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Total Factor Productivity and its Determinants of the Indian Toy Industry: Evidence from Principal Component Regression (PCR)-Auto Regressive Distributed Lag (ARDL) Framework

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Abstract

This paper analyses the performance of the Indian Toy Industry (ITI) by evaluating Total Factor Productivity (TFP) and its determinants. The TFP growth is measured using the non-parametric Data Envelopment Analysis (DEA) based Malmquist Productivity approach and Principal Component Regression (PCR)-Autoregressive Distributed Lag (ARDL) bounds testing framework is used to estimate the determinants of TFP based on annual aggregated industry-level data over the period 2005–2024. The findings show that overall TFP growth remained constant over the past two decades. The model results reveal a stable long-run equilibrium, with domestic industrial capability and export-oriented factors exerting significant positive effects on productivity. This study suggests that technical innovation, investment in human capital, and implementing measures to smooth out short-term investment volatility are necessary for strengthening productivity and enhancing the global competitiveness of ITI.

Introduction

The Indian Toy Industry (ITI) stands at a unique crossroads where it is both a modern, rapidly expanding industrial sector and a carrier of cultural memory. As a sector, it not only symbolizes Indian tradition of artisanship, but also plays a vital role in economic growth, employment, and industrial diversification (IBEF, 2025). For a long time now, toys in India have served more than just entertainment. They have passed down tales and stories, encoded local culture, and shaped early learning, becoming deeply embedded in daily social and educational activities. The ITI has its roots in traditional handicrafts, with artisans from diverse areas making toys out of natural materials like wood, clay, and cloth. These handcrafted toys often depict regional art forms and cultural narratives, therefore preserving indigenous skills and expertise (Agarwal & Gupta, 2023). The National Education Policy 2020, which emphasizes play, creativity, and experiential education in the foundational years, recognizes toys as potent pedagogical instruments that are essential to emerging toy-based learning approaches.

Over the last two decades, the structure of the ITI has remarkably transformed. On the demand side, rising incomes, rapid urbanisation, and a large young population have expanded the domestic market, while growing emphasis on educational and STEM-oriented toys has pushed firms towards more sophisticated and differentiated products (IMARC Group, 2025). On the other hand, from the supply side, the sector has diversified from largely handmade toys to a mix that includes plastic, battery-operated and electronic toys, and a growing segment of eco-friendly and educational designs, with both established brands and newer startups experimenting with technology-enabled and sustainable offerings (KPMG & FICCI, 2021).

Toy manufacturing incorporates a range of ancillary activities such as tooling and mould-making, packaging, printing, logistics, design, and retail, generating employment in both urban and semi-urban areas. Policy and industry reports often refer to this industry as a 'sunrise' industry because advancements in its manufacturing base can have spillover effects on design capabilities, infrastructure, and entrepreneurship, particularly in traditional craft belts that are now linked to larger value chains. Until recently, ITI relied heavily on imports, with a significant portion of toys sold imported from China (Kumar & Rohilla, 2024).

ITI has made an exceptional turnaround over the last decade, transitioning from chronic import dependency to an emerging net exporter status. Exports of toys (HS Codes 9503, 9504, 9505) from India rose from about US$ 152.72 million in 2017-18 to roughly US$ 347.47 million in 2024-25, while imports declined from around US$ 365.73 million to US$ 209.32 million over the same period (Export-Import Databank (Annual), DGCI&S). The share of India in global toy exports remains modest at about 0.3 percent, but the trajectory is clearly upward, with the United States, the United Kingdom, and a set of new markets in Europe, West Asia and Africa emerging as major destinations (EXIM, 2024)

Policy has played a central role in this structural shift. Since 2020, sharp increases in basic customs duty on toys, the introduction of mandatory Bureau of Indian Standards (BIS) Quality Control Orders, and the alignment of the sector with “Make in India,” “Atmanirbhar Bharat,” and “Vocal for Local” campaigns have both disincentivised low-quality imports and encouraged domestic capacity creation (Export-Import Bank of India, 2024). A case study by Singh, S. K. (2024) reports that between 2014 and 2020, the number of toy manufacturing units doubled, dependence on imported inputs fell from 33 percent to 12 percent, gross sales value grew at around 10 percent compound annual growth rate (CAGR), and labour productivity increased.

The headline trade statistics alone cannot reveal if this transition is based on a sustainable productivity base. Industry assessments continue to highlight gaps in technology adoption, design and branding, standards compliance, and skilled labor availability, particularly among micro and small-scale enterprises, that constitute the majority of manufacturing firms. The participation of ITI in global toy exports is modest compared to major exporters. Upgrading to higher-value, technology-intensive segments is not that simple. The toy manufacturing industry, classified under miscellaneous manufactured products and consumer goods manufacturing, emerges as a particularly compelling case study for productivity analysis due to its inherently labour-intensive nature, export potential, and strategic importance in the broader manufacturing ecosystem.

The existing research on Total Factor Productivity (TFP) in India focuses on aggregate manufacturing, broad two-digit industries, or large firm samples from CMIE Prowess (e.g., metals, chemicals, textiles, machinery, pharmaceuticals), with no dedicated analysis of the toy industry (Goldar, 2020; Kathuria et al., 2011; Satpathy et al., 2017). Micro-studies Goldar, 2020; Satpathy et al., (2017) focus on firm characteristics and technology variables, while macro-studies M. A. Malik et al., (2021); Teeli et al., (2023) analyse openness, inflation, financial development and related variables at the national level. There is no sector-specific work that jointly examines micro-level determinants and macro conditions for a single industry such as toys.

This study attempts to bridge this gap by evaluating TFP and its determinants in the ITI using a Principal Component Regression (PCR)-Autoregressive Distributed Lag (ARDL) framework based on annual aggregated industry-level data. This method provides a thorough examination of both long-run equilibrium associations and short-run dynamics between TFP and its structural determinants. For the ITI, which has traditionally relied on labour-intensive production methods, understanding TFP dynamics becomes crucial for evidence-based policy formulation and strategic industrial development planning.

Literature Review

The empirical literature on productivity in India's manufacturing sector provides a comprehensive framework for analysing productivity trends and key determinants in specific industries such as the toy sector. Over the past four decades, scholars have examined how structural reforms, technological change, financial development, and sectoral characteristics have influenced TFP growth across manufacturing activities (Natarajan & Duraisamy, 2008).

A significant body of research focuses on how the 1991 economic reforms affected industrial efficiency and competitiveness. Kapuria et al., (2018) observed that the pre-reform industrial regime was characterized by substantial inefficiencies due to regulatory controls. The period before 2002 witnessed accelerated output growth, although this expansion was accompanied by limited employment generation which indicated a pattern of jobless growth. Complementing this perspective, Muneer, (2024), using the Malmquist Productivity Index (MPI) across 26 manufacturing industries from 1992 to 2020, shows an average yearly TFP growth of 1.08 percent. Their findings attribute productivity improvements largely to technological advancement, whereas technical efficiency suffered a minor dip. Together, these studies suggest that reform-induced growth has largely been technology-driven rather than efficiency-led.

The divergence between organized and unorganized sectors has also received considerable attention. Natarajan & Duraisamy, (2008) found that productivity improvements in the unorganized manufacturing sector across major Indian states were mostly driven by technological efficiency gains, indicating a "catching-up" impact rather than frontier innovation. In contrast, the organized sector appears more capable of advancing the technological frontier. Kathuria et al. (2011) further highlight that TFP estimates are sensitive to methodological choices, particularly the distinction between parametric and non-parametric approaches. These insights are particularly relevant for the toy industry, where small-scale and informal units constitute a substantial share of production.

Innovation and research & development (R&D) are consistently identified as central drivers of long-term productivity growth. Kale & Rath, (2018), establish a long-run relationship between innovation indicators such as patents and scientific publications, and TFP growth by applying an ARDL bounds testing approach. They conclude that while human capital formation and foreign direct investment (FDI) may generate short-run productivity gains, sustained improvements depend on continuous innovation efforts. While sector-specific evidence presented by S. K. Malik, (2015) reveals that technological progress can stagnate in the presence of weak user producer linkages and policy distortions, as observed in the textile machinery industry. These results emphasize the necessity to improve industry linkages and steer clear of policy ideas that unintentionally discourage domestic innovation. This is especially important for the toy industry, which relies heavily on design prowess and product innovation.

Financial development is identified as another significant determinant of productivity.Manisha & Aneja, (2025) establish a unidirectional causal association between financial sector development and TFP growth, implying that effective financial intermediation improves capital allocation and encourages technology adoption. Supporting this argument,Taghavi et al., (2025) demonstrate that real credit

expansion and capital formation in machinery significantly contribute to value-added growth. They emphasize that access to industrial credit enables firms to modernize production processes and bridge the gap between current operations and technological frontier. For toys, where small and medium enterprises often face credit constraints, financial accessibility may play a decisive role in productivity enhancement.

Firm size and sub-sector characteristics also influence productivity outcomes. Joshi & Singh, (2010) in their study of the garment industry, find that small-scale firms often exhibit higher technical efficiency compared to larger enterprises, while overall industry growth remained moderate despite policy reforms aimed at enhancing global competitiveness. Kong & Tongzon, (2006) argue that productivity measurement must account for sector-specific structural and behavioural constraints, as methodological assumptions can significantly affect estimated results. Their reflections underscore the importance of productivity analysis within the unique characteristics of each industry.

Besides these broader manufacturing studies, sector-specific analyses of the Indian automobile industry offer methodological and empirical insights relevant to productivity research. Gehlot & Kumar, (2024) apply a Data Envelopment Analysis (DEA)-based MPI to measure TFP growth in the automobile industry from 2001-02 to 2019-20. Their findings indicate that productivity improvements were primarily driven by technological progress, supported by gains in technical efficiency, and positively influenced by trade openness and R&D expenditure. These studies highlight the importance of innovation, infrastructure, and openness in shaping industry-level productivity.

Limited research exists in examining toy manufacturing productivity in India. Anand et al., (2023) examined toy industry production and trade patterns since 2000, noting structural changes following de-reservation policies but lacking formal productivity analysis. The study found that despite comprehensive policy reforms, domestic toy production has not achieved sustained growth trajectories and industry output contracted in real terms during certain periods. The research also identified several structural challenges including fragmented production systems, limited technological adoption, quality control issues, and insufficient integration with global value chains. This necessitates the importance of systematic productivity analysis to understand underlying efficiency constraints and identify intervention opportunities.

While the above literature provides sufficient evidences of productivity measurement in manufacturing sector in India, direct empirical work on the ITI remains sparse. Recent institutional reports enthusiastically celebrate the post-2020 export surge and the corresponding import dip triggered by targeted government interventions. But there is a distinct, glaring lack of rigorous, empirical time-series modelling that quantifies exactly how these rapid structural shifts have impacted the underlying TFP of the ITI. The toy manufacturing industry traditionally depends on labour-intensive production methods, therefore understanding TFP dynamics becomes crucial for evidence-based policy formulation and strategic industrial development planning.

The existing methodological framework of Data Envelopment Analysis (DEA)- Malmquist decomposition, bootstrapped inference, and Principal Component Regression (PCR)- Auto Regressive Distributed Lag (ARDL) bounds-testing approach provides a viable route to address this gap by estimating toy-sector TFP, separating the roles of technical change, efficiency, scale, and testing their long-run cointegrating relationships.

Objectives of the Study

The primary objective of this study is to determine whether export competitiveness of the ITI requires a strong domestic manufacturing base supported by targeted import reduction and export promotion initiatives. The additional objectives are as follows:

1. To examine the performance of the Indian toy industry in terms of growth trends in size, output and employment using annual aggregated firm-level data.
2. To estimate the Total Factor Productivity Change (TFPC) of the Indian Toy industry to capture both efficiency catch-up and technological frontier shifts.
3. To identify the key structural determinants of efficiency of toy industry and establish both short-run and long-run cointegrating equilibrium relationship between them.

Methodology and Database

The empirical strategy of this study is bifurcated into two principal components: the measurement of TFP and the estimation of growth trends. To assess TFP accurately, we adopt the non-parametric MPI within DEA framework following Gehlot & Kumar, (2024). This methodological choice facilitates a nuanced, temporal decomposition of productivity changes without imposing restrictive parametric assumptions on the underlying production technology.

Database

The analysis employs secondary, annual time-series data collected over the period from 2005 to 2024, sourced primarily from the Annual Survey of Industries (ASI) reports, trade statistics, and relevant records from the Ministry of Commerce and Industry, New Delhi. The MPI is constructed using three core variables, (1) gross value added (GVA) (as a measure of output), (2) total persons engaged (representing labor input), and (3) capital stock.

To capture the dynamic trajectory of toy industry, the Compound Annual Growth Rate (CAGR) for critical indicators including industry size, output, employment, and trade is estimated for the period 2004-05 to 2023-24. For this purpose, a standard exponential growth model of the form- $y = ab^t e^u$, is fitted which is subsequently linearized via the semi-logarithmic transformation- $\mathbf{Ln}(\mathbf{y}) = \mathbf{Ln}(\mathbf{a}) + \mathbf{tLn}(\mathbf{b}) + \mathbf{u}$, to facilitate ordinary least squares estimation. The coefficient of the time trend derived from this specification directly yields the CAGR. All econometric computations and basic statistical analyses are executed using standard quantitative software packages.

The compound annual growth rate (CAGR) in per cent term is estimated as

Compound Annual Growth Rate equation-

$$\mathbf{CAGR} = \{\,\mathbf{antilog}\,(\mathbf{b}) - 1\} * 100$$

Concept of Productivity

The investigation of TFP occupies a foundational position within growth-oriented economic research, particularly when exploring the underlying drivers of industrial expansion and competitive resilience in developing economies (Rawat & Sharma, 2021; Erumban et al., 2021; Goldar et al., 2023). At its core, TFP represents that portion of output growth which remains unaccounted for by the measured increases in traditional factor inputs namely, capital and labour. This residual component is interpreted as a composite measure of technological progress, gains in operational efficiency, and organisational refinements (Kathuria et al., 2011). In more practical terms, TFP essentially captures the strength of the relationship between the volume of output generated and the volume of inputs consumed. A higher value signals a more effective and intense utilisation of productive resources throughout the production chain.

When we use multi-output and multi-input models in productivity analysis, the output may take many forms, such as delivered goods or rendered services. Moreover, outputs can be quantified in terms of money or physical quantities. On the other hand, labor, capital, and intermediate inputs are the most prevalent types of inputs. Single (partial) factor productivity (SFP) and total (multifactor) factor productivity (TFP) are the two most widely used productivity metrics (Gehlot & Kumar, 2024).

DEA for analysing productivity

Approaches to evaluate TFP growth generally divide into non-frontier and frontier methods. While non-frontier approaches, such as traditional index-based growth accounting or ordinary least squares regression, assume existing technical efficiency across all firms, frontier models construct a bounding function to map the absolute maximum output achievable given a specific combination of inputs and technology. Frontier methods treat any deviation from this optimal boundary as a quantifiable operational inefficiency rather than mere statistical noise.

Within the frontier-based analytical paradigm, TFP growth is divided into two distinct drivers- first, the outward displacement of the production possibility frontier, which captures the influence of genuine technological change, and second, the progressive movement of production units toward that existing frontier, which signals enhancements in technical efficiency. The literature has primarily converged upon two estimation routes- (1) the non-parametric Malmquist index, and (2) the parametric stochastic frontier analysis to empirically disentangle these effects

Non-Parametric Approaches: DEA and Malmquist Index

For inherently heterogeneous and structurally complex industrial segments such as manufacturing and the toy sector, the non-parametric family of techniques particularly DEA offers a compelling methodological advantage. Rather than imposing a rigid, ex-ante functional specification on the underlying production technology, DEA employs mathematical linear programming to construct a piecewise, empirical frontier that tightly envelops the observed input-output configurations. This data-driven flexibility makes it particularly well-suited to capturing the operational realities of the industry under investigation. In operationalising this approach, the MPI for the present study was computed using the DEAP (Data Envelopment Analysis Program) software package, as developed by Coelli, (1996), which provides a robust computational platform for executing these non-parametric decompositions.

This flexible approach allows to isolate two distinct, underlying drivers of TFP growth: the "catch-up effect" (which captures improvements in technical efficiency as lagging firms adopt industry best practices) and the "frontier effect" (which captures outward shifts in the entire production boundary driven by systemic technological progress and innovation).

The MPI, initially formalized by Caves et al. (1982) on the basis of the distance function framework introduced by Malmquist (1953), provides a rigorous metric for tracking productivity variations across discrete temporal intervals. Building on this foundation, Färe et al. (1994) extended the methodology by proposing a generalized non-parametric formulation that explicitly decomposes the Malmquist index into two methodologically distinct components: technical change and efficiency change. This index is computed as the geometric mean of two separate Malmquist indices, derived from output-oriented distance functions, thereby reconciling measurement discrepancies across base and current periods. The mathematical expression for this composite index is presented below:

$$M_0\left(y_s, x_s,\ y_t,\ x_t\right) = \frac{D_0^t\left(y_t,\ x_t\right)}{D_0^s\left(y_s,\ x_s\right)} * \left[\left\{\frac{D_0^s\left(y_t, x_t\right)}{D_0^t\left(y_t, x_t\right)}\right\} * \left\{\frac{D_0^s\left(y_s, x_s\right)}{D_0^t\left(y_s, x_s\right)}\right\}\right]^{\frac{1}{2}}$$

Where, the ratio situated outside the square brackets captures the variation in the output-oriented Farrell technical efficiency across the two discrete time periods. This efficiency-change component is operationally defined as the quotient of technical efficiency observed in period *t* relative to that realized in period *s*. The geometric mean enclosed within the square brackets delineates the intertemporal frontier shift, evaluated at both the base and current input bundles (*Xs* and *Xt*).

The Malmquist TFP index formulated above implies that productivity growth is the multiplicative outcome of these two dynamic forces. To express this decomposition more succinctly, TFP growth can be articulated as the product of technical efficiency change (the catch-up effect) and technical change (the frontier effect):

$$TFP\,Growth = Technical\,Efficiency\,Change\ \left(Catching\,up\,Effect\right)\ x$$

$$Technical\,Change\ \left(Frontier\,Effect\right)$$

This multiplicative decomposition is particularly instructive for policy analysis, as it allows researchers to discern whether productivity gains are primarily driven by lagging units catching up to industry leaders, or by the industry-wide advancement of the production possibility frontier itself.

Principal Component Analysis (PCA)-Autoregressive Distributed Lag (ARDL) Framework-

The present study measures TFP for the Indian toy sector from 2004-05 to 2023-24. The productivity model can be expressed as:

$$TFP_t = f(GREXP_t,\ PROF_t,\ CAPINT_t,\ SLR_t,\ EMOL_t,\ GRGFCF_t)$$

Where:

- **TFP** = Total Factor Productivity
- **GREXP** = Growth rate of exports
- **PROF** = Profit-output ratio (profitability)
- **CAPINT** = Capital intensity (capital-labour ratio)
- **SLR** = Skilled labour ratio
- **EMOL** = Total emoluments (labour cost)
- **GRGFCF** = Growth of gross fixed capital formation (proxy for investment growth)

A PCR-ARDL framework is used to estimate the determinants of TFP in the ITI, following Jalil et al., (2010). This study employs a dual-stage econometric technique that combines PCA-ARDL bounds testing approach to examine the underlying short-run dynamics and long-run cointegrating relationship between key determinants from selected performance indicators in ITI.

PCA is used to extract latent composite measures from our raw performance data, addressing multicollinearity at the micro-level. Then these composites are fed into an ARDL bounds test to separately identify transient short-run shocks from persistent long-run co-movement. This combination offers a statistically efficient pathway for evaluating cointegration when the order of integration among our regressors remains ambiguous. This novel approach provides the very first exhaustive, multi-stage econometric analysis of core productivity determinants of ITI during its most highly transformative historical epoch.

ASI is the principal official source of industrial statistics in India, providing annual information on factory characteristics such as, employment, capital, and output for the organized manufacturing sector. Variables drawn from this source are often highly intercorrelated, giving rise to multicollinearity problem when entered jointly in regression models. Severe multicollinearity inflates standard errors, destabilizes coefficient estimates, and complicates inference on individual regressors, even when the overall model fit appears satisfactory (Lee et al., 2015; Alibuhtto & Peiris, 2015). To address this problem, the study first applies PCA to the group of conceptually related but collinear variables.

PCA is a potent dimensionality reduction method that orthogonally transforms the initial set of highly correlated explanatory variables into a novel, smaller set of artificial variables called principal components (PCs) that are linearly uncorrelated and arranged according to the proportion of total variance they account for. The number of components to retain is determined by combining Kaiser, (1960) criterion (Eigenvalues > 1). These derived PCs enter the subsequent ARDL specification as composite regressors, curbing multicollinearity while retaining most information from the original indicators.

The ARDL bounds testing framework is employed owing to the limited temporal frequency of the annual observations and possibility of variables being integrated of different orders. This approach offers several advantages over traditional cointegration alternatives, including the Engle-Granger two-step and Johansen maximum-likelihood procedures. The ARDL bounds-testing approach propounded by Pesaran et al., (2001) allows testing for a long-run level relationship among variables regardless of whether regressors are *I(0)* or *I(1)*, and it has been widely noted for its favourable finite-sample properties relative to alternative cointegration methods. This makes the ARDL framework particularly appropriate for the present application, where the sample is small and the integration orders of the variables are a priori uncertain but can reasonably be assumed not to exceed one.

As a precondition to ARDL estimation, the stationarity properties of all underlying variables are examined using standard unit root diagnostics which is a necessary screening to rule out I(2) behavior, since the bounds-testing procedure is not valid in the presence of *I*(2) variables. The Akaike Information Criteria (AIC) are used to determine lag orders *(p, q1,...,qm)* while maintaining well-behaved residuals and avoiding overparameterization due to restricted sample size.

After extracting PCs, the model is specified with TFP as the explained variable and the selected PCs as explanatory variables. The general ARDL (p, q) specification can be expressed as:

$$\Delta TFP_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta TFP_{t-i} + \sum_{j=0}^{q} \gamma_j \Delta PC_{t-j} + \lambda_1 TFP_{t-1} + \lambda_2 PC_{t-1} + u_t$$

Where:

- PC represents the principal component(s) derived from the explanatory variables
- Δ denotes first differences
- p and q represent optimal lag lengths
- λ1 and λ2 capture the long-run equilibrium relationship
- u_t is the white-noise term

The null hypothesis of no cointegration is tested as: H0 : λ1 = λ2 = 0

If the calculated F-statistic exceeds the upper bound critical value provided by Pesaran et al., (2001), the null hypothesis is rejected, indicating the presence of a long-run relationship between the variables. Once cointegration is established, the long-run association is estimated, and the short-run dynamics are

determined using an Error Correction Model (ECM). The error correction representation of the ARDL model is represented as follows:

$$\Delta TFP_t = \delta_0 + \sum_{i=1}^{p} \delta_i \Delta TFP_{t-i} + \sum_{j=0}^{q} \theta_j \Delta PC_{t-j} + \varphi ECM_{t-1} + \epsilon_t$$

where:

- ECM_{t-1} represents the lagged error correction term derived from the long-run relationship
- φ denotes equilibrium-reverting coefficient, which captures the speed of adjustment back to the steady-state productivity path and is expected to be negative to achieve statistical significance, thereby confirming the presence of a convergent long-run dynamic.

In substantive terms, the magnitude of ECM coefficient directly quantifies the proportion of any transitory deviation from the long-run TFP equilibrium that is systematically corrected in the subsequent period.

Results and Discussion

The global toy industry is a vibrant sector of the light manufacturing and creative industries, with growing demand fuelled by shifting demographics, innovation, and changing consumer preferences. ITI has lagged behind its manufacturing potential because of import dependency, fragmented production, and a limited export orientation (Agarwal & Gupta, 2023).

Performance of Indian Toy Manufacturing Industry-

Over the last decade, ITI has undergone a remarkable transformation with policies shifting towards strategic import substitution and domestic capacity building.

Figure 1 represents a highly volatile trajectory in the number of operational firms within the organized toy sector. Between 2005 and 2008, the industry saw modest expansion, growing from 126 to 180 registered units. The subsequent period from 2009 to 2014 witnessed severe de-industrialization. The number of active enterprises collapsed to a mere 90 units by 2014. During this period, employment in registered units fell, and labour and capital productivity as well as TFP showed either weak or negative growth under pressure from low-priced imports (primarily from China), resulting in closure of many domestic factories and leaving roughly 60% of the sector in the unorganised, micro-enterprise segment (Thiagarajan & Balakrishnan, 2022; National Productivity Council, 2017).

This pattern is also consistent with broader firm-level evidence on Indian MSMEs under trade liberalisation. Mukherjee & Chanda (2025) find that tariff and non-tariff liberalisation tend to generate productivity gains primarily for larger manufacturing firms with better access to finance and technology, while many MSMEs face heightened competitive pressure and are more likely to exit if they cannot upgrade. The period post-2014 showed a massive revival. Fuelled by the ‘Make in India’ initiative and the National Action Plan for Toys (NAPT), the number of operational firms surged exponentially, peaking at 215 manufacturing units in 2024.

Figure 2 represents the total output of the industry over the last two decades. The gross output of the sector perfectly mirrors the enterprise trajectory but highlights the scale of recent capacity additions. The total output initially rose from Rs. 66,346 Lacs in 2005 to Rs. 121,880 Lacs in 2008, followed by a pronounced slump to Rs. 49,359 Lacs in 2009 and further fell to Rs. 36,341 Lacs in 2014, before entering a powerful and sustained growth phase. During this time, indigenous manufacturers were almost entirely crowded out by foreign imports, marking the ITI's lowest point (NPC, 2017).

The turnaround began gradually with output increasing to Rs. 119,509 Lacs in 2015, but achieved unprecedented exponential growth by 2022 with the total output reaching Rs. 286,176 Lacs, and by 2024, it skyrocketed to an all-time high of Rs. 404,506 Lacs. The CAGR is around 9.46 for the study period, which indicates that every year the growth in total output of the toy industry is around 9.46 per cent. The subsequent recovery since post-2014 is strongly aligned with the timing of a concerted policy push and cluster development initiatives under Make in India and Atmanirbhar Bharat Campaign, the National Action Plan for Toys (NAPT), quality control orders, and tariff changes.

Figure 3 depicts employment dynamics of ITI over the last two decades. Since the toy industry is inherently labour-intensive, the employment data serves as a critical barometer for sectoral health. In 2005, the total number of persons engaged in the industry were 8389 while the number of informal workforces were 7182 which rose to 12164 (including 10392 direct workers) in 2008. The 2009–2014 de-industrialization phase wiped out approximately 80 percent of the informal workforce, with the number of workers dropping to a staggering low of 1727 in 2014.
The aggressive push for domestic manufacturing since 2014, especially post-2020 reversed this trend entirely. By 2024, the number of formal workers had expanded to 14887, with total persons engaged reaching 17693. Overall, the workforce slightly more than doubles over the two decades, but with pronounced volatility, indicating that employment in the toy industry has been highly sensitive to cyclical shocks and restructuring episodes.

Figure 4 shows the trade pattern of Toys & Games (HS Code 95) in India for two decades since 2004-05. The figure indicates that India was a net importer of toys in the first decade till 2013-14, however, this trend was not sustained. A cyclical pattern can be observed showing a decline in both exports and import growth from 2004-05 to 2009-10, a surge in imports, and a slow rise in exports between 2009-10 and 2010-11. Again a sharp decline in imports from 2010-11 till 2013-14 and fluctuating exports.

It may be noted that since 2018-19 the toy export growth has overtaken the import growth since India became a net toy exporter in 2020-21. But it can be seen that the import growth has again started to increase in the past two years. When a trend line is fitted, it is evident that imports have been dropping while toy exports have shown little indication of an upward trend. It implies that, while the government's policy reforms, such as the 'Make in India' and 'Aatmanirbhar Bharat' initiatives, were effective in reducing import dependency, they did not contribute significantly to sustained export growth.

While the absolute growth in output, enterprise creation, and trade volumes provide a highly encouraging macroscopic view of revival of the sector, the long-term sustainability and global competitiveness of this growth hinge inseparably on fundamental productivity enhancements rather than the mere accumulation of physical factors of production. Traditional economic growth theory, rooted in the Solow-Swan neoclassical framework and expanded by endogenous growth theorists, postulates that sustained industrial competitiveness and rising standards of living are driven primarily by TFP (Solow, 1956).

Total Factor Productivity Analysis-

The MPI results for the ITI during 2006-07 to 2023-24 show that the mean TFP change (TFPCH) is 0.999, indicating an almost stagnant productivity performance over the study period (see Table 1).

Table 1
Year-wise Malmquist Index Summary of Indian Toy Industry

YEAR	EFFCH	TECHCH	PECH	SECH	TFPCH
2006-07	1.000	1.287	1.000	1.000	1.287
2007-08	1.000	0.757	1.000	1.000	0.757
2008-09	1.000	0.597	1.000	1.000	0.597
2009-10	1.000	1.695	1.000	1.000	1.695
2010-11	1.000	0.883	1.000	1.000	0.883
2011-12	1.000	0.676	1.000	1.000	0.676
2012-13	1.000	0.813	1.000	1.000	0.813
2013-14	1.000	0.986	1.000	1.000	0.986
2014-15	1.000	2.509	1.000	1.000	2.509
2015-16	1.000	0.807	1.000	1.000	0.807
2016-17	1.000	1.146	1.000	1.000	1.146
2017-18	1.000	0.737	1.000	1.000	0.737
2018-19	1.000	1.120	1.000	1.000	1.120
2019-20	1.000	0.784	1.000	1.000	0.784
2020-21	1.000	1.122	1.000	1.000	1.122
2021-22	1.000	1.294	1.000	1.000	1.294
2022-23	1.000	0.812	1.000	1.000	0.812
2023-24	1.000	1.183	1.000	1.000	1.183
Mean	1.000	0.999	1.000	1.000	0.999

Source: Authors' Computation

Note

TFPC is total factor productivity change, TEC is technical efficiency change, TP is technological progress, PTEC is pure technical efficiency change, SEC is scale efficiency change.

Table 1 reveals that efficiency change (EFFCH), pure technical efficiency change (PECH), and scale efficiency change (SECH) all remained constant at 1.000 in every year, implying that the industry neither improved nor deteriorated in terms of managerial efficiency and scale of operations.

The year-to-year variations in productivity were entirely driven by technological change (TECHCH). Significant technological progress was observed in years such as 2009-10 (TECHCH = 1.695, TFPCH-1.695) and 2014-15 (TECHCH = 2.509, TFPCH-2.509), indicating major transitions in the production frontier, possibly driven by modernization or beneficial governmental interventions. Moderate technological improvements were also recorded in 2016-17 (1.146). 2018-19 (1.120), 2020-21 (1.122), 2021-22 (1.294), and 2023-24 (1.183). In contrast, technological regress led to productivity decline in several years, notably 2008-09 (0.597), 2011-12 (0.676). 2012-13 (0.813). 2017-18 (0.737), and 2022-23 (0.812). The mean technological change value of 0.999 confirms the absence of sustained technological advancement in the industry.

Overall, the findings indicate that although the ITI consistently operated at optimal efficiency levels, its productivity performance over the period was constrained by fluctuating and largely stagnant technological progress, emphasizing the need for continuous technology upgradation and innovation to achieve long-term productivity growth.

Unit Root Test Results-

Prior to extracting PCs and ARDL model estimation, the stationarity properties of all the underlying variables are examined using the standard Augmented Dickey-Fuller (ADF) unit root test which is widely applied in economic literature (Dickey & Fuller, 1979).

Table 2
Augmented Dickey-Fuller (ADF) Unit Root Test Results

Variable	Level (t-statistic)	p-value	First Difference (t-statistic)	p-value	Order of Integration
lnTFP	-3.644	0.005	-	-	I(0)
lncapint	-3.178	0.0213	**-**	**-**	I(0)
lnTE	-0.083	0.9511	-3.164	0.0222	I(1)
GREXP	-3.922	0.0019	-	-	I(0)
PROF	-2.816	0.0561	-3.272	0.0162	I(1)
SLR	-1.877	0.3428	-3.853	0.0024	I(1)
GRGFCF	-3.935	0.0018	-	-	I(0)
Source: *Authors' computation*					
Note: The terms lnTFP, lncapint, and lnTE stands for natural logarithm of TFP, Capital Intensity, and Total Emoluments respectively. GREXP is Growth Rate of Exports, PROF is Profitability, SLR is Skilled Labour Ratio, and GRGFCF is Grwoth Rate of Gross Fixed Capital Formation.					

Table 2 reveals the results of ADF unit root test. The variables, lnTFP, lncapint, GREXP, and GRGFCF were found to be strictly stationary at level, i.e. I(0), while variables, *lnTE*, PROF, and the SLR possessed significant unit roots at their levels but achieved robust stationarity after first differencing, indicating the order of integration one i.e. I(1).

This mixed order of integration of I(0) and I(1) variables provides methodological justification to our model. Furthermore, to satisfy the strict stationarity requirements of multivariate dimensionality reduction, the first differences of variables Profitability (*dProfitability*) and Skilled Labour Ratio (*dSkilledLaborRatio*) are utilized in the subsequent Principal Component Analysis.

Principal Component Analysis-

Table 3
PCA Eigenvalues and Variance Explained

Component	Eigenvalue	Difference	Proportion	Cumulative
PC1	2.11447	0.883419	0.3524	0.3524
PC2	1.23105	0.2268	0.2052	0.5576
PC3	1.00425	0.147625	0.1674	0.7250
PC4	0.85663	0.183782	0.1428	0.8677
PC5	0.672848	0.552107	0.1121	0.9799
PC6	0.12074	-	0.0201	1.0000

Source: Authors' computation

Table 3 shows the results of PCA. In accordance with the universally accepted Kaiser (1960) criterion in multivariate statistics, only PCs that generate an eigenvalue greater than 1.0 are typically retained for subsequent economic analysis. The results from Table 3 indicate that the first three PCs explain a significant proportion of the total variation in the dataset. Specifically, PC1 accounts for 35.24 per cent of the total variance, while PC2 and PC3[1] explain an additional 20.52 and 16.74 per cent respectively. Together, these three components capture approximately 72.50% of the total variation in the dataset. This suggests that the multidimensional information contained in the original variables can be effectively summarized using just two components, thereby reducing complexity without significant loss of information.

Table 4
Scoring Coefficients (Component loadings) for Principal Components

Variable	PC1	PC2	PC3	PC4	PC5	PC6
lncapint	-0.3870	0.3302	-0.3114	-0.3553	0.7133	-0.0953
lnTE	0.3496	-0.4291	0.2489	0.3955	0.6880	-0.0446
Profitability	0.5860	0.3048	-0.3038	-0.0824	0.0934	0.6751
Skilled Labour Ratio	-0.0773	0.4266	0.8547	-0.1428	0.0931	0.2289
GREXP	-0.1643	0.5412	-0.1326	0.8116	-0.0015	-0.0621
GRGFCF	0.5929	0.3729	0.0251	-0.1774	-0.0206	-0.6905

Source: Authors' computation

Table 4 shows the precise scoring coefficients (eigenvectors) for the variables across the components. The scoring coefficients indicate that PC1 captures the domestic industrial capability dimension, reflecting profitability (0.586), labour costs (0.350), and investment growth (0.593), while PC2 shows relatively high positive loadings for export growth (0.541), skilled labour ratio (0.427), and gross fixed capital formation growth (0.373) which captures an export-oriented productivity dimension. These two components therefore represent the most meaningful structural drivers of productivity within the industry. Based on

these considerations, the scores of PC1 and PC2 were extracted and used as composite explanatory variables in the subsequent ARDL estimation to analyse the determinants of TFP of the ITI.

ARDL-ECM Estimation Results-

To investigate the dynamic association between TFP and its determinants, an ARDL-ECM framework was specified with the logarithm of TFP (lnTFP) being the regressand and the first two retained principal components (PC1, PC2) as regressors. The optimal lag-order selection criteria by the model was ARDL (1,0,1).

Table 5
ARDL (1,0,1) Error Correction Model (ECM) Results

Variable	Coefficient (β)	Std. Error	t-value	p-value	95% Confidence Interval	Component
Adjustment (ECT)						
L.lnTFP	-1.5421	0.1912	-8.07	0.000	[-1.9629, -1.1213]	Long-run Adjustment
Long-Run Coefficients						
PC1	0.14029	.025394	5.52	0.000	[0.0844, 0.1961]	Long-run
PC2	0.10386	0.04728	2.20	0.050	[-0.0002, 0.2079]	Long-run
Short-Run Dynamics						
ΔPC1	-0.11400	0.0592	-1.92	0.081	[-0.2444, 0.0164]	Short-run
Constant	-0.01731	0.0535	-0.32	0.753	[-0.1352, 0.1005]	—

Model Summary:

Statistic	Value
Observations	16
R-squared	0.9004
Adjusted R-squared	0.8642
Root MSE	0.2125

Source: Authors' computations

The estimation output is reported in Table 5. The model exhibits a high explanatory power, with an R^2 of 0.90 (and Adjusted R^2 of 0.86), implying that the constructed components account for roughly 90 per cent of the variability observed in the productivity series. Turning to the long-run point estimates, both PCs demonstrate uniformly positive associations with productivity (refer to Table 5). PC1 has a positive and

statistically significant coefficient (β = 0.140, p < 0.001), suggesting that advancements in proximate domestic industrial characteristics, encompassing profitability, investment growth, and labour cost structures, exert a significant positive influence on long run productivity trajectories within the industry. This finding implies that the efficacy with which inputs are transformed into output is enhanced by a more robust internal production base. PC2 also exhibits a positive coefficient (β = 0.104, p = .050), indicating that export expansion and improvements in skilled labour participation contribute positively to long-term productivity. The statistical significance of PC2 highlights the role of export led industrial upgrading and skill enhancement in driving productivity gains.

The negative and highly significant error correction term (ECT) confirms the presence of a stable long-run cointegrating equilibrium among the model variables. The coefficient's magnitude indicates that roughly 154 per cent of any prior period disequilibrium is corrected within one year, indicating a relatively rapid adjustment process in the industry.

On the other hand, short run dynamics are captured via the lagged first-difference term of PC2. The coefficient is negative and marginally significant (β = −0.114, p = .081), suggesting that transitory fluctuations in export growth and skill intensity may introduce temporary adjustment frictions to productivity before the steady state is restored.

Table 6
ARDL Bounds Test for Cointegration

Test Statistic	Value
F-statistic	23.351
t-statistic	-8.066

Source: Authors' Computation
Critical Values (Kripfganz & Schneider, 2020):

Significance Level	I(0) Lower Bound	I(1) Upper Bound
10%	3.830	5.099
5%	5.006	6.553
1%	8.327	10.614
Decision Rule:		

Level	Decision
10%	Reject H_0
5%	Reject H_0
1%	Reject H_0
(Note. H_0: No long-run (level) relationship exists. Since the calculated F-statistic exceeds the upper bound critical values at all significance levels, the null hypothesis is rejected, confirming cointegration among the variables.)	

The bounds testing following Pesaran, Shin & Smith (2001) was applied to ascertain the presence of a long run stable relationship among the variables. As Table 6 explains, the calculated F statistic (F = 23.351) overshoots the upper bound critical value even at 1% significance level, substantiating a robust long-run association. The t statistic associated with the lagged dependent variable (t = -8.066) falls well beyond the upper-bound critical region. These findings collectively lead to the rejection of the null hypothesis of no cointegrating relationship, affirming that total factor productivity cointegrates with principal components representing industrial structure and export dynamics.

Table 7
Skewness–Kurtosis Test for Normality

Variable	Observations	Pr(Skewness)	Pr(Kurtosis)	χ^2 (2)	p-value
Residuals	16	0.7700	0.7182	0.22	0.8978

Source: Authors' computation

Table 7 shows the outcomes of the Skewness-Kurtosis normality diagnostic applied to the residuals from the estimated ARDL specification. The results confirm that the error terms adhere to a normal distribution. The joint test statistic fails to attain statistical significance ($\chi^2(2) = 0.22$, $p = 0.8978$), hereby precluding the rejection of the null hypothesis of residual normality. Both the skewness ($p = 0.7700$) and kurtosis ($p = 0.7182$) components are individually insignificant, further affirming the conclusion that residuals follow a normal distribution.

Ensuring residual normality is critical to the validity of statistical inference, particularly within finite sample contexts. Given the satisfaction of this assumption, the estimated coefficients, associated standard errors, and corresponding hypothesis tests may be considered reliable. This diagnostic outcome thus reinforces the robustness of the ARDL estimates and affirms that the underlying classical linear regression assumptions are fulfilled.

Conclusion

Indian Toy Industry has recently undergone a remarkable transformation, shifting from chronic import reliance to an emerging net exporter. While policies like Make in India and stricter quality controls have successfully boosted factory scaling and employment, long-term global competitiveness requires deeper structural efficiency rather than just capacity expansion. To evaluate this, the study examined the TFP

change of toy manufacturing sector in India from 2004-05 to 2023-24. Using a DEA-based MPI alongside a PCR-ARDL framework, to determine the core drivers of productivity.

The overall TFP growth remained functionally stagnant over the past two decades (mean Malmquist Index of 0.999). Technical and scale efficiency scores remained constant at 1.000, and any productivity fluctuations were exclusively driven by temporary technology shifts rather than sustained operational improvements. In essence, while import substitution increased physical production, the industry struggled to achieve consistent technological advances.

To better understand the macroeconomic drivers of these productivity trends, PCA synthesized the highly correlated sectoral variables into two orthogonal components: 'domestic industrial capability dimension' (PC1) and 'export-oriented productivity dimension' (PC2). The cointegration analysis, driven by the ARDL bounds testing model, revealed that both components are highly significant, positive long-run engines for TFP. Domestic capacity expansion and profitability exhibited a significantly higher long-term influence on productivity (PC1, $\beta = 0.140$) than export-oriented skill upgrading (PC2, $\beta = 0.104$).

The short run dynamics revealed significant transitional challenges. A negative short-term impact from export-oriented upgrading was found, reflecting the immediate adjustment costs of adopting new skills and targeting highly competitive global markets. The error correction term mapped a highly reactive, oscillatory adjustment process, indicating that the industry is prone to volatile investment cycles following systemic shocks.

Thus, while recent tariffs and incentives have effectively boosted manufacturing volumes, maintaining this momentum necessitates a strategic shift. To attain global competitiveness, policymakers and industry leaders must go beyond merely boosting physical capacity and actively push profound technical innovation, consistently invest in human capital, and implement measures to smooth out short-term investment volatility.
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Declarations

Disclosure statement: No potential conflict of interest was reported by the author(s).

Author Contribution

Dinesh Gehlot conceptualized the study, as the corresponding author, and provided critical revisions. Nitya Gupta was responsible for data collection, analysis, contributed to the literature review, data organization, and final manuscript drafting. Both authors read and approved the final version of the manuscript.

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Data Availability Statement

The data used in this study were collected from secondary sources. The datasets generated and analyzed during the study are available from the corresponding author upon reasonable request. The datasets and supporting materials underlying the findings of this study are provided as supplementary files accompanying the manuscript. These materials include the relevant datasets and supporting documentation, including variable definitions, data processing and analysis procedures, and statistical code/scripts, where applicable. The supplementary materials are made available to facilitate the verification and reproducibility of the reported results.

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Footnotes

1. Despite PC3 having an eigenvalue marginally greater than unity, only PC1 and PC2 were retained for the ARDL estimation. This is enforced to preserve vital degrees of freedom and ensure robust estimator efficiency given the mathematically constrained sample size.

Figures

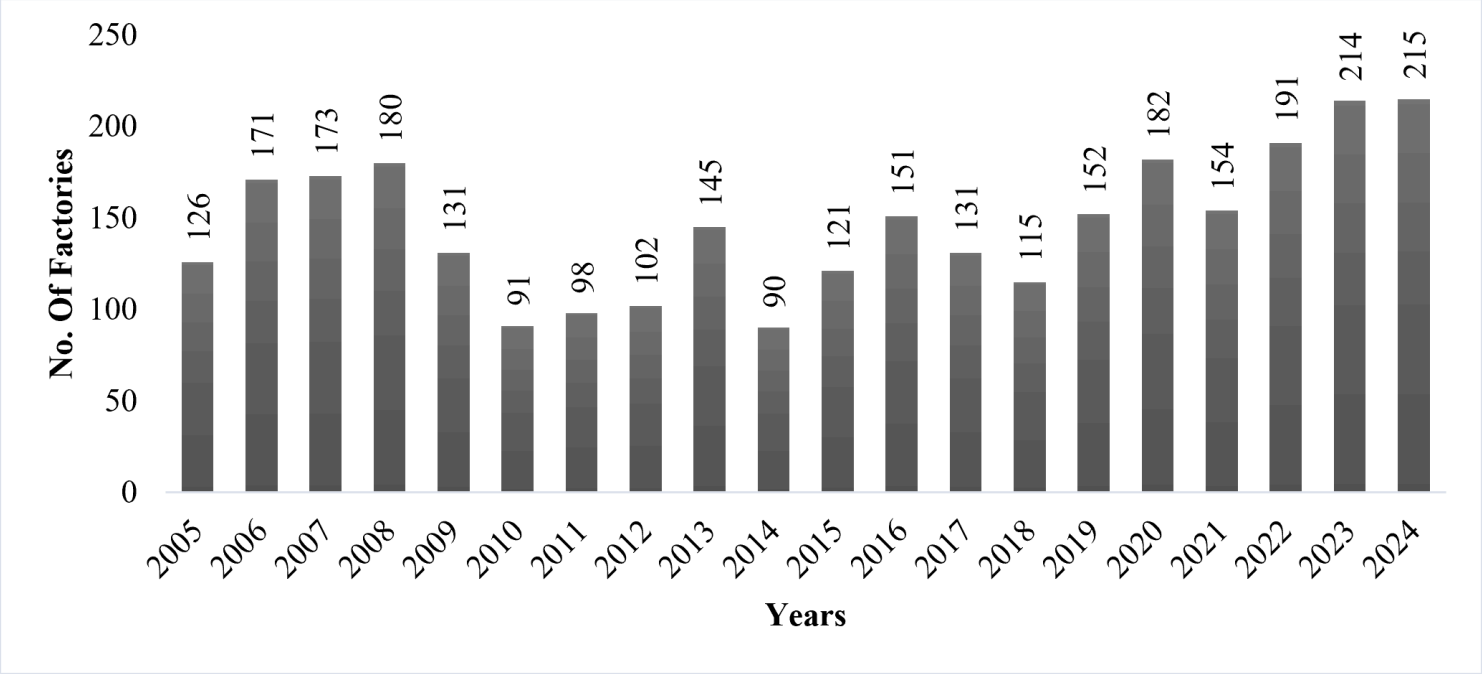


Figure 1

Trends in Number of Operational Factories of Toy Industry from 2005-2024 (In Numbers)

Source: Annual Survey of Industries (ASI).

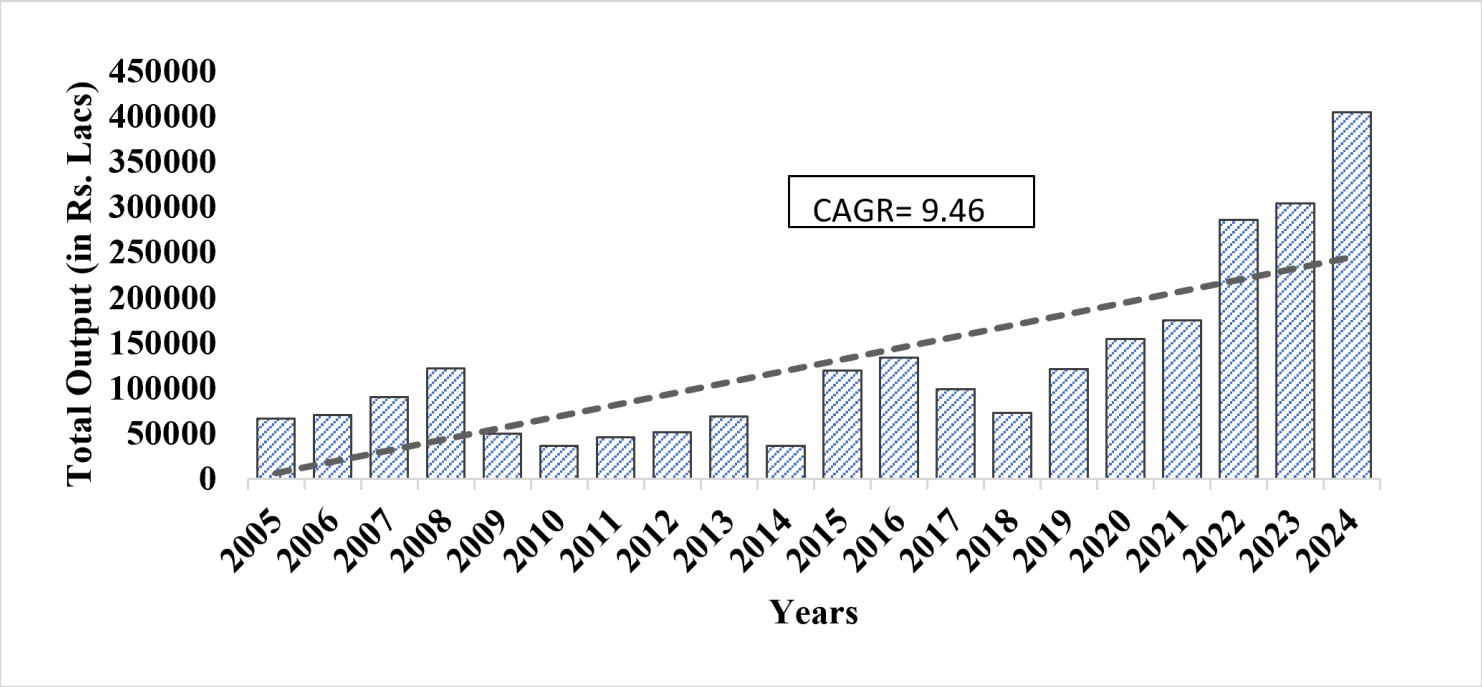


Figure 2

Trends in Total Output of Toy Industry from 2005-2024 (in Rs. Lacs)

Source: Annual Survey of Industries (ASI).

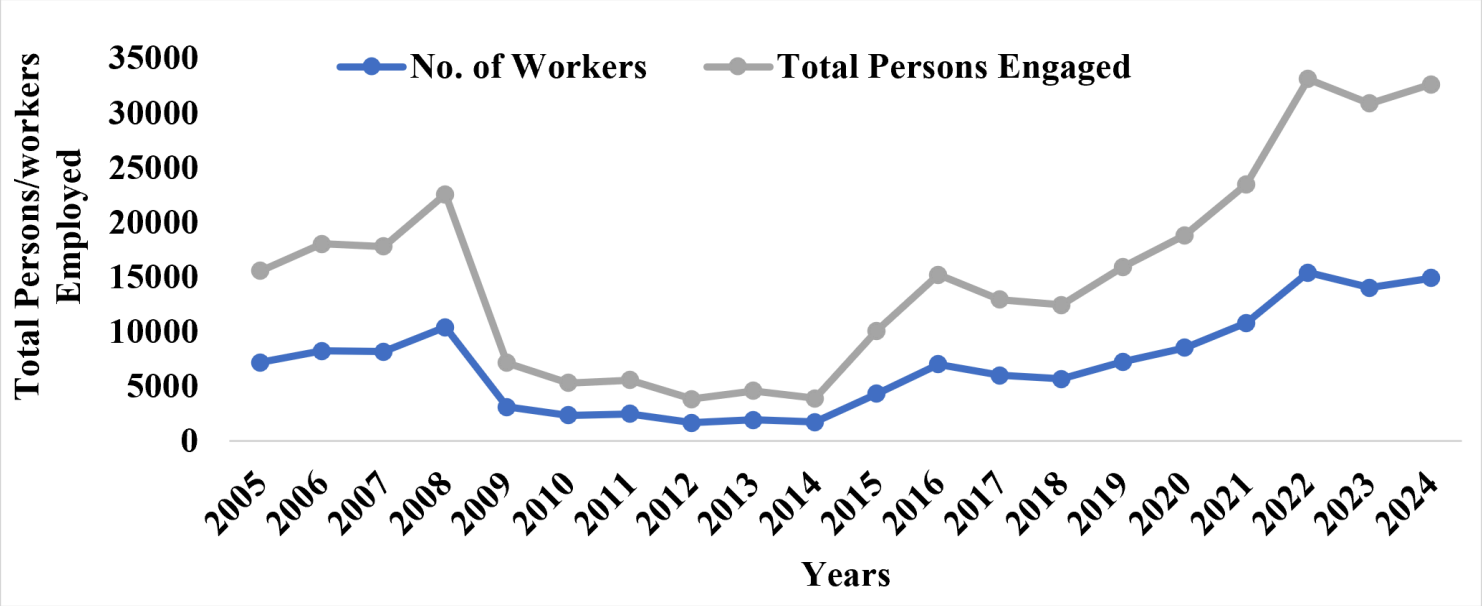


Figure 3

Trends in Total Number of Persons/workers of Toy Industry from 2005-2024 (In Numbers)

Source: Annual Survey of Industries (ASI)

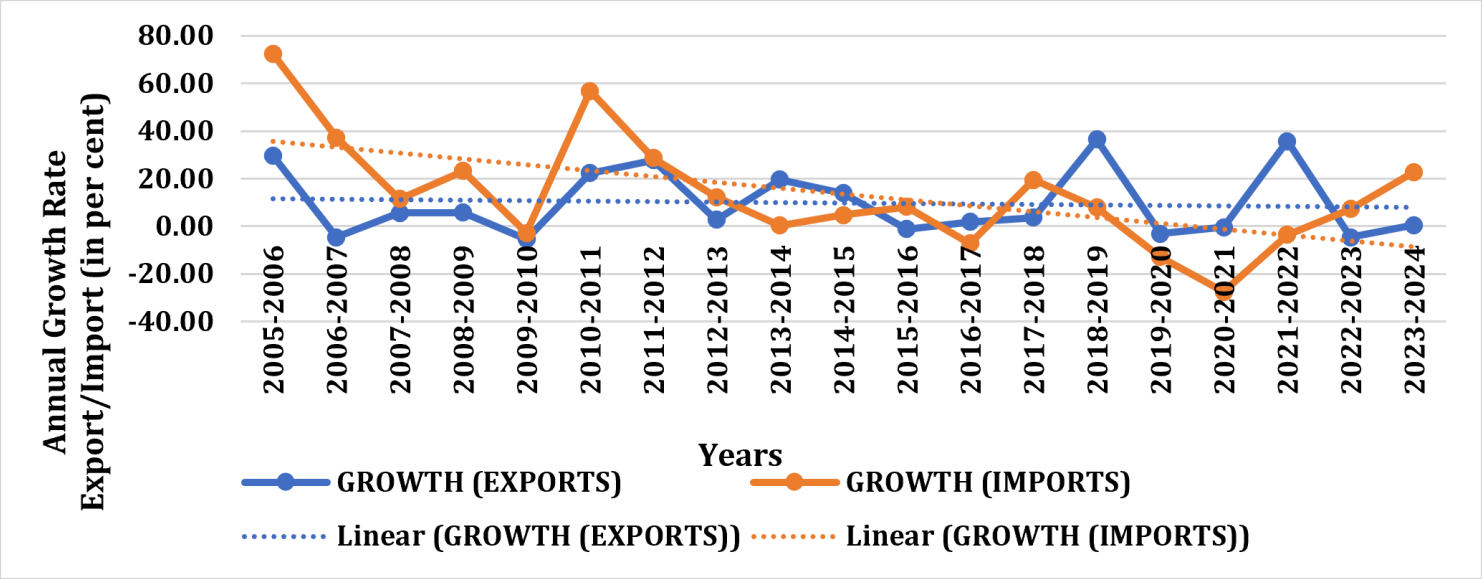


Figure 4

Trends in Trade Performance of Toys & Games in India (HS Code 95)

Source: Authors' computation of the data obtained from Export/Import Data Bank, Directorate General of Foreign Trade, Ministry of Commerce and Industry, Government of India.