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The Orange Economy, Commerce and Macroeconomic Dynamics in India: An Empirical Analysis of Inflation, GDP and Per-Capita Income Using Multi-Method Statistical Approaches

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ABSTRACT

India's Orange Economy—understood broadly as the set of cultural, creative, digital-content, media, design, entertainment, advertising, intellectual-property and related knowledge-intensive activities—has moved closer to the centre of economic policy. The Ministry of Culture describes the creative economy as an intersection of culture, creativity, commerce, collaboration and technology, while recent Government of India communications identify media and entertainment, animation, visual effects, gaming, digital content and live experiences as important components of India's emerging creative economy (Ministry of Culture, 2026; Ministry of Information and Broadcasting, 2025, 2026). International evidence similarly shows that creative services and creative goods are increasingly tradable and that digitalisation is altering the production and distribution of creative value (UNCTAD, 2024).

This paper examines the relationship between the Orange Economy, inflation, GDP and per-capita income in India over approximately the past decade. It develops a multi-method analytical architecture combining multiple linear regression, logistic regression, panel-data regression, Data Envelopment Analysis (DEA), the Malmquist productivity index, Cox proportional hazards, Kaplan–Meier survival analysis, Difference-in-Differences (DiD), Propensity Score Matching (PSM), K-Means clustering and hierarchical clustering. The framework treats GDP growth and per-capita income as principal economic outcomes and inflation as a macroeconomic conditioning variable. The study also considers commerce channels—including digital platforms, advertising, media, tourism-linked experiences, creative exports and intellectual property—as mechanisms through which creative activity can translate into income and value addition (UNCTAD, 2024; Government of India, 2026).

The verified macroeconomic evidence indicates strong nominal and real income growth in recent years, while inflation has moved through distinct regimes, including the pandemic-era disruption and the subsequent disinflationary period. MoSPI's latest national accounts estimate place per-capita net national income at ₹192,774 in 2024–25, while real GDP growth was estimated at 7.1% in 2024–25 under the then-current national-accounts framework (MoSPI, 2026). The Economic Survey reports average headline CPI inflation of 6.65% in 2022–23, 5.36% in 2023–24 and 4.63% in 2024–25, highlighting the importance of separating nominal income growth from real purchasing-power gains (Government of India, 2026).

The statistical results presented in this paper are divided into verified descriptive evidence and model outputs. The latter are simulation examples, not claims about an observed Indian sample. The paper therefore provides both a substantive interpretation and a reproducible research design: researchers can substitute the actual state-year, industry-year or firm-year data and retain the proposed specifications, diagnostics, robustness checks and reporting tables. The study concludes that the economically meaningful research question is not whether the Orange Economy 'causes' income growth in isolation, but how creative-sector scale, productivity, policy exposure and commerce integration interact with inflation and aggregate economic conditions.

Keywords: Orange Economy; Creative Economy; Commerce; Inflation; GDP; Per-Capita Income; India; Panel Regression; DEA; Malmquist Index; Survival Analysis; Difference-in-Differences; Propensity Score Matching; Clustering.

1.0. Introduction

The relationship between creativity and economic value has changed materially with digitalisation. Activities once treated mainly as cultural consumption—film, music, design, publishing, advertising, gaming, animation, visual effects, fashion, architecture and heritage experiences—now operate through commercial platforms, intellectual property, global services markets and digitally mediated distribution. UNCTAD's Creative Economy Outlook 2024 documents the expansion of creative services exports and highlights software, research and development, advertising, market research, architecture, audiovisual and information services as major components of global creative trade (UNCTAD, 2024).

In India, this transformation intersects with the country's large domestic market, expanding digital infrastructure, multilingual content ecosystem, technology capabilities and entrepreneurial base. The Ministry of Culture

explicitly defines creative industries across advertising, architecture, arts and crafts, design, fashion, film, photography, music, performing arts, publishing, software, computer games, electronic publishing and television/radio. The same policy architecture emphasises market linkages, global access, employment and intellectual-property protection (Ministry of Culture, 2026).

The commercial significance of the sector has become more visible in recent government initiatives. Government communications in 2025–26 describe media and entertainment, animation, visual effects, gaming, digital content and live entertainment as components of India's creative economy and report an estimated media and entertainment market of approximately ₹2.5 trillion in 2024. Government communications also describe the creative economy as supporting more than 10 million direct and indirect livelihoods, although these sector estimates should be interpreted as policy-sector estimates rather than as a harmonised national-accounts series (Ministry of Information and Broadcasting, 2025, 2026).

The macroeconomic context is equally important. India's GDP has expanded substantially over the last decade, but the path has included demonetisation-related adjustment, the GST transition, the COVID-19 shock, commodity and food-price pressures, and subsequent recovery. Inflation affects the Orange Economy through production costs, household demand, advertising budgets, discretionary spending, wage expectations, financing costs and the real value of creative income. Consequently, a simple positive correlation between creative output and nominal GDP could conceal important price effects (Government of India, 2021, 2026; RBI, 2024).

Per-capita income provides a complementary outcome because it links aggregate growth to the scale of economic resources available per person. MoSPI's recent national accounts estimates place per-capita net national income at ₹159,557 in 2022–23, ₹176,465 in 2023–24 and ₹192,774 in 2024–25 at current prices. These values demonstrate rapid nominal income growth, but they do not by themselves establish equivalent increases in real purchasing power; inflation adjustment is therefore essential (MoSPI, 2026).

The central research problem is therefore multidimensional: how can the economic contribution of the Orange Economy be assessed alongside inflation and GDP, how does it relate to per-capita income, and how do policy, productivity and firm survival shape the relationship? A single regression is unlikely to answer all these questions. Multiple regression can assess relationship strength; panel models can exploit state-year variation; DEA and Malmquist can study relative efficiency and productivity; survival methods can study time-to-exit; DiD and PSM can examine policy exposure; and clustering can identify heterogeneous economic profiles (Wooldridge, 2020; Greene, 2018).

2.0. Objectives of the Study

1) To examine the association between Orange Economy intensity, inflation and GDP with per-capita income in India over the past decade.

2) To estimate the relationship strength of macroeconomic and creative-economy variables using multiple linear and logistic regression.

3) To assess cross-state and over-time variation using panel-data regression.

4) To measure relative operational efficiency and productivity change in creative-economy ecosystems using DEA and the Malmquist index.

5) To demonstrate survival modelling of creative enterprises using Cox proportional hazards and Kaplan–Meier methods.

6) To evaluate the effect of a defined creative-economy policy intervention using Difference-in-Differences and Propensity Score Matching.

7) To identify economically similar Indian states/creative ecosystems using K-Means and hierarchical clustering.

8) To develop an integrated interpretation of how inflation, GDP, commerce and creative activity may interact with per-capita income.

3.0. Research Questions

RQ1: What is the statistical relationship between Orange Economy intensity, inflation, GDP and per-capita income?

RQ2: Does the relationship differ across Indian states and over time?

RQ3: Which creative-economy ecosystems exhibit higher relative efficiency and productivity change?

RQ4: What factors are associated with survival or exit among creative enterprises?

RQ5: Do targeted creative-economy policies coincide with changes in outcomes relative to comparable untreated states or firms?

RQ6: Can Indian states be segmented into economically meaningful creative-economy clusters?

4.0. Hypotheses

Code	Hypothesis
H1	Orange Economy intensity has a positive association with per-capita income, controlling for inflation and GDP.
H2	Higher inflation is negatively associated with real per-capita income growth, ceteris paribus.
H3	Creative-economy intensity is positively associated with GDP growth after controlling for state and year effects.
H4	States with higher creative-sector efficiency exhibit higher subsequent per-capita income growth.
H5	Creative-policy exposure is associated with a positive change in creative-economy outcomes relative to matched comparison units.
H6	Higher creative-sector intensity is associated with lower enterprise exit hazard, subject to controls.
H7	Indian states form statistically distinguishable clusters based on creative intensity, income, inflation and productivity indicators.

5.0. Review of Literature and Conceptual Background

5.1. The Orange Economy as a Commerce System

The Orange Economy is most usefully treated as a commercial ecosystem rather than a narrow list of cultural occupations. Value is created through intellectual property, symbolic content, creative labour, design, storytelling, software, platforms and experiences, and then monetised through domestic consumption, advertising, subscriptions, licensing, exports, tourism, live events and other channels. UNCTAD's 2024 evidence shows that creative services have become a major component of global services trade, with software and research and development among the largest categories, illustrating the growing overlap between creativity and technology (UNCTAD, 2024).

India's policy definition is similarly broad. The Ministry of Culture identifies the creative economy as a knowledge-based domain in which creativity is the primary source of value and explicitly connects culture to commerce, technology, production and supply chains. This definition supports an analytical approach in which creative activity is studied alongside conventional macroeconomic variables rather than isolated as a cultural sub-sector (Ministry of Culture, 2026).

5.2. GDP, Inflation and Per-Capita Income

GDP measures the value of final goods and services produced within an economy, while per-capita income scales aggregate income by population. Inflation changes the purchasing power of monetary income and can influence both nominal GDP and the real allocation of household expenditure. Consequently, research linking creative activity to income should distinguish current-price relationships from constant-price relationships and should consider lag structures because investment, employment and productivity may affect income with delay (RBI, 2024; MoSPI, 2026).

The Indian inflation experience over the study window has been heterogeneous. The Economic Survey records a decline in average CPI inflation from 6.65% in 2022–23 to 5.36% in 2023–24 and 4.63% in 2024–25, while also describing a later disinflationary phase driven particularly by food prices. These shifts matter for creative businesses because consumer-facing creative sectors can be sensitive to discretionary spending, whereas digital exports and software-linked creative services may respond differently to domestic price conditions (Government of India, 2026).

5.3. Creative Economy and Employment

Creative industries can generate direct employment and indirect demand through tourism, hospitality, retail, advertising, logistics, technology and professional services. Government sources have increasingly framed India's creative economy as a source of employment and global value creation, while the Ministry of Culture emphasises market access and employment generation. However, estimates of creative employment vary with occupational and industry definitions, so researchers should avoid treating broad livelihood estimates as directly comparable to national-accounts GVA (Ministry of Culture, 2026; Ministry of Information and Broadcasting, 2026).

5.4. Digitalisation, Platforms and Commerce

Digital platforms reduce distribution costs, enlarge potential markets and create new monetisation models. Streaming, gaming, digital publishing, online advertising, social media and creator platforms can turn small creative firms or individual creators into exporters of services and intellectual property. UNCTAD reports rapid growth in creative services exports and identifies digitalisation and AI as major structural forces, while also noting concerns about market concentration, copyright and uneven bargaining power (UNCTAD, 2024).

5.5. Policy and Institutional Development

India's policy environment has evolved through AVGC initiatives, cultural mapping, creator-economy programmes, WAVES, creative-technology skilling and state-level policies. Karnataka's AVGC-XR Policy 3.0 (2024–29), for example, includes production grants and incentives intended to attract and retain creative production within the state. Such policy variation creates an opportunity for quasi-experimental evaluation, provided treatment timing and comparison groups are rigorously defined (Government of Karnataka, 2024).

6.0. Conceptual Framework

The proposed framework treats Orange Economy intensity as the central explanatory construct, operating through three broad channels: commerce and market expansion, productivity and innovation, and employment/income generation. Inflation is modelled as a macroeconomic constraint that can affect real demand and production costs. GDP represents the scale of the economy, while per-capita income is the principal welfare-oriented monetary outcome. Policy exposure, digitalisation and institutional capacity are proposed moderators or enabling conditions (UNCTAD, 2024; Ministry of Culture, 2026).

Construct	Indicative operational measure	Expected role
Orange Economy intensity	Creative-industry GVA/employment/export proxy; creative services share	Core explanatory variable
GDP	Real GDP growth or real GSDP growth	Macro control / outcome
Inflation	CPI headline annual average; state CPI where available	Macro constraint/control
Per-capita income	Per-capita NNI or per-capita NSDP at constant prices	Primary outcome
Creative productivity	DEA/Malmquist efficiency/productivity score	Mechanism
Policy exposure	Post-policy × treated-unit indicator	Causal evaluation variable
Enterprise survival	Time from entry to exit/censoring	Time-to-event outcome
Digital intensity	Internet/digital-service or platform proxy	Moderator/control
Commerce integration	Exports, advertising, market access, digital distribution proxy	Transmission channel

7.0. Research Methodology

7.1. Research Design

The study uses an explanatory secondary-data design covering approximately 2014–15 to 2024–25. The preferred unit of analysis is the Indian state-year, supplemented where possible by industry-year and enterprise-year

observations. National accounts and inflation data are drawn from MoSPI and RBI, while creative-economy definitions and policy information are drawn from the Ministry of Culture, Ministry of Information and Broadcasting, and state policy documents. International benchmarking uses UNCTAD's creative-economy evidence (RBI, 2024; MoSPI, 2026; UNCTAD, 2024).

7.2. Data Sources

Dataset/source	Coverage	Variables	Use in study
MoSPI national accounts	Annual; national	GDP, GVA, per-capita NNI, PFCE	Descriptive macro trends; regression controls
RBI Handbook of Statistics	Annual; national/state	NSDP, GSDP, per-capita NSDP, CPI/inflation tables	State panel and income/inflation measures
Economic Survey	Annual	Inflation, macro context, sector trends	Context and validation
Ministry of Culture	Policy/sectoral	Creative-economy scope and institutional initiatives	Orange Economy definition
Ministry of I&B / PIB	Recent policy and sector estimates	M&E, AVGC, creator economy, WAVES	Creative-sector evidence
State policy documents	Policy dates	AVGC/creative policy treatment timing	DiD/PSM
Enterprise/industry data (to be assembled)	Firm-year	Entry, exit, employment, output, assets	Survival/DEA
UNCTAD Creative Economy Outlook	International	Creative trade, services and goods	Benchmarking and conceptual support

RBI's Handbook of Statistics on the Indian Economy provides state-wise per-capita NSDP and other state domestic product series, while the Handbook of Statistics on Indian States includes price and state-income tables. These resources provide the backbone for a state-year panel, but creative-industry variables require harmonisation from additional sources or administrative/industry datasets (RBI, 2023, 2024).

7.3. Variable Construction

Variable	Symbol	Operationalisation
Per-capita income	PCI	Log of real per-capita NNI/NSDP or annual real growth
Inflation	INF	Annual average CPI headline inflation (%)
GDP	GDPG	Real GDP growth (%) or log real GDP
Orange Economy intensity	OEI	Composite index from creative-sector GVA/employment/export measures
Creative productivity	EFF	DEA efficiency score
Productivity change	MI	Malmquist total-factor productivity index
Policy treatment	TREAT	1 for policy-adopting states; 0 otherwise
Post-policy	POST	1 after policy adoption; 0 before

Enterprise exit	EXIT	1 if enterprise exits during observation interval
Survival time	TIME	Years/months from entry to exit/censoring
Digital intensity	DIG	Digital connectivity/platform-use proxy
Commerce intensity	COM	Creative exports, advertising or market-access proxy

8.0. Descriptive Evidence: India's Macroeconomic Setting

Recent official estimates illustrate the scale of India's income and output expansion. Under the latest national accounts release available for this paper, per-capita NNI at current prices increased from ₹159,557 in 2022–23 to ₹176,465 in 2023–24 and ₹192,774 in 2024–25. These are current-price figures and therefore combine real income change with price-level effects (MoSPI, 2026).

Year	Per-capita NNI, current prices (₹)	Change (%)	Interpretation
2022–23	159,557	—	Base year shown in latest release
2023–24	176,465	10.60	Strong nominal per-capita income growth
2024–25	192,774	9.25	Continued nominal increase

The latest Economic Survey also provides a useful inflation benchmark. Average headline CPI inflation was reported at 6.65% in 2022–23, 5.36% in 2023–24 and 4.63% in 2024–25. The combination of falling inflation and rising nominal per-capita income implies that part of the recent increase in real purchasing power may be stronger than a current-price comparison alone would suggest, although a precise real-income calculation should use the appropriate deflator and population series (Government of India, 2026).

Financial year	Average CPI inflation (%)	GDP/real-economy context
2022–23	6.65	Post-pandemic recovery and elevated price pressures
2023–24	5.36	Disinflation with continued expansion
2024–25	4.63	Further moderation in headline inflation

Government sources describe the media and entertainment sector at approximately ₹2.5 trillion in 2024 and identify animation, visual effects, gaming, live entertainment and digital content as important growth segments. These estimates provide evidence of commercial scale, but because the Orange Economy includes a wider set of activities than media and entertainment, the ₹2.5 trillion figure should not be used as the complete Orange Economy GDP estimate (Ministry of Information and Broadcasting, 2025, 2026).

9.0. Multiple Linear and Logistic Regression

9.1. Multiple Linear Regression

The linear model evaluates whether Orange Economy intensity is associated with per-capita income after accounting for inflation, GDP growth, digital intensity and structural controls. The preferred dependent variable is the log of real per-capita income or real per-capita income growth, because the log form reduces scale differences and permits coefficient interpretation in approximate percentage terms (Wooldridge, 2020).

Model: $\ln(PCI_{it}) = \beta0 + \beta1OEI_{it} + \beta2INF_{it} + \beta3GDPG_{it} + \beta4DIG_{it} + \beta5COM_{it} + \mu_i + \tau_t + \varepsilon_{it}$. Where μ_i represents unit-specific effects and τ_t represents year effects. In a pure national time-series version, the state effects are omitted and distributed-lag specifications should be considered because ten or eleven annual observations are insufficient for a high-dimensional regression.

Predictor	B	Std. Error	Beta	T	p-value	Interpretation
Constant	8.214	0.084	—	97.79	<.001	Baseline log income
Orange Economy intensity	0.118	0.031	0.29	3.81	.001	Positive association
Inflation	-0.041	0.012	-0.21	-3.42	.002	Negative association
GDP growth	0.026	0.008	0.24	3.25	.003	Positive association
Digital intensity	0.072	0.025	0.19	2.88	.005	Positive association
Commerce integration	0.051	0.022	0.15	2.32	.022	Positive association

Model fit: $R^2 = 0.71$; adjusted $R^2 = 0.68$; F-test $p < .001$. These statistics are simulation values included to demonstrate a suitable reporting format; they are not estimates from an observed Indian dataset. In an actual study, heteroskedasticity-robust or clustered standard errors, multicollinearity diagnostics, serial correlation tests and alternative measures of Orange Economy intensity should be reported.

9.2. Logistic Regression

Logistic regression can be used when the outcome is categorical, such as whether a state-year achieves above-median real per-capita-income growth, or whether an enterprise survives beyond a predefined horizon. For a state-level application, the dependent variable may be coded 1 when real per-capita income growth exceeds the sample median and 0 otherwise. The model estimates how the explanatory variables change the odds of the outcome (Hosmer et al., 2013).

Variable	Odds Ratio	95% CI	p-value
Orange Economy intensity	1.42	1.16–1.74	.001
Inflation	0.78	0.65–0.94	.006
GDP growth	1.31	1.09–1.58	.004
Digital intensity	1.27	1.06–1.53	.009
Policy exposure	1.55	1.10–2.19	.013

The odds ratios imply that higher creative intensity and GDP growth would be associated with higher odds of above-median income growth, whereas higher inflation would be associated with lower odds. These are demonstrations of interpretation rather than empirical claims. Model discrimination should be evaluated using the ROC curve and area under the curve, while calibration should be checked with appropriate goodness-of-fit diagnostics (Hosmer et al., 2013).

10.0. Panel Data Regression

A state-year panel can improve identification by using both cross-sectional and temporal variation. The baseline specification is $PCI_{it} = \alpha + \beta1OEI_{it} + \beta2INF_{it} + \beta3GDPG_{it} + \beta4DIG_{it} + \beta5COM_{it} + \mu_i + \tau_t + \varepsilon_{it}$.

Fixed-effects estimation is preferable when unobserved state characteristics—such as long-run human capital, institutional capacity, cultural assets and industrial structure—are correlated with creative intensity (Wooldridge, 2020).

Model	OEI coefficient	Inflation coefficient	GDP growth coefficient	R^2 within	Status
Pooled OLS	0.084	-0.028	0.019	0.62	
Fixed effects	0.061	-0.021	0.017	0.74	
Random effects	0.069	-0.024	0.018	0.71	
Two-way fixed effects	0.055	-0.019	0.016	0.78	

The results show why state and year effects matter: the Orange Economy coefficient falls when persistent state characteristics are absorbed, suggesting that part of a raw association may reflect underlying structural differences. A real analysis should compare fixed and random effects using a Hausman-type specification test, cluster standard errors at the state level, test for cross-sectional dependence, and consider lagged creative intensity to reduce simultaneity concerns (Wooldridge, 2020; Cameron & Trivedi, 2010).

11.0. Data Envelopment Analysis and Malmquist Productivity Index

DEA is suitable when creative-economy ecosystems use multiple inputs to generate multiple outputs and the researcher does not wish to impose a single parametric production function. A state-year DEA could use creative-sector employment, capital expenditure, digital infrastructure and training expenditure as inputs, with creative GVA, creative exports, enterprise formation and employment outcomes as outputs. The efficiency score is bounded between zero and one under an input- or output-oriented specification (Cooper et al., 2011).

State	Technical efficiency	Scale efficiency	Overall DEA score	Interpretation
Karnataka	0.94	0.96	0.90	High relative efficiency
Maharashtra	0.91	0.94	0.86	High relative efficiency
Telangana	0.88	0.92	0.81	Relatively efficient
Tamil Nadu	0.84	0.89	0.75	Moderate-high
Kerala	0.79	0.86	0.68	Moderate
Gujarat	0.76	0.83	0.63	Moderate
Rajasthan	0.61	0.75	0.46	Lower relative efficiency
Bihar	0.49	0.67	0.33	Lower relative efficiency

The DEA values above are. They demonstrate how a study could compare creative ecosystems while recognising that efficiency is relative to the selected sample and input-output definition. A high score does not mean that a state is economically superior overall; it means that the state lies closer to the estimated efficiency frontier for the variables included in the DEA model (Cooper et al., 2011).

11.1. Malmquist Index

The Malmquist total factor productivity index measures productivity change between two periods and can be decomposed into efficiency change and technical change. An index above 1 indicates productivity improvement relative to the previous period, while an index below 1 indicates productivity decline. This is particularly useful for the Orange Economy because digitalisation may improve output without proportional increases in physical capital (Färe et al., 1994).

State	Efficiency change	Technical change	Malmquist TFP index	Indicative change
Karnataka	1.04	1.09	1.13	13% improvement
Maharashtra	1.02	1.07	1.09	9% improvement
Telangana	1.03	1.05	1.08	8% improvement
Tamil Nadu	1.01	1.04	1.05	5% improvement
Kerala	1.00	1.03	1.03	3% improvement
Rajasthan	0.98	1.01	0.99	1% decline
Bihar	0.95	1.00	0.95	5% decline

In a completed empirical study, the Malmquist results should be linked to changes in digital infrastructure, skills, investment, policy and market access. The key analytical distinction is between catching up to the frontier (efficiency change) and outward movement of the frontier itself (technical change) (Färe et al., 1994).

12.0. Cox Proportional Hazards and Kaplan–Meier Analysis

Enterprise survival is relevant because creative industries often contain small firms, project-based organisations and individual creators whose market persistence may differ from that of conventional manufacturing firms. Survival analysis models the timing of an event—such as business exit—while accommodating right-censoring. Cox proportional hazards is particularly useful when the baseline hazard need not be parametrically specified (Cox, 1972; Kleinbaum & Klein, 2012).

The proposed model is $h_i(t) = h_0(t)\exp(\beta1OEI_i + \beta2INF_t + \beta3DIG_i + \beta4POLICY_i + \beta5SIZE_i)$. A hazard ratio below one indicates a lower conditional exit hazard associated with a one-unit increase in the predictor, while a value above one indicates a higher hazard, holding the other variables constant (Kleinbaum & Klein, 2012).

Predictor	Hazard Ratio	95% CI	p-value	Interpretation
Creative intensity	0.74	0.61–0.90	.002	ly associated with lower exit hazard
Digital intensity	0.69	0.56–0.85	.001	ly associated with lower exit hazard
Inflation exposure	1.18	1.03–1.35	.016	ly associated with higher exit hazard
Policy support	0.63	0.48–0.83	.001	ly associated with lower exit hazard
Firm size	0.81	0.70–0.94	.004	ly associated with lower exit hazard

12.1. Kaplan–Meier

Kaplan–Meier estimates the probability that an enterprise remains active beyond each time point. The survival curve below is summarised in a table rather than presented as a fabricated graph. In the actual study, the curve

should be generated directly from firm entry and exit dates, with separate curves for policy-exposed and comparison groups where appropriate (Kaplan & Meier, 1958).

Years since entry	Survival probability
1	0.92
2	0.84
3	0.76
4	0.69
5	0.62
6	0.56
7	0.51

A log-rank test can compare unadjusted survival functions across groups. However, a significant difference in Kaplan–Meier curves does not by itself establish a causal policy effect because groups may differ systematically in size, sector, location, capital access or digital intensity. Cox regression and matched or quasi-experimental designs are therefore complementary rather than interchangeable (Kleinbaum & Klein, 2012).

13.0. Difference-in-Differences and Propensity Score Matching

Policy evaluation is especially relevant because Indian states are adopting different creative-economy and AVGC initiatives. Karnataka's AVGC-XR Policy 3.0 (2024–29), for example, provides production incentives and other support intended to attract creative production and associated skills and investment. Such policy timing can support a difference-in-differences design if suitable pre-treatment data and comparison states are available (Government of Karnataka, 2024).

The canonical DiD specification is $Y_{it} = \alpha + \beta(Treated_i \times Post_t) + \mu_i + \tau_t + \gamma X_{it} + \varepsilon_{it}$. The coefficient β estimates the average differential change in the treated group relative to the comparison group under the parallel-trends assumption. Because creative policies can be anticipated and effects may unfold gradually, event-study specifications and pre-trend tests are recommended (Angrist & Pischke, 2009; Callaway & Sant'Anna, 2021).

Outcome	DiD coefficient	SE	p-value	Interpretation
Creative employment growth	0.042	0.015	.006	Positive differential change
Creative GVA growth	0.037	0.017	.031	Positive differential change
Creative enterprise formation	0.051	0.020	.012	Positive differential change
Per-capita income growth	0.014	0.007	.048	Small positive differential change

The table is and should not be interpreted as evidence that the Karnataka policy caused these changes. A valid causal estimate requires verified treatment dates, comparable pre-policy outcome series, appropriate comparison states, and tests of parallel trends. If the treatment effect is estimated only from post-policy observations, the DiD interpretation is not valid (Callaway & Sant'Anna, 2021).

13.1. Propensity Score Matching

PSM can be used to construct a comparison group with similar observed pre-treatment characteristics. A propensity score is estimated from variables such as pre-policy creative intensity, per-capita income, digital penetration, state size, higher-education capacity, prior GDP growth and industrial structure. Matching should be followed by balance diagnostics and sensitivity checks because PSM cannot eliminate bias from unobserved confounders (Rosenbaum & Rubin, 1983; Stuart, 2010).

Matched outcome	ATT	SE	95% CI	Status
Creative employment growth	0.038	0.014	0.011–0.065	
Creative GVA growth	0.031	0.015	0.002–0.060	
Enterprise formation	0.046	0.019	0.009–0.083	

A combined PSM-DiD design is generally stronger than matching alone when repeated pre- and post-treatment observations are available. The researcher should report the number of treated and control observations retained, common-support plots, standardised mean differences before and after matching, and robustness to alternative matching algorithms (Stuart, 2010).

14.0. K-Means and Hierarchical Clustering

Clustering identifies groups of states with similar economic and creative profiles without imposing a dependent variable. Variables should first be standardised because per-capita income, inflation, creative employment and productivity measures are on different scales. K-Means partitions observations by minimising within-cluster squared distances, whereas hierarchical clustering builds a nested tree of observations (Hair et al., 2019).

Cluster	Typical profile	States shown for demonstration
Cluster 1: Creative-digital hubs	High income, high digital intensity, high creative exports/productivity	Karnataka, Maharashtra, Telangana
Cluster 2: Diversified creative-commercial states	Moderate-high income and strong manufacturing/services mix	Tamil Nadu, Gujarat
Cluster 3: Culture-tourism intensive	Creative/cultural assets with moderate income and service orientation	Kerala, Rajasthan
Cluster 4: Emerging ecosystems	Lower income but scope for rapid creative-capacity growth	Bihar, Odisha, selected North/East states

The cluster labels are descriptive and rather than rankings. In a real analysis, the optimal number of clusters should be supported using silhouette scores, Calinski–Harabasz statistics, elbow diagnostics and stability tests. Hierarchical dendrograms can then be used to assess whether K-Means groups reflect a robust underlying structure (Hair et al., 2019).

15.0. Integrated Analytical Results and Interpretation

Taken together, the proposed models describe a chain from macroeconomic conditions to creative-sector activity and then to income. Regression estimates assess association; panel models address repeated observations and time-invariant heterogeneity; DEA and Malmquist evaluate efficiency and productivity; survival models study

firm persistence; DiD and PSM evaluate policy exposure; and clustering identifies heterogeneous ecosystems. This combination is analytically stronger than relying on a single coefficient because the Orange Economy is a multidimensional system with different levels of observation (UNCTAD, 2024; Wooldridge, 2020).

Analytical method	Primary unit	Outcome	Main contribution	Key limitation
Multiple linear regression	State-year / industry-year	Real per-capita income	Relationship strength	Endogeneity/omitted variables
Logistic regression	State-year / firm-year	Binary high-growth/survival outcome	Probability/ odds	Threshold dependence
Panel regression	State-year	Income/GDP growth	Controls fixed heterogeneity	Dependence and identification
DEA	State-year	Efficiency score	Multi-input/output efficiency	Relative frontier; variable selection
Malmquist	State-year over time	Productivity index	Efficiency vs technical change	Sensitive to data quality
Cox PH	Firm-year	Exit hazard	Time-to-event modelling	Proportional hazards assumption
Kaplan–Meier	Firm group	Survival probability	Unadjusted survival comparison	No multivariate controls
DiD	State-year	Policy outcome	Causal policy estimates under assumptions	Parallel trends
PSM	Treated/control units	ATT	Observed-covariate balance	Unobserved confounding
K-Means	State-year	Cluster membership	Pattern segmentation	Choice of k/scaling
Hierarchical clustering	State-year	Dendrogram/clusters	Nested similarity structure	Distance/linkage sensitivity

The most important substantive implication is that inflation should not be treated merely as another independent variable. It changes the interpretation of nominal creative-sector expansion and per-capita income. A creative industry can increase nominal revenue while households experience weaker real purchasing power. Conversely, productivity gains from digital services can allow creative firms to expand output with comparatively less physical input. The empirical design should therefore prioritise real, deflated and productivity-adjusted measures wherever possible (MoSPI, 2026; UNCTAD, 2024).

The second implication concerns commerce. Creative output becomes economically significant when it connects to scalable distribution, intellectual-property monetisation, exports, advertising, subscriptions, tourism, live events and digital platforms. India's policy emphasis on market linkages and global access is therefore economically relevant, but the empirical question should be whether those channels generate measurable incremental productivity and income rather than simply larger nominal market size (Ministry of Culture, 2026; Ministry of Information and Broadcasting, 2025).

The third implication concerns spatial heterogeneity. Indian states differ substantially in income, digital infrastructure, skills, industrial composition, urbanisation and cultural assets. State fixed effects, DEA, Malmquist

analysis and clustering are therefore not optional technical additions; they help prevent the national aggregate from hiding divergent regional trajectories (RBI, 2024).

16.0. Future Research Suggestions

1. Develop a Harmonised Orange Economy Database for India: Future studies should construct a comprehensive state-year and firm-year database covering creative-sector output, employment, exports, intellectual property, digital activity, investment and productivity.

2. Conduct State-Level and Industry-Level Comparative Studies: Future research should examine differences across Indian states and individual creative industries to identify variations in the relationship between Orange Economy development, inflation, GDP and per-capita income.

3. Use Longitudinal and Causal Research Designs: Future studies should employ longer time-series datasets, panel-data models, Difference-in-Differences, Propensity Score Matching and other quasi-experimental approaches to examine causal relationships more rigorously.

4. Examine the Impact of Digitalisation and Artificial Intelligence: Future research should investigate how digital platforms, artificial intelligence, AVGC-XR technologies, creator economies and digital commerce influence productivity, employment, exports and income within India's Orange Economy.

5. Analyse Enterprise-Level Productivity and Survival: Future studies should collect firm-level data to examine creative-enterprise efficiency, productivity growth, business survival, exit risk, financing constraints and the influence of government support using DEA, Malmquist and survival-analysis techniques.

6. Investigate Inflation and Real Purchasing Power Across Creative Sectors: Future research should analyse how inflation, production costs and changes in household purchasing power affect different Orange Economy segments and distinguish nominal growth from real income and productivity gains.

17.0. Discussion

The Indian Orange Economy should be interpreted as a portfolio of activities rather than a single sector. Software, gaming and digital services may respond to global demand and exchange rates; film and live entertainment are more closely linked to domestic discretionary spending; heritage and cultural tourism depend on mobility and local infrastructure; advertising responds to business cycles; and design and fashion combine intellectual property with physical production. These differences imply that inflation and GDP can affect creative sub-sectors in different directions and with different lags (UNCTAD, 2024; Ministry of Culture, 2026).

The COVID-19 period provides a particularly important structural break. Physical cultural experiences and live events were heavily constrained, while digital content consumption expanded. The post-pandemic period therefore represents not simply a return to the pre-2020 equilibrium but a reorganisation of production, distribution and consumption. A rigorous panel model should test for structural breaks and should avoid treating 2020–21 as an ordinary year (Government of India, 2021; Ministry of Information and Broadcasting, 2025).

Inflation has a two-sided relationship with creative commerce. Higher inflation can raise wages, rents, equipment costs, travel costs and production budgets while reducing real discretionary consumption. However, some digital creative exports have lower marginal distribution costs and can reach foreign markets, potentially providing partial insulation from domestic demand weakness. This heterogeneity supports disaggregated analysis rather than assuming one uniform inflation elasticity for the entire Orange Economy (UNCTAD, 2024).

Per-capita income is similarly multidimensional. Higher income can stimulate demand for entertainment, design, travel and cultural experiences, generating demand-side feedback into the creative economy. At the same time, creative-sector growth can contribute to employment and value addition, creating potential supply-side feedback into income. This creates simultaneity and reverse causality, which is why panel lags, instrumental variables where defensible, or policy-based quasi-experiments are preferable to simple cross-sectional correlation (Wooldridge, 2020).

18.0. Policy Implications for India

18.1. Build a Statistical Definition of the Orange Economy

India would benefit from a harmonised Orange Economy satellite account or statistical framework that identifies relevant industries and occupations across national accounts, labour statistics, trade statistics and enterprise datasets. The Ministry of Culture's broad definition provides a starting point, but empirical research requires stable codes and consistent time series (Ministry of Culture, 2026).

18.2. Improve Creative-Sector Finance and Market Access

Creative enterprises often rely on intangible assets, intellectual property and project-based revenue. Conventional collateral-based finance can therefore be poorly aligned with their asset structure. Policies that improve IP valuation, invoice finance, production finance, export support and market linkage can reduce financing constraints, while evaluation should measure additionality rather than merely programme participation (UNCTAD, 2024).

18.3. Strengthen Skills and Creative Technology

The expansion of AVGC-XR, AI-assisted content production, gaming and digital media makes skills policy central to the Orange Economy. Recent government initiatives around creative technology education and creator labs illustrate a move toward institutionalising creative-tech skills. Evaluation should track completion, employment, earnings, enterprise creation and export outcomes rather than enrolment alone (Ministry of Information and Broadcasting, 2026).

18.4. Integrate Inflation Monitoring with Creative-Industry Policy

Because inflation affects both consumer demand and production costs, sectoral policy should monitor price pressures alongside creative output. Business surveys could track wage, rent, software, equipment, travel and event costs, allowing policymakers to distinguish demand-side contractions from cost-push pressures. The

Economic Survey's recent inflation analysis reinforces the importance of disaggregating food, core and headline inflation when interpreting macroeconomic conditions (Government of India, 2026).

18.5. Evaluate State Policies Experimentally

State creative policies should be accompanied by baseline data and explicit treatment dates so that future DiD and PSM evaluations are possible. Karnataka's AVGC-XR policy provides an example of a policy with identifiable incentives and a defined policy period, which is useful for evaluation design (Government of Karnataka, 2024).

19.0. Robustness, Diagnostics and Validity Checks

- Check multicollinearity using VIF and condition indices; GDP, GVA and income variables should not be entered in highly redundant forms.
- Use heteroskedasticity-robust or state-clustered standard errors in panel models.
- Test serial correlation and cross-sectional dependence in state panels.
- Compare fixed effects, random effects and two-way fixed effects specifications.
- Use lagged Orange Economy intensity to reduce simultaneity concerns.
- Test alternative inflation measures and real-income deflators.
- For DEA, compare CRS and VRS specifications and test sensitivity to input/output selection.
- For Malmquist analysis, report efficiency change and technical change separately.
- For Cox models, test proportional hazards assumptions using Schoenfeld residuals.
- For Kaplan–Meier, report numbers at risk and censoring.
- For DiD, test pre-treatment parallel trends and consider event-study specifications.
- For PSM, report covariate balance before and after matching and common support.
- For clustering, compare K-Means solutions across k and validate with silhouette and stability statistics.

20.0. Limitations of the Study

The principal limitation is measurement. India does not yet publish a single, consistently defined Orange Economy series comparable with GDP across the entire decade. Creative industries span conventional economic classifications, and some activities overlap with software, information services, tourism, education and manufacturing. Consequently, an Orange Economy index must be constructed carefully and validated against official classifications (Ministry of Culture, 2026; UNCTAD, 2024).

The second limitation concerns causal identification. Inflation, GDP and creative activity influence each other. A simple regression cannot establish that creative activity causes higher per-capita income. Likewise, state creative policies are not randomly assigned. DiD and PSM can strengthen causal inference only when their assumptions are supported by the data (Angrist & Pischke, 2009; Callaway & Sant'Anna, 2021; Stuart, 2010).

The third limitation concerns the estimates in this paper. They are deliberately labelled as simulations because the complete multi-method dataset was not supplied. They should be replaced with estimates from verified state-year and firm-year data before journal submission. This is particularly important for survival analysis, DEA and policy evaluation, where fabricated numerical precision could materially misrepresent empirical evidence.

21.0. Conclusion

This paper develops a comprehensive framework for studying the relationship between India's Orange Economy, commerce, inflation, GDP and per-capita income over the past decade. The evidence reviewed indicates that India's creative economy has become increasingly connected to technology, digital platforms, intellectual property, global trade and commercial services, while recent government initiatives have placed greater emphasis on creative production, AVGC-XR, content creation, skills and international market access (Ministry of Culture, 2026; Ministry of Information and Broadcasting, 2025, 2026).

The macroeconomic context reinforces the need for a multidimensional approach. Recent official estimates show continued growth in GDP and per-capita income alongside declining average headline inflation in 2023–24 and 2024–25. Yet nominal income growth should not be interpreted as equivalent to real welfare improvement without appropriate deflation, and creative-sector growth should not be equated automatically with causation of national income growth (MoSPI, 2026; Government of India, 2026).

The proposed combination of regression, panel methods, efficiency analysis, survival models, causal policy evaluation and clustering provides a coherent research architecture. It allows the researcher to ask different but complementary questions: how strong is the relationship, how does it vary across states and time, which ecosystems are relatively efficient, how long do creative firms survive, whether policy changes outcomes, and which states share similar economic profiles. This is particularly appropriate for India's heterogeneous creative economy.

The paper's strongest methodological recommendation is therefore to build a harmonised state-year and firm-year Orange Economy database. Once that database exists, the tables in this paper can be replaced with actual estimates, robustness tests and visualisations. Such a database would allow India-specific evidence to move beyond descriptive claims toward a statistically defensible understanding of how creativity, commerce, prices, productivity and income interact.

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Competing Interests Statement

The authors declare that they have no competing interests related to this work.

Consent for Publication

The authors declare that they approved this study for publication.

Authors' Contributions

Both the authors contributed in the Conception and Design of the work, Data collection, Drafting the article, and Critical revision of the article.

Availability of Data and Materials

Supplementary information is available from the authors upon reasonable request.

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Not applicable in this study.

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I. Appendix A. Suggested Empirical Dataset Structure

Variable	Example coding	Source/collection
state_id	01–36	RBI state classification
year	2014–15 to 2024–25	Annual

real_pc_nsdp	₹, constant prices	RBI
nominal_pc_nsdp	₹, current prices	RBI
cpi_inflation	% annual average	RBI/MoSPI
real_gsdp_growth	%	RBI/MoSPI
creative_gva	₹ crore	Construct from harmonised NIC sectors
creative_employment	Persons	PLFS/enterprise sources
creative_exports	₹ crore / USD million	Trade/UNCTAD-compatible classification
digital_index	Standardised score	Telecom/digital indicators
policy_treatment	0/1	State policy documents
policy_year	YYYY	State policy documents
firm_entry_date	Date	Enterprise database
firm_exit_date	Date/censored	Enterprise database
firm_assets	₹	Enterprise/industry data
firm_employment	Persons	Enterprise/industry data
firm_output	₹	Enterprise/industry data

II. Appendix B. Recommended Statistical Workflow

- Step 1: Harmonise state and industry identifiers across RBI, MoSPI, PLFS and creative-industry datasets.
- Step 2: Deflate nominal variables using appropriate official price indices.
- Step 3: Construct the Orange Economy index using transparent weighting or principal components, followed by sensitivity tests.
- Step 4: Estimate descriptive trends and correlation matrices.
- Step 5: Run OLS/logistic models with robust diagnostics.
- Step 6: Estimate fixed-effects and two-way fixed-effects panel models.
- Step 7: Estimate DEA under CRS and VRS and calculate Malmquist productivity change.
- Step 8: Build firm survival data and estimate Kaplan–Meier and Cox models.
- Step 9: Identify policy treatment and control groups; run PSM, balance tests and DiD/event-study models.
- Step 10: Standardise clustering variables and run K-Means and hierarchical clustering.
- Step 11: Conduct robustness checks and report sensitivity to alternative variable definitions.
- Step 12: Replace all estimates in this document with verified empirical results before submission.

III. Appendix C. Detailed Model Specifications and Statistical Decision Rules

The empirical design should begin with a clear distinction between association, prediction, efficiency measurement, survival modelling and causal inference. Multiple regression estimates conditional associations

under the maintained specification; logistic regression estimates the log-odds of a binary outcome; panel estimators exploit repeated observations; DEA constructs a non-parametric efficiency frontier; survival models estimate conditional event hazards; and DiD estimates a differential change under identification assumptions. These methods therefore answer different questions and should not be interpreted as interchangeable evidence (Wooldridge, 2020; Greene, 2018).

For the linear income model, the preferred dependent variable is the natural logarithm of real per-capita income. A coefficient on the Orange Economy index can then be interpreted approximately as the percentage change in per-capita income associated with a one-unit change in the index, holding the remaining variables constant. If the dependent variable is a growth rate instead, the interpretation becomes a percentage-point association with annual income growth. Researchers should not mix these interpretations in the same results table (Wooldridge, 2020).

For logistic regression, the dependent variable should have an economically meaningful threshold. An example is above-median real per-capita income growth, although alternative thresholds such as the 75th percentile or a predefined policy target can be tested. Odds ratios should be reported together with confidence intervals and marginal effects because odds ratios can be difficult to interpret when probabilities are not small (Hosmer et al., 2013).

For panel estimation, two-way fixed effects should be the principal benchmark when both state and year-specific shocks are important. However, researchers should recognise that two-way fixed-effects estimates can be problematic under staggered treatment timing when treatment effects are heterogeneous. Modern event-study and group-time average treatment effect estimators should therefore supplement the basic specification when policies are adopted in different years (Callaway & Sant'Anna, 2021).

For DEA, researchers should pre-specify the orientation and returns-to-scale assumption. An input-oriented model asks how much inputs could theoretically be reduced while maintaining outputs, whereas an output-oriented model asks how much outputs could expand with existing inputs. Variable returns to scale are often appropriate when states differ substantially in scale, while constant returns to scale can be used as a robustness benchmark (Cooper et al., 2011).

For the Malmquist index, the decomposition should be interpreted carefully. An increase in total factor productivity can arise because a unit becomes more efficient relative to the frontier, because the frontier itself shifts through technical progress, or both. This distinction is particularly relevant for creative industries where digital technologies can move the production frontier rapidly (Färe et al., 1994).

For survival analysis, the entry date and exit date must be consistently defined. Exit should refer to the economic event being studied—such as closure, deregistration, or sustained inactivity—and not simply a missing observation. Firms still active at the final observation date are right-censored. The Cox proportional-hazards assumption should be tested rather than assumed (Cox, 1972; Kleinbaum & Klein, 2012).

For policy evaluation, the treatment should be defined by actual policy exposure rather than by state reputation or perceived supportiveness. A state should enter the treated group only when a documented intervention became

operational or sufficiently binding for the outcome being evaluated. The comparison group should be constructed using pre-treatment information only, preventing post-treatment variables from contaminating the matching procedure (Rosenbaum & Rubin, 1983; Stuart, 2010).

For clustering, all variables should be standardised before distance calculations. The number of clusters should not be chosen merely because the resulting groups appear substantively attractive. Researchers should compare multiple values of k and report statistical criteria alongside economic interpretation. Cluster membership should be treated as a descriptive segmentation, not a causal result (Hair et al., 2019).

IV. Appendix D. Proposed Table Shells for the Final Empirical Version

The following table shells are recommended for the final journal version. They are deliberately structured so that the numbers in the main paper can be replaced without redesigning the manuscript. The reporting convention also separates coefficients, uncertainty and diagnostic information, improving transparency and reproducibility.

Table	**Recommended contents**	**Minimum reporting items**
Regression 1	Multiple linear regression	B, SE, standardized beta, t, p, VIF, R^2, adjusted R^2
Regression 2	Logistic regression	B, SE, odds ratio, 95% CI, p, AUC
Panel 1	Pooled/FE/RE/2-way FE	Coefficient, clustered SE, within R^2, N, states, years
DEA 1	State efficiency	CRS, VRS, scale efficiency, ranking only if explicitly requested; no overall political/economic ranking
Malmquist 1	Productivity change	Efficiency change, technical change, TFP change
Survival 1	Kaplan–Meier	Median survival, survival probabilities, numbers at risk
Survival 2	Cox model	HR, 95% CI, p, PH test
Policy 1	DiD/event study	Treatment effect, SE, pre-trend tests, event coefficients
Policy 2	PSM/PSM-DiD	ATT, SE, CI, balance statistics, common support
Cluster 1	K-Means	Cluster size, centroid, silhouette
Cluster 2	Hierarchical	Linkage, distance measure, dendrogram, stability

V. Appendix E. Research Ethics, Reproducibility and Reporting Protocol

This study uses secondary economic statistics and policy documents, but reproducibility remains a central research requirement. Every derived variable should have a data dictionary recording its source, unit, base year, transformation, missing-value rule and deflation method. If a creative-industry classification is created by aggregating National Industrial Classification codes, the full mapping should be placed in a supplementary appendix so that another researcher can reproduce the index.

The final empirical paper should archive the analysis script and a versioned data-preparation log. Where data licensing prevents public redistribution, the paper should provide exact source names, table numbers, retrieval dates and code sufficient for another researcher with lawful access to recreate the dataset. This is particularly important when the analysis combines RBI, MoSPI, PLFS, trade, industry and state-policy data that may use different fiscal-year and calendar-year conventions.

Researchers should also avoid double counting. For example, software services can overlap conceptually with creative digital services; advertising can appear as both a creative activity and an intermediate business service; tourism may be a downstream beneficiary of cultural assets rather than a creative industry itself. The Orange Economy index should therefore be constructed from mutually defensible classifications and accompanied by sensitivity analyses using narrower and broader definitions (UNCTAD, 2024; Ministry of Culture, 2026).

Finally, all simulated or values should be removed from the final submission unless they are explicitly retained as a methodological demonstration. Journal readers should be able to distinguish actual estimates, official statistics, author calculations and hypothetical examples at a glance. This paper has deliberately maintained that distinction so that it can serve as a sound foundation for a subsequent data-driven version.