Manufacturing Concentration and Convergence Clubs: District-Level Evidence from Maharashtra, India

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ABSTRACT

Maharashtra is India's largest manufacturing state, yet its industrial base and income remain concentrated in a few western districts. This study asks whether district incomes in Maharashtra are converging to a common level and how the distribution of organised manufacturing relates to the resulting pattern. Drawing on cumulative causation and new economic geography, it applies the Phillips–Sul log t test and club clustering algorithm, with the von Lyncker–Thoennessen merging procedure, to real per capita District Domestic Product for 34 districts from 2011–12 to 2021–22. It complements this with σ- and β-convergence measures and links the club structure to Annual Survey of Industries district data for 2017–18 to 2020–21, summarised through a k-means typology. The test rejects convergence to a single steady state ($t = -24.35$). Districts sort into six convergence clubs, while Mumbai, Thane and Pune each follow distinct paths that converge neither with one another nor with any club. Income dispersion shows no significant trend over the decade, and β-convergence is weak, with a half-life of about 60 years. Manufacturing size is strongly associated with income levels (Spearman's $\rho = 0.74$) but not with growth, and the three metropolitan districts hold 56% of the state's organised manufacturing gross value added. Regional inequality in Maharashtra therefore takes the form of persistent stratification rather than widening divergence. Policy should target the low-income clubs as groups and help manufacturing capability spread beyond the Mumbai–Pune corridor.

Keywords: club convergence, Phillips–Sul test, regional inequality, manufacturing, district domestic product, Maharashtra

INTRODUCTION

India's growth story is increasingly told through its states, and each state's growth through its districts. Maharashtra is a central case. It accounts for the largest share of India's organised manufacturing gross value added (GVA), 15.67% in the Annual Survey of Industries (ASI) for 2021–22, and the state government has set a target of a USD 1 trillion economy by 2027–28 (Government of Maharashtra, 2024). Yet this industrial strength is spatially narrow. A small number of districts generate more than half of Gross State Domestic Product, and the Mumbai–Thane–Pune belt has dominated industrial activity since at least the 1970s (Paranjape, 1988). The state has twice appointed high-level committees on regional imbalance, under V. M. Dandekar in 1984 and Vijay Kelkar in 2011–2013, and both documented large and persistent gaps between western Maharashtra and the Marathwada and Vidarbha regions (Government of Maharashtra, 1984, 2013).

Whether such gaps narrow over time is a question about convergence, and the answer depends on theory. The neoclassical model predicts that poorer regions grow faster and converge to a common steady state (Barro & Sala-i-Martin, 1992). Theories of cumulative causation and new economic geography predict the opposite for activities with increasing returns. Manufacturing, as an activity with strong scale economies and agglomeration benefits, tends to reinforce the advantages of places where it is already established (Kaldor, 1966; Krugman, 1991; Myrdal, 1957). Between these poles lies the club convergence hypothesis, under which regions with similar initial conditions and structural characteristics converge towards one another, while different groups settle at different levels (Galor, 1996; Quah, 1996).

This study tests these competing predictions for Maharashtra's districts and asks how manufacturing relates to the outcome. It makes three contributions. First, it provides, to our knowledge, the first application of the Phillips and Sul (2007, 2009) club convergence framework to district incomes within an Indian state. Existing Indian applications work at the state level (Akram & Ali, 2021; Ghosh et al., 2013; Kar & Jha, 2021) or examine agricultural outcomes (Sinha, 2020). Second, it applies the full procedure, including the merging step proposed by von Lyncker and Thoennessen (2017), reassignment of initially non-convergent districts, and a set of robustness checks, and it reports σ- and β-convergence alongside the club results so that the conclusions do not rest on a single test. Third, it links the club structure to district-level ASI data, so that the role of manufacturing is examined directly rather than assumed.

Two research questions guide the analysis:

RQ1: Do Maharashtra's districts converge in real per capita income towards a common steady state, or do they form distinct convergence clubs?

RQ2: How is a district's position in this structure related to the size and productivity of its organised manufacturing base?

The results reject convergence to a single steady state but do not show widening dispersion. Instead, districts sort into six stable clubs, and the three metropolitan districts of Mumbai, Thane and Pune remain on separate paths. Manufacturing size tracks the hierarchy of income levels closely but is unrelated to the pace of growth, which is consistent with cumulative causation locking in relative positions. The remainder of the paper reviews theory and evidence, describes the data and methods, presents the results and discusses their implications for regional policy.

THEORETICAL FRAMEWORK AND LITERATURE

Manufacturing, Increasing Returns, and Uneven Regional Growth

Kaldor (1966, 1967) argued that manufacturing is the engine of growth because productivity in manufacturing rises with output through static and dynamic increasing returns, and because manufacturing expansion draws labour from lower-productivity activities. Cross-country evidence broadly supports a special role for manufacturing in development, though the relationship varies across periods and income levels (Szirmai, 2012). Rodrik (2013) shows that labour productivity in organised manufacturing industries converges unconditionally across countries, while aggregate incomes do not, because manufacturing's share of employment is small in poor economies. This distinction matters for subnational analysis: a dynamic manufacturing sector can coexist with persistent income gaps if manufacturing remains spatially concentrated.

Spatial theories explain why such concentration persists. Myrdal (1957) described cumulative causation, in which capital, skilled labour and enterprise flow towards growing centres (backwash effects) faster than growth diffuses to the periphery (spread effects). Hirschman (1958) similarly expected polarisation to precede any trickling down. New economic geography formalised these ideas: with increasing returns and moderate transport costs, manufacturing agglomerates in a core, and the core–periphery pattern can be self-sustaining (Krugman, 1991). These theories do not predict that every lagging region falls further behind. They predict multiple equilibria, in which regions settle into groups with different levels of income according to their initial industrial endowments. The econometric counterpart of this prediction is club convergence (Galor, 1996; Quah, 1996).

Hypotheses

The theories above yield three testable propositions for Maharashtra's districts. If the neoclassical model holds, districts converge to a common steady state (H1). If cumulative causation operates, convergence to a single steady state is rejected and districts instead form multiple convergence clubs, with the established industrial core distinct from the rest (H2). If manufacturing is the mechanism, club position is associated

with the size and productivity of a district's manufacturing base (H3). Because the manufacturing data cover a shorter window than the income data, H3 is examined as an association, not a causal effect.

Evidence on Regional Convergence in India

Studies of Indian states generally find that disparities widened after the 1991 reforms (Bhattacharya & Sakthivel, 2004; Kurian, 2000). Club convergence methods refine this picture. Ghosh et al. (2013) applied the Phillips–Sul procedure to fifteen major states and found divergence in aggregate income alongside convergence clubs at the sectoral level. Akram and Ali (2021) found sector-specific clubs in output across states, Kar and Jha (2021) examined the policy implications of state-level clubs in the post-reform period, and Raj et al. (2024) studied club convergence in human development and economic growth. At the district level, Sinha (2020) applied club convergence to crop yields. To our knowledge, no study has applied the framework to district incomes within a single Indian state.

Work on industrial location explains why industrial geography shapes these patterns. Chakravorty (2003) and Lall and Chakravorty (2005) found that post-reform private industrial investment favoured existing industrial and coastal districts, producing divergence between regions and convergence within them. Saikia (2011) reported continued concentration of organised manufacturing in a few states, and Ghani et al. (2012) found that India's organised manufacturing has been moving out of urban cores into surrounding rural and peri-urban districts.

Manufacturing and Regional Imbalance in Maharashtra

Maharashtra, Tamil Nadu, Gujarat and Andhra Pradesh together account for about 48% of India's organised manufacturing employment (Sharma, 2017). Within this group, Maharashtra leads in GVA, ranks second to Tamil Nadu in organised manufacturing employment, and has shown little growth in total factor productivity (Khanna & Sharma, 2021). Burange (1999) traced a shift in the state's industrial composition towards capital and intermediate goods from the late 1970s to the mid-1990s, accompanied by rising capital intensity and slow employment growth, and Burange (2004) documented continuing increases in capital intensity alongside falling labour intensity in the organised sector. The state is also a leading location for micro, small and medium enterprises (Jena & Thatte, 2017; Manna & Mistri, 2017).

The spatial dimension of this industrial base has long been recognised. Paranjape (1988) estimated that the Mumbai–Thane–Pune belt accounted for about 60% of the state's industrial activity, and that several Marathwada and Vidarbha districts were less industrialised than the least industrialised major states. The Kelkar Committee later recommended district-based indicators and targeted investment to correct these imbalances (Government of Maharashtra, 2013). What remains missing is a formal test of whether district incomes are converging and of how the club structure, if any, maps onto manufacturing. This study addresses that gap.

DATA AND METHODS

Data and Unit of Analysis

The convergence analysis uses per capita District Domestic Product (DDP) at constant 2011–12 prices, published by the Directorate of Economics and Statistics, Government of Maharashtra, for the eleven financial years from 2011–12 to 2021–22. The panel is balanced and covers 34 districts. The difference from the present count of 36 districts arises because the DDP series follows 2011 boundaries: Mumbai City and Mumbai Suburban are reported together as Mumbai, and Palghar, created from Thane in 2014, is included in Thane. To keep the unit of analysis identical across all parts of the study, the ASI district data are aggregated to the same 34 units.

Manufacturing data come from the ASI district tables for Maharashtra for 2017–18 to 2020–21, the four years for which comparable district-level tables were available to us (Ministry of Statistics and Programme Implementation [MoSPI], various years). The ASI covers the organised (registered) manufacturing sector.

We use the number of factories, workers, total output and GVA, all in current prices. District wage series are not used in the comparative analysis, because the 2017–18 tables report wages to workers while the later tables report wages and salaries to all employees, so the two are not comparable.

The Phillips–Sul Convergence Test

Phillips and Sul (2007) write the log of per capita income for district i at time t as $\log y_{it} = \delta_{it}\, \mu_t$, where μ_t is a common trend and δ_{it} is a time-varying idiosyncratic loading. Convergence means that δ_{it} tends to a common value δ for all districts as t grows. Because δ_{it} cannot be estimated directly, the method works with the relative transition coefficient

$$h_{it} = \log y_{it} / [(1/N) \Sigma_i \log y_{it}],$$

which traces each district's path relative to the cross-section average, and its cross-sectional variance $H_t = (1/N) \Sigma_i (h_{it} - 1)^2$. Under convergence $H_t \to 0$. The log t test estimates

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

with $L(t) = \log t$, for $t = [rT] + 1, \ldots, T$, after discarding an initial fraction r of the sample. The null hypothesis of convergence is $b \geq 0$, tested against $b < 0$ with a one-sided t-test based on heteroskedasticity- and autocorrelation-consistent standard errors; the null is rejected at the 5% level when $t_b < -1.65$. The coefficient b equals twice the speed at which δ_{it} approaches δ. Values of $b \geq 2$ indicate convergence in levels, values of $0 \leq b < 2$ indicate relative (conditional) convergence, in which growth rates converge but level gaps may persist, and a significantly negative b rejects convergence (Phillips & Sul, 2007). Rejecting the null for the full panel does not imply that every district diverges. It implies only that there is no single steady state, and it motivates the search for clubs.

Following Phillips and Sul (2007) and Du (2017), the series are first smoothed with the Hodrick–Prescott filter ($\lambda = 400$) to remove business-cycle variation (Hodrick & Prescott, 1997). With $T = 11$, we set $r = 1/3$, so the first four years are discarded and the regression uses seven observations, in line with the recommendation of $r \approx 0.3$ for short panels (Phillips & Sul, 2007).

Club Clustering and Merging

The clustering algorithm proceeds in four steps (Phillips & Sul, 2007). (a) Districts are ordered by income in the final year. (b) A core group is formed from the highest-ranked districts by adding members while the log t statistic for the group rises and remains above −1.65. (c) Each remaining district is added to the core in turn and retained if the log t statistic for the core plus that district exceeds a sieve criterion, here zero; the enlarged group must itself pass the log t test. (d) The procedure is repeated on the districts not yet assigned, and districts that cannot form a core with any other district are classified as non-convergent.

Because the algorithm can over-identify clubs, Phillips and Sul (2009) recommend testing whether adjacent clubs can be merged. We apply the refinement of von Lyncker and Thoennessen (2017): when two consecutive pairs of clubs both pass the merging test, the pair with the larger t statistic is merged first, and the process is repeated until no further merger passes. Each initially non-convergent district is then tested against every final club and assigned to the club with which it yields the highest log t statistic, provided that statistic exceeds −1.65. Estimation used the psecta suite in Stata (Du, 2017); the merging, reassignment and robustness steps were implemented in Python using the same estimator. This implementation reproduces the Stata coefficients to four decimal places and the t statistics to within about 1%.

Complementary Measures

The club analysis is complemented by two conventional measures. σ-convergence is assessed with the standard deviation of log per capita DDP, the coefficient of variation, the Theil index and the Gini coefficient. Absolute β-convergence is estimated by regressing average annual growth from 2011–12 to

2021–22 on the log of initial income, with heteroskedasticity-robust standard errors (Barro & Sala-i-Martin, 1992).

To address H3, we compare the manufacturing profile of the clubs using district averages for 2017–18 to 2020–21 and report Spearman rank correlations between manufacturing indicators and both the level and the growth of per capita DDP. We also construct a descriptive typology of district manufacturing with k-means clustering. Four indicators enter the clustering: the log of GVA (size), the log of GVA per worker (labour productivity), the log of workers per factory (plant scale) and the ratio of GVA to output (value-added intensity). Indicators are standardised over the pooled 2017–18 and 2020–21 observations so that the same cluster definitions apply in both years and movements between clusters are meaningful. The number of clusters is chosen by the average silhouette width (Rousseeuw, 1987). Because the ASI window is short and its values are nominal, the typology is used to describe structure, not to infer trends.

RESULTS

Organised Manufacturing in Maharashtra, 2017–18 to 2020–21

Table 1 summarises the state's organised manufacturing sector at the start and end of the ASI window. The number of factories in operation fell by 15.5% and the number of workers by 7.6%, while fixed capital rose by 18.0%, raising fixed capital per worker from ₹24.4 lakh to ₹31.2 lakh. Nominal GVA was 9.9% lower in 2020–21 than in 2017–18, a decline that reflects both the slowdown of 2019–20 and the pandemic year. These four years are too few, and too affected by the pandemic, to establish a trend. They do, however, show an organised sector that is becoming more capital-intensive and is not expanding employment, which is consistent with earlier findings for the state (Burange, 1999, 2004).

Table 1 Organised Manufacturing in Maharashtra, 2017–18 and 2020–21

Indicator	Unit	2017–18	2020–21	Change (%)
Factories	Number	31,668	25,883	−18.3
Factories in operation	Number	25,222	21,316	−15.5
Workers	Number	1,571,842	1,452,694	−7.6
Total persons engaged	Number	2,227,568	2,039,588	−8.4
Fixed capital	₹ crore	383,670	452,760	18.0
Working capital	₹ crore	135,095	196,254	45.3
Total output	₹ crore	1,316,592	1,300,279	−1.2
Gross value added	₹ crore	278,903	251,294	−9.9
Net value added	₹ crore	241,567	212,098	−12.2
Gross fixed capital formation	₹ crore	52,027	49,032	−5.8

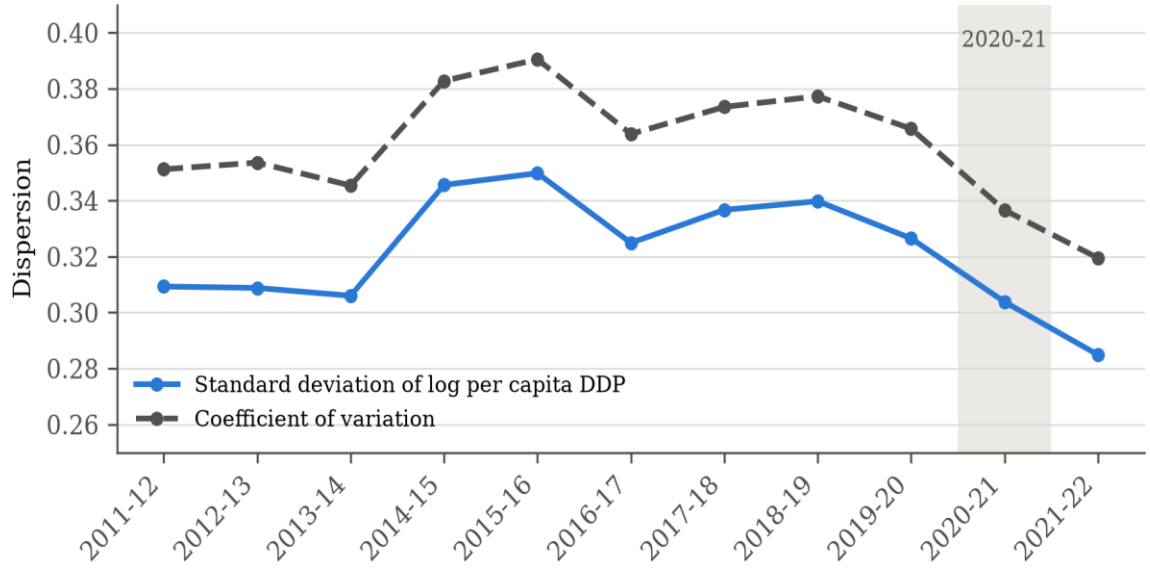
Note. Monetary values are at current prices. Data are from the Annual Survey of Industries, Ministry of Statistics and Programme Implementation (2017–18 and 2020–21).

Manufacturing is also highly concentrated across districts. Taken together, the three metropolitan districts (Mumbai, including Mumbai Suburban; Thane, including Palghar; and Pune) accounted for 49.9% of the state's organised manufacturing GVA in 2017–18 and 57.8% in 2020–21, an average of 55.9% over the four years.

Dispersion and β-Convergence

Figure 1 shows that dispersion in per capita DDP did not trend steadily in either direction. The standard deviation of log income rose from 0.309 in 2011–12 to a peak of 0.350 in 2015–16, remained near 0.34 until 2018–19, and then fell to 0.285 by 2021–22. Much of the late decline reflects the sharper contraction of the metropolitan economies in 2020–21. A log-linear trend in the standard deviation over the full decade is small and not statistically significant (−0.3% per year, p = .66). The Theil index (0.055 to 0.046) and the Gini coefficient (0.181 to 0.165) follow the same pattern. There is thus no evidence of σ-divergence, but neither is there clear σ-convergence before the pandemic.

Figure 1 Dispersion of Real per Capita District Domestic Product, 2011–12 to 2021–22



Note. N = 34 districts. The shaded band marks the pandemic year 2020–21.

The β-convergence regression gives a negative and significant coefficient on initial income (b = −1.09, SE = 0.47, p = .021, R^2 = .18). The implied speed of convergence is 1.15% per year, a half-life of about 60 years. When the three metropolitan districts are excluded, the coefficient is similar in size but less precisely estimated (b = −1.32, SE = 0.76, p = .083, N = 31). Lower-income districts have therefore grown slightly faster on average, but the pace is far too slow to close existing gaps within a policy-relevant horizon. A negative β is also compatible with convergence within groups rather than towards a common level, which the club analysis examines directly.

Phillips–Sul Test for the Full Panel and Initial Clubs

The log t test for all 34 districts gives b = −0.889 with t = −24.35 (Table 2), so the null hypothesis of convergence to a single steady state is rejected decisively and H1 is not supported. The clustering algorithm identifies eight initial clubs and five districts that cannot form a core with any other district: Mumbai, Thane, Pune, Satara and Nandurbar. In every initial club the log t statistic exceeds −1.65, so the null of convergence within the club is not rejected. This includes Club 8 (Buldhana and Gadchiroli), whose negative coefficient is far from significant (t = −0.02) because of its very large standard error. The point estimates of b all lie between 0 and 2, indicating relative rather than level convergence within clubs. With only seven regression observations and standard errors of 0.11 to 0.17, the differences in b between clubs are not precisely estimated and should not be read as differences in convergence speed.

Table 2 Phillips–Sul Log t Test: Full Panel and Initial Club Classification

Group	Districts	n	b	SE	t
Full panel	All districts	34	−0.889	0.037	−24.35*

Club 1	Nagpur, Raigad	2	0.299	0.136	2.20
Club 2	Kolhapur, Nashik, Sindhudurg, Solapur	4	0.278	0.145	1.92
Club 3	Ahmednagar, Ratnagiri, Sangli, Wardha	4	0.105	0.113	0.93
Club 4	Aurangabad, Chandrapur	2	0.244	0.136	1.79
Club 5	Akola, Amravati, Latur	3	0.085	0.134	0.64
Club 6	Bhandara, Dhule, Gondia, Hingoli, Jalgaon, Nanded	6	0.244	0.165	1.48
Club 7	Beed, Jalna, Osmanabad, Parbhani, Washim, Yavatmal	6	0.161	0.129	1.25
Club 8	Buldhana, Gadchiroli	2	−0.072	3.398	−0.02
Non-convergent	Mumbai, Nandurbar, Pune, Satara, Thane	5	−0.882	0.036	−24.65*

Note. Dependent series: Hodrick–Prescott trend ($\lambda = 400$) of log real per capita District Domestic Product, 2011–12 to 2021–22; first four years discarded ($r = 1/3$). Clubs are ordered by final-year income. Estimated with psecta in Stata (Du, 2017). b is the log t coefficient. * The null hypothesis of convergence is rejected at the 5% level ($t < -1.65$).

Club Merging and the Final Club Structure

Table 3 reports the merging tests. Three adjacent pairs pass: Clubs 3 and 4 ($t = -0.63$), Clubs 5 and 6 ($t = -1.09$) and Clubs 6 and 7 ($t = -0.57$). Because Clubs 5 and 6 and Clubs 6 and 7 cannot both be merged, the von Lyncker–Thoennessen rule merges the pair with the larger statistic, Clubs 6 and 7. No further merger passes, and the sequential rule of Phillips and Sul (2009) leads to the same number of clubs.

Reassignment then places Satara in the merged Club 3 and Nandurbar with Buldhana and Gadchiroli. Mumbai, Thane and Pune cannot be placed in any club, and none of them converges with another: the pairwise statistics are −20.12 for Mumbai and Thane, −14.54 for Mumbai and Pune and −5.14 for Thane and Pune.

Table 3 Merging Tests for Adjacent Initial Clubs

Clubs tested	n	b	t	Decision
1 + 2	6	−0.788	−19.54*	Not merged
2 + 3	8	−0.337	−4.93*	Not merged
3 + 4	6	−0.058	−0.63	Merged
4 + 5	5	−0.965	−33.83*	Not merged
5 + 6	9	−0.120	−1.09	Passes; not merged (6 + 7 larger)
6 + 7	12	−0.065	−0.57	Merged
7 + 8	8	−0.532	−13.40*	Not merged
8 + non-convergent	7	−0.903	−25.84*	Not merged

Note. Estimated with scheckmerge in Stata (Du, 2017). Merging follows von Lyncker and Thoennessen (2017). * The null hypothesis of convergence is rejected at the 5% level.

The final structure, in Table 4 and Figure 2, consists of six clubs and three non-convergent metropolitan districts. Club 1 (Nagpur and Raigad) and Club 2 (Kolhapur, Nashik, Sindhudurg and Solapur) form an upper tier below the metropolitan districts.

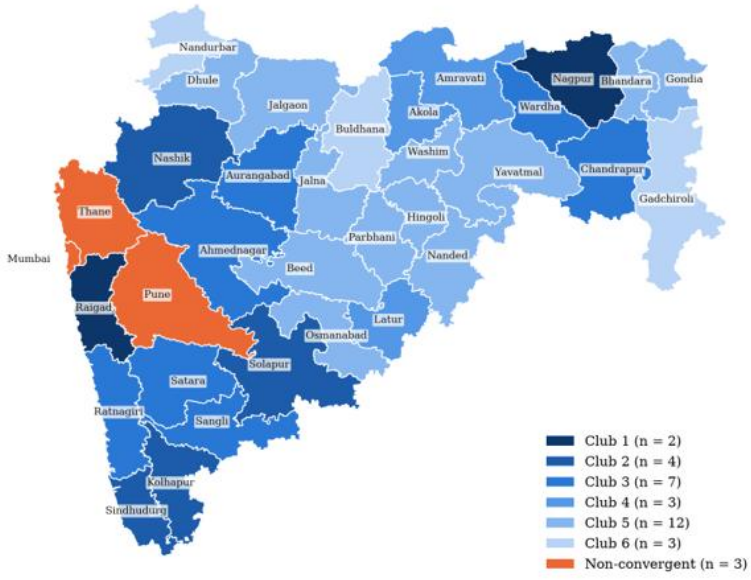
Club 3 brings together seven districts with established industrial towns, including Aurangabad, Ahmednagar and Satara. Clubs 4 and 5 contain most of Marathwada and Vidarbha, and Club 6 groups three of the poorest districts, Buldhana, Gadchiroli and Nandurbar.

Table 4 Final Convergence Clubs After Merging and Reassignment

Club	Districts	n	b	SE	t	Mean PCDDP 2021–22 (₹)
1	Nagpur, Raigad	2	0.299	0.136	2.21	185,719
2	Kolhapur, Nashik, Sindhudurg, Solapur	4	0.278	0.145	1.91	153,362
3	Ahmednagar, Aurangabad, Chandrapur, Ratnagiri, Sangli, Satara, Wardha	7	−0.051	0.093	−0.54	136,433
4	Akola, Amravati, Latur	3	0.085	0.134	0.63	112,470
5	Beed, Bhandara, Dhule, Gondia, Hingoli, Jalgaon, Jalna, Nanded, Osmanabad, Parbhani, Washim, Yavatmal	12	−0.065	0.114	−0.57	104,031
6	Buldhana, Gadchiroli, Nandurbar	3	−0.392	0.390	−1.00	82,971
Non-convergent	Mumbai, Thane, Pune	3	—	—	—	236,810

Note. PCDDP = real per capita District Domestic Product at 2011–12 prices. Estimates for merged and reassigned clubs are from the Python replication of the psecta estimator described in the text. In no club is the null hypothesis of convergence rejected at the 5% level.

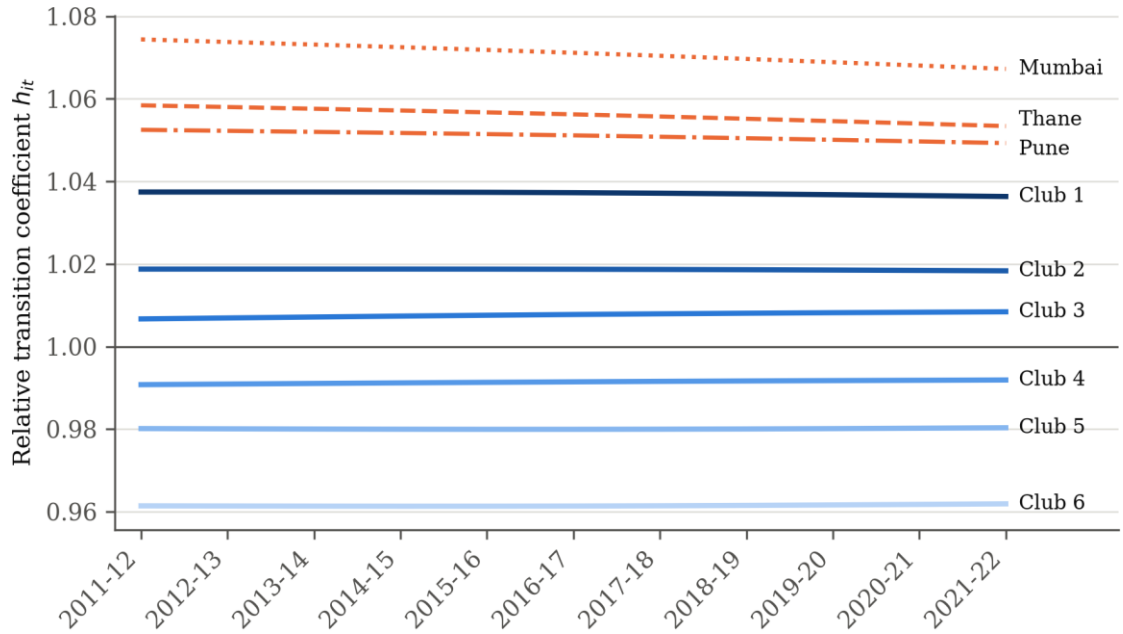
Figure 2 Convergence Clubs in Maharashtra, 2011–12 to 2021–22



Note. District boundaries are from the 2011 Census (DataMeet, CC BY 4.0). Mumbai combines Mumbai City and Mumbai Suburban; Thane includes Palghar. Clubs are ordered from highest (1) to lowest (6) income.

Figure 3 shows the relative transition paths. The club averages are close to flat, so relative positions changed little over the decade and the ranking of clubs is preserved. The three metropolitan districts lie well above all clubs and drift slowly towards the state average, yet they do so on separate paths: the gaps between them do not narrow, which is why they fail the test both with one another and with the clubs below them. This pattern supports H2. It also shows that rejecting convergence for the full panel reflects persistent stratification, not a widening gap between rich and poor districts.

Figure 3 Relative Transition Paths by Convergence Club



Note. The relative transition coefficient h_{it} is the ratio of a district's filtered log per capita income to the cross-section average; club lines are club means. A value of 1 equals the state average.

Robustness

Table 5 reports alternative specifications. Rejection of convergence for the full panel holds in every case. The finding that Mumbai, Thane and Pune do not converge holds in every filtered specification, including the pre-pandemic sample that ends in 2019–20. Club membership is reasonably stable when fewer initial years are discarded or a smaller smoothing parameter is used (adjusted Rand index between 0.63 and 0.83 relative to the baseline; Hubert & Arabie, 1985). It is less stable in the pre-pandemic sample, which has only nine years and yields a more fragmented structure. Without filtering, the year-to-year volatility of district income dominates and the algorithm finds only two broad groups. This is consistent with Phillips and Sul's (2007) advice to remove the cyclical component before testing.

Table 5 Robustness of the Phillips–Sul Results

Specification	Full-panel t	Clubs	Non-convergent districts	ARI
Baseline: HP λ = 400, first 4 years discarded	−23.97*	6	Mumbai, Thane, Pune	1.00
First 3 years discarded	−19.78*	7	Mumbai, Thane, Pune	0.83
First 2 years discarded	−15.77*	7	Mumbai, Thane, Pune, Chandrapur, Beed, Nandurbar	0.63
HP λ = 100	−16.24*	5	Mumbai, Thane, Pune	0.73

Unfiltered log series	−4.16*	2	None	0.15
Pre-pandemic, 2011–12 to 2019–20, first 3 years discarded	−36.90*	9	Mumbai, Thane, Pune, Kolhapur, Nashik, Sindhudurg	0.32

Note. All rows use the Python replication, including merging and reassignment, so the baseline t differs slightly from the Stata value in Table 2. ARI = adjusted Rand index of agreement with the baseline classification (1 = identical). * The null hypothesis of convergence is rejected at the 5% level.

Manufacturing and the Club Structure

Table 6 compares the clubs' manufacturing profiles. Organised manufacturing is heavily concentrated at the top. The three non-convergent metropolitan districts account for 55.9% of state manufacturing GVA, and Clubs 1 and 3 for a further 31.0%. Clubs 4 and 6 together account for less than 1%. The median district in the metropolitan group has more than 4,600 factories, against 77 in Club 5 and 28 in Club 6. Labour productivity is less clearly ordered. It is highest in Club 1, where Raigad's petrochemical complex yields GVA of ₹39.5 lakh per worker, and several lower-club districts record moderate productivity on a very small base.

Table 6 Manufacturing Profile of the Convergence Clubs, Average of 2017–18 to 2020–21

Club	n	Share of state manufacturing GVA (%)	Median factories	Median GVA per worker (₹ lakh)	PCDDP growth, 2011–21 (% per year)
Non-convergent	3	55.86	4,618	17.31	3.28
1	2	16.72	1,228	25.77	3.70
2	4	9.17	859	8.72	3.77
3	7	14.31	437	14.60	3.92
4	3	0.51	164	9.81	3.95
5	12	3.24	77	11.84	4.02
6	3	0.20	28	6.75	3.88

Note. Manufacturing indicators are four-year averages from Annual Survey of Industries district tables at current prices, aggregated to 34 districts. PCDDP growth is the mean compound annual growth rate of real per capita District Domestic Product across the districts in each club.

Rank correlations confirm the pattern. Across the 34 districts, manufacturing GVA is strongly correlated with the level of per capita DDP in 2021–22 ($\rho = 0.74$, $p < .001$), as are the number of factories ($\rho = 0.72$) and workers ($\rho = 0.77$). GVA per worker is more weakly correlated with income ($\rho = 0.35$, $p = .041$). None of these indicators is correlated with growth in per capita DDP over the decade: the correlation for GVA is −0.19 ($p = .28$) and for GVA per worker 0.00 ($p = .98$). Manufacturing therefore maps onto the hierarchy of income levels that defines the clubs, which supports H3, but it does not distinguish faster-growing from slower-growing districts. This combination is what cumulative causation predicts: an established industrial base sustains a district's relative position without generating catch-up elsewhere.

A Typology of District Manufacturing

The silhouette criterion favours two clusters (average silhouette width 0.40, against 0.28 for three clusters and 0.25 to 0.26 for four to six). Table 7 reports the cluster centroids. Cluster 1 groups districts with a larger, more productive and more value-adding manufacturing base. Its typical district has GVA of about ₹5,100 crore, GVA per worker of ₹15.9 lakh, 60 workers per factory and a GVA-to-output ratio of 0.19. Cluster 2

groups districts with a small base, about ₹170 crore of GVA, ₹6.5 lakh per worker, 30 workers per factory and a ratio of 0.09.

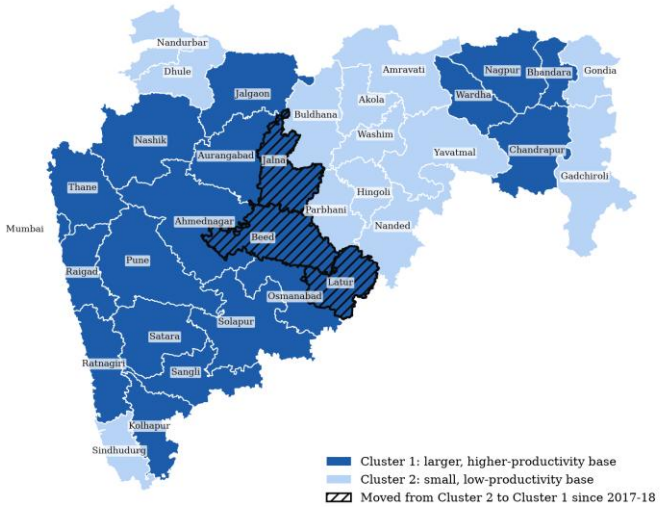
Table 7 K-Means Typology of District Manufacturing: Cluster Centroids and Membership

	Cluster 1: larger, higher-productivity base	Cluster 2: small, low-productivity base
GVA (₹ crore)	5,112	173
GVA per worker (₹ lakh)	15.9	6.5
Workers per factory	59.8	30.3
GVA / output	0.19	0.09
Districts, 2017–18	18	16
Districts, 2020–21	21	13
Members, 2020–21	Ahmednagar, Aurangabad, Beed, Bhandara, Chandrapur, Jalgaon, Jalna, Kolhapur, Latur, Mumbai, Nagpur, Nashik, Osmanabad, Pune, Raigad, Ratnagiri, Sangli, Satara, Solapur, Thane, Wardha	Akola, Amravati, Buldhana, Dhule, Gadchiroli, Gondia, Hingoli, Nanded, Nandurbar, Parbhani, Sindhudurg, Washim, Yavatmal

Note. Centroids are back-transformed from the standardised log scale and so correspond to geometric means. Clustering uses pooled 2017–18 and 2020–21 observations for 34 districts (k = 2 selected by silhouette width). Beed, Jalna and Latur moved from Cluster 2 to Cluster 1 between 2017–18 and 2020–21.

Only three districts changed cluster between 2017–18 and 2020–21: Beed, Jalna and Latur, all in Marathwada, moved into Cluster 1 (Figure 4). The typology corresponds closely to the club structure. All metropolitan districts and all members of Clubs 1 and 3 are in Cluster 1, and all members of Club 6 are in Cluster 2. Clubs 4 and 5 are split between the two. Given the short and nominal ASI window, these movements should be read as signs of emerging industrial capability in parts of Marathwada rather than as a durable shift.

Figure 4 K-Means Typology of District Manufacturing, 2020–21



Note. Hatched districts moved from Cluster 2 to Cluster 1 between 2017–18 and 2020–21. Boundaries as in Figure 2.

DISCUSSION

The results answer the two research questions clearly. On RQ1, Maharashtra's districts are not converging towards a common income level. They form six convergence clubs, and the three metropolitan districts each follow a separate path above them. Dispersion has not risen over the decade, and lower-income districts have grown marginally faster on average, but the club structure and the very long half-life imply that existing gaps will persist without a change in the forces that sustain them. The appropriate description is persistent stratification, not cumulative divergence. This distinction matters for interpretation, because a strongly negative full-panel log t statistic is often read as evidence that inequality is rising, which these data do not show.

On RQ2, the club hierarchy closely follows the hierarchy of manufacturing capacity, while manufacturing indicators do not explain who grows faster. This is consistent with the cumulative causation and new economic geography accounts set out above. Agglomeration in the Mumbai–Pune corridor and in a few secondary centres, notably Nagpur, Raigad, Nashik and Aurangabad, sustains their relative positions, and spread effects to the rest of the state are weak. It also echoes Rodrik's (2013) distinction between manufacturing productivity and aggregate income: the organised sector can be productive and growing in a few districts without lifting incomes in districts where it is small. The finding that Raigad, Ratnagiri and Chandrapur have high GVA per worker but sit in the middle or lower-middle tiers is a reminder that capital-intensive enclaves do not by themselves raise district incomes, a point also made by earlier studies of rising capital intensity in the state (Burange, 1999, 2004).

Two qualifications apply. First, the association between manufacturing and club position is cross-sectional and covers only four years of ASI data, so it should not be read as a causal effect of manufacturing on income. Reverse causation, in which richer districts attract manufacturing, is equally consistent with these results. Second, the metropolitan non-convergence result partly reflects the fact that Mumbai, Thane and Pune are each large, distinctive economies whose income is driven by services as well as manufacturing.

Policy Implications

Three implications follow. First, because districts form clubs, regional policy can be designed for groups of districts with shared trajectories rather than district by district. Clubs 5 and 6, which contain fifteen districts across Marathwada, Vidarbha and northern Maharashtra, are natural units for coordinated investment in industrial infrastructure, connectivity and skills, in line with the district-indicator approach recommended by the Kelkar Committee (Government of Maharashtra, 2013). Second, the weak link between manufacturing and growth suggests that attracting large, capital-intensive plants is not sufficient. Policy should favour labour-absorbing manufacturing and the micro, small and medium enterprises in which Maharashtra already has a large presence, and should strengthen linkages between existing secondary centres such as Aurangabad, Nagpur and Nashik and their hinterlands. Third, the entry of Beed, Jalna and Latur into the larger-base manufacturing cluster indicates that capability can spread along existing corridors. Monitoring such movements with district-level ASI data, as these become available for more years, would allow policy to identify and support emerging centres early.

CONCLUSION

This study applied the Phillips–Sul club convergence framework to real per capita income in Maharashtra's districts and linked the resulting structure to the distribution of organised manufacturing. Convergence to a single steady state is firmly rejected, but dispersion has not widened. Districts instead fall into six persistent clubs, and the metropolitan districts of Mumbai, Thane and Pune remain apart. Manufacturing capacity tracks the hierarchy of income levels but not the pace of growth, consistent with cumulative causation sustaining relative positions.

The study has limitations that suggest directions for further work. The income panel spans eleven years, short by the standards of the log t test, and the ASI district data cover only four years at current prices. Several districts, notably Hingoli and Washim, show unusually large increases in per capita DDP in 2021–

22 that may reflect data revisions, and these affect the final-year ordering used by the clustering algorithm. The 34-unit panel also cannot separate Mumbai City from Mumbai Suburban or Palghar from Thane. Future research could extend the ASI series to 2022–23 and 2023–24, deflate manufacturing values, model the determinants of club membership with ordered response methods (Bartkowska & Riedl, 2012), and examine sectoral convergence within the state.

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Data Availability Statement

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APPENDIX

Table A1 District Data, Club Membership and Manufacturing Cluster

District	PCDDP 2011–12 (₹)	PCDDP 2021–22 (₹)	Growth (% per year)	Club	Manufacturing GVA share (%)	GVA per worker (₹ lakh)	Cluster 2017–18	Cluster 2020–21
Mumbai	196,681	266,428	3.08	NC	9.40	18.9	1	1
Thane	164,223	226,517	3.27	NC	17.61	14.7	1	1
Pune	154,422	217,485	3.48	NC	28.85	17.3	1	1
Nagpur	133,613	188,731	3.51	1	3.49	12.1	1	1
Raigad	124,861	182,706	3.88	1	13.22	39.5	1	1
Kolhapur	116,907	158,034	3.06	2	2.99	9.5	1	1
Sindhudurg	105,306	154,850	3.93	2	0.04	4.9	2	2
Solapur	101,660	150,794	4.02	2	1.08	7.9	1	1
Nashik	100,641	149,769	4.06	2	5.06	14.6	1	1
Ratnagiri	95,441	143,225	4.14	3	1.98	33.4	1	1
Sangli	102,792	140,911	3.20	3	1.02	10.2	1	1
Ahmednagar	91,207	139,222	4.32	3	1.35	12.0	1	1
Satara	95,204	137,701	3.76	3	2.43	14.6	1	1
Aurangabad	94,660	134,561	3.58	3	6.20	18.7	1	1
Wardha	86,031	130,850	4.28	3	0.37	8.4	1	1
Chandrapur	85,475	128,562	4.17	3	0.95	27.3	1	1
Akola	79,873	115,417	3.75	4	0.12	9.8	2	2
Hingoli	56,697	114,912	7.32	5	0.04	10.1	2	2
Latur	76,571	112,533	3.93	4	0.29	14.4	2	1
Amravati	72,744	109,461	4.17	4	0.10	6.1	2	2
Dhule	79,022	109,055	3.27	5	0.22	7.2	2	2
Osmanabad	78,823	107,087	3.11	5	0.16	13.7	1	1
Jalgaon	77,998	106,482	3.16	5	1.26	13.6	1	1
Bhandara	74,769	104,541	3.41	5	0.26	16.1	1	1

Gondia	71,894	103,995	3.76	5	0.01	1.9	2	2
Jalna	74,892	103,380	3.28	5	0.42	13.3	2	1
Nanded	69,516	102,728	3.98	5	0.11	9.9	2	2
Washim	58,245	101,916	5.75	5	0.06	18.3	2	2
Parbhani	73,617	100,225	3.13	5	0.12	9.0	2	2
Yavatmal	62,972	99,931	4.73	5	0.50	17.5	2	2
Beed	67,661	94,125	3.36	5	0.08	10.4	2	1
Buldhana	55,630	88,946	4.80	6	0.13	6.8	2	2
Gadchiroli	60,440	80,631	2.92	6	0.02	7.8	2	2
Nandurbar	54,115	79,337	3.90	6	0.04	5.1	2	2

Note. PCDDP = real per capita District Domestic Product at 2011–12 prices. NC = non-convergent. Manufacturing indicators are 2017–18 to 2020–21 averages. Districts are ordered by PCDDP in 2021–22.