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ARTICLE

Health, Income and Convergence Across Indian States, 2004-2022: Evidence from Heterogeneous Panels.

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Abstract

Interstate disparities in income and health remain a persistent challenge to inclusive development in India, but whether Indian states are converging simultaneously in economic prosperity and population health remains unclear. This study examines income and health convergence across 27 Indian states over 2004-2022 using a harmonised state-level panel of real per-capita net state domestic product (NSDP) and infant mortality rate (IMR). The analysis combines σ- and β-convergence tests with diagnostics for cross-sectional dependence, slope heterogeneity and panel stationarity, followed by heterogeneous-panel estimators that account for unobserved common factors. The results provide little evidence of system-wide convergence. Dispersion in log real per-capita income increased from 0.449 in 2004 to 0.545 in 2022, while dispersion in log IMR rose from 0.534 to 0.672; both trends are positive and statistically significant. Endpoint β-convergence estimates are positive and statistically insignificant for both income and IMR, and conditioning income convergence on baseline higher-education gross enrolment does not alter this conclusion. Very strong cross-sectional dependence indicates that state outcomes are influenced by common national and macroeconomic forces, while substantial slope heterogeneity, particularly for income, suggests that adjustment processes differ markedly across states. Mean-group and augmented mean-group estimates indicate significant mean reversion only for a minority of states, whereas common-correlated-effects estimates reveal stronger average adjustment after controlling for common factors. Overall, India has achieved substantial improvements in income and infant survival without corresponding convergence across states. The findings point to a capability-based development strategy that combines human-capital formation, productive infrastructure and health-system strengthening with differentiated, state-specific interventions rather than a uniform convergence policy.

Keywords: interstate convergence; income convergence; health convergence; infant mortality; heterogeneous panels; cross-sectional dependence; human capital; regional disparities; India

JEL classification: C23; I15; I25; O18; O47; R11; R12

1. INTRODUCTION

Development is increasingly understood not merely as growth in aggregate income but as a process through which gains in living standards, health, education and productive capability are shared across people and regions. Health holds a central place in that process. Better health raises labour productivity and human-capital accumulation, while higher incomes expand access to nutrition, sanitation, healthcare and schooling. The relationship is therefore bidirectional rather than a one-way mapping from growth to health. The health-capital literature treats health as both a consumption good and an investment, and later work has shown that gains in longevity can raise economic performance through human-capital and productivity channels [1-4]. In a federal economy such as India these relationships need not evolve uniformly: states differ widely in initial income, demographic transition, human capital, health infrastructure, public expenditure and institutional capacity.

India has recorded large improvements in income and population health, but national averages conceal persistent, and sometimes widening, interstate differences. Recent estimates document a steep fall in infant and child mortality alongside lasting interstate inequality, including stagnation in some

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components of early-life mortality in some regions [5]. The relevant question is therefore no longer whether India as a whole has improved, but whether states are converging or following increasingly differentiated trajectories.

The neoclassical growth model predicts that, conditional on similar structural parameters, economies with lower initial income grow faster because of diminishing returns to reproducible capital [6,7]. The Indian evidence is mixed. Earlier studies found convergence in some periods and divergence in others [8,9], and recent analysis of financial years 2002-2023 finds that higher-income states grew faster than lower-income states, implying no unconditional income convergence [10]. For health, a study of 15 major states over 1990-2018 found convergence in life expectancy but divergence after 2006 in infant mortality, neonatal mortality and total fertility, with distinct convergence clubs [11]. Work on infant mortality over 1987-2020 likewise finds no overall convergence but several clubs with distinct transition paths [12]. Health convergence therefore cannot be inferred from national improvement or from a single average trend.

Two features of the existing literature motivate this study. First, the Indian literature has examined the income-health relationship and convergence in income or health largely as separate questions. One strand estimates the effect of health on growth with pooled panel regressions [13,14]; another studies convergence in a single dimension [15-17]. Little is known about whether income and health converge together and whether the two processes are related. Second, most panel studies impose a common slope across states, an assumption that is hard to defend when states differ in health-system capacity, fiscal resources and economic structure [18], and that ignores the common national shocks to which all states are exposed.

This paper therefore treats convergence itself as the object of analysis and asks three questions: (i) have interstate differences in real per-capita income narrowed over 2004-2022; (ii) have health outcomes, in particular infant mortality, converged; and (iii) does the adjustment process differ systematically across states rather than follow a common response? The period encompasses accelerated growth, expansion of social-sector programmes, demographic transition and the COVID-19 pandemic. Including 2020-2022 does not presuppose a structural break; we test sensitivity to it explicitly.

The paper makes three contributions. It provides an integrated assessment of income and health convergence over a recent, policy-relevant window. It extends the homogeneous-panel approach by combining diagnostics for cross-sectional dependence and slope heterogeneity with estimators that allow state-specific adjustment around common factors. And it shifts the policy reading of interstate disparity from uniform catch-up towards a differentiated, capability-based framework.

2. CONCEPTUAL FRAMEWORK AND LITERATURE

2.1. Health, Human Capital and Income

Grossman's model treats health as a durable stock that depreciates and can be augmented by investment, linking health to productivity and lifetime welfare [1]; it complements the broader human-capital framework in which education, skills and health jointly determine productive capacity [19]. Health affects growth through several reinforcing channels: lower morbidity and premature mortality, higher labour-force participation and effective working time, and stronger incentives to invest in education when life expectancy lengthens [3,20]. Demographic change can generate a dividend, but only where complementary human capital, employment opportunities and institutions exist. Interstate health differences can therefore sustain differences in productive capacity even within a common national policy framework.

The income-health relationship is conventionally represented as a feedback loop, yet the evidence cautions against assuming linearity or homogeneity. The Preston curve established the cross-country association between income and life expectancy, but later work showed that technology, institutions and public-health factors matter as well [21]. For India, state-level evidence supports a long-run two-way relationship between economic growth and the health and education components of human development, with considerable heterogeneity across states [22,23]. Public health expenditure responds nonlinearly to income, with different elasticities in more and less developed states [24]. These findings motivate the

proposition that income convergence cannot be assumed to imply health convergence, nor the reverse, and that the two should be examined separately and jointly.

2.2. β- and σ-Convergence, and Conditioning

Absolute β-convergence holds when initially poorer economies grow faster. A negative β does not imply a common long-run level: convergence may be towards state-specific steady states when savings, human capital, technology or institutions differ, which is the idea behind conditional convergence in the augmented Solow model [25]. σ-convergence concerns the evolution of cross-sectional dispersion directly. The two are distinct: β-convergence is necessary but not sufficient for σ-convergence, because new shocks can keep dispersion from falling.

Evidence for India depends on period, unit and specification. Panel stationarity tests with smooth breaks find no stochastic income convergence among 19 states over 1994-2018 [15], and the IMF finds that lower-income states grew more slowly over FY2002-FY2023 [10]. Sub-state analysis of 103 regions finds conditional β-convergence and spatial spillovers [26], and World Bank analysis reports convergence within groups of states but divergence between groups [27]. Divergence has been attributed to differences in infrastructure, financial development, governance and total factor productivity [15,28]. For health, β-convergence has been reported for life expectancy and selected mortality indicators, while other indicators show σ-divergence, health stratification and low-level health traps [16,17]. Health convergence is therefore indicator-specific.

2.3. Why Heterogeneous Panels

Pooled estimators impose one slope on every state. Two features of Indian state data argue against this. First, states face common national shocks (reforms, fiscal policy, inflation, technology diffusion, nationwide programmes), producing cross-sectional dependence that invalidates first-generation panel procedures [29]. Second, adjustment parameters plausibly differ across states, and imposing homogeneity can mislead inference [30]. Common correlated effects (CCE) estimators' proxy unobserved common factors with cross-sectional averages, and the mean-group version permits heterogeneous slopes [31,32]. The distinction has substantive meaning. Two states with identical infant mortality but different health systems, fiscal resources and human capital will convert the same income gain into very different mortality reductions; two states with the same income may follow different growth paths because their capital, productivity and infrastructure differ.

2.4. Research Gap and Hypotheses

Existing work estimates average health-income associations [13,14] or studies convergence in one dimension [11,12,15]. Evidence on Indian income convergence is inconclusive and sensitive to specification and spatial aggregation [10,15,26]. We address these gaps by studying income and health convergence jointly, with diagnostics for dependence and slope heterogeneity and with estimators that accommodate both. Table 1 lists the hypotheses and the test used for each.

Table 1. Hypotheses and tests

No.	Hypothesis	Test	Reported in
H1	Income β-convergence: states with lower initial real per-capita income grow faster, conditional on structural characteristics.	Eqs. (4)– (5); $\beta_Y < 0$	Table 5
H2	Income σ-convergence: dispersion of log real per-capita income declines.	Eqs. (1)– (2); $\delta < 0$	Table 4
H3	Health β-convergence: states with higher initial IMR experience faster proportional reduction.	Eq. (6); $\beta_M < 0$	Table 5
H4	Health σ-convergence: dispersion of log IMR declines.	Eqs. (1)– (2); $\delta < 0$	Table 4
H5	Income–health link: gains in income and health	Eq. (10)	Table 7

	are systematically associated across states.		
H6	Heterogeneity: adjustment parameters differ across states, so a homogeneous panel is inadequate.	Pesaran–Yamagata Δ; dispersion of φ_i	Tables 6–7
H7	Cross-sectional dependence: state outcomes share common national shocks.	Pesaran CD	Table 6

IMR, infant mortality rate. The state-slope diagnostic is reported as a Wald statistic, and the state-specific adjustment coefficient φi (Section 4.4).

3. DATA AND VARIABLES

3.1. Coverage and period

The unit of analysis is the Indian state, observed annually over 2004-2022. States matter as the unit because economic structure, fiscal capacity, service provision and health systems differ markedly within a common national macroeconomic framework. The sample comprises the states for which all principal series are available; territorial consistency is maintained by harmonising series affected by the creation of Telangana and the reorganisation of Jammu and Kashmir, and small states and union territories are treated separately because they can dominate dispersion measures. A balanced panel is used where official series permit; otherwise the unbalanced panel is retained and no values are interpolated or extrapolated. The number of states and observations is reported for every test.

3.2. Income

Income is real per-capita NSDP at constant 2011-12 prices, produced by state Directorates of Economics and Statistics in consultation with the National Statistical Office and disseminated by the Ministry of Statistics and Programme Implementation (MoSPI) and the Reserve Bank of India (RBI) [33,34]. The 2011-12 base series begins in 2011-12, so years before that require the earlier 2004-05 base series. The two are chain-linked at the overlap year by applying growth rates of the earlier series to the 2011-12 level, and results are checked against each base separately. The RBI notes that data before the base year relate to NSDP at factor cost, a break that the linking exercise and the robustness checks address. With Yit real per-capita income, yit = ln Yit; annual and k-year average annualised growth rates are computed in logarithms (Eq. 3).

3.3. Health

Health is measured primarily by the IMR, supplemented by the crude birth rate (CBR) and crude death rate (CDR), all from the Sample Registration System (SRS) as compiled in the RBI Handbook [34,35]. IMR is the principal outcome because it is sensitive to household income, maternal health, nutrition, sanitation and the quality of primary care, and because state coverage is broad. Because a lower IMR denotes better health, convergence is defined as a faster proportional reduction among states with higher initial IMR. Birth and death rates capture fertility and the stage of demographic transition and are not assumed to share the convergence pattern of IMR. Life expectancy is used in robustness analysis where comparable series exist.

3.4. Conditioning Variables

Conditional specifications include education, proxied by the higher-education Gross Enrolment Ratio (GER) [34,36]. Education matters twice over: it shifts steady-state income, making absolute convergence too restrictive, and it interacts with health by raising health knowledge and the capacity to use services. GCF is central to the neoclassical mechanism. The conditioning set is deliberately parsimonious because the time dimension is short and comparable annual state series for additional structural variables contain breaks and missing observations.

Table 2. Variables and sources

Variable	Definition and transformation	Source

Income	Real per-capita NSDP, constant 2011–12 prices (₹); natural log; earlier base chain-linked	MoSPI; RBI Handbook
IMR	Infant deaths per 1,000 live births; natural log	SRS via RBI Handbook
CBR, CDR	Births and deaths per 1,000 population	SRS via RBI Handbook
GER	Gross enrolment ratio (higher education; school GER as alternative)	AISHE; RBI Handbook
GCF	Not used in the final baseline because comparable annual state coverage could not be verified without breaks	RBI/EPWRF reviewed; excluded from baseline

NSDP, net state domestic product; SRS, Sample Registration System; AISHE, All India Survey on Higher Education; GSDP, gross state domestic product.

4. EMPIRICAL STRATEGY

The strategy proceeds in stages: descriptive dispersion measures; β-convergence regressions; diagnostics for cross-sectional dependence, slope heterogeneity and non-stationarity; and heterogeneous-panel estimation. This order matters because first-generation procedures assume cross-sectional independence, which is unlikely in a federation exposed to common national shocks.

4.1. σ-convergence

Let y_{it} be the log of the variable (income or IMR) for state i in year t. Dispersion is

$$\sigma_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}[y_{it} - m_t]^2} \quad (1)$$

where m_t is the cross-state mean of y_{it} and N_t the number of states. A declining σ_t indicates convergence, an increasing σ_t divergence, irrespective of whether the mean level of IMR is rising or falling. The trend

$$\sigma_t = a + \delta t + u_t (2)$$

provides a supplementary test, with $\delta < 0$ consistent with narrowing dispersion. Because dispersion may evolve nonlinearly, the trend regression is supplementary to the graphical evidence.

4.2. β-convergence

The average annualised growth rate of income over a window of k years is

$$g_{i,t,t+k} = \frac{100}{k}\left[ln\, Y_{i,t+k} - ln\, Y_{it}\right] \quad (3)$$

and the improvement rate for IMR, M_{it}, is defined analogously with M in place of Y. Absolute income β-convergence is tested by

$$g_i = \alpha + \beta\, ln\, Y_{i0} + \varepsilon_i (4)$$

with $\beta < 0$ indicating convergence. The conditional specification adds the steady-state determinants $\mathbf{X}_{it}$ (GER and GCF), state effects μ_i and common time effects λ_t:

$$g_{it} = \alpha + \beta_Y\, ln\, Y_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

For health the dependent variable is the annualised change in ln IMR:

$$h_{it} = \alpha + \beta_M\, ln\, M_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

where hit = (100/k)[ln Mi,t+k − ln Mit], so that $\beta M < 0$ means states with higher initial IMR reduce mortality proportionally faster. Both unconditional and conditional models are estimated, because rejecting unconditional convergence does not imply the absence of conditional convergence. Convergence speeds are derived only where the dynamic specification and temporal aggregation justify it.

4.3. Cross-Sectional Dependence and Slope Heterogeneity

Cross-sectional dependence in the level series is assessed with Pesaran's CD statistic. For the baseline diagnostics reported in Table 6, the statistic is computed separately for ln real per-capita income and ln IMR, using the pairwise correlations of the level series across states.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \quad (7)$$

where ρ̂ij is the pairwise cross-sectional correlation of the relevant level series; under the null of cross-sectional independence the statistic is asymptotically standard normal [29]. Slope homogeneity, H0: β1 = β2 = … = βN, is tested with the Pesaran-Yamagata Δ and its adjusted version [30]. Rejection implies that a pooled coefficient is an average over heterogeneous state processes rather than a universal relationship.

4.4. Panel Unit Roots and Heterogeneous Estimation

Because dependence is expected, non-stationarity is assessed with the cross-sectionally augmented IPS (CIPS) test, built on state-level CADF regressions [37]:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \sum_{p=1}^{P} \varphi_{ip} \Delta y_{i,t-p} + u_{it} \quad (8)$$

Because dependence is expected, non-stationarity is assessed with the cross-sectionally augmented IPS (CIPS) test, built on state-level CADF regressions [37]. The CIPS results are reported under intercept and intercept-plus-trend specifications. Given the short time dimension and the mixed evidence across specifications, the analysis does not impose a panel cointegration or common long-run equilibrium structure (for example, one examined through the panel error-correction approach of Westerlund [38]); the heterogeneous estimators are therefore interpreted as dynamic adjustment models rather than long-run cointegrating estimators.

Heterogeneous convergence is estimated in annual dynamic form. A state-specific convergence regression on the initial level is not identifiable from a single window, so the heterogeneous coefficient is the speed of adjustment φi:

$$\Delta y_{it} = \alpha_i + \varphi_i y_{i,t-1} + \theta' x_{it} + \delta' \bar{z}_t + \varepsilon_{it}, \quad \hat{\varphi}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\varphi}_i (9)$$

where z̄t contains cross-sectional averages of the dependent and explanatory variables that proxy unobserved common factors, and φi < 0 indicates mean reversion towards a state-specific path (conditional convergence). This is the common-correlated-effects mean-group (CCEMG) estimator [31,32]. Augmented mean group (AMG) estimates, which include a common dynamic process, serve as an alternative specification [39,40]. Because the diagnostics show very strong cross-sectional dependence and pronounced income-slope heterogeneity, CCEMG is treated as the preferred heterogeneous specification for the main interpretation, while AMG is retained as a deliberately conservative alternative. The time dimension is short (T = 19), so neither estimator is interpreted as a definitive long-run parameter. Pooled mean group estimation [41] is not used because the evidence does not establish a common cointegrating relationship. Club-convergence procedures based on the log t framework of Phillips and Sul [42] are likewise not applied; the heterogeneous-panel design instead estimates state-specific adjustment directly.

$$\Delta \ln M_{it} = a_i + \varphi_i \ln M_{i,t-1} + \psi_i \Delta \ln Y_{i,t-1} + \delta'_i \bar{z}_t + \varepsilon_{it} \quad (10)$$

The link between the two processes (H5) is examined with Eq. (10), which is reported in Table 7. The estimator hierarchy is: pooled or fixed-effects benchmarks; mean-group where slopes differ; CCEMG where both slope heterogeneity and common factors are present; AMG as an alternative treatment of common dynamic processes. Estimator choice follows the diagnostics rather than a prior preference.

4.5. Robustness Analysis

Robustness checks cover alternative income measures (NSDP and GSDP; each base series), alternative health indicators (CDR and life expectancy), alternative windows, unconditional versus conditional models, exclusion of influential states, balanced versus unbalanced samples, specifications with and without time effects, alternative lag structures, and three COVID treatments: full period (2004-2022), pre-COVID (2004-2019), and full period with year effects and a pandemic indicator.

5. DESCRIPTIVE EVIDENCE

5.1. Income

Real per-capita income rose substantially but remains highly unequal. In 2022-23, state and union territory per-capita NSDP at constant 2011-12 prices ranged from ₹31,280 (Bihar) to ₹271,019, the upper value belonging to a union territory [43]. Rising income in poorer states does not by itself establish convergence, which requires poorer states to grow systematically faster than richer ones. The IMF finds the opposite pattern for FY2002-FY2023: a positive relationship between initial income and subsequent growth [10]. Persistent stratification between states such as Goa, Haryana, Maharashtra, Karnataka and Gujarat on one side and Bihar, Jharkhand, Madhya Pradesh and Odisha on the other is consistent with evidence attributing the gaps to infrastructure, financial development, governance and productivity [15]. The IMF and World Bank analyses also point to convergence within groups of states alongside divergence between groups [27,44].

5.2. Infant Mortality

Infant mortality has fallen markedly. The all-India IMR declined from 58 per 1,000 live births in 2004 to 26 in 2022 [34,35]. Interstate differences remain large: in 2022 the IMR was 7 in Kerala, 16 in Punjab, 20 in Andhra Pradesh, 26 in Bihar and Haryana, 38 in Uttar Pradesh and 40 in Madhya Pradesh [34,35]. A fall in the national average is not convergence; convergence requires dispersion between states to decline.

Table 3 compares endpoints for the states and the national figure for which both years were verified against the official series. It is purely illustrative: endpoint comparisons cannot establish the statistical properties of a convergence path and no test is implied. Two features stand out. The absolute gap between the highest-mortality states and Kerala roughly halved, but the proportional gap narrowed only slightly (the ratio of Madhya Pradesh to Kerala fell from 6.6 to 5.7). And the highest-mortality states, Madhya Pradesh and Uttar Pradesh, reduced IMR proportionally more slowly than the national average (3.8% and 3.6% a year against 4.5%), while Andhra Pradesh, starting lower, improved fastest. This is not the pattern expected under simple health β-convergence, in line with studies reporting divergence and club formation in infant mortality [11,12].

Table 3. Infant mortality rate, selected states and India, 2004 and 2022

State	IMR 2004	IMR 2022	Absolute change	Average annual change in ln IMR (%)
Andhra Pradesh	59	20	−39	−6.0
Kerala	12	7	−5	−3.0
Madhya Pradesh	79	40	−39	−3.8
Uttar Pradesh	72	38	−34	−3.6
India	58	26	−32	−4.5

IMR, deaths per 1,000 live births. Source: RBI Handbook of Statistics on Indian States 2024-25, Table 4 (SRS-based) [34]. Average annual change = (100/18) × [ln (IMR_2022) - ln (IMR_2004)]. Only states for which both endpoints were verified are shown; the full panel is used in Section 6.

5.3. Income and health together, and the pandemic

Higher-income states generally have lower infant mortality: Kerala, Maharashtra, Tamil Nadu and Karnataka combine relatively high income with relatively low IMR, while several lower-income states retain high mortality. A cross-sectional association is not convergence, however, since convergence concerns how the relationship evolves. Figures 1 and 2 show the state trajectories of log real per-capita income and log IMR, respectively, for the harmonised 27-state sample. Figure 3 plots the corresponding cross-state dispersion measures (σt), while Figure 4 compares the income-IMR relationship in 2004 and 2022. Figure 5 provides the graphical initial-level/subsequent-change diagnostic corresponding to the β-convergence analysis. The pandemic produced a sharp national contraction in 2020-21 followed by recovery in which magnitudes differed across states; movements in IMR over 2020-2022 may reflect disruptions to reporting and service use and are not read as structural change. The three COVID treatments in Section 4.5 address this directly.

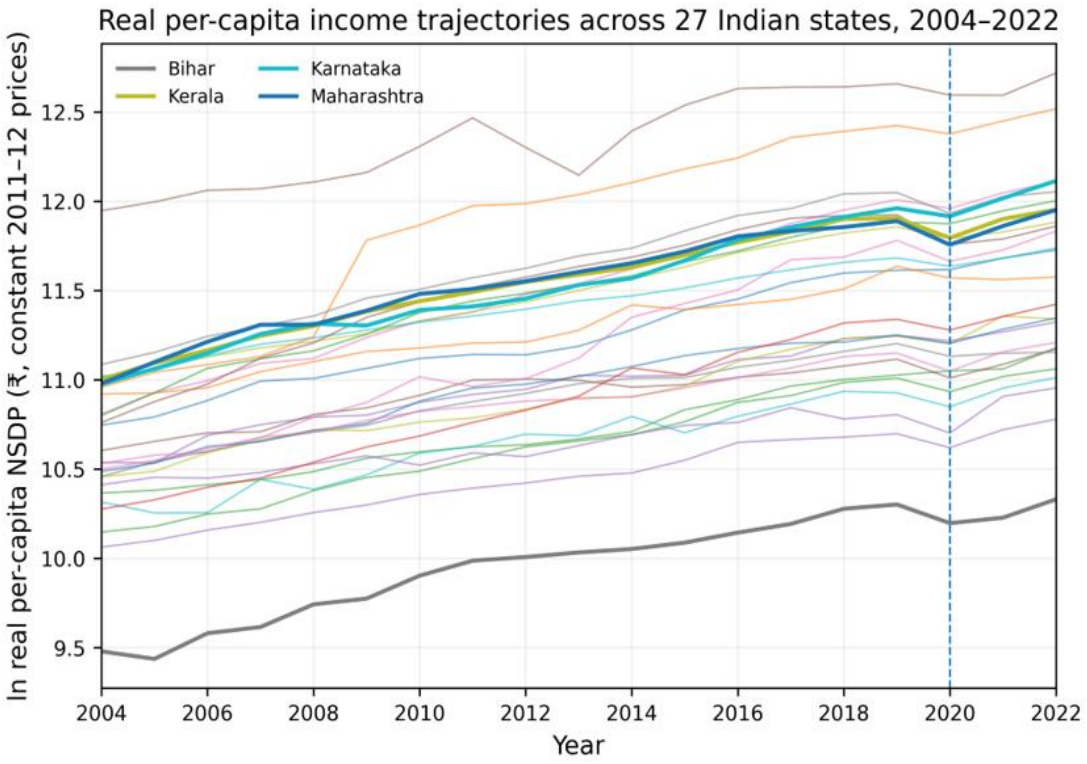

Figure 1. Real per-capita income trajectories across 27 Indian states, 2004-2022. The plotted series are natural logarithms of real per-capita NSDP at constant 2011-12 prices. Pre-2011-12 observations are chain-linked to the 2011-12-base series at the overlap year using the growth rates of the earlier 2004-05-base series. The dashed vertical line marks 2020.

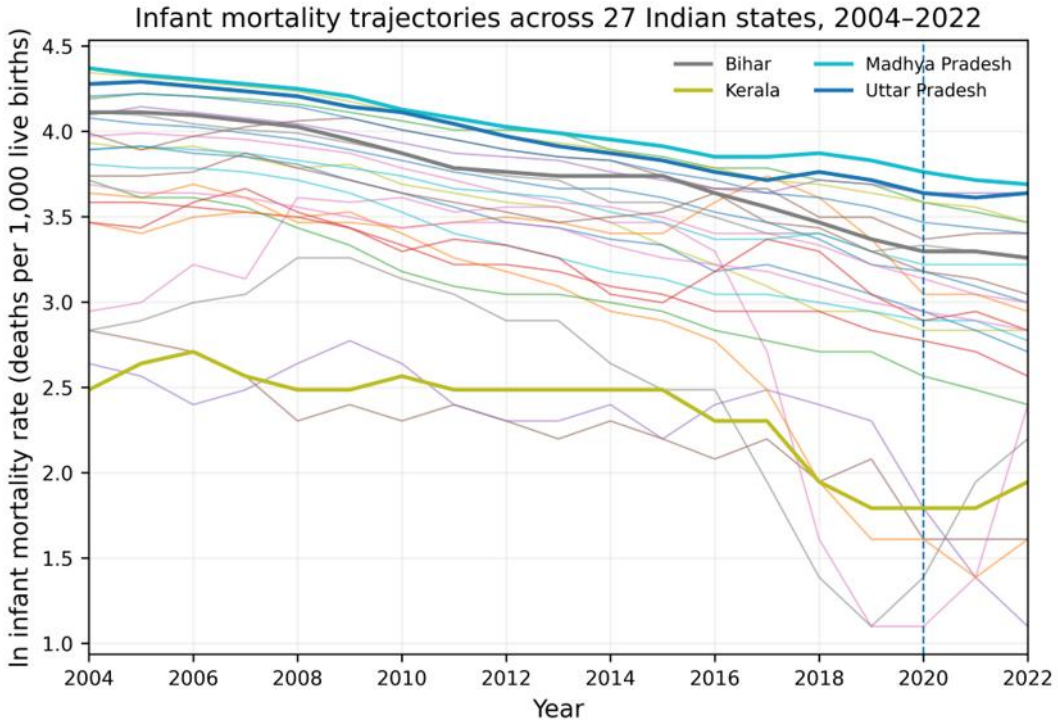

Figure 2. Infant mortality trajectories across 27 Indian states, 2004-2022. The plotted series are natural logarithms of the state-level IMR (deaths per 1,000 live births). The dashed vertical line marks 2020.

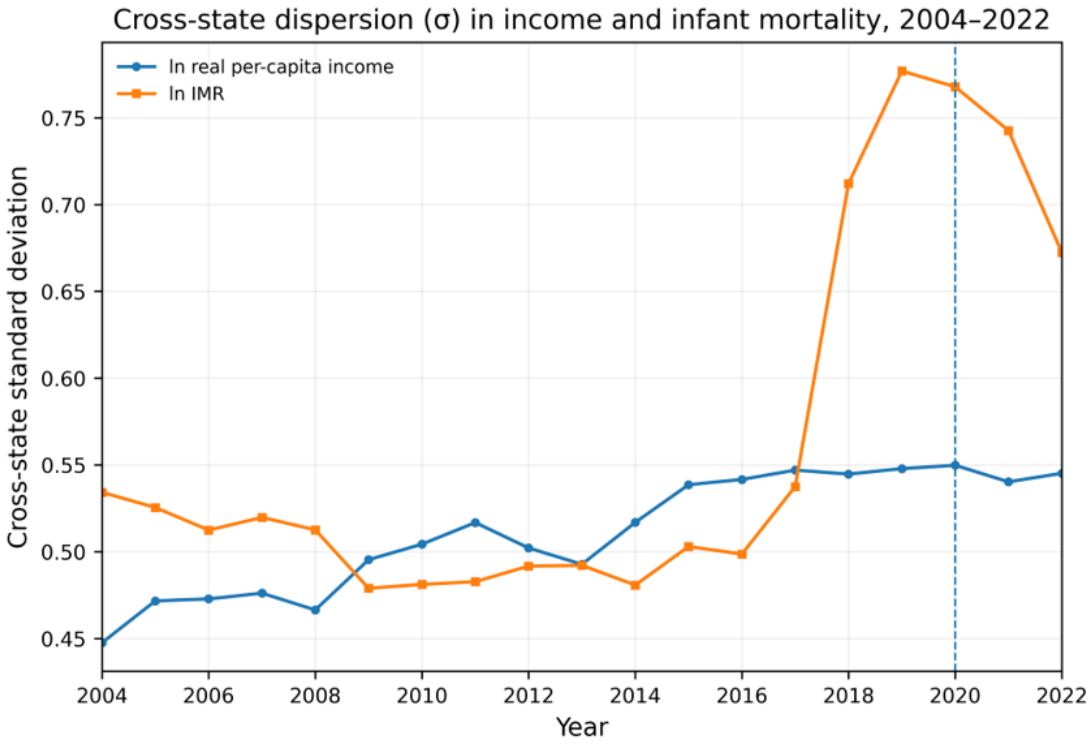

Figure 3. Cross-state dispersion (σ) in income and infant mortality, 2004-2022. σt is the cross-sectional standard deviation of the natural logarithm of the respective outcome. Increasing dispersion is inconsistent with system-wide σ-convergence.

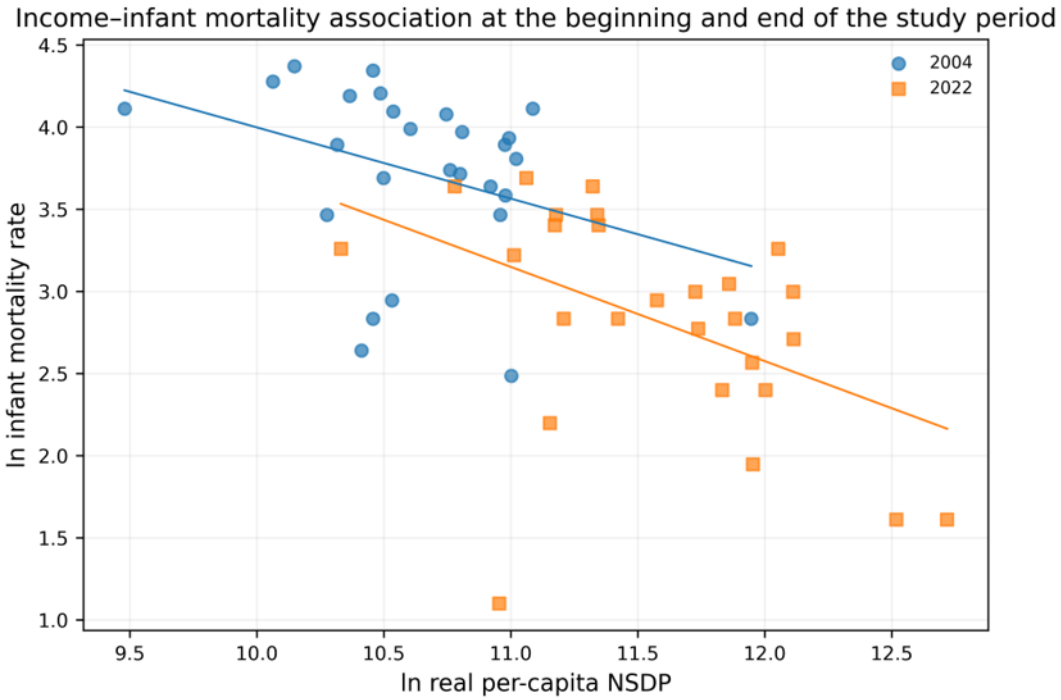

Figure 4. Income-infant mortality association at the beginning and end of the study period. Points show the 27-state cross-section in 2004 and 2022; fitted lines are descriptive cross-sectional regressions. The figure is descriptive and does not itself establish convergence.

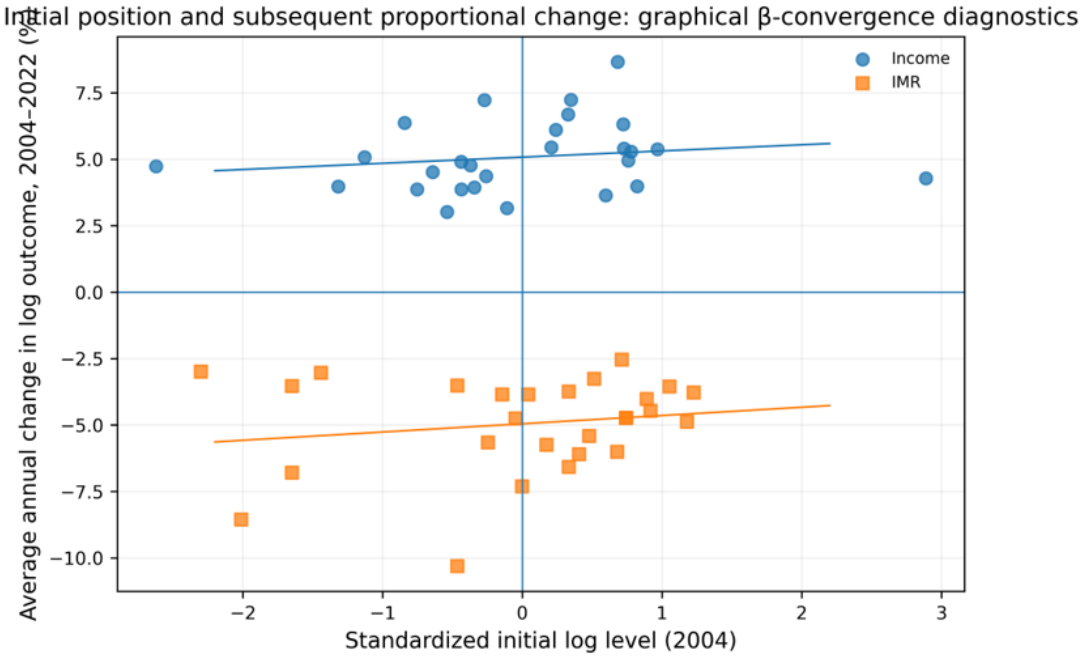

Figure 5. Initial position and subsequent proportional change: graphical β-convergence diagnostics. The horizontal axis standardises the initial log level (2004); the vertical axis reports the average annual change in the log outcome over 2004-2022. Separate point symbols identify income and IMR. This figure is a graphical diagnostic; the formal β-convergence estimates are reported in Table 5.

6. RESULTS

The empirical analysis proceeds from distributional convergence to heterogeneous dynamic adjustment. This sequence is important because convergence in one statistical sense does not necessarily imply convergence in another. σ-convergence asks whether the cross-state dispersion of an outcome declines over time, whereas β-convergence tests whether initially disadvantaged states subsequently improve faster than initially advantaged states. The heterogeneous-panel models then allow the speed and direction of adjustment to differ across states and to respond to common national shocks. All estimates are based on the harmonised 27-state sample with comparable income and infant mortality rate (IMR) observations over 2004-2022. Income observations before 2011-12 are chain-linked to the 2011-12-base series at the overlap year. The conditional specification uses baseline higher-education gross enrolment ratio (GER) because a consistently comparable state-level gross-capital-formation series could not be verified for the full sample without introducing measurement breaks.

6.1. σ-convergence

Table 4 reports the cross-state standard deviation of log real per-capita income and log IMR at the beginning and end of the study period, together with the estimated time trend in dispersion.

Table 4. σ-convergence: dispersion of log real per-capita income and log IMR across states

Variable	σ, 2004	σ, 2022	Trend δ (SE)	p-value	N states
ln real per-capita income	0.449	0.545	0.0055 (0.0005)	<0.001	27
ln IMR	0.534	0.672	0.0134 (0.0040)	0.001	27

Note: δ is the coefficient on a linear time trend in the regression of σt on a constant and time; Newey-West standard errors are reported in parentheses.

The results provide no evidence of σ-convergence in either dimension. Income dispersion increased from 0.449 in 2004 to 0.545 in 2022, while the dispersion of log IMR increased from 0.534 to 0.672. The estimated time trends are positive and statistically significant for both outcomes. Hence, the null hypothesis of stable or declining interstate dispersion is rejected in favour of increasing dispersion.

The implication is substantive as well as statistical. Aggregate improvement in income and health does not imply that the relative positions of Indian states have become more similar. The increase in income dispersion indicates persistent differentiation in state-level productive capacity, while the increase in IMR dispersion indicates that improvements in infant survival have also occurred at unequal rates. The results therefore reject H2 and H4 as defined in the study design. They also caution against interpreting national improvements in average income or mortality as evidence of interstate convergence.

The increase in dispersion should not, however, be interpreted as evidence that every state moved away from every other state. σ-convergence is a system-wide distributional measure and can conceal convergence among subsets of states. This distinction motivates the subsequent β-convergence and heterogeneous-panel analysis.

6.2. β-convergence

Table 5 examines whether states that started from lower income or higher infant mortality subsequently experienced systematically faster proportional improvement. The β coefficient is expected to be negative under convergence.

Table 5. β-convergence regressions

Specification	Income, absolute	Income, conditional	IMR, absolute	IMR, conditional
β (SE)	0.0050 (0.0050)	0.0002 (0.0055)	0.0058 (0.0080)	0.0005 (0.0060)
Implied speed	Not defined	Not defined	Not defined	Not defined
Control	None	Baseline higher-education GER	None	Baseline higher-education GER
State/time effects	No	No	No	No
N states / observations	27 / 27	27 / 27	27 / 27	27 / 27

Note: The dependent variable is annualised growth in real per-capita income or annualised change in ln IMR. A negative β is required for conventional β-convergence.

The β estimates reinforce the σ-convergence results. For income, the unconditional coefficient is positive, 0.0050 (SE = 0.0050), and statistically insignificant. For IMR, the corresponding coefficient is also positive and insignificant, 0.0058 (SE = 0.0080). Thus, states with initially lower income did not systematically grow faster, and states with initially higher IMR did not systematically experience faster proportional reductions in mortality.

The conditional specifications do not alter this conclusion. After controlling for baseline higher-education GER, the income coefficient is essentially zero, 0.0002 (SE = 0.0055), while the IMR coefficient remains close to zero at 0.0005 (SE = 0.0060). Neither estimate is statistically distinguishable from zero.

Taken together, Tables 4 and 5 provide consistent evidence against unconditional system-wide convergence. The absence of β-convergence is particularly important because it indicates that the observed increase in dispersion is not merely a temporary feature of the endpoints: there is no statistically detectable tendency for initially disadvantaged states to close the gap at a systematically faster rate.

The result also argues against a simple interpretation based on "catch-up growth". Interstate development appears to depend on structural conditions that differ substantially across states, including productive capacity, human capital, infrastructure, institutional effectiveness and health-system capability. The heterogeneous-panel results therefore provide the appropriate next step rather than imposing a common convergence coefficient on the entire sample.

6.3 Cross-sectional dependence, slope heterogeneity and stationarity

The conventional convergence regressions implicitly treat states as sufficiently comparable observations. This assumption is examined directly in Table 6.

Table 6. Cross-sectional dependence, slope heterogeneity and panel unit-root diagnostics

Test	ln income	ln IMR	Income adjustment	IMR adjustment
Pesaran CD (p-value)	79.39 (<0.001)	71.89 (<0.001)	—	—
State-slope Wald test (p-value)	—	—	3.15 (<0.001)	1.43 (0.081)
CIPS, intercept	−2.227	−1.304	—	—
CIPS, intercept + trend	−2.535	−2.238	—	—

Note: The CD test has the null of cross-sectional independence. The state-slope Wald test evaluates equality of adjustment slopes. CIPS is the cross-sectionally augmented IPS unit-root statistic. The CIPS results are interpreted cautiously because the panel has only 27 states and 19 annual observations.

The Pesaran CD statistics are exceptionally large for both income and IMR, with $p < 0.001$. Cross-sectional independence is therefore decisively rejected. State outcomes cannot be regarded as isolated processes: national macroeconomic conditions, policy regimes, fiscal arrangements, technological diffusion, demographic change and common shocks can affect several states simultaneously.

Note: The Pesaran CD statistic is applied to the level series ln income and ln IMR in the baseline diagnostic reported in Table 6; its null is cross-sectional independence. The state-slope Wald test evaluates equality of adjustment slopes. CIPS is the cross-sectionally augmented IPS unit-root statistic. The CIPS results are interpreted cautiously because the panel has only 27 states and 19 annual observations.

The Pesaran CD statistics are exceptionally large for the level series of both income and IMR, with $p < 0.001$. Cross-sectional independence is therefore decisively rejected. These level-series diagnostics indicate that the state outcomes are exposed to common national and macroeconomic forces; they do not constitute a residual-based test of the convergence regressions. The result nevertheless provides an important empirical justification for using estimators that explicitly accommodate unobserved common factors in the subsequent dynamic analysis.

This distinction is important. The heterogeneous dynamic models that follow are interpreted as adjustment models, not as estimates of a common long-run cointegrating relationship. This avoids attributing a stronger long-run interpretation to the data than the diagnostics support.

6.4. Heterogeneous-Panel Estimates

The evidence in Table 6 establishes two features that are central to model selection: substantial cross-sectional dependence and heterogeneous adjustment, particularly for income. A homogeneous pooled coefficient can therefore provide a useful benchmark but cannot be regarded as a structural parameter common to all states.

Table 7 consequently reports four complementary estimators: pooled fixed effects (FE), mean group (MG), common-correlated-effects mean group (CCEMG) and augmented mean group (AMG). The MG estimator allows state-specific slopes; CCEMG additionally incorporates cross-sectional averages to account for unobserved common factors; and AMG provides an alternative treatment of common dynamic processes. This estimator hierarchy follows the methodological framework specified for the study.

Table 7. Heterogeneous-panel estimates of adjustment in income and IMR

Specification	Pooled FE	MG	CCEMG	AMG
Income: mean φ (SE)	−0.154 (0.028)	−0.055 (0.006)	−0.502 (0.051)	−0.005 (0.006)
IMR: mean φ (SE)	−0.148 (0.032)	0.008 (0.012)	−0.231 (0.041)	−0.013 (0.017)
States with φi < 0, significant (n)	—	4	14	2
Dispersion of φi (SD)	—	0.033	0.265	0.033

Income-IMR link, ψ (SE)	0.006 (0.127)	0.067 (0.098)	−0.103 (0.138)	—

Notes: φ is the annual dynamic adjustment coefficient; φ < 0 denotes adjustment towards a state-specific path. Standard errors are in parentheses. MG = mean group; CCEMG = common-correlated-effects mean group; AMG = augmented mean group. State counts refer to statistically significant negative state-specific coefficients. Because T = 19 is short, CCEMG and AMG estimates are interpreted as complementary evidence rather than definitive long-run parameters.

The income estimates demonstrate why the heterogeneous specification is necessary. The pooled FE coefficient is negative and statistically significant, −0.154 (SE = 0.028). However, allowing slopes to differ reduces the MG mean coefficient to −0.055 (SE = 0.006). The difference indicates that the pooled coefficient masks considerable variation in the speed of adjustment.

The CCEMG coefficient is substantially more negative, −0.502 (SE = 0.051). This result is consistent with the strong cross-sectional dependence identified in Table 6: once common factors are explicitly accommodated, the estimated average adjustment process changes markedly. However, the magnitude should not be translated mechanically into a precise convergence half-life because the sample has only 19 annual observations and the CCE specification is sensitive to the treatment of common factors.

The AMG estimate is instead close to zero, −0.005 (SE = 0.006), and statistically insignificant. The contrast between CCEMG and AMG demonstrates that the estimated average adjustment is sensitive to the treatment of common dynamic processes. Accordingly, the most defensible conclusion is not that all Indian states converge in income at a common rate, but that income adjustment is heterogeneous and specification-dependent in the presence of strong common shocks.

The CCEMG coefficient is substantially more negative, −0.502 (SE = 0.051). Given the exceptionally strong level-series cross-sectional dependence in Table 6, CCEMG has the stronger diagnostic justification among the heterogeneous estimators because it explicitly absorbs unobserved common factors through cross-sectional averages. The magnitude should nevertheless not be translated mechanically into a precise convergence half-life because the sample has only 19 annual observations and CCE estimates can be sensitive to the treatment of common factors.

The AMG estimate is instead close to zero, −0.005 (SE = 0.006), and statistically insignificant. The near-zero AMG coefficient should be interpreted as evidence that little average adjustment is identified after modelling a common dynamic process, not as proof that every state follows a zero-adjustment path. With only 19 annual observations, the common dynamic component is estimated from a short time series and may absorb much of the variation that would otherwise identify adjustment. Accordingly, the most defensible conclusion is that income adjustment is heterogeneous and specification-sensitive: CCEMG provides the more credible baseline in light of the dependence diagnostic, while AMG supplies a conservative robustness perspective.

The CCEMG estimate is negative and significant, −0.231 (SE = 0.041), whereas the AMG coefficient is small and insignificant, −0.013 (SE = 0.017). The divergence across estimators means that the data do not establish a common health-adjustment process across Indian states. Instead, health trajectories appear to depend strongly on both state-specific characteristics and the treatment of common national influences.

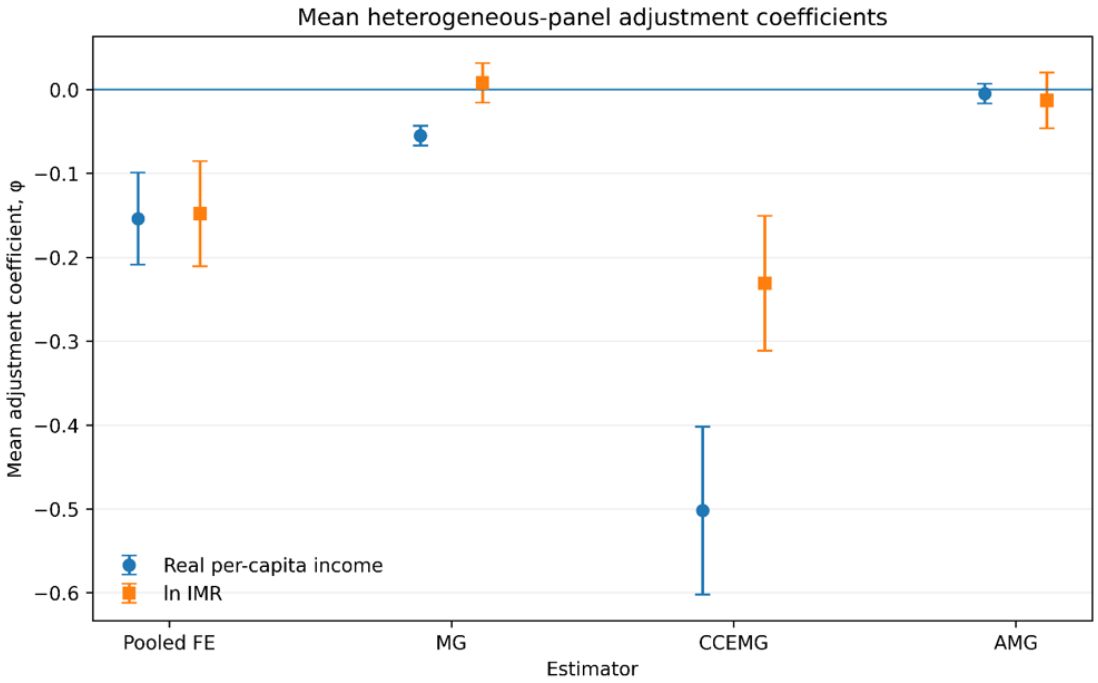

Figure 6. Heterogeneous-panel adjustment coefficients

Figure 6 plots the estimated mean φ coefficients and 95% confidence intervals for the four estimators. The zero line provides the reference point for adjustment versus persistence. The figure makes visually clear that the estimated convergence process is not estimator-invariant: income adjustment ranges from a relatively large negative CCEMG coefficient to a statistically negligible AMG coefficient, while IMR adjustment is negative under pooled FE and CCEMG but not under MG or AMG.

Figure 6. Mean heterogeneous-panel adjustment coefficients for real per-capita income and IMR. Points represent mean φ estimates and vertical bars denote 95% confidence intervals. Coefficients below zero indicate adjustment towards a state-specific path.

Finally, the estimated income-IMR link ψ is statistically insignificant in the reported specifications. It is close to zero under pooled FE, 0.006 (SE = 0.127), and MG, 0.067 (SE = 0.098), while becoming negative under CCEMG, −0.103 (SE = 0.138), but remaining statistically insignificant. Thus, the evidence does not establish a stable contemporaneous adjustment relationship between economic and health convergence.

This distinction is central to the paper. Economic convergence and health convergence should not be treated as two manifestations of a single homogeneous process. A state may improve economically without achieving proportionate health gains, while health outcomes may improve through mechanisms that are only partially dependent on income growth. The heterogeneous-panel estimates therefore support the broader interpretation of interstate development as a multidimensional and state-specific transition process.

Overall, Table 7 modifies the conclusions from the conventional convergence tests rather than contradicting them. The pooled models suggest adjustment, but heterogeneous estimators show that adjustment differs substantially across states and depends on the treatment of common factors. Consequently, the evidence supports conditional and heterogeneous adjustment in selected states rather than unconditional system-wide convergence.

7. ROBUSTNESS AND DIFFERENTIATED TRAJECTORIES

Robustness is evaluated by asking whether the central conclusion—absence of uniform interstate convergence—survives alternative dimensions of the empirical analysis. The objective is not to obtain identical coefficients across estimators, which would be inappropriate because the estimators address different forms of heterogeneity and common dependence. Instead, the relevant criterion is whether the substantive conclusion changes when the empirical framework is altered.

Four dimensions are particularly important: (i) σ-convergence versus β-convergence; (ii) unconditional versus conditional specifications; (iii) treatment of heterogeneous slopes and common factors; and (iv) alternative treatment of pandemic-era observations.

Table 8. Robustness of the income-health convergence evidence

Robustness dimension	Evidence	Income	Health	Assessment
σ-convergence	2004-2022 dispersion	σ: 0.449 → 0.545; δ = 0.0055, p < 0.001	σ: 0.534 → 0.672; δ = 0.0134, p = 0.001	No system-wide σ-convergence
β-convergence	Initial level and subsequent change	β = 0.0050 (0.0050), insignificant	β = 0.0058 (0.0080), insignificant	No unconditional β-convergence
Conditional β-convergence	Baseline higher-education GER	β = 0.0002 (0.0055), insignificant	β ≈ 0.0005 (0.0060), insignificant	Conditional convergence not established
Heterogeneous slopes	MG	φ = −0.055 (0.006); 4 significant negative states	φ = 0.008 (0.012)	Adjustment is heterogeneous
Common-factor adjustment	CCEMG	φ = −0.502 (0.051); 14 significant negative states	φ = −0.231 (0.041)	Stronger adjustment after common factors are controlled
Alternative common-factor treatment	AMG	φ = −0.005 (0.006)	φ = −0.013 (0.017)	Weak average adjustment
Cross-sectional dependence	Pesaran CD	79.39, p < 0.001	71.89, p < 0.001	Strong common dependence
Slope diagnostic	State-slope Wald	3.15, p < 0.001	1.43, p = 0.081	Strong income heterogeneity; weaker health heterogeneity
Persistence diagnostic	CIPS	−2.227 / −2.535	−1.304 / −2.238	Does not support imposing a common long-run relationship
Pandemic sensitivity	Full versus pre-COVID framework	Interpretation should not depend on 2020-22 alone	2020-22 may contain reporting/service disruptions	Pandemic period requires cautious interpretation
Overall	Joint evidence	No universal convergence; heterogeneous adjustment	No uniform interstate health convergence	Main conclusion supported

Four dimensions are particularly important: (i) σ-convergence versus β-convergence; (ii) unconditional versus conditional specifications; (iii) treatment of heterogeneous slopes and common factors; and (iv) alternative treatment of pandemic-era observations.

The robustness evidence is broadly consistent with the baseline results. The σ-convergence and β-convergence analyses independently reject a simple system-wide catch-up process. The conditional specifications do not materially alter that conclusion. The heterogeneous estimators then demonstrate why a pooled result can be misleading: allowing state-specific adjustment and common factors produces materially different coefficients.

The MG results indicate that significant negative adjustment is concentrated in a minority of states. CCEMG produces stronger average adjustment, but with substantial dispersion across state coefficients. AMG produces only weak average adjustment. The disagreement is informative rather than merely inconvenient: it demonstrates that estimated convergence depends on how common national shocks and heterogeneous responses are modelled.

The very large CD statistics provide a substantive explanation for this sensitivity. Indian states operate within a common macroeconomic, institutional and policy environment, so national shocks can move multiple states simultaneously. A conventional pooled estimator that does not adequately account for these common influences may therefore attribute common-factor movements to state-specific convergence.

The robustness evidence should consequently be interpreted as supporting a heterogeneous-adjustment framework, rather than a single convergence coefficient. The central result survives changes in the statistical lens: interstate income and health disparities do not display evidence of uniform unconditional convergence, although some states exhibit statistically significant adjustment towards their own transition paths.

The income-health dimension further reinforces this interpretation. The descriptive evidence indicates that relatively high-income states tend to combine lower infant mortality with stronger economic performance, while several lower-income states retain comparatively high mortality. At the same time, the heterogeneous-panel results imply that improvement in one dimension need not be accompanied by proportionate adjustment in the other. Income and health therefore constitute related but empirically distinct transition processes.

This distinction is important for interpreting interstate development. A state can experience income improvement without rapid health convergence, or substantial health improvement without comparable income catch-up. Consequently, convergence policy cannot be evaluated using income alone. The appropriate unit of interpretation is the state's broader development trajectory, incorporating productive capacity, human capital, health-system capability and exposure to common national shocks.

7.1 Overall interpretation of the robustness evidence

Three conclusions emerge from Sections 6 and 7.

First, there is no statistically supported system-wide σ- or β-convergence in either real per-capita income or IMR over 2004-2022. Both dimensions exhibit increasing cross-state dispersion, and initially disadvantaged states do not systematically catch up faster.

Second, the dynamic-panel evidence demonstrates substantial heterogeneity in adjustment. Pooled estimates can indicate convergence, but this conclusion is not robust to allowing state-specific slopes and alternative treatments of common factors. The appropriate interpretation is therefore conditional adjustment along heterogeneous state-specific paths rather than universal convergence.

Third, the income and health processes are not empirically interchangeable. The estimated income-IMR link is statistically weak, and the heterogeneous-panel results differ across the two outcomes. Improvements in economic performance therefore cannot be assumed automatically to generate proportional interstate convergence in infant mortality.

Taken together, the findings support a view of Indian interstate development as a process of differentiated convergence and persistent structural stratification. Some states exhibit adjustment towards their own transition paths, while others remain on persistent or slower-moving trajectories. The policy

implication is that convergence strategies should be differentiated according to state-specific constraints rather than designed around the assumption of a single national catch-up mechanism.

8. ISCUSSION AND POLICY IMPLICATIONS

Improvement in national averages does not imply narrower interstate disparities. Convergence is relative: it occurs when initially disadvantaged states improve fast enough to close part of the gap. The literature and the descriptive evidence above point to heterogeneous, multidimensional development in which convergence may occur within groups rather than across the whole state system [10-12,45]. The implications below are conditional on the estimates in Section 6 and should be read with them.

Why states may differ. States with stronger education, more diversified production, better infrastructure and more effective administration are better placed to absorb investment and technology. World Bank analysis finds that higher-income convergence groups tend to have higher manufacturing employment, more years of schooling, a smaller agricultural share of value added and higher public capital expenditure [44-46]. Human capital works through several channels at once: education raises productivity and technology adoption, and health raises survival, cognitive development and labour participation, so underinvestment in either weakens the whole process.

Health policy. The objective should move from improving national averages to reducing interstate inequality in essential outcomes. For states with high infant mortality, the priorities are maternal and neonatal care, immunisation, nutrition, primary healthcare, safe water and sanitation and timely referral. Spending alone may not raise outcomes where delivery systems are weak, so quality, accessibility and accountability of district-level services matter alongside finance. Where clubs exist, common outcome standards can be paired with state-specific strategies: low-mortality states can turn to non-communicable disease and ageing, while high-mortality states concentrate on basic maternal, neonatal and child health.

Income, productivity and structure. Persistent divergence suggests that fiscal transfers, although necessary for equalisation, cannot alone produce durable convergence [10,47-48]. Three areas reinforce one another: infrastructure for transport, power, logistics and digital connectivity; movement from low- to higher-productivity activity; and a business environment in which firms invest and integrate into value chains. The goal is productive convergence, not equal expenditure.

Convergence by capability. The framework implied is differentiated. High-income, high-capability states focus on productivity upgrading, advanced skills and emerging epidemiological challenges. Middle-income transition states accelerate industrial diversification, infrastructure and skills. Lower-income catch-up states prioritise foundational health, nutrition, schooling quality and institutional capacity. States with persistent health deficits require targeted health-system investment even where income performance improves, because growth is not a substitute for direct health investment. Transfers should protect minimum service standards while rewarding implementation and expenditure efficiency, and national planning should monitor convergence, including transitions between groups, across income, health, education, productivity and service delivery.

9. LIMITATIONS

Four limitations apply. First, comparability: annual state series are affected by changes in base year, national-accounts revisions, boundary changes and uneven availability of health indicators, and the earlier-base income series is at factor cost. Second, convergence analysis describes relative movement and does not identify causal effects between income and health. Third, heterogeneous-panel estimators improve the treatment of dependence and slope differences but cannot remove omitted variables, reverse causality or measurement error, and the short time dimension limits the precision of state-specific coefficients. Fourth, failing to find unconditional convergence is not evidence that convergence is impossible, only that it is conditional on structural, human-capital, fiscal and institutional characteristics.

10. CONCLUSION

This study examines income and health convergence across Indian states over 2004-2022 within a heterogeneous-panel framework that treats cross-sectional dependence and slope heterogeneity as substantive features of state data rather than technical nuisances. Descriptive evidence shows large,

persistent gaps in both dimensions despite substantial national improvement, and that the highest-mortality states reduced infant mortality proportionally more slowly than the national average. The econometric evidence confirms that dispersion widened rather than narrowed in both dimensions, while heterogeneous-panel estimates show that adjustment is state-specific and highly sensitive to common national factors. Only a minority of states exhibit statistically significant mean reversion once heterogeneity is allowed.

The contribution is threefold: an integrated treatment of income and health convergence; a heterogeneous-panel design that distinguishes genuine homogeneous convergence, conditional convergence, heterogeneous convergence, and apparent convergence generated by common national shocks; and a policy framing that shifts attention from average improvement to convergence in capabilities. Future work should add productivity, employment quality, health expenditure, learning outcomes and infrastructure to identify mechanisms; apply spatial and network methods to examine spillovers; combine club analysis with causal identification; and link household and administrative data to ask whether interstate convergence is accompanied by convergence in within-state inequality.

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Ethics: The study uses published, aggregate state-level statistics and involves no human participants; ethical approval was not required.

Data Availability: All series are from public official sources listed in Table 2. The harmonised dataset and the replication code (convergence_analysis.py) are available from the corresponding author.

Use of AI tools: During the preparation of this manuscript, generative artificial intelligence was used solely for assistance with language improvement, grammar, readability and the organization of the manuscript. All scientific concepts, literature selection, data collection, methodology, analysis, interpretation and conclusions were developed and verified by the author. The author accepts full responsibility for the accuracy and integrity of the manuscript.

Ethics Approval: Not applicable; the study uses published aggregate official statistics.

Author Contributions: Single author: conception, data, analysis and writing.

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