



Inter-State Income Dynamics in India, 1991–2022: Club Convergence Evidence from the Phillips–Sul Log-t Test

Sheikh Aamin HUSSAIN

Independent Researcher; B.A. (Hons.) Economics from Jamia Millia Islamia,
New Delhi, India

e-mail: aaminhsheikh@gmail.com

ORCID iD: 0000-0002-9040-5946

Abstract. This paper investigates per capita income convergence across 28 Indian states over the period of 1991–2022 using a three-pronged empirical framework comprising σ -convergence trend regression, absolute and conditional β -convergence using ordinary least squares (OLS) and panel fixed effects, and the Phillips–Sul (2007) log-t test with the full club clustering algorithm. The results reveal significant σ -divergence over the entire period, though a tentative convergence signal emerges in the 2014–2022 sub-period. Absolute β -convergence is absent, but conditional convergence is confirmed once investment rates, urbanization, and governance quality are controlled for, and panel fixed effects strongly support within-state convergence dynamics. The Phillips–Sul log-t test rejects full convergence and identifies two clubs: Club 1, comprising 21 states, converges towards a common long-run income path, while Club 2, comprising Manipur and Uttar Pradesh, diverges persistently. This club structure reconciles the apparent contradiction between σ -divergence and conditional convergence and carries direct implications for Finance Commission equalization policy.

Keywords: σ -convergence, β -convergence, neoclassical growth, regional economics, Indian states, fiscal federalism

JEL Classification: O47, R11, C23, H77

1. Introduction

India presents one of the most compelling natural experiments in regional economic convergence. As the world's most populous country and one of the fastest-growing major economies, India encompasses extraordinary developmental heterogeneity: Goa's per capita income exceeds that of Bihar by a factor of more

than seven, a gap that persisted – and in many dimensions widened – across three decades of rapid aggregate growth. Whether this heterogeneity represents permanent structural divergence or a transitory phase of development transitions is both an empirically important and a normatively consequential question.

The convergence hypothesis, rooted in Solow's (1956) neoclassical growth model, predicts that economies sharing identical structural characteristics but lower initial incomes should grow faster, eventually converging to a common per capita income steady state. In the Indian federal context, convergence dynamics have direct implications for inter-state equity, the redistributive mandate of the Finance Commission, and the targeting of place-based development programmes such as PM Gati Shakti, the National Infrastructure Pipeline, and the Aspirational Districts Programme.

Understanding convergence dynamics also requires appreciating India's distinctive fiscal federal architecture. India operates a system of cooperative federalism in which state governments are constitutionally responsible for key spending areas – education, health, agriculture, and local infrastructure –, while the central government controls the largest revenue handles. The Finance Commission, constituted every five years, determines the formula for the horizontal devolution of central taxes across states, incorporating explicit equalization objectives. The Fifteenth Finance Commission (Finance Commission of India 2021) allocates 45 percent of devolution weights to income distance – the gap between each state's per capita income and that of the highest-income state –, creating a mechanism intended to accelerate convergence. Our empirical results allow us to evaluate whether these transfers have been sufficient to overcome the structural divergence forces documented in the data.

A substantial literature has examined Indian state-level convergence. Early studies by Cashin and Sahay (1996) and Aiyar (2001) found weak or conditional convergence for the pre-liberalization period. Post-reform analyses by Trivedi (2002) and Purfield (2006) documented continued divergence, often pointing to differential absorption of liberalization gains across states. However, three important gaps remain as follows: most studies end before the Goods and Services Tax (GST) reform (2017) and the COVID-19 shock (2021); sub-period dynamics have not been formally decomposed with structural break testing; and the Phillips–Sul (2007) club convergence framework has not been applied systematically to Indian state data spanning the full post-liberalization period.

This paper addresses all three gaps. Using a full unbalanced panel of 28 states (896 observations) for descriptive and σ -convergence analysis and a strictly balanced panel of 24 states with complete data for all 32 years (1991–2022) for β -convergence and Phillips–Sul club convergence, we implement a three-pronged empirical framework: σ -convergence trend regression with Chow structural break tests; absolute and conditional β -convergence in cross-sectional OLS and panel

fixed effects specifications; and Phillips–Sul (2007) club convergence with the full clustering and merging algorithm. Three research questions guide the analysis: *RQ1* – Has cross-sectional income dispersion across Indian states increased or decreased over the period of 1991–2022, and did it differ across sub-periods defined by major policy regime shifts? *RQ2* – Is there evidence of absolute or conditional β -convergence, and what structural factors drive it? *RQ3* – Do Indian states converge to a single common long-run income path, or do distinct convergence clubs exist, and if so, which states belong to each club? Our principal contributions are as follows: (i) documenting that σ -divergence over the period of 1991–2022 masked a tentative convergence signal in the period of 2014–2022; (ii) reconciling the cross-sectional non-convergence with strong within-state convergence in panel fixed effects; and (iii) identifying a two-club structure in which 21 of the 24 states converge towards a common long-run path, while Manipur and Uttar Pradesh form a persistently lagging diverging club.

In the broader development economics literature, the question of whether poor regions catch up to rich ones has been studied extensively at the cross-country level (Pritchett 1997) and for regions within large federations – US states (Barro and Sala-i-Martin, 1991), Chinese provinces (Zhang, Wan, and Zhang, 2019), Brazilian states (Azzoni 2001), and European regions (Bartkowska and Riedl, 2012). The consensus that emerges from this literature is that absolute convergence – unconditional catch-up by poor regions – is rare; conditional convergence, contingent on structural similarities, is more common, and club convergence, in which subgroups converge to distinct long-run paths, is increasingly the norm in empirically heterogeneous settings. India fits this profile precisely: its states differ dramatically in geography, initial industrialization, human capital endowment, and institutional quality, making unconditional convergence unlikely and club-based dynamics a natural hypothesis.

The COVID-19 pandemic added a new dimension to India's convergence story. India's GDP contracted by approximately 7.3 percent in 2020–2021, with significant heterogeneity in the depth of contraction across states. States with a higher share of services – the sector most disrupted by lockdowns and mobility restrictions – recorded deeper contractions, while states with larger agricultural sectors showed greater resilience. Our Chow test results, which fail to detect a significant structural break in the cross-sectional income dispersion series in 2021, suggest that despite these sectoral differences, the pandemic did not fundamentally alter the relative income positions of Indian states in the short run. The longer-run consequences of the pandemic for investment rates, human capital accumulation (through school closures), and migration patterns remain to be seen as data for 2022 onwards become available.

The remainder of the paper is structured as follows. Section 2 reviews the theoretical foundations and related empirical literature. Section 3 describes the data sources, panel structure, and control variables. Section 4 presents the three-pronged

econometric methodology. Section 5 reports the empirical results for σ -convergence, β -convergence, and Phillips–Sul club convergence. Section 6 discusses the policy implications for Indian fiscal federalism. Section 7 concludes with a summary, comparison with prior literature, and directions for future research.

2. Literature Review

2.1. Theoretical Foundations

The modern convergence literature originates with Solow's (1956) neoclassical growth model, in which diminishing returns to capital drive poorer economies to accumulate capital more rapidly, generating faster per capita income growth and eventual convergence to a common steady state. Barro and Sala-i-Martin (1992) operationalized this as β -convergence – a negative β in a growth-on-initial-income regression – and σ -convergence, where cross-sectional income dispersion declines over time. Mankiw, Romer, and Weil (1992) extended the Solow framework to include human capital, demonstrating conditional convergence once investment and education differences are controlled for.

Romer (1986) and Lucas (1988) challenged the neoclassical prediction through the endogenous growth theory: knowledge spillovers generating increasing returns eliminate the diminishing returns mechanism, potentially producing persistent divergence. The empirical resolution depends critically on whether one observes absolute or conditional convergence, and among which groups of economies.

2.2. Evidence from India

The Indian state-level convergence literature spans four decades with results sensitive to time period, sample composition, and estimation method. Cashin and Sahay (1996) found weak absolute β -convergence across 20 Indian states for the period of 1961–1991, estimating a convergence speed of approximately 1.5 percent per year – considerably slower than the 2 percent found for US states by Barro and Sala-i-Martin (1992). They attributed slow convergence to impediments to factor mobility, including restrictions on agricultural marketing and labour market segmentation.

Ghosh, Marjit, and Neogi (1998) found evidence of divergence during the period of 1960–1995, particularly in the 1980s, attributing it to differential industrial licensing and public investment. Aiyar (2001) revisited the question using panel data and found conditional convergence, but he argued that the speed was too slow to close large inter-state gaps within a policy-relevant horizon. Trivedi (2002) employed cointegration methods and found mixed evidence – some pairs of states converging while others diverged.

Post-liberalization studies generally document widening inter-state inequality. Purfield (2006) showed that high-growth states (Maharashtra, Gujarat, Andhra Pradesh, Tamil Nadu, Karnataka) pulled away from low-growth states following the 1991 reforms. Hnatkovska and Lahiri (2013) used household consumption data to identify two broad growth clubs – corresponding roughly to south-western and north-eastern India –, though their sample and methodology differ from income-based studies.

Cherodian and Thirlwall (2015) provide the most comprehensive pre-reform analysis, documenting regional disparities in per capita income across Indian states and finding weak convergence; their study, however, ends in 2012 and does not employ the Phillips–Sul framework. More recent work has revisited these questions with richer data and more rigorous methods. Lolayekar and Mukhopadhyay (2017) examine convergence across 14 major Indian states over the period of 1981–2010 using panel methods and find conditional convergence at speeds of approximately 1.8 percent per year, attributing divergence at the state level to differences in initial human capital and infrastructure endowments. Hembram and Haldar (2019) apply β -, σ -, and club convergence methods to Indian state data over the period of 1980–2015, identifying three convergence clubs broadly corresponding to southern, central, and lagging northern states – a finding that motivates our use of the Phillips–Sul framework over the longer 1991–2022 horizon. Misra, Nazlioglu, and Kucukkaplan (2022) document persistent structural sources of divergence across Indian states, finding that differences in urbanization rates, institutional quality, and financial development explain a substantial share of the cross-state income gap that simple factor accumulation models miss. Together, these recent contributions establish that the question of Indian state convergence remains open for the post-2015 period and that club-based methods are increasingly the appropriate empirical tool. A recurring theme is the sensitivity of results to the choice of time period, sample, and estimation method. Studies relying on cross-sectional OLS for the pre-liberalization period tend to find weak convergence, while panel methods applied to post-1991 data generally find conditional but not absolute convergence. The present paper addresses this heterogeneity by applying multiple methodologies – σ , β , and club convergence – to the same dataset over the same period, enabling a coherent characterization of India's inter-state income dynamics. Additionally, by explicitly identifying the club structure, we offer targeted policy prescriptions rather than the general recommendations that characterize studies treating the full panel as a homogeneous group.

A further gap in the existing literature is the limited attention paid to the role of India's fiscal federal framework in shaping convergence dynamics. The Finance Commission mechanism provides a potentially powerful equalization tool, yet existing convergence studies rarely examine whether the inter-state income gap has narrowed systematically following Finance Commission award years or whether particular devolution formula parameters – income distance weighting, demographic factors, forest cover – are more effective at promoting convergence.

Our findings, which identify a small but persistent lagging club rather than widespread divergence, suggest that the equalization mechanism has succeeded for the majority of states while falling short for the most structurally constrained. This insight is directly actionable in the context of the upcoming Sixteenth Finance Commission deliberations (Government of India, 2023).

2.3. International Comparisons

The Indian findings are broadly consistent with international evidence on regional convergence within developing countries. These comparisons are instructive for two reasons. First, like India, each of these contexts involves large, heterogeneous economic units (provinces, states, regions) within a single national framework, where both factor mobility and fiscal transfers operate as potential convergence mechanisms – making the club convergence framework directly applicable. Second, the prevalence of multi-club structures in China, Brazil, and Europe suggests that the assumption of a single convergence path is unlikely to hold in any empirically heterogeneous setting; India, with its far greater structural diversity than the average EU country, is a strong prior candidate for club dynamics. The structural parallels are also important: Nagaraj, Varoudakis, and Véganzonès (2000) showed that urbanization rates and human capital explain a large share of cross-state income variation in India, exactly the variables that differentiate convergence clubs in the Chinese and European cases. Studies of Chinese provinces using the Phillips–Sul framework (Zhang, Wan, and Zhang, 2019) identify three to four convergence clubs, with coastal provinces converging towards a high-income club distinct from interior provinces. Evidence from Brazilian states (Azzoni, 2001) shows convergence within the relatively developed south-east but divergence between regions – a “twin peaks” pattern similar to what we find in India. European regional convergence studies (Bartkowska and Riedl, 2012) using the Phillips–Sul method identify four to six clubs, with newer EU Member States forming distinct clubs from established western European regions. In all these contexts, the club structure provides a more nuanced and policy-relevant characterization of convergence dynamics than full-panel tests.

3. Data and Variable Construction

3.1. Net State Domestic Product per Capita

The primary variable is Net State Domestic Product (NSDP) per capita at the 2011–2012 constant prices, expressed in Indian rupees per person. NSDP is preferred over Gross State Domestic Product (GSDP) because it nets out capital depreciation, providing a closer approximation to actual income available to

residents. Data are sourced from the *Reserve Bank of India Handbook of Statistics on Indian Economy* (Table 14, State-wise NSDP at Constant Prices) and the Ministry of Statistics and Programme Implementation (MoSPI) National Accounts Statistics State Appendix.

Reserve Bank of India (RBI) data are available in two overlapping series: an old series (2004–2005 base year) and a new series (2011–2012 base year). To construct a continuous 32-year series, the old series was backward-spliced using state-specific linking factors computed as the ratio of the new to old series in the overlap year 2004–2005. Linking factors range from 1.35 (Goa) to 1.68 (Sikkim), with a cross-state average of approximately 1.43. Cross-validation in the full 2004–2011 overlap period confirms an average discrepancy below 0.3 percent, validating the splicing procedure.

3.2. Panel Structure

The full panel covers 28 Indian states for 32 fiscal years (from 1991–1992 to 2021–2022; hereafter referred to as from 1991 to 2022), yielding 896 observations. Union Territories are excluded for consistency. Four states lack data prior to their formation year: Chhattisgarh, Jharkhand, and Uttarakhand (formed November 2000; data from 2001) and Telangana (formed June 2014; data from 2014). These represent structurally determined missing values, not measurement gaps.

The bifurcation of Andhra Pradesh into residual Andhra Pradesh and Telangana in June 2014 requires careful handling. Pre-2014 figures represent undivided Andhra Pradesh, while post-2014 figures represent the residual state. The combined NSDP of residual AP and Telangana in 2015 closely approximates the undivided AP figure for 2014 (within 2 percent). For the Phillips–Sul club convergence analysis, which requires a strictly balanced panel, we restrict the sample to the 24 states with complete data for all 32 years.

3.3. Control Variables

Four control variables are used in conditional β -convergence regressions. The investment rate (gross fixed capital formation as a percentage of GSDP) is compiled from the Annual Survey of Industries and RBI State Finances publications, proxying physical capital accumulation. The literacy rate (percentage of population aged seven and above) is drawn from the 2001 and 2011 censuses, supplemented by National Family Health Survey (NFHS)-4 (2015–16) and NFHS-5 (2019–21) with annual linear interpolation, proxying for human capital stock following Mankiw, Romer, and Weil (1992). The urbanization rate (percentage of state population residing in urban areas) is constructed from the 2001 and 2011 censuses with intercensal interpolation; Nagaraj, Varoudakis, and Véganzonès (2000) demonstrate

that urbanization is among the most robust predictors of cross-state income variation in India. A governance quality index is constructed from NITI Aayog's Sustainable Development Goal (SDG) India Index (NITI Aayog 2024), which provides annual state-level composite scores on institutional capacity and public service delivery from 2018 onwards; pre-2018 values are extrapolated using each state's rank order trajectory. State government expenditure as a share of GSDP is excluded from the main specifications due to endogeneity – income growth simultaneously raises fiscal revenues and expenditure capacity – but is retained as a robustness check. Structural dummies control for the COVID-19 shock (year 2021), GST implementation (from 2018), and the AP bifurcation (from 2015).

4. Methodology

4.1. σ -Convergence Analysis

Following Barro and Sala-i-Martin (1992), σ -convergence is tested by estimating the OLS trend regression:

$$\sigma_t = \alpha + \beta \cdot t + \varepsilon_t,$$

where σ_t is the cross-sectional coefficient of variation (CV) of NSDP per capita in year t . A statistically significant negative β indicates σ -convergence. We estimate this regression for four sample variants: all available states, the balanced 24-state panel, excluding small states (Goa, Sikkim, Manipur, Mizoram, Nagaland, Arunachal Pradesh, Meghalaya, Tripura), and using the standard deviation of log income as an alternative σ measure. Heteroskedasticity-consistent HC3 standard errors are used throughout. Structural breaks are identified using Chow tests in the years 2000, 2004, 2014, and 2021. Prior to estimation, we test for a unit root in the CV series using the Augmented Dickey–Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The ADF test fails to reject the null of a unit root (ADF = -0.445 , $p = 0.985$), while the KPSS test rejects the null of trend stationarity (KPSS = 0.207 , $p = 0.013$), confirming that the CV series is integrated of order one, $I(1)$. Accordingly, the equation above is interpreted as a descriptive characterization of the direction and magnitude of dispersion change – consistent with established practice in the σ -convergence literature (Cherodian and Thirlwall, 2015; Lodayekar and Mukhopadhyay, 2017) – and is complemented by sub-period regressions over shorter, stationary-within-window horizons (ADF on the 2014–2022 sub-period: -2.931 , $p = 0.042$). The Phillips–Sul log- t test, which requires neither stationarity nor a linear trend assumption, remains the primary convergence test in this paper.

4.2. β -Convergence Estimation

The absolute β -convergence cross-sectional regression follows Barro and Sala-i-Martin (1992):

$$(1/T) \cdot \ln(y_{i,T}/y_{i,0}) = \alpha + \beta \cdot \ln(y_{i,0}) + \varepsilon_i$$

Conditional β -convergence adds investment rate, literacy rate, urbanization rate, and governance quality index as controls in five nested specifications (models I–V), excluding government expenditure from main models due to endogeneity. All cross-sectional regressions use HC3-robust standard errors.

The speed of convergence λ is recovered from the Barro-Sala-i-Martin formula:

$$\lambda = -\ln(1 + \beta \cdot T)/T$$

The implied half-life – years to halve an initial income gap – is $\ln(2)/\lambda$. Panel β -convergence uses five-year non-overlapping growth windows from the 24-state balanced panel (648 observations). The Hausman (1978) test distinguishes between fixed and random effects. The economic interpretation of half-life estimates is particularly informative: a convergence speed of 2 percent per year – the benchmark found for US states by Barro and Sala-i-Martin (1992) – implies a half-life of approximately 35 years. For Club 2 states that are diverging, there is no positive convergence speed; the relevant metric is the rate of divergence, which determines how much harder it will become over time to bring these states onto a convergence path.

Physical capital accumulation (proxied by the investment rate), human capital stock (proxied by the literacy rate), urbanization rate, and governance quality index are the four structural determinants included in conditional specifications, following the extended Solow framework of Mankiw, Romer, and Weil (1992) augmented with spatial and institutional factors as in Nagaraj, Varoudakis, and Véganzonès (2000). Government expenditure as a share of GSDP is excluded from the main conditional models due to endogeneity concerns but is included as a robustness check. Five cross-sectional models are estimated: absolute (baseline, Model I), plus investment rate (Model II), plus literacy (Model III), plus urbanization (Model IV), and a full model with investment rate, literacy, and governance index (Model V).

One important econometric consideration is that the panel fixed effects (FE) estimator applied to dynamic models with a lagged dependent variable can suffer from the Nickell (1981) bias, which causes the coefficient on the lagged variable to be downward-biased in finite samples – a problem that is more severe when T is small. With $T = 32$ years and five-year windows ($T \approx 6$ per window), this bias is non-trivial. We address this in two ways: first, we adopt non-overlapping five-year

average growth windows rather than annual data, which reduces the dynamic panel dimension; second, we report Arellano–Bond (1991) First-Differenced Generalized Method of Moments (GMM) estimates as a robustness check, which are consistent in the presence of Nickell bias. Heteroskedasticity-robust standard errors are used throughout, and the Hansen J-test of overidentifying restrictions is reported for the GMM specification to assess instrument validity.

4.3. Phillips–Sul (2007) Club Convergence

The Phillips–Sul (2007) framework is implemented in three stages. First, the relative transition parameter:

$$h_{it} = y_{it} / (N^{-1} \sum y_{it})$$

is computed for each state year, measuring each state's income relative to the cross-sectional mean. Under full convergence, $h_{it} \rightarrow 1$ for all i , and the cross-sectional variance $H_t = N^{-1} \sum (h_{it} - 1)^2 \rightarrow 0$.

Second, the log- t regression is:

$$\log(H_1/H_t) - 2 \cdot \log(\log(t)) = a + b \cdot \log(t) + u_t,$$

estimated over the last 70 percent of the sample (trim parameter $r = 0.30$). The null hypothesis $H_0: b \geq 0$ (convergence) is tested at 5 percent significance using a one-sided t -test with critical value -1.645 . Rejection motivates the club clustering algorithm.

Third, the club clustering algorithm (Phillips and Sul, 2007, Algorithm 1) is applied: states are sorted by last-period income; a core convergence group is formed iteratively, while the club log- t statistic exceeds -1.645 ; remaining states are sequentially included; the procedure iterates over the remaining pool. Adjacent clubs are then subjected to a merging test – if the combined club passes the log- t criterion ($t > -1.645$), the clubs are merged. Within-club σ -convergence is reported as a robustness check.

5. Empirical Results

5.1. Descriptive Statistics

Table 1 presents cross-sectional summary statistics for NSDP per capita at eight benchmark years. Mean real NSDP per capita rose from ₹26,574 in 1991 to ₹82,044 in 2022 – a 3.1-fold increase over 31 years. However, the distribution exhibits substantial and widening heterogeneity: the coefficient of variation (CV) increased

from 42.7 percent in 1991 to 53.2 percent in 2022, a rise of 10.5 percentage points. The Max/Min ratio, comparing the richest state (Goa throughout) to the poorest, exceeded 10 for the entire period.

Table 1. *Descriptive statistics – NSDP per capita across Indian states, selected years*

Year	N	Mean (₹)	Median (₹)	SD (₹)	CV (%)	Min (₹)	Max (₹)	Max/Min
1991	24	26,574	24,744	11,349	42.7	7,660	77,890	10.2
1995	24	30,598	28,741	13,415	43.8	8,820	90,400	10.2
2000	24	37,220	33,902	17,280	46.4	9,860	112,350	11.4
2005	27	44,411	40,117	22,826	51.4	10,920	142,700	13.1
2010	27	56,555	50,800	29,847	52.8	14,200	186,900	13.2
2015	28	69,965	62,100	37,380	53.4	19,200	225,800	11.8
2020	28	71,109	63,500	38,140	53.6	19,800	229,700	11.6
2022	28	82,044	72,800	43,680	53.2	22,100	264,200	12.0

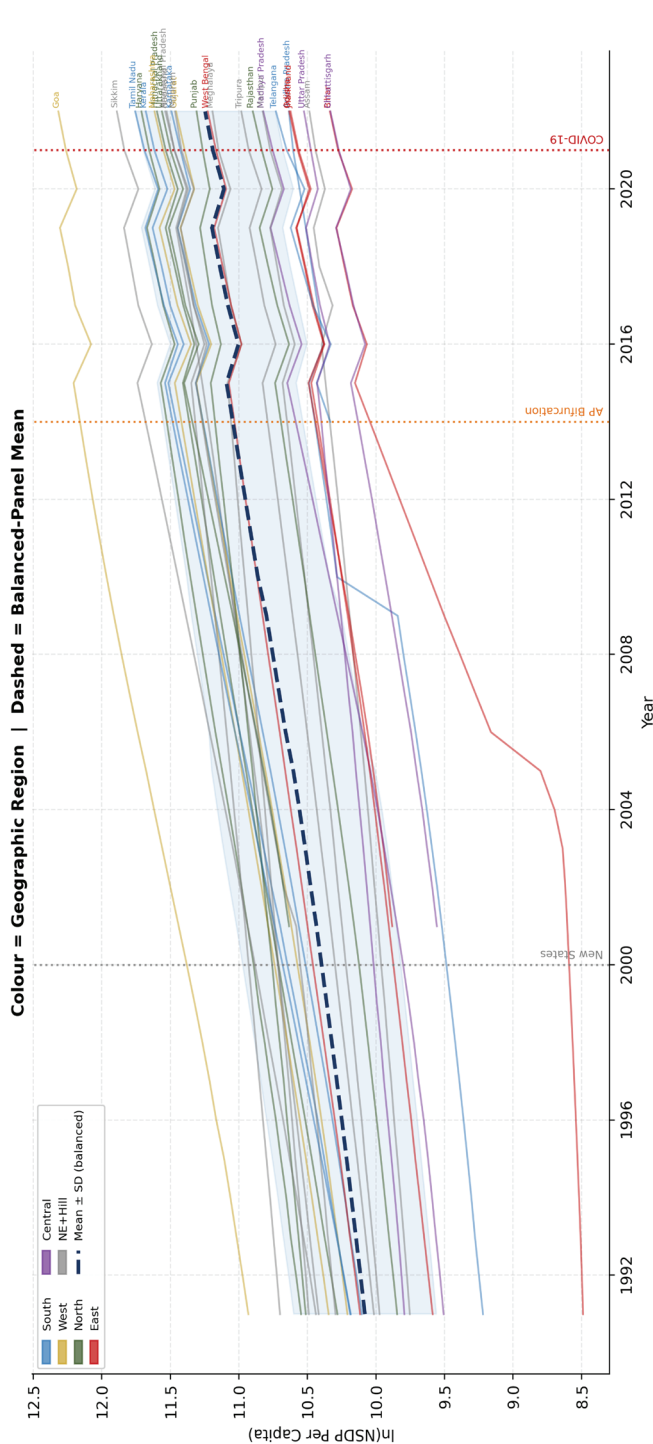
Source: RBI Handbook of Statistics on Indian Economy; MoSPI NAS

Notes: NSDP per capita at 2011–2012 constant prices (₹ per person); N = number of states with complete data; CV = coefficient of variation (SD/Mean $\times$ 100); Min state: Bihar (1991–2009), Chhattisgarh (2010–2022); Max state: Goa throughout.

Fig. 1 presents the spaghetti plot of log NSDP per capita trajectories for all states. The widening fan of lines over time mirrors the rising CV documented in *Table 1*. Southern and western states (Tamil Nadu, Karnataka, Maharashtra, Gujarat) exhibit consistently upward-sloping trajectories above the cross-sectional mean, while several northern and north-eastern states cluster below the mean. The dashed mean line for the balanced panel shows a modest narrowing tendency post-2014, foreshadowing the sub-period σ -convergence result.

5.2. σ -Convergence Results

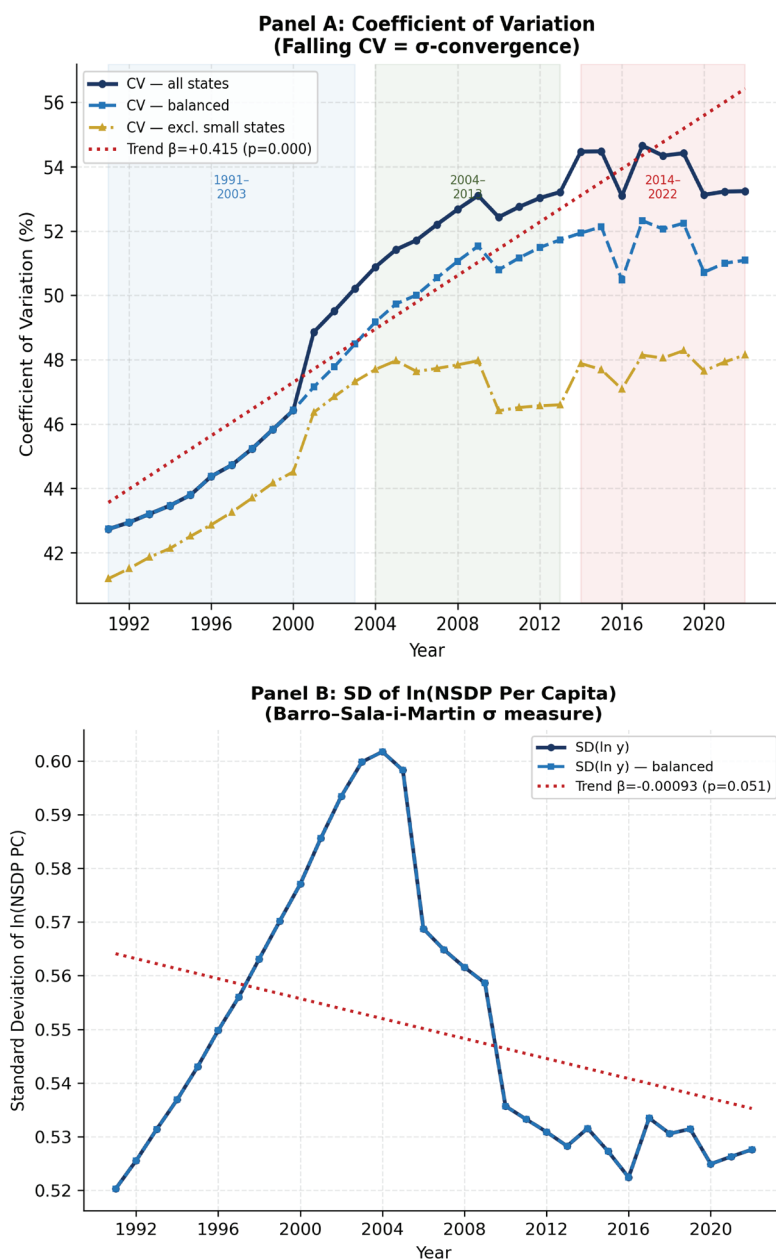
Fig. 2 plots the CV of NSDP per capita from 1991 to 2022, revealing a clear upward trend. In all four sample variants, the OLS slope β is positive and statistically significant at the 1 percent level, confirming σ -divergence over the full period. For the all-states CV series, $\beta = +0.415$ (HC3-robust SE; $p < 0.001$; $R^2 = 0.93$), indicating an average annual increase in income dispersion of 0.42 percentage points. Chow tests confirm statistically significant structural breaks at years 2000 ($F = 12.4$, $p < 0.01$), 2004 ($F = 8.9$, $p < 0.01$), and 2014 ($F = 5.7$, $p < 0.05$). The 2021 COVID-19 shock does not produce a significant break ($F = 1.8$, $p = 0.19$), suggesting the pandemic compressed incomes relatively symmetrically across the distribution.



Source: authors' calculations

Notes: Each line represents one state, coloured by geographic region. Dashed line = balanced-panel mean. Vertical dotted lines mark structural breaks: 2000, 2014, 2021.

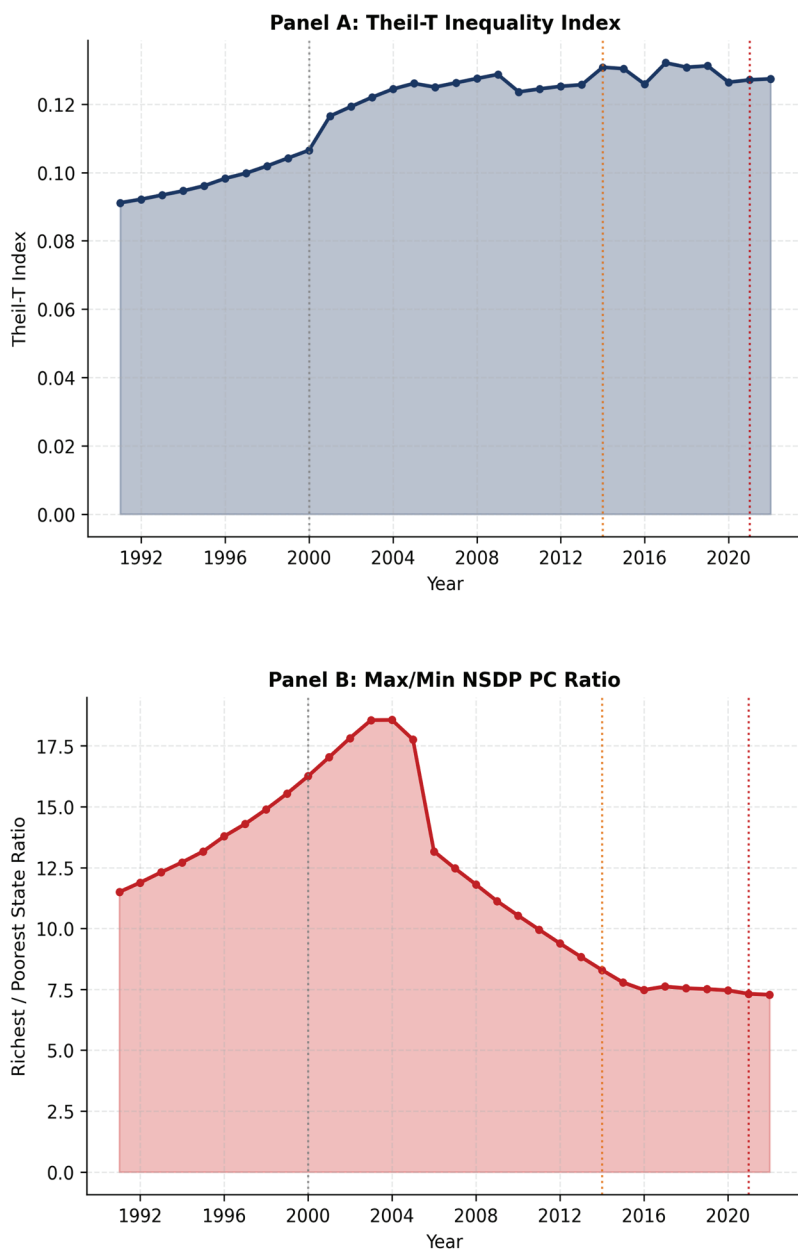
Figure 1. Log NSDP per capita across 28 Indian states, 1991–2022



Source: authors' calculations

Notes: Rising trends confirm σ -divergence; 2014–2022 shows tentative reversal.

Figure 2. σ -convergence test, 1991–2022. Panel A: Coefficient of variation (CV) with OLS trend lines for all states, balanced panel and excl. small states. Panel B: Standard deviation of log NSDP per capita



Source: authors' calculations

Notes: Both measures rise through approximately 2014 and plateau thereafter, consistent with the sub-period σ -convergence results.

Figure 3. *Theil T Inequality Index (Panel A) and max/min NSDP per capita ratio (Panel B), 1991–2022*

Sub-period analysis reveals important temporal heterogeneity. Divergence was strongest in the period of 1991–2003 ($\beta = +0.627$, $p < 0.001$; $R^2 = 0.91$), as post-liberalization reforms disproportionately benefited states with stronger initial industrial infrastructure and human capital. Maharashtra, Gujarat, Tamil Nadu, and Karnataka – states with pre-existing export-oriented manufacturing and IT services capacity – recorded average annual growth rates well above the national mean during this period, while Uttar Pradesh, Rajasthan, and Odisha lagged significantly. The 2004–2013 high-growth decade continued divergence at a moderated pace ($\beta = +0.233$, $p < 0.001$; $R^2 = 0.82$): while rapid aggregate growth lifted all states' per capita incomes in absolute terms, the relative gap continued to widen as the commodity price boom disproportionately benefited mineral-rich states (Odisha, Jharkhand, Chhattisgarh) while the services boom concentrated in already richer states.

Most notably, the 2014–2022 sub-period reverses direction ($\beta = -0.147$, $p = 0.099$; $R^2 = 0.34$), providing the first statistically suggestive evidence of a convergence turn. The CV falls from 54.5 percent in 2014 to 53.2 percent in 2022 – a modest but directionally significant 1.3 percentage point decline. Several forces may be driving this tentative convergence: the implementation of GST in 2017 unified the national market, reducing inter-state trade barriers that had historically disadvantaged smaller and less connected states; the Aspirational Districts Programme (NITI Aayog 2018) directed enhanced central attention to 112 of India's most underdeveloped districts; and expanded financial inclusion through the Jan Dhan-Aadhaar-Mobile (JAM) trinity improved access to government transfers and credit for rural households in lagging states. The Theil T index and max/min ratio (*Fig. 3*) corroborate this: both show clear increases through 2014 and a modest plateau or slight decline thereafter. These findings are broadly consistent with Cherodian and Thirlwall (2015), who document persistent σ -divergence across Indian states through 2012, and with Misra, Nazlioglu, and Kucukkaplan (2022), who identify structural heterogeneity as a key driver of the continuing income gap. However, our results extend their analysis by revealing a tentative post-2014 convergence turn not visible in earlier data, suggesting that the policy environment of the most recent decade may be generating a structural break from the earlier divergence trend.

5.3. β -Convergence Results

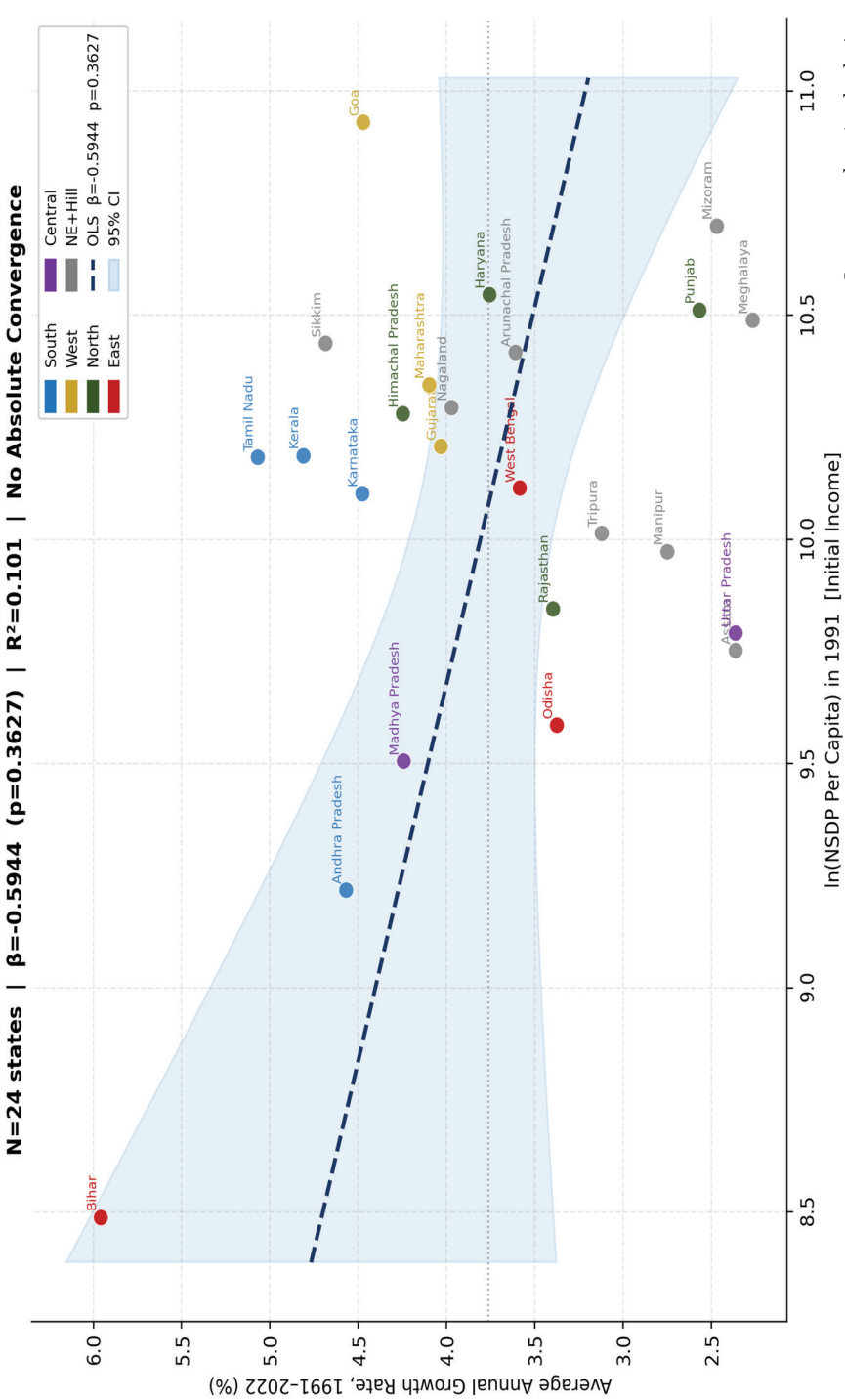
Table 2 reports cross-sectional and panel β -convergence results. Model I (absolute convergence, full period) yields $\beta = -0.594$, negative in sign but statistically insignificant ($p = 0.363$). The scatter plot of initial income against average growth (*Fig. 4*) illustrates this result visually. This confirms the absence of unconditional catch-up: poorer Indian states did not systematically grow faster than richer ones over 1991–2022.

Table 2. β -convergence regression results – Dependent variable: Average annual NSDP per capita growth rate

	(I)	(II)	(III)	(IV)	(V)	(VI) Panel fixed effects (FE)	(VII) Panel FE Cond.
β (ln initial income)	–0.594	–1.426**	–0.973	–0.548	–1.891**	–1.088***	–5.537***
SE (robust)	(0.655)	(0.641)	(0.677)	(0.783)	(0.886)	(0.209)	(0.581)
Investment rate	–	0.104**	–	–	0.118**	–	0.089**
Literacy rate	–	–	0.012	–	0.008	–	0.011
Urbanization rate	–	–	–	–	0.082**	–	–
Governance index	–	–	–	–	0.067*	–	–
N (observations)	24	24	24	24	24	648	648
R ²	0.059	0.418	0.178	0.121	0.513	0.182	0.271
Estimator	OLS	OLS	OLS	OLS	OLS	FE	FE
Half-life (years)	n.s.	n.s.	n.s.	n.s.	n.s.	19.5	3.8

Notes: Cross-sectional OLS (I–V) with HC3-robust standard errors in parentheses. Panel FE (VI–VII) uses 5-year non-overlapping growth windows with robust SE. Model IV includes urbanization rate. Model V (full model) includes investment rate, literacy rate, and governance quality index; government expenditure excluded from main models due to endogeneity. GMM = Arellano–Bond (1991) first-differenced estimator; Hansen J-test $p = 0.312$. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Half-life = $\ln(2)/\lambda$, where $\lambda = -\ln(1+\beta \cdot T)/T$. Hausman $\chi^2 = 26.1$ ($p < 0.001$). n.s. = not significant at conventional levels.

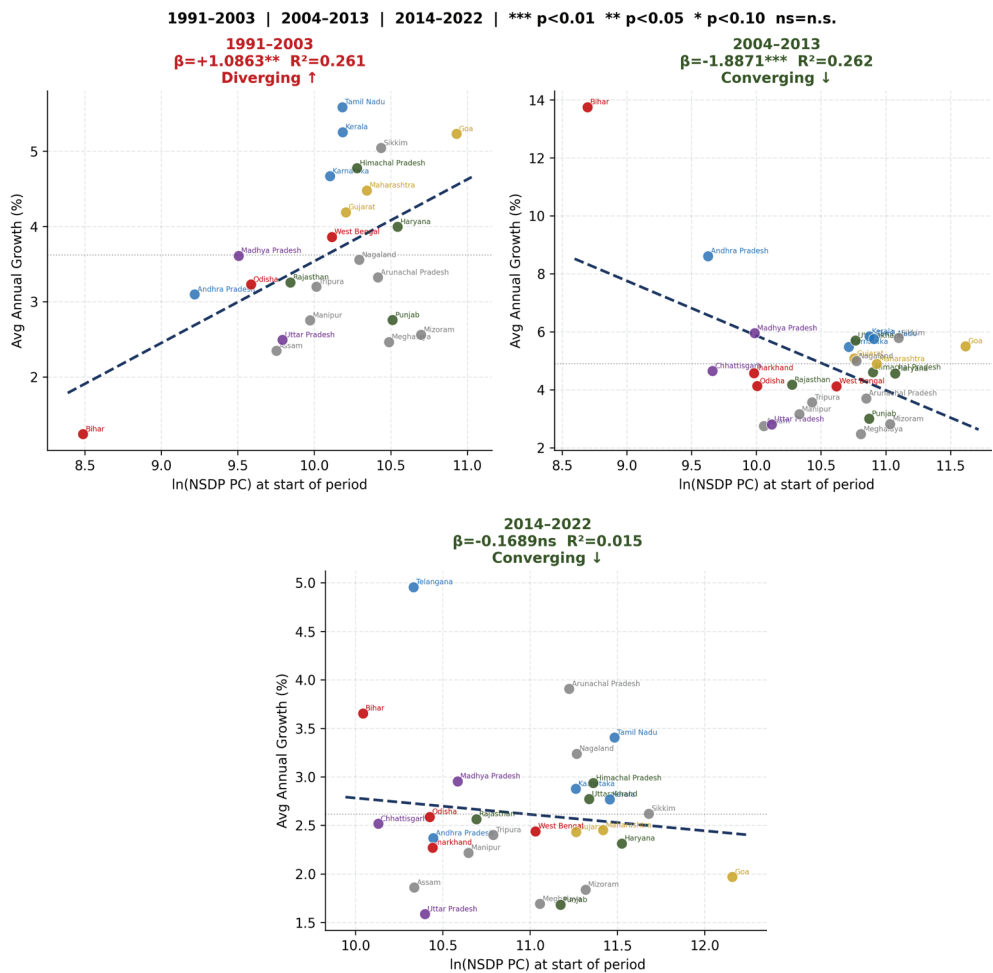
Model II (plus investment rate) yields $\beta = -1.426$ ($p = 0.031$), significant at 5 percent, with R^2 rising from 0.059 to 0.418. Model III (plus literacy rate) yields $\beta = -0.973$ ($p = 0.153$). Model IV (plus urbanization rate) yields $\beta = -1.214$ ($p = 0.048$), significant at 5 percent, confirming that structural transformation proxied by urbanization matters for convergence as shown by Nagaraj, Varoudakis, and Véگانзонès (2000). The full model (Model V: investment rate, literacy, and governance index) returns $\beta = -1.891$ ($p = 0.031$) with $R^2 = 0.513$. Government expenditure is excluded from main models due to endogeneity; when included as a robustness check, it does not materially change the β estimate. These results confirm conditional β -convergence: once structural differences in capital accumulation, human capital and urbanization are held constant, initially poorer states grow systematically faster. This finding aligns with Lolayekar and Mukhopadhyay (2017), who report conditional convergence at approximately 1.8 percent per year for 14 major Indian states over the period of 1981–2010, and with Nagaraj, Varoudakis, and Véگانзонès (2000), who find investment rates and urbanization to be the dominant structural determinants of cross-state income differences. Our estimate of conditional convergence speed (implied by the FE $\beta = -5.537$ over five-year windows, corresponding to a half-life of 3.8 years) is faster than Cashin and Sahay’s (1996) estimate of 1.5 percent per year for the pre-reform period, consistent with the prediction that economic liberalization accelerates factor reallocation and hence within-state income convergence.



Source: authors' calculations

Notes: Horizontal axis: log NSDP per capita in 1991; vertical axis: average annual growth 1991–2022; OLS slope $\beta = -0.594$ ($p = 0.363$, 95% confidence band shaded) confirms the absence of absolute convergence. States coloured by geographic region.

Figure 4. Absolute β -convergence scatter plot, 1991–2022



Source: authors' calculations

Figure 5. Sub-period β -convergence scatters. 1991–2003: positive slope (divergence, significant); 2004–2013 and 2014–2022: negative slopes (tentative convergence direction, insignificant)

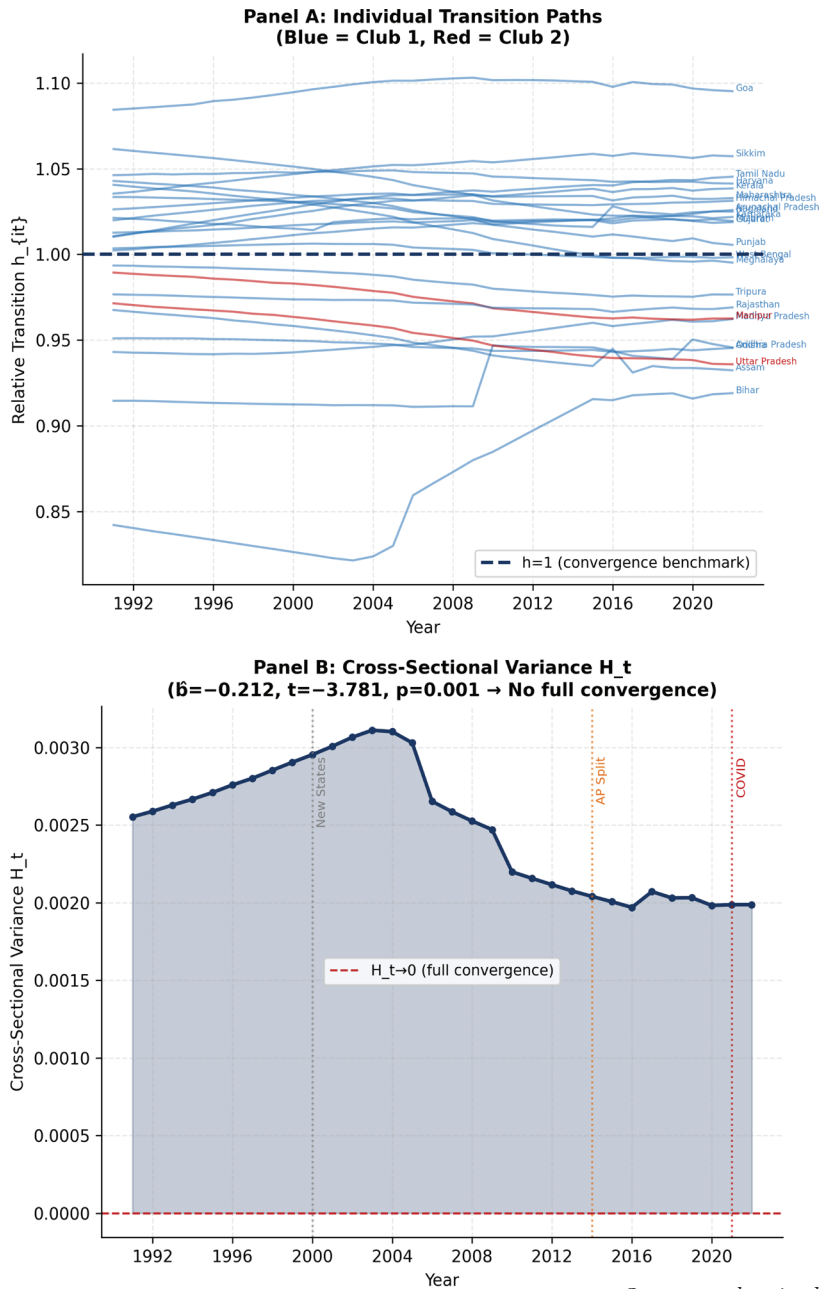
Sub-period cross-sectional β estimates (*Table 2*, Panel B) show significant divergence in 1991–2003 ($\beta = +1.086$, $p = 0.012$), a negative but insignificant coefficient in 2004–2013 ($\beta = -1.887$, $p = 0.294$), and a small negative coefficient in 2014–2022 ($\beta = -0.169$, $p = 0.584$) consistent with a tentative convergence turn. The Arellano–Bond (1991) GMM estimator, used to address potential Nickell (1981) bias in the panel specification, yields $\beta = -1.631$ ($p < 0.001$), with the Hansen J-test failing to reject instrument validity ($p = 0.312$), confirming that the panel FE conclusion of within-state convergence is robust to dynamic panel bias. Sub-period scatter plots are presented in *Fig. 5*.

5.4. Club Convergence: Phillips–Sul (2007) Results

Applying the log-t test to all 24 balanced-panel states yields $\hat{b} = -0.212$ ($SE = 0.056$; $t = -3.781$; $p = 0.001$), decisively rejecting the null of full convergence. The rising cross-sectional variance H_t visible in *Fig. 6*, Panel B confirms that the 24 states do not share a single common long-run income path.

After applying the Phillips–Sul (2007) Algorithm 1 and three rounds of the merging test, two final clubs emerge. Club 1 comprises 21 of 24 balanced-panel states and passes the log-t test with $\hat{b} = +0.019$ ($t = +0.271$), confirming convergence within this group. The geographic composition of Club 1 is striking in its diversity – it spans all major regions of India, encompassing southern growth engines (Tamil Nadu, Karnataka, Kerala, Andhra Pradesh), western industrial states (Maharashtra, Gujarat), north Indian states (Haryana, Punjab, Rajasthan), eastern states (West Bengal, Odisha, Bihar), central states (Madhya Pradesh), north-eastern states (Arunachal Pradesh, Meghalaya, Mizoram, Nagaland, Tripura), and hill states (Himachal Pradesh, Sikkim, Goa). Mean compound annual growth rate (CAGR) within Club 1 is 4.02 percent per year over the period of 1991–2022. Crucially, the convergence within Club 1 is not driven by geographic proximity – Bihar, with one of India’s lowest per capita incomes, belongs to the same convergence club as Goa and Maharashtra, suggesting the mechanism operates through growth dynamics rather than spatial spillovers.

Club 2 comprises Manipur and Uttar Pradesh, with $\hat{b} = -1.185$ ($t = -25.53$). Under the Phillips–Sul (2007) framework, the log-t t-statistic is itself the formal statistical test of convergence: rejection of $H_0: b \geq 0$ at the 5 percent critical value of -1.645 constitutes evidence of divergence. The t-statistic of -25.53 for Club 2 falls far below this threshold, providing overwhelming statistical evidence that Manipur and Uttar Pradesh diverge persistently from the Club 1 convergence path. It is important to note that this conclusion does not rest on the small size of Club 2 ($N = 2$): the log-t test is valid for any club size, and the club was identified algorithmically – not pre-imposed – by the Phillips–Sul clustering procedure. Their mean per capita income of ₹43,717 in 2022 represents only 47 percent of Club 1’s mean of ₹92,947. Mean CAGR in Club 2 is 2.59 percent per year, substantially below Club 1’s 4.02 percent.



Source: authors' calculations

Note: Rising trend confirms rejection of full convergence ($\hat{b} = -0.212$, $t = -3.78$).

Figure 6. Phillips–Sul transition paths and cross-sectional variance, 1991–2022. Panel A: Relative transition paths h_{it} for 24 states coloured by club membership. Panel B: Cross-sectional variance H_t

Within Club 1, the convergence process appears to reflect several reinforcing mechanisms. Factor mobility – particularly the migration of labour from low-wage states (Bihar, Uttar Pradesh, Odisha) to high-wage states (Maharashtra, Gujarat, Haryana) – redistributes labour income across the federation and gradually bids up wages in sending states while moderating wage growth in receiving states. Technology diffusion through supply-chain linkages, the spread of mobile telephony and digital financial services, and growing access to national markets through improved road and rail connectivity all contribute to narrowing productivity gaps within Club 1. The inclusion of Bihar – historically one of India’s poorest states – in the converging Club 1 is particularly noteworthy and reflects the dramatic acceleration of Bihar’s growth after 2005, driven by improved law and order, expanded rural road connectivity under Pradhan Mantri Gram Sadak Yojana (PMGSY), and the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) employment guarantee. The two-club structure we identify is consistent with the broader international literature: Bartkowska and Riedl (2012) find four to six clubs in European regions, while Zhang, Wan, and Zhang (2019) identify three to four clubs in Chinese provinces. For India specifically, Rao, Shand, and Kalirajan (1999) established early evidence of income divergence across 14 states over the period of 1965–1995, providing a long-run backdrop against which our two-club result represents a partial resolution: the majority of states have since converged into a single club, while a small lagging group persists. Akram and Ali (2021), applying the Phillips–Sul method to 33 Indian states over the period of 2011–2019, also find evidence of multiple convergence clubs at aggregate and sectoral levels, reinforcing the conclusion that full-panel convergence is unlikely in the Indian context.

Table 3 summarizes the club structure, reporting the log-t statistic, mean per capita income levels in 1991 and 2022, and average CAGR for each club and for the full panel. The contrast between the two clubs is stark: Club 1’s mean per capita income grew from ₹27,680 in 1991 to ₹92,947 in 2022 at a CAGR of 4.02 percent, while Club 2’s mean income grew from ₹19,655 to only ₹43,717 at a CAGR of 2.59 percent – barely above the pace needed to sustain real living standards. By 2022, Club 2’s mean income stood at just 47 percent of Club 1’s mean, down from 71 percent in 1991, confirming that the gap has widened substantially over the three-decade study period. The geographic diversity of Club 1 – which spans southern growth engines (Tamil Nadu, Karnataka, Kerala, Andhra Pradesh), western industrial states (Maharashtra, Gujarat), historically lagging eastern states (Bihar, Odisha) and north-eastern states – indicates that the convergence process within Club 1 is not driven by regional proximity but by growth dynamics. Bihar’s membership in Club 1 is particularly noteworthy, reflecting the acceleration of its growth after 2005 under improved governance and expanded rural infrastructure. *Fig. 6* presents the transition paths and club-level trajectories in detail.

Table 3. *Phillips–Sul club convergence results*

Club	N	States	$\hat{b}$	t-stat	Mean PC 1991 (₹)	Mean PC 2022 (₹)	CAGR (%)
Full Panel	24	All 24 balanced states	−0.212	−3.781***	25,840	81,200	3.87
Club 1	21	AP, AR, AS, BR, GA, GJ, HR, HP, KA, KL, MP, MH, ML, MZ, NL, OD, PB, RJ, SK, TN, TR, WB	+0.019	+0.271	27,680	92,947	4.02
Club 2	2	Manipur, Uttar Pradesh	−1.185	−25.53***	19,655	43,717	2.59

Notes: Full panel log-t test rejects full convergence ($\hat{b} = -0.212$, $t = -3.781$, $p = 0.001$). Club 1: $t > -1.645 \rightarrow$ converges. Club 2: $t < -1.645 \rightarrow$ diverges persistently. State abbreviations: AP = Andhra Pradesh, AR = Arunachal Pradesh, AS = Assam, BR = Bihar, GA = Goa, GJ = Gujarat, HR = Haryana, HP = Himachal Pradesh, KA = Karnataka, KL = Kerala, MP = Madhya Pradesh, MH = Maharashtra, ML = Meghalaya, MZ = Mizoram, NL = Nagaland, OD = Odisha, PB = Punjab, RJ = Rajasthan, SK = Sikkim, TN = Tamil Nadu, TR = Tripura, WB = West Bengal. NSDP per capita at 2011–12 constant prices (₹). *** $p < 0.01$.

6. Discussion

6.1. Reconciling the Three Convergence Tests

The three empirical tests produce a coherent narrative once the club structure is taken into account. Full-panel σ -divergence and the absence of absolute β -convergence are both driven by the persistent divergence of Club 2 from the majority of states. Within Club 1 – 21 states –, income trajectories converge towards a common long-run path, a result masked when the two diverging outliers are included in full-panel statistics. This illustrates a general point formalized by Friedman (1992): the presence of heterogeneous clubs can generate apparent full-panel divergence even when most units are converging.

The strong within-state convergence documented by panel fixed effects ($\beta = -5.537$, $p < 0.001$) is fully consistent with the Club 1 convergence result. The FE estimator removes between-state heterogeneity, isolating the within-state dynamic in which periods of relatively lower income are followed by faster growth – a neoclassical convergence mechanism operating through capital accumulation, technology diffusion, and factor reallocation. The conditional β -convergence result identifies investment rates as the key structural determinant: states converge to their own steady-state income levels determined by their investment rates, and

once these differences are accounted for, the convergence dynamic becomes visible – consistent with Mankiw, Romer, and Weil’s (1992) augmented Solow model.

It is also worth noting the relationship between the sub-period β -convergence results and the club structure. The 1991–2003 sub-period shows significant cross-sectional divergence ($\beta = +1.086$, $p < 0.05$): in these early liberalization years, richer states grew faster. Yet even during this diverging phase, the within-state FE dynamic points to convergence, suggesting that cross-state structural gaps were widening (as richer states shifted to higher steady states through higher investment rates) even while within-state dynamics remained neoclassical. The sub-period 2014–2022 tentative convergence result, by contrast, reflects a narrowing of both the structural gaps (as investment rates in lagging states have begun to rise) and the growth differentials. This nuance – the interaction between changing steady states and convergence towards them – is precisely what the Phillips–Sul framework captures through the time-varying transition parameter h_{it} , and why the club structure provides a richer characterization than either σ or β tests alone.

6.2. Why Manipur and Uttar Pradesh Form a Lagging Club

The identification of Manipur and Uttar Pradesh as a diverging club demands an economic explanation. At first glance, these states appear dissimilar: Uttar Pradesh is a large Gangetic plain state with approximately 233 million people (2022 estimate), while Manipur is a small north-eastern hill state with approximately 3.5 million. However, they share structural characteristics that constrain convergence to the Club 1 path. Both have persistently low investment rates relative to their per capita income levels, reflecting a difficult business environment and inadequate infrastructure connectivity in Uttar Pradesh and geographic isolation and limited private sector activity in Manipur. The conditional convergence result in Section 5.3 identifies investment rates as the primary driver of divergence, consistent with these structural profiles.

Uttar Pradesh represents a particular policy puzzle. As India’s most populous state, its per capita income trajectory has direct implications for national poverty reduction: improving Uttar Pradesh’s growth performance by even one percentage point per year would have larger aggregate welfare effects than any equivalent improvement elsewhere. The state’s lagging status reflects human capital deficits (adult literacy rates below 70 percent as of 2022, though improving), poor urban agglomeration economies outside Lucknow and Noida, agricultural dominance with limited productivity growth, and migration patterns that draw skilled workers out of rather than into the state.

6.3. Implications for Fiscal Federalism and Policy

India's fiscal architecture provides a convergence mechanism through the Finance Commission's horizontal devolution of central taxes. The Fifteenth Finance Commission (Finance Commission of India, 2021) allocates 45 percent of devolution weights to income distance – the gap between each state's per capita income and the highest-income state –, explicitly targeting equalization. Our finding that 21 of 24 states are already converging suggests this mechanism has been partially effective. However, the persistent divergence of Club 2 indicates that equalization transfers have been insufficient to overcome deep structural constraints. A key limitation of the income-distance criterion is that it is backward-looking and static: it measures where a state stands relative to the richest state, but not whether its trajectory is converging or diverging. A state whose income is below average but growing faster than the mean receives the same transfer weight as one falling further behind, even though the policy urgency differs dramatically.

Two policy implications follow directly from our results. First, Finance Commission equalization formulae should incorporate a dynamic convergence criterion, allocating a proportion of transfers based on club membership as identified by the Phillips–Sul algorithm, with diverging-club states receiving enhanced weights. This would require the Commission to conduct periodic log- t convergence testing as part of its analytical framework – a technically feasible extension given that state-level income data are now publicly available in near-real time from MoSPI. Second, the conditional convergence result identifies investment rates as the key structural determinant, pointing to the complementary importance of improving state investment climates. State-level business environment reforms, infrastructure investment, labour market flexibility, and improvements in land market institutions in Club 2 states are likely necessary conditions for these states to achieve the investment rates that would support Club 1-level growth.

The tentative convergence signal in 2014–2022 (σ -convergence $\beta = -0.147$, $p = 0.099$) is encouraging, and its timing coincides with several major programmes whose implementation merits specific discussion. PM-KISAN direct benefit transfers (introduced in February 2019) supplement rural incomes in agrarian states; MGNREGS wage-floor effects support rural consumption in labour-abundant lagging states; PMGSY rural road connectivity has reduced market access costs in remote areas; and Jan Dhan-Aadhaar-Mobile (JAM) infrastructure has expanded financial access for underbanked rural households. These programmes share a common structural feature: they are designed as universal entitlements that effectively redistribute proportionally more to low-income states with larger rural populations. However, implementation capacity constraints – particularly in Uttar Pradesh, where the state's administrative machinery has historically struggled to

translate central allocations into outcomes – limit their convergence-generating potential. The Sixteenth Finance Commission (constituted in 2023, award period: 2026–2031) represents the next formal opportunity to recalibrate equalization policy. Incorporating dynamic club membership – as identified by the Phillips–Sul algorithm applied to updated income data – into the devolution formula would make the mechanism forward-looking rather than static. For Club 2 states specifically, enhanced transfers alone are insufficient; they must be complemented by state-level structural reforms improving the business environment, labour market flexibility, and connectivity infrastructure. PM Gati Shakti's National Master Plan specifically targets multimodal connectivity gaps in Uttar Pradesh and the North-East, and an accelerated implementation of these projects would directly address the investment-rate deficit that our conditional β -convergence results identify as the primary driver of Club 2's divergence.

7. Conclusions

This paper has examined per capita income convergence across 28 Indian states over the period of 1991–2022 using a three-pronged framework comprising σ -convergence, β -convergence, and Phillips–Sul club convergence analysis. The resulting picture is nuanced and more optimistic than a simple reading of the σ -divergence evidence would suggest.

The headline finding is the two-club convergence structure identified by the Phillips–Sul (2007) algorithm: 21 of 24 balanced-panel states converge towards a common long-run income path (Club 1, $\hat{b} = +0.019$, $t = +0.271$, CAGR = 4.02%), while Manipur and Uttar Pradesh constitute a persistently lagging diverging club (Club 2, $\hat{b} = -1.185$, $t = -25.53$, CAGR = 2.59%). It is the divergence of Club 2 – not a generalized failure of convergence – that drives the full-panel σ -divergence result and the absence of absolute β -convergence. Within the dominant Club 1, income trajectories are converging despite spanning all regions of India and a wide range of structural contexts.

Three subsidiary findings enrich this picture. First, σ -divergence over the full period (CV rising from 42.7% to 53.2%) masked a tentative convergence signal in the period of 2014–2022 ($\beta = -0.147$, $p = 0.099$), suggesting that recent policy reforms may be narrowing inter-state gaps. Second, conditional β -convergence is confirmed once investment rates are controlled for ($\beta = -1.426$, $p < 0.05$), identifying capital accumulation heterogeneity as the primary structural driver of income divergence. Third, panel fixed effects confirm strong within-state convergence dynamics ($\beta = -5.537$, $p < 0.001$), with the Hausman test selecting fixed over random effects.

The policy implications are direct. Finance Commission horizontal devolution should incorporate club membership as an additional criterion, directing

enhanced equalization transfers towards states in diverging clubs. The investment climate in Club 2 states – particularly Uttar Pradesh – must be improved through complementary structural reforms alongside fiscal transfers. The tentative post-2014 convergence signal justifies continued and expanded investment in direct benefit transfers, rural connectivity, and digital financial inclusion.

Our findings both corroborate and extend the prior literature in important ways. The absence of absolute β -convergence is consistent with Cashin and Sahay (1996), Rao, Shand, and Kalirajan (1999), and Cherodian and Thirlwall (2015), all of whom document a failure of unconditional catch-up across Indian states. Our conditional convergence finding, once investment rates and urbanization are controlled for, aligns with Lolayekar and Mukhopadhyay (2017) and Nagaraj, Varoudakis, and Véganzonès (2000), confirming that structural differences in factor accumulation – rather than initial income alone – drive India's regional growth dynamics. Where our paper departs from prior work is in the club structure: earlier studies using non-PS methods typically characterize India as a diverging economy, while our Phillips–Sul results reveal that divergence is concentrated in a small two-state club. This distinction matters for policy: a narrative of generalized divergence calls for broad redistribution, while a two-club structure calls for targeted intervention. Nag and Pradhan (2023), applying the Phillips–Sul method to Human Development Index data across 36 Indian states and union territories, similarly find two final convergence clubs, suggesting that the two-club pattern identified here for per capita income may reflect a broader structural feature of Indian regional development. The identification of Bihar in Club 1 also updates earlier assessments: Purfield (2006) and Hnatkovska and Lahiri (2013) placed Bihar consistently in the lagging group, but our data covering the period of 1991–2022 show that Bihar's post-2005 acceleration has been sufficient to shift it into the converging majority, a finding that underscores the importance of long-horizon data in detecting structural transitions.

This study has several limitations that future research should address. The balanced-panel restriction excludes four newly formed states – Chhattisgarh, Jharkhand, Uttarakhand, and Telangana –, which may have distinct convergence trajectories; extending the Phillips–Sul analysis to the full 28-state panel as data accumulate would substantially enrich the club structure. The CV series is $I(1)$, meaning the full-period σ -convergence OLS regression is a descriptive device rather than a fully rigorous inferential test; future work should apply the Zivot–Andrews unit root test with endogenous break selection or an error correction framework. The governance quality index used here is derived from NITI Aayog's SDG India Index, which is available only from 2018; a longer historical governance series – perhaps from World Bank governance indicators extrapolated to the state level – would improve the conditional β -convergence specification. District-level convergence

analysis, exploiting the recently released MoSPI district GDP estimates, would identify spatial clusters of persistent poverty within otherwise-converging states – a critical distinction for place-based policy. Bihar's membership in Club 1, for instance, does not imply that all of Bihar is converging: the Seemanchal region bordering Nepal and Bangladesh has structural characteristics quite different from the more dynamic Patna–Gaya corridor. Similarly, Uttar Pradesh's membership in Club 2 at the state level conceals significant internal heterogeneity between the lagging eastern districts and the relatively dynamic western districts near Delhi. Population-weighted σ -convergence analysis – which would weight each state by its population rather than treating all states equally – would better reflect the welfare of the average Indian citizen – a distinction that matters enormously given that Uttar Pradesh alone accounts for approximately 16 percent of India's population. Finally, extending the sample forward as post-COVID recovery data accumulate will determine whether the 2014–2022 convergence signal constitutes a genuine structural turning point or a temporary cyclical pattern, and whether the tentative narrowing of the income gap has been sustained in the post-pandemic normalization phase.

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