Beyond Overcompetition: A Data-Driven Framework to Diagnose and Project Involution in China's Manufacturing Sector

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Abstract

This study develops an integrated analytical framework to assess and predict "involution-style" competition among Chinese enterprises, combining CRITIC-Entropy weighting, TOPSIS evaluation, and Prophet time-series forecasting. By systematically analyzing inter-indicator conflicts, innovation metrics, and market dynamics, we identify high-weight factors that mitigate involution and structural drivers that exacerbate it. Sectoral analysis reveals divergent patterns, with traditional industries trapped in moderate involution while light-asset models enable escape pathways. Prophet projections forecast intensifying involution through 2028 due to global trade tensions and domestic consumption weakness. The findings highlight the urgency of multidimensional policy interventions to break destructive competition cycles during China's economic transition.

Keywords

Involution-style Competition, CRITIC-Entropy Weighting, TOPSIS Evaluation, Prophet Forecasting, Chinese Manufacturing, Innovation Capacity.

1. Introduction

The rising phenomenon of "involution-style" competition among Chinese enterprises has become a pressing issue amid economic transformation and market saturation. This self-reinforcing cycle of intense competition with diminishing returns particularly affects traditional industries facing overcapacity and homogeneous products. While existing studies have explored aspects of excessive competition, few offer systematic approaches to measure and predict this complex phenomenon. This study addresses this gap by developing an integrated analytical framework combining objective weighting methods, multi-criteria evaluation, and time-series forecasting to assess both current patterns and future trends of corporate involution, providing valuable insights for strategic decision-making during China's critical transition to high-quality development.

Recent scholarly investigations have systematically examined the phenomenon of malignant competition in China's manufacturing sector through various methodological lenses. Foundational work by Fan and Lin (2010) established an entropy-weighted fuzzy comprehensive evaluation framework that identified key drivers of destructive competition patterns in traditional industrial clusters, particularly highlighting the roles of intellectual property protection deficiencies and innovation incentive gaps [1]. Subsequent studies have expanded this analytical approach, with Fu and Chu (2020) developing an enhanced CRITIC-entropy integrated TOPSIS model to assess regional industrial coordination within the Yangtze River Delta integration strategy, demonstrating how quantitative methods can illuminate competitive dynamics in evolving economic contexts [2]. These methodological innovations have enabled researchers to move beyond qualitative descriptions and develop more precise measurements of competition intensity and its economic consequences.

The empirical literature reveals multiple dimensions of malignant competition's impact on manufacturing ecosystems. Tang and Su's (2003) early cluster analysis identified distinct patterns of destructive competition, including predatory pricing and technological imitation, which Wang and Zhang (2025) later conceptualized as "involutionary" competition characterized by diminishing productivity returns [7,8]. Regional studies by Wang (2019) and Liu and Wang (2024) have documented how localized industrial clusters often degenerate into homogeneous competition, creating self-reinforcing cycles of overcapacity and margin compression that undermine sustainable development [6,9]. Particularly insightful is Jiang and Zhang's (2022) political economy analysis, which traces these competitive distortions to institutional factors including GDP-centric local governance and fragmented industrial policies that inadvertently encourage redundant investments [4]. Scholars have developed several explanatory frameworks for the persistence of malignant competition in China's industrial landscape. Liu (2023) applies the concept of the "middle-income technology trap" to explain how manufacturing firms become locked in imitation-based strategies that prevent transition to innovation-driven growth [5], while Guo (2022) emphasizes structural constraints in factor markets that maintain path dependencies in low-value production [3]. Complementary quantitative analyses, such as Wu et al.'s (2019) dynamic weighting model, demonstrate how distorted factor prices (particularly labor costs) systematically shape competitive behaviors in ways that discourage productivity-enhancing investments [10]. Together, these studies suggest that addressing malignant competition requires simultaneous interventions at multiple levels - from enterprise innovation strategies to regional policy coordination and national institutional reforms - to break the cycle of diminishing returns in industrial development.

The main contributions of this study can be summarized as: (1) developing an innovative CRITIC-Entropy combined weighting approach that systematically integrates inter-indicator conflict analysis with information entropy measurement to objectively evaluate corporate involutionary competition; (2) constructing a comprehensive evaluation framework through TOPSIS methodology that reveals distinct patterns of involution across different industries and firm types, with empirical evidence showing how innovation capacity and market strategies differentially affect competitive dynamics; and (3) employing Prophet time-series forecasting to quantitatively project China's corporate involution trajectory for the first time, identifying key external drivers (global trade tensions) and internal factors (supply-demand imbalances) that will likely intensify involutionary pressures through 2028, thereby providing both methodological advances and policy-relevant insights for addressing this critical challenge in China's economic transition.

The structure of this paper is as follows: The introduction section establishes the research background and significance of investigating involution-style competition within China's manufacturing industry. The second section provides a comprehensive review of relevant theoretical frameworks, covering the Entropy Weight Method, CRITIC technique, TOPSIS approach, and Prophet forecasting methodology. The third section elaborates on the experimental design, systematically explaining the combined CRITIC-Entropy weighting procedure, the standalone Entropy Weight Method implementation, the TOPSIS evaluation mechanism, and the Prophet time-series analytical process. The fourth section presents detailed results and analysis, including findings from the CRITIC-Entropy weighting analysis, outcomes of the TOPSIS evaluation, and projections derived from the Prophet forecasting model. The concluding section synthesizes key insights and discusses their policy implications, followed by a complete reference list. This carefully designed structure facilitates a rigorous examination spanning from theoretical foundations through empirical analysis to predictive insights regarding corporate involutionary competition patterns.

2. Related Theories

Entropy weight method is a objective weighting technique based on information entropy, which measures the amount of information contained in each indicator within a decision-making system. The core idea lies in determining indicator weights by calculating the entropy value, where a smaller entropy value indicates greater variation in the data and thus higher importance. This method effectively reduces subjectivity in weight assignment by quantifying the uncertainty in data distribution. It is particularly suitable for multi-criteria decision analysis when the interrelationships between indicators are unclear or when subjective weighting proves difficult.

CRITIC method stands for Criteria Importance Through Intercriteria Correlation, which determines weights by considering both the contrast intensity of data and the conflicts between criteria. It calculates standard deviations to measure contrast intensity while using correlation coefficients to evaluate inter-criteria conflicts. The weight of each criterion increases with higher contrast intensity and lower correlation with other criteria. This approach provides a balanced perspective by incorporating both data variability and interdependencies, making it robust for complex decision systems with interrelated indicators.

TOPSIS, or Technique for Order Preference by Similarity to Ideal Solution, is a widely used multi-criteria decision analysis method that ranks alternatives based on their relative closeness to ideal solutions. It constructs positive and negative ideal solutions in a normalized decision matrix and calculates Euclidean distances to these reference points. The best alternative is identified as having the shortest distance to the positive ideal solution and the farthest from the negative one. This intuitive geometric interpretation makes TOPSIS particularly valuable for practical decision-making scenarios requiring comparative assessment of multiple options.

Prophet is a forecasting procedure developed by Facebook for time series data, combining additive modeling with nonlinear trends. It accommodates seasonality, holidays, and changepoints through decomposable components, using a Bayesian approach for uncertainty estimation. The method's strength lies in its ability to handle missing data and abrupt changes while remaining computationally efficient. Unlike traditional ARIMA models, Prophet requires minimal parameter tuning and automatically detects pattern changes, making it accessible for non-experts in forecasting applications across various domains.

The four methods discussed-entropy weight method, CRITIC, TOPSIS, and Prophet-each offer distinct approaches to decision-making and data analysis. The entropy weight method provides an objective way to assign weights based on information entropy, reducing subjectivity in multi-criteria evaluations. CRITIC enhances weighting accuracy by considering both data variability and inter-indicator conflicts, making it suitable for complex systems with interdependent factors. TOPSIS simplifies comparative decision-making by measuring alternatives' proximity to ideal solutions, offering an intuitive geometric interpretation. Finally, Prophet stands out in time series forecasting with its flexibility in handling trends, seasonality, and missing data while requiring minimal manual tuning. Together, these methods demonstrate diverse yet complementary techniques for data-driven decision-making, spanning from weight determination to ranking alternatives and predictive modeling.

3. Experiments

3.1. CRITIC

In the CRITIC method, the correlation and information content of indicators are reflected through two aspects: conflict and discrimination. The conflict between indicators is based on their correlation-the stronger the positive correlation between two indicators, the lower their conflict. Discrimination is measured by standard deviation, which represents the degree of deviation of data points from the mean within the same indicator. A larger standard deviation indicates greater dispersion and thus stronger discrimination.

① The conflict measure for the i-th indicator relative to other indicators is quantified as:

$$C_i = \sigma_i \sum_{k=1}^{n} (1 - r_{ki}) \qquad i = 1, 2, \cdots m \tag{1}$$

A correlation heatmap illustrating the correlations among indicators is shown in Figure 1.

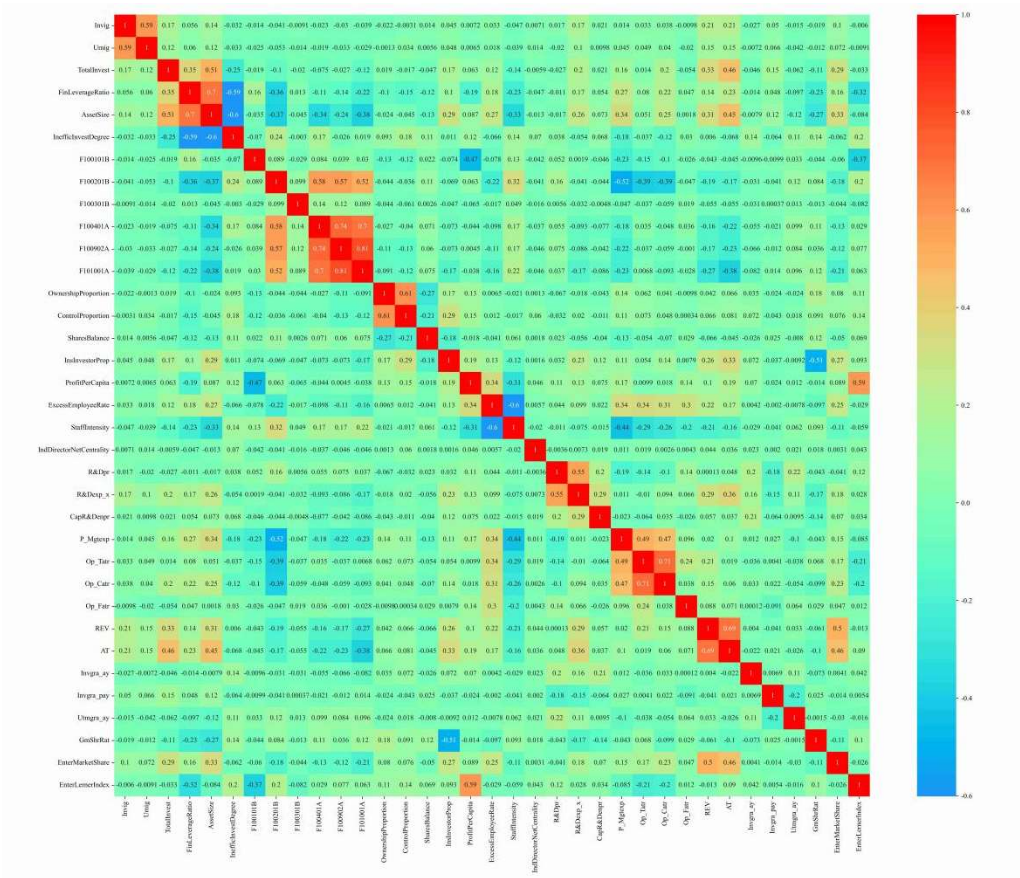

Figure 1. Correlation Heatmap of Indicators

② Consequently, the objective weight of the i-th indicator is given by (2):

$$w_1 = \frac{C_i}{\sum_{i=1}^{m} C_i} \qquad i = 1, 2, \cdots m \tag{2}$$

3.2. Entropy Weight Method

To more accurately and comprehensively determine the weights of indicators for measuring "involution-style" competition among enterprises, this paper first calculates the weights using the CRITIC method and then refines them through the entropy weight method. The entropy weight method determines weights based on the amount of information contributed by the observed values of each indicator. The information contributed by the data is positively correlated with its degree of variation-the greater the variation, the more information it provides, and thus the larger the weight assigned in the comprehensive evaluation. By employing information entropy to analyze the information content and variability of indicators, the calculated weights become more reliable. The specific calculation steps are as follows:

① Calculate the proportion of the j-th sample in the i-th indicator, as shown in Formula (3):

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{s} x'_{ij}} \tag{3}$$

② Compute the entropy value of each indicator using Formula (4):

$$e_i = -k \sum_{i=1}^{s} p_{ij} \ln(p_{ij}) \tag{4}$$

③ Determine the entropy redundancy, which reflects the amount of information provided by the indicator, as expressed in Formula (5):

$$d_i = 1 - e_i \tag{5}$$

④ Finally, calculate the indicator weights using Formula (6):

$$w_2 = \frac{d_i}{\sum_{i=1}^{\mathrm{m}} d_i} \tag{6}$$

3.3. TOPSIS

After determining the weights of indicators for measuring "involution-style" competition among enterprises, this study employs the TOPSIS method to calculate the scores of each indicator. By using the weights to amplify differences in critical indicators, the approach enables a more precise and targeted assessment of disparities between indicators. The TOPSIS method evaluates the comprehensive superiority or inferiority of assessment objects, facilitating decision-making based on their relative rankings.

① The normalized matrix is constructed as shown in (7):

$$V=\begin{pmatrix} v_{11} & \cdots & v_{m1} \\ \vdots & \ddots & \vdots \\ v_{1s} & \cdots & v_{ms} \end{pmatrix} \tag{7}$$

② The positive ideal solution (PIS) and negative ideal solution (NIS) are defined in (8) and (9), respectively:

$$V^{+}=\left(V_1^{+},\cdots,V_m^{+}\right)=\left(\max\left\{v_{11},v_{12},\cdots,v_{1s}\right\},\cdots,\max\left\{v_{m1},v_{m2},\cdots,v_{ms}\right\}\right) \tag{8}$$

$$V^{-}=\left(V_1^{-},\cdots,V_m^{-}\right)=\left(\min\left\{v_{11},v_{12},\cdots,v_{1s}\right\},\cdots,\min\left\{v_{m1},v_{m2},\cdots,v_{ms}\right\}\right) \tag{9}$$

These solutions consist of the maximum and minimum values of each column vector.
③ The distances from the j-th evaluation object (j = 1, 2, ..., s) to the PIS and NIS are calculated using (10) and (11):

$$D_j^{+}=\sqrt{\sum_{i=1}^{m}\left(v_{ij}-V_i^{+}\right)^2} \tag{10}$$

$$D_j^{-}=\sqrt{\sum_{i=1}^{m}\left(v_{ij}-V_i^{-}\right)^2} \tag{11}$$

④ The relative closeness of the j-th evaluation object to the PIS is computed to derive the similarity score, as expressed in (12):

$$\delta_j=\frac{D_j^{-}}{D_j^{-}+D_j^{+}} \tag{12}$$

3.4. Prophet

To examine the temporal evolution of China's corporate "involution-style" competition index, this study employs the Prophet time-series forecasting method, renowned for its robust predictive capabilities. The Prophet model offers exceptional interpretability, enabling clear visualization of the analytical process and key influencing factors. Beyond its forecasting strength and transparency, Prophet excels in handling daily periodic data with significant outliers and trend shifts while simultaneously modeling multiple seasonal cycles. Preliminary findings suggest the corporate involution index exhibits distinct annual periodicity and may be influenced by seasonal variations, making Prophet particularly suitable for generating accurate and comprehensive forecasts.
The Prophet model decomposes time series as shown in equation (13):

$$y(t)=g(t)+s(t)+h(t)+\varepsilon(t) \tag{13}$$

This formulation partitions time series y(t) into four components:

① Trend Component: Captures long-term, non-periodic patterns reflecting the overarching upward or downward trajectory of the data.

② Seasonality Component: Models recurring cycles at various temporal scales (weekly, monthly, quarterly, or annually).

③ Holiday Effects: Accounts for anomalies induced by festivals or special events.

④ Noise Term: Represents stochastic, unpredictable fluctuations assumed to follow independent and identically distributed (i.i.d.) Gaussian distribution, conforming to normal distribution properties.

This decomposition enables systematic analysis of both deterministic patterns and random variations in the involution index dynamics.

4. Results and Analysis

4.1. Results and Analysis of EWM and CRITIC

This study adopts a "CRITIC-Entropy Weight Combined Weighting Model" to systematically evaluate three key dimensions: inter-indicator conflict, redundancy, and information content, effectively mitigating the randomness inherent in single weighting methods. The research combines weights derived from CRITIC and entropy methods at a 1:1 ratio, generating composite weights that reflect each indicator's significance in assessing corporate "involution-style" competition. The results are presented in Figure 2:

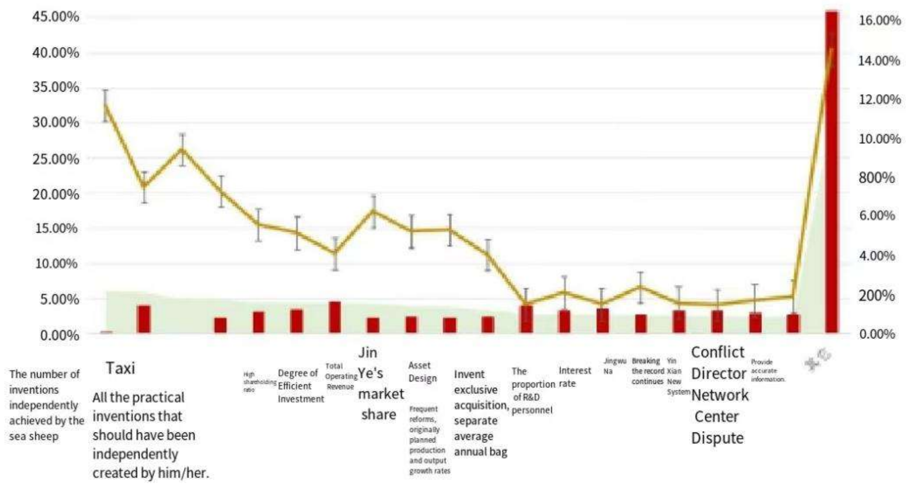

Figure 2. Histogram of Indicator Weights Based on CRITIC-Entropy Method

① High-Weight Indicators

These predominantly relate to core competitiveness and market valuation, exerting substantial influence on corporate involution. Key metrics include annual independently obtained invention patents, price-to-earnings ratio, and utility model patents. Invention patent quantity serves as a critical measure of autonomous innovation capacity and R&D capability within a given year. Requiring rigorous examination, invention patents represent high technological value and novelty. Enterprises securing numerous independent inventions demonstrate deep R&D investment and long-term competitive potential, enabling them to construct sustainable advantages.

② Medium-Weight Indicators

These provide fundamental support to involutionary competition, encompassing aspects like total operating revenue, market share, and R&D personnel ratio. Market share reflects industry positioning but often correlates with monopolistic advantages or cutthroat competition-firms frequently adopt aggressive strategies to expand resources and dominance. The new energy vehicle sector exemplifies this: competition has evolved from pure price wars to comprehensive battles across branding, product performance, service systems, and post-sales support. This multidimensional rivalry forces enterprises to optimize all operational aspects, creating complex market dynamics. When analyzing market share's role in involution, distinguishing between growth through healthy competition versus "involutionary expansion" becomes crucial.

③ Low-Weight Indicators

In involutionary competition, latent monopolistic forces may significantly influence outcomes, potentially limiting the index's predictive accuracy. Nevertheless, the Lerner index can guide resource allocation-firms with higher values may secure preferential resources/policies, amplifying market dominance. Though classified as low-weight, such indicators collectively enrich the holistic evaluation framework.

The hierarchical weighting system-spanning high, medium, and low-impact indicators-enables nuanced identification of involution drivers while maintaining methodological rigor against subjective biases.

4.2. Results and Analysis of TOPSIS

This study employs a TOPSIS evaluation model based on the combined weighting of CRITIC and entropy methods to measure and assess the degree of corporate "involution-style" competition, with representative enterprises selected for detailed analysis. The results indicate that Suning.com exhibits the most pronounced degree of involutionary competition, Chongqing Sanxia A falls within the moderate range, while Hunan TV & Broadcast Intermediary demonstrates relatively low competitive intensity.

Chongqing Sanxia A demonstrates moderate involutionary competition. As a key player in China's coatings industry, the company possesses brand influence but lags behind industry leaders in market share. Limitations in production scale and technological accumulation constrain its expansion capabilities. While attempting to enhance competitiveness through innovation, its efforts yield limited results, with products facing homogenization risks. Though maintaining production bases and sales networks across multiple regions, its R&D investments and channel coverage remain inferior to top competitors, preventing breakthrough advancements. Two asset divestitures optimized financial statements but failed to achieve structural upgrades in core operations, leaving its involutionary state persistently intermediate.

Hunan TV & Broadcast Intermediary registers the lowest involutionary competition, attributable to declining traditional operations and delayed digital transformation. Early diversification strategies diluted resources without cultivating core competencies, but recent shifts toward a capital-light "culture + technology + tourism" model have enabled successful restructuring. This innovative approach reduces investment risks and has achieved standardized replication across Hunan province, offering a potential pathway to escape industry involution. The tiered analysis-spanning high, moderate, and low involution cases-reveals how market positioning, strategic choices, and operational models collectively shape competitive dynamics, providing empirical insights into China's corporate involution mechanisms.

4.3. Results and Analysis of Prophet

The Prophet time series forecasting model demonstrates strong resistance to data gaps and significant trend changes, making it particularly suitable for data spanning from annual to monthly intervals with distinct seasonal patterns. The Chinese corporate "involution-style" competition index measured in this study consists of annual data. After applying Lagrange interpolation to estimate monthly data, Prophet still maintains high accuracy and good interpretability for future predictions.

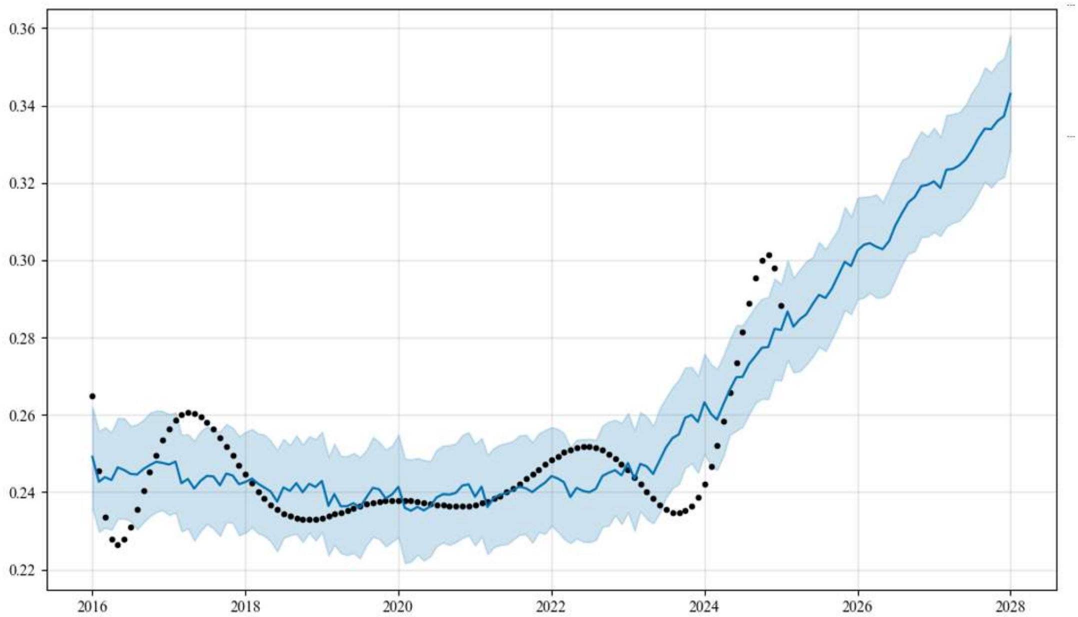

Figure 3. Prophet Time Series Forecast

Figure 3 simultaneously displays the historical and predicted data trends from the Prophet model. The black dots represent the original annual corporate "involution-style" competition index data and the monthly index data supplemented using Lagrange interpolation. The blue line shows the Prophet model's monthly index predictions, while the blue shaded area indicates the confidence interval of the forecast. We calculated the goodness-of-fit metrics-MAE, MSE, and RMSE-based on the actual values and the predicted values from the Prophet model, obtaining values of 0.007624, 0.000101, and 0.010042, respectively. MAE (Mean Absolute Error) reflects the average absolute difference between predicted and actual values, directly indicating the magnitude of error. MSE (Mean Squared Error) averages the squared errors, amplifying the impact of larger errors. RMSE (Root Mean Squared Error) is the square root of MSE, providing a more intuitive interpretation of error. Smaller values for these three metrics indicate lower overall model error and higher prediction accuracy. Given the small calculated values, the model exhibits low error, high goodness-of-fit, and strong predictive performance.

From the figure, we can observe that during the 2016-2025 historical period, the monthly index from historical data aligns well with the Prophet model's predictions, suggesting that the forecasting model will yield relatively accurate results for the next three years. This provides meaningful guidance for understanding the future trajectory of the corporate "involution-style" competition index. Thus, we conclude that over the next three years, despite normal monthly fluctuations, the overall trend of the corporate "involution-style" competition index will continue to rise significantly, indicating that China's corporate involution will intensify at a relatively high rate. Therefore, to ensure the healthy and sustainable development of Chinese enterprises, it is crucial to study, address, and seek solutions to "involution-style" competition.

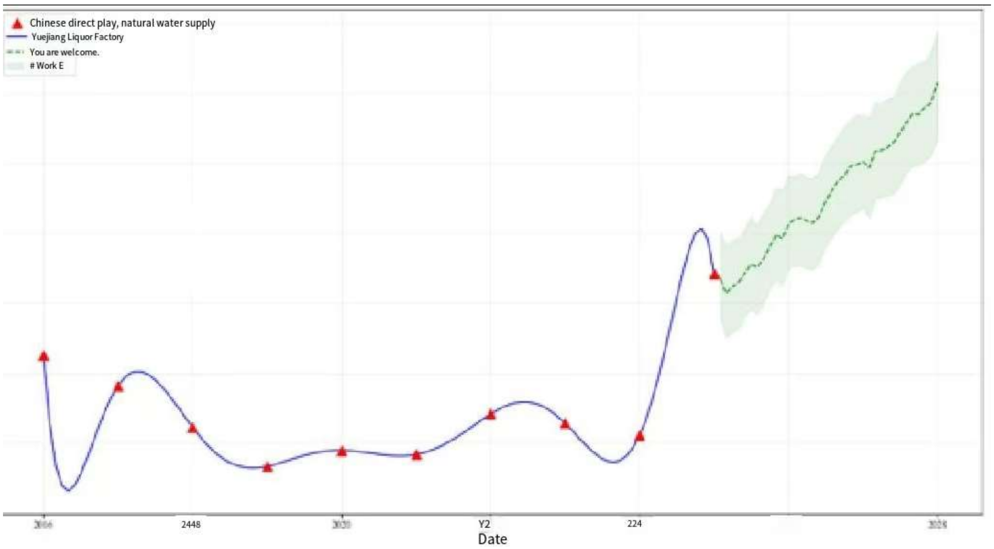

Figure 4. Prophet Annual Trend Decomposition

Figure 4 presents the actual values of China's corporate "involution-style" competition index from 2016 to 2024 and the predicted values for 2025 to 2028. From 2016 to 2024, the index showed minor fluctuations, remaining relatively stable with an overall downward trend. For 2025 to 2028, Prophet predicts a continued upward trend in China's corporate "involution-style" competition index. Internationally, the global economic landscape is characterized by trade frictions and deglobalization trends, such as the intense U.S.-China tariff war, which has hindered Chinese exports and further compressed overseas market opportunities. This forces firms to engage in price wars to capture limited domestic demand, leading to frequent occurrences of competition and driving up the involution index. Domestically, weak demand and consumption downgrades are evident. For example, salary cuts for middle-to-high-income groups in 2023-2024, combined with asset depreciation, have reduced household consumption capacity and demand. Meanwhile, policy stimuli have focused primarily on supply-side capacity investments, exacerbating supply-demand imbalances. The combination of international and domestic factors will lead to an increase in China's corporate "involution-style" competition index from 2025 to 2028.

5. Conclusion

This study combines the CRITIC-Entropy weighting method with TOPSIS evaluation and Prophet forecasting to systematically analyze corporate "involution-style" competition in China, revealing a concerning intensification trend driven by both structural market factors and policy dynamics. The integrated methodology demonstrates that high-weight innovation indicators like patents significantly mitigate involution, while excessive market share pursuit and supply-demand imbalances exacerbate it, with sectoral analysis showing traditional industries like coatings facing moderate involution versus media companies successfully transitioning through light-asset models. The Prophet projections particularly highlight how global trade tensions and domestic consumption weakness will likely accelerate involutionary pressures through 2028, suggesting that without strategic interventions balancing innovation incentives with market regulation, Chinese firms risk being trapped in increasingly destructive competition patterns that undermine sustainable development. These findings collectively emphasize the need for multidimensional policy solutions addressing both the symptoms and root causes of corporate involution.

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