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District-Level Salary Trends and Regional Economic Convergence: Evidence from Gujarat

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ABSTRACT

This study investigates district-level salary trends and tests for regional economic convergence across Gujarat's 33 districts over a fifteen-year panel (2008–2023). Using a harmonised dataset drawn from the Annual Survey of Industries (ASI), Periodic Labour Force Survey (PLFS), Employee Provident Fund Organisation (EPFO) administrative records, and state government payroll data, we construct a comprehensive District Salary Index (DSI) that encompasses both formal and informal employment across agriculture, manufacturing, construction, and services. The analysis employs three complementary methodological frameworks: (i) absolute and conditional β-convergence regressions in a panel fixed-effects specification with time-varying controls; (ii) σ-convergence analysis tracking cross-sectional wage dispersion over time; and (iii) non-parametric distributional dynamics via stochastic kernel estimation to characterise the full transition of the district wage distribution. Empirical results confirm conditional β-convergence at a speed of 3.4% per annum (half-life approximately 20 years), driven primarily by catch-up in the lagging eastern tribal belt districts of Dahod, Narmada, Chhota Udaipur, and Dang. Stochastic kernel estimates reveal bimodal persistence in the wage distribution, reflecting a polarisation between a high-wage industrial cluster (Ahmedabad, Surat, Vadodara, Bharuch) and a mid-to-low wage rural periphery. Infrastructure endowment, manufacturing employment density, and proximity to Special Economic Zones (SEZs) are identified as robust determinants of both wage levels and convergence speed. Robustness checks using synthetic panel methods and Bonferroni-corrected multiple inference confirm the baseline findings. The paper concludes with evidence-based recommendations for spatially targeted industrial policy, skills development, and infrastructure investment to accelerate inclusive convergence.

***Keywords**: Regional Wage Convergence, District Salary Trends, Stochastic Kernel, β-Convergence, Gujarat, Industrial Corridors, Spatial Inequality, PLFS, EPFO.*

***JEL Codes:** J31, O15, O18, R11, R12, C23, C14*

Introduction

Gujarat has long been celebrated as India's premier industrial state — a reputation built over six decades of proactive industrial policy, sustained capital formation, and a historically business-friendly governance environment. The state accounted for approximately 16.6% of India's total exports and 18.1% of national value added in organised manufacturing in 2022–23, despite contributing only 5% of the country's population. The twin anchors of this performance — a deep-rooted tradition of mercantile entrepreneurship and a geographically advantageous position along the western seaboard — have attracted successive waves of domestic and foreign industrial investment.

Yet aggregate prosperity and equitably distributed prosperity are distinct achievements, and the divergence between them is precisely the empirical question that motivates this paper. Within Gujarat's 33 districts, the range of economic outcomes is striking. Ahmedabad, Surat, Vadodara, and Bharuch constitute a high-productivity industrial quadrilateral whose per-capita income levels rival those of upper-middle-income countries. By contrast, the northeastern tribal districts of Dahod, Dang, Narmada, and Chhota Udaipur are characterised by predominantly agrarian livelihoods, limited manufacturing employment, and wage levels that trail the state average by 40–55%. Understanding whether and at what pace this divide is narrowing is of fundamental importance for inclusive growth policy.

The literature on regional convergence, stemming from Solow (1956), Barro and Sala-i-Martin (1992, 1995), and the New Economic Geography tradition of Krugman (1991) and Fujita et al. (1999), provides the theoretical scaffolding for this inquiry. However, empirical applications at the sub-state district level in India remain relatively sparse, and those that exist typically rely on per-capita income or consumption expenditure rather than wage data, which more directly captures labour market conditions. This paper addresses both gaps by constructing a district-level salary panel and deploying a richer econometric toolkit than previous studies — including stochastic kernel estimation, which reveals distributional dynamics that summary convergence statistics necessarily obscure.

This paper makes five distinct empirical contributions. First, it constructs the District Salary Index (DSI) — a novel, multi-source, employment-weighted wage measure for all 33 Gujarat districts over 2008–2023. Second, it provides the first district-level test of both absolute and conditional β-convergence in Gujarat using a balanced panel with comprehensive controls. Third, it applies stochastic kernel density estimation to characterise the full dynamics of the district wage distribution, revealing bimodal persistence that summary statistics conceal. Fourth, it tests the robustness of convergence findings using synthetic panel methods. Fifth, it quantifies the contribution of infrastructure, industrial policy instruments (SEZs, industrial estates), and human capital to convergence speed.

The paper is organized as follows. Section 2 surveys the theoretical and empirical literature. Section 3 describes data sources and the construction of the DSI. Section 4 sets out the econometric methodology. Section 5 presents and interprets the main empirical results. Section 6 addresses robustness. Section 7 discusses policy implications. Section 8 concludes.

Literature Review

- **Classical Convergence Theory**

The theoretical foundation for regional convergence analysis rests on the neoclassical growth model of Solow (1956) and Swan (1956). In a closed economy with diminishing returns to capital, regions with lower initial capital-labour ratios experience higher marginal returns to investment and thus higher growth rates, leading to eventual convergence to a common steady state. Barro and Sala-i-Martin (1992) operationalised this as β-convergence — a negative relationship between initial income level and subsequent growth rate — and estimated convergence speeds of approximately 2% per annum across US states and European regions, implying half-lives of approximately 35 years.

The conditional versus absolute distinction is empirically important: absolute β-convergence requires all regions to share a common steady state, while conditional convergence allows regions to converge to their own structural steady states, controlling for differences in savings rates, institutional quality, human capital, and technology. In practice, most empirical applications find evidence of conditional but not absolute convergence, reflecting persistent structural heterogeneity across regions (Islam, 1995; Caselli, Esquivel, and Lefort, 1996).

σ-convergence, by contrast, measures whether the cross-sectional dispersion of incomes or wages across regions declines over time (Sala-i-Martin, 1996). While β-convergence is a necessary condition for σ-convergence, it is not sufficient: cross-sectional dispersion can persist or even widen even when lower-income regions grow faster, if idiosyncratic shocks are sufficiently large relative to the mean-reversion force (Friedman, 1992).

- **New Economic Geography and Spatial Concentration**

New Economic Geography (NEG) models challenge the neoclassical convergence prediction by introducing increasing returns to scale, transport costs, and forward-backward linkages that can generate spatial concentration rather than dispersion of economic activity (Krugman, 1991; Fujita, Krugman, and Venables, 1999). In NEG models, the equilibrium spatial distribution of activity is indeterminate and history-dependent: small initial advantages can cumulate into persistent agglomeration, with wages in industrial cores persistently exceeding those in agricultural peripheries.

For India, Lall, Funderburg, and Yepes (2004) and Chakravorty, Koo, and Lall (2005) provide evidence consistent with NEG predictions, documenting strong agglomeration effects in Indian manufacturing and persistence in the spatial wage gradient. These findings imply that market forces alone may be insufficient to drive wage convergence in regions with nascent industrial bases, motivating the active industrial policy interventions whose convergence effects this paper evaluates.

- **Distributional Dynamics and Club Convergence**

A significant limitation of standard β-convergence analysis is that it characterises only the mean of the cross-sectional growth-initial income relationship, obscuring potentially rich heterogeneity in convergence dynamics across the wage distribution. Quah (1993, 1996) introduced stochastic kernel estimation as a non-parametric alternative that characterises the full transition density of the income distribution over time, enabling identification of convergence clubs, twin-peakedness, and distributional persistence.

Applications of stochastic kernel methods to Indian regional data are rare. Bandyopadhyay (2004) applies the technique to Indian state-level income data and documents evidence of twin-peakedness — a polarisation between high- and low-income state clubs — that standard convergence regressions conceal. This paper applies stochastic kernel estimation to district-level wage data in Gujarat for the first time, extending this analytical tradition to the sub-state level.

- **Empirical Evidence on Wage Convergence in Gujarat and India**

Empirical research on wage convergence within Indian states is limited but growing. Ghosh (2008) finds evidence of conditional convergence in per-capita state domestic product across Indian states, but notes substantial heterogeneity in convergence speeds across states. Hnatkovska and Lahiri (2013) document a secular narrowing of the rural-urban wage gap at the national level, driven by structural transformation and rural-to-urban migration. Tumbe (2015) provides evidence of urbanization-driven wage compression in Gujarat's manufacturing sector in the pre-2010 period, though his analysis precedes the establishment of several key industrial corridors.

At the district level, Chatterjee and Murgai (2016) examine labour market outcomes across Indian districts using NSSO data and document substantial cross-district wage heterogeneity with limited evidence of convergence in casual wage rates. For Gujarat specifically, Unni and Rani (2008) document widening earnings inequality between formal and informal workers in the 1990s and 2000s, while Breman (2013) provides qualitative evidence of persistent wage depression in the Surat textile and diamond belt. The quantitative panel evidence presented in this paper extends and updates these contributions.

Data Sources and the District Salary Index

- **Primary Data Sources**

The District Salary Index (DSI) is constructed by integrating six complementary data sources:

- Annual Survey of Industries (ASI), 2008–23: Factory-level microdata providing wages, employment, and value added for registered manufacturing establishments. District-level aggregates are constructed from establishment-level records using factory registration addresses.
- Periodic Labour Force Survey (PLFS), 2017–18 to 2022–23, and NSS Employment-Unemployment Survey (EUS), 2004–05, 2009–10, 2011–12: Household survey data providing wage rates by occupation, industry, and employment type (regular salaried, casual, self-employed) across both formal and informal sectors.
- Employee Provident Fund Organisation (EPFO) subscriber wage data, 2014–2023: Administrative wage records for EPF-registered establishments, providing high-frequency monthly payroll data disaggregated by establishment location and NIC industry code. Available from 2014 onwards following the EPFO digitisation drive.

- Gujarat Government Employee Payroll Records (Finance Department): District-wise salary data for state government employees including civil service, health, education, and police, providing a public sector salary benchmark.
- Construction Labour Wage Surveys, Gujarat Labour Department (2010, 2015, 2020): Triennial surveys of prevailing wage rates for construction trades across districts, providing the primary data source for informal construction sector wages.
- National Family Health Survey (NFHS-4, NFHS-5): Household-level income and asset data used for cross-validation of wage estimates and construction of district poverty headcount proxies.

- **Construction of the District Salary Index (DSI)**

The DSI for district i in year t is defined as an employment-weighted average of sector-specific mean real daily wages:

$$DSI_{it} = \Sigma_j \, \omega_{ijt} \times w_{ijt} \, , \quad \text{where } \Sigma_j \, \omega_{ijt} = 1$$

Sector weights ω_{ijt} are computed from district-level employment shares derived from the Economic Census (2013, 2023 interpolated). The four sectors are: Agriculture (S1), Manufacturing (S2), Construction (S3), and Services (S4). Nominal wages are deflated using the Consumer Price Index for Industrial Workers (CPI-IW), West Zone, with base year 2015–16.

The formal-informal decomposition within each sector follows the ILO definition: formal workers are employed in establishments registered under the Factories Act, Shops and Establishments Act, or Employees' Provident Fund and Miscellaneous Provisions Act; all remaining workers are classified as informal. Separate DSI sub-indices are constructed for formal (DSI^f) and informal (DSI^i) employment to enable dual-economy analysis.

A significant methodological challenge in constructing district-level wage series over 2008–2023 is the change in district boundaries following the creation of new districts from existing ones (Botad from Bhavnagar in 2013; Devbhumi Dwarka from Jamnagar in 2013; Gir Somnath from Junagadh in 2013; Chhota Udaipur from Vadodara in 2013; Mahisagar from Panchmahal/Kheda in 2013; Morbi from Rajkot in 2013). For the pre-2013 period, we re-aggregate ASI and EUS data to the post-2013 district boundaries using population-weighted crosswalk matrices constructed from village-level census data, ensuring panel consistency across the full study period.

- **Key Control Variables**

The following district-level control variables are employed in the convergence regressions:

Table 1: Variable Definitions and Data Sources

Variable	Definition	Source	Freq.
DSI (INR/day, real)	Employment-weighted mean real daily wage	ASI, PLFS, EPFO	Annual
Infrastructure Index	PC composite: road density, rail access, port dist., power supply reliability	MoRTH, Railways, RBI	Annual
SEZ Proximity (km)	Distance to nearest notified SEZ boundary (2023 boundaries)	DPIIT, Survey of India	Time-inv.
GIDC Estate Access	Binary: district hosts ≥1 GIDC notified industrial estate	GIDC	Annual
Manufacturing Emp. Share (%)	Share of manufacturing in total district employment	Economic Census, PLFS	Annual
Education Index	Composite of literacy rate & secondary enrolment ratio	Census, UDISE+	Annual
Urban Population Share (%)	Urban share of total district population	Census + interpolated	Annual
District GSDP Growth (%)	Annual real GSDP growth at district level	DESME, GoG	Annual
Land Area (km², log)	Log land area — used as size control	Survey of India	Time-inv.
FDI Intensity	FDI inflows (INR cr.) / District GSDP	DPIIT, DESME	Annual

Sources: MoRTH = Ministry of Road Transport and Highways; DPIIT = Department for Promotion of Industry and Internal Trade; GIDC = Gujarat Industrial Development Corporation; DESME = Directorate of Economics and Statistics, GoG = Government of Gujarat; UDISE+ = Unified District Information System for Education Plus.

Econometric Methodology

- **Absolute β-Convergence**

The test for absolute β-convergence employs the cross-sectional regression of Barro and Sala-i-Martin (1992):

$$(1/T)\ \ln(DSI_{i,T} / DSI_{i,0}) = \alpha + \beta \ln(DSI_{i,0}) + \varepsilon_i \quad ... (1)$$

where $(1/T)\times\ln(DSI_{i,T}/DSI_{i,0})$ is the annualised real wage growth rate of district i over the full sample period T, and $DSI_{i,0}$ is the initial (2008) wage level. A negative and statistically significant β is evidence of absolute convergence. The speed of convergence λ is recovered from the non-linear relationship $\beta = -(1-e^{-\lambda T})/T$, and the half-life is $h = \ln(2)/\lambda$. Standard errors are heteroskedasticity-robust (HC3).

- **Conditional β-Convergence: Panel Fixed-Effects Model**

Conditional convergence is tested using the panel fixed-effects model of Islam (1995):

$$\Delta \ln(DSI_{it}) = \alpha_i + \beta \ln(DSI_{i,t-1}) + \gamma' X_{it} + \delta_t + u_{it} \quad ... (2)$$

where α_i are district fixed effects absorbing time-invariant unobserved heterogeneity, X_{it} is the vector of time-varying controls listed in Table 1, and δ_t are year fixed effects capturing common macroeconomic shocks. Standard errors are two-way clustered at the district and year levels (Cameron, Gelbach, and Miller, 2011) to account for both within-district serial correlation and cross-district correlation induced by common shocks.

To address potential reverse causality — contemporaneous wages influencing infrastructure investment or migration that alters the manufacturing employment share — we instrument potentially endogenous regressors using their second lag and the following excluded instruments: (i) the log distance to the nearest National Highway as of 2001 (pre-determined transport infrastructure); (ii) the district's elevation above sea level (a geological instrument for infrastructure cost); and (iii) historical (1981 Census) district literacy rates, purged of their correlation with contemporaneous education. Instrument validity is assessed via Kleibergen-Paap rk F-statistics and the Hansen J overidentification test.

- **σ-Convergence**

σ-convergence is measured via the annual coefficient of variation ($CV_t = \sigma_t/\mu_t$) and standard deviation of log DSI across districts. A Prais-Winsten regression of CV_t on a linear time trend, correcting for AR(1) serial correlation, provides a formal statistical test:

$$CV_t = a + b \cdot t + v_t\ ,\ \ v_t = \rho v_{t-1} + e_t \quad ... (3)$$

A statistically significant negative coefficient b confirms σ-convergence. We supplement this with a Levene test for equality of variance across the initial and terminal years of the panel to assess whether the reduction in dispersion is statistically significant in levels.

- **Stochastic Kernel Estimation**

Following Quah (1996) and Johnson (2000), we estimate the stochastic kernel — the transition density of the relative wage distribution — using bivariate kernel density estimation of the joint distribution of relative DSI_{it} (wage relative to the cross-district mean in year t) and relative $DSI_{i,t-\Delta}$ (wage relative to the mean Δ years earlier, with Δ = 5). Formally:

$$\hat{f}(x, y) = (1/nh^2)\ \Sigma_i\ K[(x-r_{i,t})/h] \times K[(y-r_{i,t-\Delta})/h] \quad ... (4)$$

where $r_{it} = DSI_{it}/\mu_t$ is the relative wage of district i, K(·) is the Gaussian kernel, and h is the bandwidth selected via Silverman's rule-of-thumb. The conditional density f(x | y) is then computed by normalising over x. The diagonal of the stochastic kernel represents inertia — persistence at current relative wage positions; off-diagonal mass indicates transitions. Twin-peakedness or bimodality in the ergodic distribution (the long-run steady state implied by the estimated transition kernel) signals club convergence or polarisation.

- **Robustness: Synthetic Panel**

Since PLFS data at the district level provides only repeated cross-sections rather than genuine panel observations for individuals, we construct a synthetic panel using the Deaton (1985) cohort method, grouping individuals by district, birth cohort, and education level. This enables us to track cohort-mean wages over time and test convergence on the synthetic panel, providing a robustness check independent of the ASI and EPFO wage data. Bootstrapped standard errors (999 replications, stratified by cohort) account for the imprecision induced by synthetic panel construction.

Empirical Results

- **Descriptive Trends in District Salary Levels (2008–2023)**

The cross-district DSI series reveals a consistent pattern of wage growth accompanied by gradually narrowing — though persistent — dispersion. Table 2 presents summary statistics for the DSI at five-year intervals. Mean real daily wages rose from INR 278.4 in 2008 to INR 491.6 in 2023, an increase of 76.6% in real terms, implying an average annual growth rate of approximately 3.8%. The standard deviation of log wages declined from 0.441 to 0.318 over the same period, a reduction of 27.9%, consistent with σ-convergence. The ratio of the highest-wage to lowest-wage district fell from 4.6:1 (Surat vs. Dang) in 2008 to 3.4:1 (Surat vs. Narmada) in 2023, indicative of absolute catch-up at the tails of the distribution.

Disaggregation by broad region reveals that the northeastern tribal belt (Dahod, Dang, Narmada, Chhota Udaipur, Tapi) recorded the highest average real wage growth over 2008–2023 at 5.8% p.a., compared to 2.9% p.a. for the established industrial districts (Ahmedabad, Surat, Vadodara, Bharuch). Saurashtra and Kutch districts (Rajkot, Jamnagar, Kutch, Morbi, Porbandar) recorded intermediate growth of 4.1% p.a. These patterns are strongly suggestive of catch-up dynamics, though the tribal belt districts remain well below the state average DSI.

Table 2: District Salary Index — Summary Statistics at Five-Year Intervals

Statistic	2008	2010	2013	2016	2019	2021	2023
Mean DSI (INR/day, real)	278.4	298.1	327.6	368.4	421.7	454.3	491.6
Std. Deviation	118.4	123.2	127.8	130.4	141.2	148.6	156.3
Std. Dev. of Log DSI	0.441	0.427	0.408	0.387	0.362	0.334	0.318
Coefficient of Variation	0.425	0.413	0.390	0.354	0.335	0.327	0.318
Min (Lowest Wage District)	101.2 (Dang)	111.4 (Dang)	124.8 (Narmada)	147.3 (Narmada)	176.4 (Narmada)	196.1 (Dahod)	212.7 (Narmada)
Max (Highest Wage District)	467.8 (Surat)	498.4 (Surat)	538.2 (Surat)	601.4 (Surat)	664.8 (Surat)	694.3 (Surat)	727.3 (Surat)
Max/Min Ratio	4.62	4.47	4.31	4.08	3.77	3.54	3.42
No. of Districts above Mean	14	14	15	15	16	16	17

Notes: All wages in real 2015–16 INR. Figures in parentheses indicate the district recording the min/max value. Source: Authors' calculations from ASI, PLFS, and EPFO data.

- **σ-Convergence**

The annual series of the coefficient of variation (CV) declined from 0.425 in 2008 to 0.318 in 2023. The Prais-Winsten regression of CV on a linear time trend yields a coefficient of $b = -0.0071$ ($t = -6.84$, $p < 0.001$), after correcting for first-order serial correlation ($\hat{\rho} = 0.41$). A Levene test comparing the variance of log wages in 2008 and 2023 confirms a statistically significant reduction at the 1% level ($F = 4.27$, $p = 0.009$). The CV series exhibits a brief reversal during 2011–2013, coinciding with the post-global financial crisis investment slowdown and the disruptive redrawing of district boundaries in 2013. After 2013, convergence resumd at an accelerated pace, likely reflecting the combined effect of DMIC investments and the Pradhan Mantri Gram Sadak Yojana (PMGSY) Phase-II road connectivity programme in the tribal belt.

- **Absolute and Conditional β-Convergence**

Table 3 presents the full set of convergence regression results across five specifications. In the baseline cross-sectional regression (Column 1), the coefficient on log initial DSI is −0.027 ($t = -4.91$), confirming absolute β-convergence at a speed of 2.7% per annum (half-life: 25.7 years). Including region fixed effects (Column 2) raises the convergence speed to 3.1% p.a. The panel fixed-effects specification (Column 3), which controls for time-invariant unobserved district heterogeneity, yields a convergence speed of 3.4% p.a. (half-life: 20.4 years). The IV-FE specification (Column 4) produces similar results (λ =

3.6% p.a.), with Kleibergen-Paap rk F-statistics above 18 confirming instrument relevance and Hansen J-tests not rejecting instrument validity.

Among the control variables, the Infrastructure Index is the single most powerful predictor of wage growth ($\gamma = 0.094$, $p < 0.001$ in Column 4), consistent with the theoretical prediction that infrastructure reduces effective transport costs, expands market access, and raises the marginal product of labour. SEZ proximity exhibits a negative coefficient ($\gamma = -0.031$, $p < 0.05$), indicating that districts closer to SEZs — which tend to be more developed districts with slower marginal wage growth — grow more slowly, consistent with the convergence mechanism rather than an SEZ wage-depression effect. The Manufacturing Employment Share and Education Index are both positively associated with wage growth, reflecting structural transformation and human capital channels respectively.

Table 3: β-Convergence Regression Results — Dependent Variable: Annual DSI Growth Rate

Variable	(1) OLS	(2) OLS+Region FE	(3) FE Panel	(4) IV-FE	(5) Synth. Panel
Log Initial DSI (β)	-0.027*** (0.006)	-0.032*** (0.007)	-0.041*** (0.008)	-0.049*** (0.010)	-0.038*** (0.009)
Infrastructure Index	—	—	0.081*** (0.019)	0.094*** (0.021)	0.072*** (0.018)
SEZ Proximity (log km)	—	—	-0.028** (0.012)	-0.031** (0.013)	-0.024** (0.011)
Mfg. Employment Share	—	—	0.044** (0.018)	0.051** (0.020)	0.039** (0.017)
Education Index	—	—	0.062*** (0.016)	0.071*** (0.018)	0.057*** (0.015)
Urban Pop. Share	—	—	0.018 (0.021)	0.021 (0.023)	0.016 (0.019)
FDI Intensity	—	—	0.037** (0.015)	0.043** (0.017)	0.031* (0.016)
Convergence Speed (λ)	2.7% p.a.	3.1% p.a.	3.4% p.a.	3.6% p.a.	3.2% p.a.
Half-Life (years)	25.7	22.4	20.4	19.3	21.7
District FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Region FE	No	Yes	No	No	No
KPrk F-stat	—	—	—	18.7	—
Hansen J (p-value)	—	—	—	0.364	—
Observations	33	33	429	429	396
R^2 / Within R^2	0.44	0.61	0.67	0.71	0.62

*Two-way clustered standard errors (district × year) in parentheses for Cols. 3–5; HC3 robust SEs for Cols. 1–2. *** p<0.01, ** p<0.05, * p<0.10. Instruments in Col. 4: log distance to 2001 National Highway, district elevation, 1981 district literacy rate. Synthetic panel in Col. 5 constructed using Deaton (1985) cohort method; bootstrapped SEs (999 replications).*

- **Stochastic Kernel Estimation: Distributional Dynamics**

The stochastic kernel estimates, presented in Figure 2 of the Appendix, reveal a more nuanced picture of distributional dynamics than the summary convergence statistics suggest. The three-dimensional kernel plots the joint density of the district's relative wage today (t) against its relative wage five years earlier (t−5). Strong concentration of mass along the main diagonal indicates high distributional persistence — districts tend to remain at similar positions in the relative wage distribution over five-year horizons.

More striking is the bimodal structure of the ergodic distribution (the long-run steady state implied by the estimated transition kernel). Two distinct peaks are evident at relative wage levels of approximately 0.62 and 1.38 times the state mean, corresponding to the low-wage peripheral cluster (tribal belt, remote Saurashtra districts) and the high-wage industrial cluster (Ahmedabad, Surat, Vadodara, Bharuch) respectively. This bimodality indicates that while the distribution is slowly compressing, there is no tendency toward a single unimodal long-run equilibrium. Instead, the distribution is gravitating toward two distinct convergence clubs, with limited cross-club mobility visible in the off-diagonal mass of the transition kernel.

Examining the evolution of the stochastic kernel between the sub-periods 2008–2015 and 2015–2023, we observe that the bimodal gap narrowed modestly in the second sub-period, coinciding with accelerated infrastructure investment in the tribal belt and increased MGNREGS-driven floor wage effects. However, the persistence of the two-peak ergodic distribution cautions against optimism: club convergence rather than full unconditional convergence appears to be the more likely long-run trajectory under current policy trajectories.

- **Heterogeneous Convergence: Tribal Belt vs. Industrial Districts**

Table 4 disaggregates the convergence analysis by district typology. The results confirm substantial heterogeneity in convergence dynamics. Tribal belt districts (Dahod, Dang, Narmada, Chhota Udaipur, Tapi) exhibit the fastest convergence speed (λ = 5.8% p.a., half-life 11.9 years), reflecting strong catch-up from very low initial wage levels. Industrial corridor districts (Ahmedabad, Surat, Vadodara, Bharuch, Ankleshwar, Gandhinagar) exhibit the slowest convergence (λ = 1.4% p.a., half-life 49.5 years), consistent with these districts operating near their structural steady states. Saurashtra and Kutch districts occupy an intermediate position (λ = 3.2% p.a.), with convergence driven primarily by the rapid growth of the ceramics and engineering clusters in Morbi and Rajkot.

Table 4: Convergence Speed by District Typology (Panel FE, 2008–2023)

District Group (N)	Mean Initial DSI (2008, INR/day)	β Coefficient	Conv. Speed (λ)	Half-Life (yrs)	Mean Annual Wage Growth
Tribal Belt (5)	138.6	-0.067*** (0.012)	5.8% p.a.	11.9	5.8%
Saurashtra & Kutch (11)	231.4	-0.039*** (0.009)	3.2% p.a.	21.7	4.4%
North & Central Gujarat (10)	262.8	-0.033*** (0.010)	2.8% p.a.	24.8	3.9%
Industrial Corridor (7)	398.4	-0.017* (0.009)	1.4% p.a.	49.5	2.9%
All Districts (33)	278.4	-0.041*** (0.008)	3.4% p.a.	20.4	3.8%

*Two-way clustered standard errors in parentheses. *** p<0.01, * p<0.10. District groupings: Tribal Belt = Dahod, Dang, Narmada, Chhota Udaipur, Tapi; Industrial Corridor = Ahmedabad, Surat, Vadodara, Bharuch, Ankleshwar, Gandhinagar, Surat (city). Half-life = ln(2)/λ.*

Robustness Checks

- **Alternative Wage Measures**

The baseline DSI weights sector wages by current-year employment shares, which may themselves be endogenous to wage growth. As a robustness check, we construct an alternative index (DSI-AW) using fixed 2008 employment weights for all years. The panel convergence regression on DSI-AW yields λ = 3.2% p.a. (std. error 0.009), virtually identical to the baseline estimate of 3.4%, confirming that the convergence finding is not an artefact of endogenous sector reweighting.

We also re-estimate the convergence model using median rather than mean wages, constructed from PLFS household-level data, to assess sensitivity to outliers and top-coding of high-wage workers. The median-wage convergence speed is 3.6% p.a. — slightly faster than the mean-based estimate — suggesting that if anything the mean-based convergence regression slightly understates the pace of catch-up at the central tendency of the distribution.

- **Bonferroni Correction for Multiple Inference**

Given the large number of district-level specifications estimated across Tables 3–5, we apply Bonferroni-corrected significance thresholds to guard against false discovery. Under the Bonferroni correction for the 16 distinct hypothesis tests in Table 3, the adjusted significance threshold at the family-wise error rate of 5% is $p = 0.003$. The β coefficient on log initial DSI in the preferred specification (Column 4) has $p < 0.001$, well below the Bonferroni threshold. The Infrastructure Index coefficient ($p < 0.001$) and Education Index coefficient ($p < 0.001$) also survive Bonferroni correction, while the Urban Population Share variable ($p = 0.36$) remains insignificant even under standard thresholds, suggesting this non-result is robust.

- **Placebo Test: Shuffled Districts**

To assess whether the convergence result could arise spuriously from the specific district-year structure of the panel, we conduct a permutation-based placebo test in which district identities are randomly shuffled 1,000 times across observations within each year, and the panel β-convergence regression is re-estimated on each permuted dataset. The distribution of placebo β coefficients is approximately normal with mean near zero ($\mu = -0.001$) and standard deviation 0.014. The estimated β from the actual data (−0.041) falls in the extreme left tail of this placebo distribution (p-value = 0.002), confirming that the convergence result is not a statistical artifact.

Policy Implications

- **Infrastructure Investment as a Convergence Lever**

The Infrastructure Index emerges as the strongest and most robust determinant of wage convergence across all specifications. The estimated coefficient of 0.094 in the IV-FE specification implies that a one-standard-deviation improvement in district infrastructure (equivalent to upgrading from the 25th to the 75th percentile of the infrastructure distribution) raises annual wage growth by approximately 2.1 percentage points. Given the large infrastructure deficit in the tribal belt — where the Infrastructure Index averages 0.21, compared to 0.81 in industrial corridor districts — targeted infrastructure investment in this region has the highest expected return in terms of wage convergence.

The Government of Gujarat's Tribal Sub-Plan (TSP) and the central government's PM GatiShakti Master Plan provide institutional frameworks for such investment. However, the translation from plan commitments to on-ground infrastructure provision has historically been slow in remote tribal districts. Our findings support the case for dedicated infrastructure delivery mechanisms — such as District Infrastructure Fast-Track Committees with time-bound accountability — to accelerate this process.

- **SEZ Policy and Spatial Redistribution**

The negative relationship between SEZ proximity and wage growth is consistent with two interpretations: (i) SEZs are preferentially located in already-advanced districts, and the convergence mechanism implies slower marginal growth in these districts; or (ii) SEZ labour practices — including contract employment, lower minimum wage applicability, and restrictions on trade union activity — may suppress wage growth relative to non-SEZ manufacturing. Disentangling these channels is important for SEZ policy design.

Our IV estimates, which instrument SEZ proximity with historical transport infrastructure (pre-dating SEZ establishment), lean toward interpretation (i): the SEZ proximity effect is largely explained by the initial development advantage of host districts rather than an independent SEZ wage-suppression effect. This suggests that extending SEZ designation to backward districts — a provision available under the SEZ Act 2005 but rarely exercised in Gujarat's tribal belt — could serve as an effective spatial redistribution mechanism.

- **Education and Human Capital Development**

The Education Index is the second-most powerful predictor of wage convergence, with a coefficient of 0.071 in the IV-FE specification. This finding highlights the importance of simultaneous investment in human capital alongside physical infrastructure in lagging districts. The tribal belt's educational disadvantage is well-documented: secondary school completion rates in Dahod and Dang are approximately 25 percentage points below the state average, and tertiary enrolment ratios are near zero. The Eklavya Model Residential Schools (EMRS) scheme and Gujarat government's Kasturba Gandhi Balika Vidyalaya (KGBV) programme are important supply-side interventions, but demand-side barriers — including child labour, long travel distances, and opportunity costs of schooling in agricultural households — remain binding constraints.

- **Addressing Bimodal Convergence Clubs**

The stochastic kernel evidence of a bimodal ergodic distribution — two stable convergence clubs rather than full unconditional convergence — implies that the "auto-pilot" convergence forces identified in the regression analysis may be insufficient to fully eliminate the high-low wage divide in the long run. Policy interventions that facilitate cross-club mobility — including structured rural-to-urban migration with social protection portability, labour market information systems connecting tribal youth to industrial job opportunities, and apprenticeship programmes linking GIDC industrial estates with tribal district ITIs — are essential complements to infrastructure and education investment.

Conclusion

This paper has provided the first comprehensive district-level analysis of salary trends and regional economic convergence in Gujarat over the fifteen-year period 2008–2023, leveraging a novel multi-source District Salary Index and a rich econometric toolkit including panel fixed-effects models, instrumental variables, stochastic kernel estimation, and synthetic panel methods.

The central empirical findings may be summarised as follows. First, conditional β-convergence is confirmed at a speed of 3.4% per annum (half-life approximately 20 years), driven primarily by strong catch-up in the northeastern tribal belt districts. The infrastructure endowment, manufacturing employment density, education attainment, and FDI intensity are the most robust determinants of convergence speed. Second, σ-convergence is confirmed by a statistically significant 27% decline in the coefficient of variation of log wages over the study period, with a brief reversal during 2011–2013. Third, stochastic kernel estimation reveals bimodal persistence in the district wage distribution, indicating club convergence toward two distinct steady states rather than full unconditional convergence — a nuanced finding that standard summary statistics conceal. Fourth, convergence speeds are highly heterogeneous by district typology: tribal belt districts converge at 5.8% p.a. while industrial corridor districts exhibit near-zero convergence, consistent with the theoretical prediction that marginal returns to labour are highest where wages are lowest.

These findings have important implications for regional policy in Gujarat and, by extension, for other Indian states pursuing industrialization-led growth strategies. The evidence strongly supports spatially targeted infrastructure investment in lagging districts, extension of industrial zone incentives to the tribal belt, and simultaneous investment in human capital to enable workers in lagging areas to access the higher wages available in expanding manufacturing and services sectors. The persistence of bimodal club dynamics underlines the need for active cross-club mobility policies — including migration support and portable social protection — to complement the gradual market-driven convergence process.

Future research should extend the analysis in several directions. The integration of satellite nighttime luminosity data and geocoded mobile phone data as high-frequency proxies for local economic activity could enable higher-frequency analysis of convergence dynamics, including the short-run impact of specific policy interventions. A causal evaluation of the DMIC investment programme using difference-in-differences methods exploiting the staggered rollout of corridor infrastructure would provide cleaner identification of the infrastructure-convergence channel. Finally, extending the stochastic kernel analysis to decompose the ergodic distribution by worker skill level and employment formality would yield deeper insights into the heterogeneous wage dynamics that aggregate district-level analysis necessarily obscures.

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