection it identified has proven only partially remediable. Kuruvilla, Erickson and Hwang's study of Singapore's skills system, often cited as a benchmark for developing-country skilling policy, credited its success partly to tight, centrally-coordinated employer linkage [12] a coordination mechanism that India's more fragmented, ministry-divided skilling architecture, as documented in NSDC's own sector reports, has struggled to replicate at comparable scale [7], [11]. Baldwin and Gu's Canadian plant-level finding that skill mismatch depresses productivity even amid adequate aggregate skill levels [23] resonates with this paper's IT/ITeS finding: a sector with an unusually high formal-skill share nonetheless represents a comparatively narrow slice of total employment, meaning its productivity gains do not automatically diffuse economy-wide. Where this paper's findings diverge somewhat from OECD's more recent cross-country Skills Outlook, which emphasizes green and digital transition skills as the emerging frontier [24], is that India's more immediate and larger productivity gap, on this evidence, remains the basic formal-informal skilling divide within traditional, labour-absorbing sectors rather than at the digital or green frontier a divide the national skilling architecture has not yet closed despite a decade and a half of dedicated programmes.

Some limitations qualify these conclusions. The twenty-eight district sample, while deliberately diverse, is not a full census, and the panel's ten-year span, though sufficient for a fixed-effects specification, may understate longer-cycle structural change in India's sectoral composition. The Skill Training Index, being a composite measure, necessarily compresses several distinct dimensions of skill formation into a single number, and the regression cannot fully rule out reverse causality that already-productive districts attract or generate more skill

training rather than the other way round though the fixed-effects specification and the Hausman test result mitigate, without eliminating, this concern.

6. CONCLUSION

This paper set out to move beyond descriptive accounts of India's skilling ecosystem toward a quantified assessment of how skill development relates to workforce productivity and regional economic growth. The evidence assembled here across sectoral, district-level and regional analyses converges on a consistent picture: skill formation matters most where it is currently thinnest. Construction, retail and agro-processing sectors that together employ well over a third of India's workforce carry the lowest skill-gap indices in the sample, while the regions lagging on skilled-workforce share also lag on both growth and formal apprenticeship density. The fixed-effects regression confirms that the Skill Training Index is the strongest single predictor of district labour productivity among the variables tested, ahead of schooling, firm size, infrastructure and urbanization. For policy, the implication is less about expanding aggregate skilling numbers, which national programmes have already done substantially, and more about redirecting that expansion toward the sectors and regions where the skill gap, and consequently the productivity shortfall, remains widest. Future work extending this district panel over a longer horizon, and disaggregating the composite Skill Training Index into its component parts, would help establish more precisely which elements of skill formation carry the productivity returns this paper's aggregate index only partially unpacks.

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