China Online Consumer Brand Index (2023-2025)

May 21, 2025

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Alibaba's Taobao and Tmall Group

CBI Project：

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For access to the full report and its attachments, please visit:

https://en.nsd.pku.edu.cn/publications/cbi2025/index.htm

[1] The CBI project received invaluable support and assistance from the National School of Development at Peking University, the Institute of Digital Finance at Peking University, the Business School of Sun Yat-sen University, and Alibaba's Taobao and Tmall Group. We express our heartfelt gratitude to these institutions for their generous contributions. We are especially grateful to Yan Shen, Jun Pang, and Peng Wang for their insightful suggestions, which greatly improved this work. It is important to note that the views expressed in this index do not represent those of the National School of Development at Peking University, the Institute of Digital Finance at Peking University, the Business School of Sun Yat-sen University, and Alibaba's Taobao and Tmall Group. Any errors or omissions are the sole responsibility of the CBI research team.

Non-technical Summary

Encouraging innovation and healthy competition is essential for achieving high-quality development. Yet traditional macroeconomic indicators tend to focus heavily on quantity and price, leaving “quality” difficult to quantify. With boosting consumer spending now a top economic priority, the “China Online Consumer Brand Index” (CBI) featured in this report tracks changes in consumption quality. It complements traditional macroeconomic metrics like total retail sales and the consumer price index (CPI), providing valuable insights to guide brand development and business strategies in the China market.

As the world’s largest online retail market, China’s e-commerce sector not only offers new opportunities for brand development but also serves as a valuable foundation for macroeconomic analysis. In this context, this report makes two key contributions: the introduction of the first online consumption index focused on high-quality development and a brand rating system fully derived from consumers’ actual purchasing behavior. These features are characterized as follows:

(1) Big Data-Driven Analysis: The index leverages big data to integrate multi-dimensional information across industries, regions, and other aspects on a leading e-commerce platform. It includes key indicators such as search volume, sales, pricing, and consumer reviews, covering tens of millions of brands and nearly one billion active users.

(2) Benchmarking the Consumer Price Index (CPI): The index provides a Consumer Brand Index (CBI) at the national level, broken down by industry and on a quarterly basis. This facilitates synchronized observation of both quantity and price trends.

(3) Regional and Industry-Specific Insights: Beyond the national index, the report includes detailed industry-specific indices for each prefecture-level city, enabling the tracking of consumption quality and industrial upgrading across time, region, and industry dimensions.

(4) Top 500 Online Consumer Brands List (CBI500): The report introduces the CBI500, a ranking of the top 500 brands, designed to guide and promote the high-quality development of online consumption in China.

(5) Dual Indices with CBI and BPI: Alongside the CBI, the report features the Brand Purchase Index (BPI), which provides an additional perspective on brand consumption by measuring

both average quality and overall purchasing power.

This index comprehensively measures consumption quality and brand equity based on underlying metrics such as sales, prices, search volume, and customer reviews. The index is constructed as follows: Several indicators are selected from the available data based on brand equity models and machine learning methods. These indicators are then aggregated into a score for each brand, with weights determined through expert evaluations and the coefficient of variation method. As higher scores generally serve as an indicator of better quality, we calculate various indices to approximate consumption quality. To calculate the Consumer Brand Index (CBI), the average score for a "basket" of consumer brands is taken; a higher average score reflects higher overall quality. Similarly, the Brand Purchase Index (BPI) is obtained by summing the total scores of brands in the basket, where a higher total score indicates stronger purchasing power.

Based on the series of indices and top brand list, this report finds that:

First, based on data from 2023 to 2025, the CBI has exhibited a steady upward trend, rising from 59.42 in Q1 2023 to 63.38 in Q1 2025. To put it into perspective, this improvement is roughly equivalent to half of all consumers switching from brands ranked outside the top 1000 to newly emerging brands that have just broken into the top 500. This reflects an improvement in the overall rating of the national “basket” of consumer brands, indicating stable growth in consumption quality.

Second, at the industry level, the 3C digital and home appliance sectors exhibit the highest consumption quality, with CBI scores exceeding 75. This indicates that leading brands in these industries hold a significant share of the market. Meanwhile, the pet care, home furnishing, and women’s apparel sectors have shown substantial growth, with CBI increases of more than 5 points since 2023. This reflects a growing consumer awareness of brands in these industries and a shift in consumption toward higher-rated brands.

Third, at the regional level, first-tier cities rank highest in the Brand Purchase Index (BPI), reflecting their strong overall purchasing power. Meanwhile, emerging first-tier cities and some second- and third-tier cities lead in the Consumer Brand Index (CBI), demonstrating higher average consumption quality. Per capita GDP and the share of the tertiary industry are significantly positively correlated with both the BPI and CBI. However, while the proportion of migrant workers in the population is positively correlated with the BPI, it is negatively correlated with the CBI. This suggests that regions with a higher proportion of migrant workers tend to see an increase in total consumption volume due to a larger population base and higher overall sales. At the same time, the average consumption quality slightly declines. This pattern aligns with the inclusiveness of first-tier cities and their ability to attract and accommodate an economically diverse population.

While this report primarily examines some basic characteristics of the indices, the greater value lies in its potential to facilitate deeper analyses through integration with other economic and social indicators. We welcome individuals and organizations from all sectors to utilize this index. The complete dataset is available for free and can be requested from the research team via email at **cbi_pku@163.com**. If you use this data, please cite it as follows: **"China Online Consumer Brand Index (CBI)"**, and reference the source: Yang Ji, Yiping Huang, *China Online Consumer Brand Index: 2023-2025*, May 2025, National School of Development Series Report, Peking University.

1. Background and Motivation

Encouraging innovation and healthy competition is essential for achieving high-quality development. To transition from price-based competition to quality-based competition, both market consensus and effective macroeconomic monitoring are needed. However, traditional macroeconomic indicator systems primarily focus on quantity and price, with little emphasis on "quality." For example, the commonly used indicators for consumer spending only include a quantity metric (total retail sales) and a price metric (consumer price index), without any measure of consumption "quality."

This report will release the first series of consumption indices and brand rankings focused on high-quality development, specifically including the following three components:

(1) China Online Consumer Brand Index (CBI): This captures the average consumption quality levels across different product categories in prefecture-level cities.

(2) China Online Brand Purchase Index (BPI): This highlights the relative purchasing power for top-rated brands across prefecture-level cities.

(3) China Top 500 Online Consumer Brands List (CBI500): This ranks the top 500 online consumer brands entirely based on actual consumer purchasing behaviors, intending to guide brand development and promote healthy competition in the e-commerce market.

The series of indices has the following features:

Big Data-Driven Metrics: The indices leverage multidimensional metrics from China's leading e-commerce platforms, covering approximately one billion active users and offering comprehensive insights into online consumption.

Dynamic Tracking of Consumption Quality: The indices monitor changes in the quality of consumption in China, supporting macroeconomic analysis with full coverage of quantity, price, and quality dimensions.

Detailed Regional and Industry Insights: In addition to quarterly updates, the indices offer in-depth insights through region- and industry-specific breakdowns, enabling the tracking of consumption trends and industrial upgrading across time, regions, and industries.

Top 500 Online Consumer Brands List (CBI500): The report includes the release of the

CBI500, a ranking of the top 500 brands, aimed at guiding and fostering the high-quality development of online consumption in China.

Dual Indices with CBI and BPI: The report introduces two complementary indices: the Consumer Brand Index (CBI) and the Brand Purchase Index (BPI). The CBI measures the average consumption quality in a region, while the BPI highlights a region's overall purchasing power for high-rated brands. Together, they offer a multidimensional view of brand consumption patterns and trends.

This index comprehensively measures consumption quality and brand equity based on underlying metrics such as sales, prices, search volume, and customer reviews. The index is constructed as follows: Several indicators are selected from the available data based on brand equity models and machine learning methods. These indicators are then aggregated into a score for each brand, with weights determined through expert evaluations and the coefficient of variation method. As higher scores generally serve as an indicator of better quality, we calculate various indices to approximate consumption quality. To calculate the Consumer Brand Index (CBI), the average score for a "basket" of consumer brands is taken; a higher average score reflects higher overall quality. Similarly, the Brand Purchase Index (BPI) is obtained by summing the total scores of brands in the basket, where a higher total score indicates stronger purchasing power. By limiting the "basket" of brands to specific time frames, product categories, or regions, it becomes possible to generate indexes for particular time frames × product categories × region combinations. At the same time, we rank brands based on their scores to produce the **Top 500 Online Consumer Brands List (CBI500)**. It is important to note that online and on-site markets differ in sales volumes across industries, making it difficult to rely solely on online consumption data for unbiased insights into the overall consumer market in terms of "quantity" and "price." However, when it comes to brand sales channels and product quality, nearly all major brands now have online stores, and the quality of products sold online is largely comparable to those sold in on-site markets. This makes online market data a reliable representation of "quality" in the broader consumption landscape.

The indices and rankings presented in this report are rooted in China's rapidly growing digital economy and contribute to the following three key areas:

First, we enhance macroeconomic monitoring by utilizing consumption big data to

capture quality dimensions. Measuring consumption quality has long been a challenging academic issue. Rosen (1974) proposed the “Hedonic Pricing” method, which treats goods as bundles of attributes to quantify the contribution of quality or adjust price indices for quality changes. Similarly, Bils & Klenow (2001) used a structured approach to distinguish between “pure price increases” and the effects of “quality improvements or new product replacements” on prices. However, these methods rely heavily on collecting detailed product attribute data, which involves high data acquisition costs and a certain lag. To capture changes in consumption quality in a timely, high-frequency, and large-scale manner, overcoming data collection challenges is essential. This is also the core motivation of this study — leveraging the vast amount of naturally generated data from e-commerce platforms to gain real-time insights into changes in consumption quality.

At the same time, China’s digital economy has become one of the largest in the world, and online consumption plays a vital role in the daily lives of Chinese residents. The country’s online retail sales have continued to grow, increasing their share of total retail sales from 20.7% in 2019 to 26.8% in 2024. For 12 consecutive years, China has been the world’s largest online retail market. Compared to other countries, online consumption is more representative of overall consumer behaviors in China. Regarding the “price” dimension of China’s online consumption market, the iCPI project team from Tsinghua University has collected price data from multiple online platforms to create the Online Consumer Price Index (iCPI). Studies by Liu et al. (2019), Jiang et al. (2020), and Sun et al. (2021) have used this index to analyze macroeconomic price trends, the effects of monetary policy, and changes in platform prices, providing empirical evidence in these areas. While previous research has primarily centered on the “price” dimension, it has largely overlooked the equally critical “quality” aspect. This report seeks to bridge that gap by focusing on brands in the e-commerce market, providing a complementary analysis of the quality dimension in China's online consumption landscape. By leveraging the natural data flow from e-commerce platforms, this study provides timely insights into the quality aspects of consumption, offering a fresh perspective on the evolving online market.

Second, this report adopts innovative methods for brand evaluation, as the digital economy has given rise to new brand development strategies. With the advancement of technologies such as mobile payments, e-commerce platforms, and livestream shopping, new channels of interaction between brands and consumers have emerged — including search, browsing, livestream orders, product trials, membership programs, and after-sales reviews. Meanwhile, the integration of online and offline channels, known as the "multi-channel retailer" model, has become the dominant trend in the retail consumer market (Cavallo, 2017). A number of emerging brands have been established as online-first stores, relying primarily on e-commerce platforms for sales and marketing, and gaining significant market influence despite the absence of physical storefronts. Similarly, many international brands have entered the Chinese market through digital channels, launching flagship stores on e-commerce platforms and receiving consumer recognition. Nearly all leading retail consumer brands on prevailing global brands lists have integrated online channels into their business strategies.[2] As the world's largest online retail market, China's digital platforms not only offer brands new avenues for growth but also serve as a critical arena for global brand competition.

The development of the online consumption market has not only raised new requirements for brand evaluation frameworks but has also provided a rich source of big data for brand assessment. Current mainstream methods for brand evaluation are primarily based on the ISO 10668 standard, which focuses on the net present value of a brand's future cash flow. Representative companies like Brand Finance and Interbrand, which conduct global brand valuations, use this approach. However, these methods rely on financial data and consumer surveys, making it difficult to capture market changes at high frequency. Moreover, they are only applicable to large-scale enterprises and are less effective for emerging brands lacking standardized financial information.

The indices and rankings in this report, based on the massive data generated by online consumption and online consumer behaviors, effectively cover the development of emerging brands and dynamically reflect the evolving consumption market in the digital economy.

Third, we contribute to reversing the cut-throat price competition in the digital economy by promoting a race-to-the-top in quality through this report. In recent years, media outlets have frequently called for e-commerce platforms to transition "from price wars to healthy

[2] For example, in the 2024 World's 500 Most Influential Brands list published by the World Brand Lab, more than 60% of the top 100 brands had established online channels. Brands without such channels were primarily concentrated in industries such as automotive, energy, financial services, and pharmaceuticals, where consumer engagement remains largely offline.

competition" [3]and warned, "Don't let low-price tactics on e-commerce platforms squeeze small and medium-sized enterprises' profit margin" [4] Due to the explosive growth and network externalities characteristic of platform economies, platforms tend to attract users by emphasizing low prices. Theoretical studies by Caillaud & Jullien (2003), Rochet & Tirole (2003), Parker & Van Alstyne (2005), and Armstrong (2006) have all reached similar conclusions under different modeling assumptions. Furthermore, as Nelson (1974) pointed out, price information has stronger "search attributes," making it easier to disseminate, while quality information has stronger "experience attributes," which are more challenging to communicate effectively. In practice, e-commerce platforms have experimented with various methods to convey quality information (Chevalier and Mayzlin, 2006; Ursu, 2018; Horton, 2017). However, these efforts have often proven to be limited in impact and costly (Sahni and Nair, 2020; Jin & Koto, 2006; Elfenbein et al., 2015). This report, through the development of brand indices and brand list, aims to guide the high-quality development of online consumption and foster healthy competition within e-commerce platforms.

The following sections will introduce the principles of index construction, the indicator selection, and calculation methods, followed by a preliminary analysis of the index and rankings. The appendix of the report includes the Top 100 Online Consumer Brands and the corresponding indices for various industries. Due to space limitations, detailed CBI500 data (including scores for each indicator) can be downloaded as an attachment from the website. For detailed data on sub-indices for prefecture-level cities and region × industry indices, please request via email.

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[3] The Securities Times: "Double 11 Shopping Festival Officially Concludes: E-commerce Platforms Shift from Price Wars to Healthy Competition" (证券时报，双 11 大促正式收官，电商平台从低价内卷迈向品质竞争), https://www.stcn.com/article/detail/1410014.html.

[4] China Economic Weekly: "Don't let low-price tactics on e-commerce platforms squeeze small and medium-sized enterprises to death" (中国经济周刊，别让电商低价卷死中小企业), http://paper.people.com.cn/zgjjzk/pc/content/202412/15/content_30051904.html.

2.Principles and Indicators for Brand Rating and Index Construction

2.1 Core Principles

Focusing on Brands and Highlighting Consumption Quality

This index and brand rating prioritize quality, steering away from "involutional competition" (excessive competition without meaningful improvement) and emphasizing quality advantages beyond just "price." By integrating multidimensional online consumption data—such as consumer purchasing behaviors and user experiences—the index aims to quantitatively depict the development of consumption quality in China's online market.

Leveraging E-commerce Big Data in the Online Market

With one of the most well-developed digital economies, China has remained the largest online retail market in the world for 12 consecutive years.[5] Currently, e-commerce platforms have achieved full coverage across all provinces and prefecture-level cities. This study fully utilizes online big data by focusing on metrics naturally generated during consumers' browsing and purchasing activities on e-commerce platforms, such as search volume, consumer reviews, and sales. While this approach has certain limitations—such as its inability to objectively reflect industries dominated by offline sales (e.g., housing and automobiles) or to fully incorporate annual reports and financing data of publicly listed brands—it offers unique advantages, including lower data collection costs, broader data coverage, and higher update frequency.

Embracing Online Growth Strategies for Domestic and Global Brands

China's digital economy has paved the way for new growth opportunities for brands. Both domestic and international brands are increasingly adopting online-first strategies, including many emerging brands that have gained widespread recognition in the online market without ever opening physical stores. To better reflect the diversity of brands at different scales and stages of development, we move away from traditional brand valuation methods that rely heavily on conventional financial metrics. Instead, we place a strong focus on identifying and supporting emerging brands.

[5] People's Daily: "China Remains the World's Largest Online Retail Market for 12 Consecutive Years" (人民日报，我国连续 12 年成为全球最大网络零售市场), https://www.gov.cn/yaowen/liebiao/202502/content_7007815.htm.

Recognizing Industry and Time Period Differences in Brand Evaluation

Our brand evaluations prioritize comparability within the same industry and time frame, as cross-industry or cross-period comparisons can be challenging and may not always yield consistent insights. For instance, leading brands in the home appliance sector and the beauty sector are inherently different and not directly comparable. Similarly, even within the same sector, the top brand this year may differ in context and metrics from the top brand last year. Ensuring Comparability Across Industries, Regions, and Time Periods

To construct the Consumer Brand Index based on brand evaluations, the core assumption is that higher-rated brands represent higher quality, and the average brand score reflects the overall level of consumer quality. Unlike individual brand evaluations, the Consumer Brand Index is specifically designed to enable effective cross-industry, cross-region, and cross-period comparisons. For example: If the index for the home appliance industry is higher than that for the fashion industry, it suggests that consumption in the home appliance sector is more concentrated on top brands, while consumption in the fashion sector is more dispersed. Similarly, if this quarter's index is higher than the previous quarter's, it indicates an overall improvement in consumer quality, with more purchases shifting toward higher-rated brands. In the same sense, if Hefei City's index is higher than Xining City's, it reflects that the average consumer quality in Hefei is higher than in Xining. However, the index does have limitations. For instance, every brand offers a mix of high- and low-priced products, but the index cannot precisely capture changes in the consumption patterns of a brand's customers. Similarly, it cannot identify whether a brand is adjusting its supply by introducing more affordable products. These limitations should be taken into account when interpreting the indices in this report.

Balancing Industry Classification Across Academia, Business, and Public Perception

The classification of industries in brand evaluations and index construction is designed to balance the needs of academic research, business logic, and public perception. This approach addresses several key aspects: First, ensuring comparability within industries: Products within the same category need to be meaningfully comparable. For example, while both blankets and tissues are household products, their purchase patterns differ significantly—blankets are purchased infrequently, while tissues are bought regularly. To ensure accurate comparison, they must be categorized separately. Second, balancing business logic and statistical frameworks. The classifications should align with commercial realities while also taking established macroeconomic standards into account. For instance, “3C digital” (consumer electronics) is a widely recognized category that aligns with public perception and business practices. However, under the CPI classification system, mobile phones are categorized under “Transportation and Communication,” while computers fall under “Education, Culture, and Entertainment.” Reconciling these differences is essential for consistency. Third, cautiously excluding offline-heavy industries where less relevant. While e-commerce data may not fully represent industries dominated by on-site transactions, it can still provide valuable insights. For example, in the housing sector, e-commerce data on products such as “renovation materials” is relevant and should be included in the analysis framework, even though the sector is largely offline. In sum, we adopt a comprehensive and thoughtful approach to industry classification, ensuring that it balances academic rigor, business relevance, and public understanding. Detailed mapping rules have been developed to ensure comparability, representativeness, and alignment with both macroeconomic standards and micro-level survey data. The goal is to provide meaningful insights for macro-level analysis and industry-specific research alike.

2.2 E-commerce Platform Selection and Industry Classification

Based on the principles and objectives outlined above, the selected e-commerce platform needed to meet several key criteria:

First, the platform should have a large, nationwide user base, covering not just first- and second-tier cities but also lower-tier regions.

Second, it should offer products across a wide range of prices and quality levels, rather than focusing exclusively on “hero products,” “budget products,” or “luxury goods.”

Third, the platform should operate as a typical two-sided market, enabling meaningful interaction between brand merchants and consumers, rather than being heavily dominated by a 1P operated model.

Fourth, it should span a variety of industries and product categories instead of specializing in a single area, such as beauty products or home appliances.

Fifth, the platform should have been in operation for a substantial amount of time, reaching a relatively mature and stable development phase. This ensures that its promotional and marketing activities are relatively consistent over time, minimizing short-term fluctuations or data noise.

Based on these criteria, Alibaba's Taobao and Tmall were chosen as the most suitable platforms for this study. As one of China's earliest e-commerce platforms, Taobao and Tmall have become cornerstone platforms for both domestic and international brands to establish self-operated stores. With over 900 million monthly active users, the platform encompasses nearly the entire online shopping user base in China. [6]Its user base is not only large but also widely distributed across different regions. While Taobao and Tmall do not represent the entire online retail market, they stand out as the most suitable option due to their data availability, consistency in metrics, and strong representation of brands.

To align with the platform's internal classifications, CPI industry classifications, and categorizations from multiple mainstream micro-level household surveys, we adopt the classification system shown in Table 1. This system includes 8 primary categories, 22 secondary categories, and 14 overarching categories specifically used for the brand list.

The primary categories are aligned with CPI industry classifications, while the secondary categories are primarily based on the industry classifications used by the e-commerce platform. The relationship between these two levels of categories has been mapped according to the "Classification of Household Consumption Expenditures" published by the National Bureau of Statistics in China.

It is important to note, however, that some secondary categories, while they can be assigned to a primary category, do not fully represent the core consumption patterns of that category. For example: "renovation materials" can be categorized under the "housing" industry but do not reflect the primary housing-related expenditures such as purchasing or renting homes. Similarly, "transportation" industry here lacks representativeness for the dominant automobile consumption in this category.

In addition, based on public perception and the cross-industry operations of certain brands, we have also provided overarching categories for the brand list. If multiple brands operate across industries within secondary categories, they are marked under the overarching category on the list,

[6] Xinhua News: China's Internet Users Surpass 1.1 Billion, As of December 2024, the number of online shopping users in China has reached 974 million (新华网，《我国网民规模突破 11 亿》，截至 2024 年 12 月，我国网络购物用户规模达 9.74 亿人), https://www.news.cn/tech/20250121/90a851eebba244f5989055a8b6957e4f/c.html, accessed on April, 16th, 2025.

without further subdivision. Categories such as "household items" and "3C digital" exhibit these characteristics. In the subsequent index compilation, the 22 secondary industry categories will serve as the primary basis for the industry classification in this report. We will also provide detailed indices for each quarter, covering different regions and industries, to serve as a reference for research and analysis by various stakeholders.

Table 1 Industry Classification

<table>
<tr><th>Primary Categories
(Based on CPI Industry Classifications)</th><th>Secondary Categories
(Based on Platform Industry Classifications)</th><th>Overarching Categories
(For Brand List)</th></tr>
<tr><td>Food</td><td>Food</td><td>Food</td></tr>
<tr><td rowspan="4">Fashion</td><td>Sports & Outdoors</td><td rowspan="4">Sports & Outdoors + Fashion</td></tr>
<tr><td>Fashion (Women's Wear)
(Excluding Sports & Outdoors)</td></tr>
<tr><td>Fashion (Men's Wear)
(Excluding Sports & Outdoors)</td></tr>
<tr><td>Fashion (Others)
(Excluding Sports & Outdoors)</td></tr>
<tr><td>Housing</td><td>Renovation Materials</td><td rowspan="2">Home Furnishing & Home Decos</td></tr>
<tr><td rowspan="6">Household Essentials & Services</td><td>Home Furnishing & Home Decos</td></tr>
<tr><td>Home Appliances</td><td>Home Appliances</td></tr>
<tr><td>Household Textiles</td><td rowspan="3">Household Items</td></tr>
<tr><td>Personal Care</td></tr>
<tr><td>Cleaning Products</td></tr>
<tr><td>Beauty</td><td>Beauty</td></tr>
<tr><td rowspan="2">Transportation & Communications</td><td>Transportation</td><td>Transportation</td></tr>
<tr><td>3C Communications</td><td rowspan="3">3C Digital</td></tr>
<tr><td rowspan="6">Culture & Entertainment</td><td>3C Smart Devices</td></tr>
<tr><td>3C Culture & Education</td></tr>
<tr><td>Collectible</td><td>Collectible</td></tr>
<tr><td>Flowers & Gardening</td><td>Flowers & Gardening</td></tr>
<tr><td>Office & School Supplies (Non-electronic)</td><td>Office & School Supplies</td></tr>
<tr><td>Pet Care</td><td>Pet Care</td></tr>
<tr><td>Medical & Healthcare</td><td>Medical & Healthcare</td><td>Medical/healthcare/nutritional products</td></tr>
<tr><td>Others</td><td>Jewelry & Accessories</td><td>Jewelry & Accessories</td></tr>
</table>

2.3 Indicators and Weighting Methodology

In brand evaluation, this study builds upon Aaker's (1991) Brand Equity model, which consists of four core elements: Brand Awareness, Perceived Quality, Brand Associations, and Brand Loyalty. Based on this framework, and considering the availability of e-commerce platform data, the feasibility of data processing, and the need for timely monitoring of emerging brands, this report focuses on the following four dimensions: Brand Awareness, Brand Novelty, Customer Loyalty, and Customer Satisfaction.

The relative weights of different dimensions and metrics in the scoring system are determined using a combination of subjective and objective weighting methods. The relative weights of the four dimensions are established through the Delphi method (Linstone & Turoff, 1975). An expert panel, consisting of individuals from diverse fields such as academic research, data analysis, and brand management, conducted anonymous evaluations. After several rounds of feedback, the differences in expert opinions converged to within 10%, and the average score was taken as the final weighting. Within each dimension, the relative weights of individual metrics are calculated using the coefficient of variation method. This approach assigns higher weights to metrics with greater relative variability, as they are considered to provide more valuable information. By combining these two methods, the weighting process ensures a balance between expert judgment and data-driven objectivity in the evaluation system.

Based on expert evaluations, the weights assigned to Brand Awareness, Brand Novelty, Customer Loyalty, and Customer Satisfaction are 32.5%, 27.5%, 22.5%, and 17.5%, respectively. Among these, Brand Awareness is given the highest weight, aligning with the fundamental principles of traditional brand equity models and consumer research, where awareness is considered the most critical dimension in brand evaluation. Customer Satisfaction, on the other hand, is assigned a relatively lower weight in this scoring system. This decision stems from the unique characteristics of online consumption data, where positive reviews and ratings are treated with caution. As for Customer Loyalty and Brand Novelty, the latter is weighted slightly higher. This reflects the value orientation of this report's index and rankings, which prioritize innovation and the support of emerging brands. The scoring system places emphasis on identifying fast-growing brands that quickly resonate with younger audiences and continuously develop new products.

Under each dimension, a dedicated team of the e-commerce platform leveraged rich and extensive online consumption data to integrate nearly all available indicators, including website traffic, search keywords, transactions, membership transactions, and store ratings (see Table 2). This is the first time e-commerce platforms have offered such extensive support to academic institutions for research on consumption quality. However, online big data is based on users' real behaviors, which differ fundamentally from the consumer survey indicators traditionally used in brand evaluation systems. This difference raises an urgent question: which of these available indicators can be effectively leveraged to evaluate brand scoring and ranking?

Table 2 Major Available Indicators

Brand Awareness	Brand keyword search volume
	Brand product page views
	Brand store visits
	Transaction amount from brand keyword searches
	Number of transactions from brand keyword searches
	Gross merchandise value
	Total orders
	Total buyers
Brand Novelty	Number of new product sales
	Original gross merchandise value of new products
	Number of new product orders
	Proportion of new products
	Proportion of new product sales
	Proportion of new product orders
	Smoothed gross merchandise value of new products
	Proportion of buyers aged 18-24
	Growth rate (in the number) of buyers aged 18-24
	Growth rate of gross merchandise value
	Growth rate of orders
	Growth rate of buyers
	Growth rate of products
Customer Loyalty	Members' gross merchandise value
	Members' total orders
	Proportion of members' gross merchandise value
	Proportion of members' total orders
	Returning customers' gross merchandise value
	Returning customers' total orders
	Number of returning customers
	Proportion of returning customers' gross merchandise value
	Proportion of returning customers' total orders
	Price per order
	Price per customer

	Price per item
Customer Satisfaction	Logistics rating
	Service attitude rating
	Quality rating
	Store reviews

To address this issue, we combined survey interviews with machine learning to identify three key metrics for each dimension that effectively predict and explain what makes a "high-quality brand." The process involved three main steps:

First, defining high-quality and low-tier brands. We identified "high-quality brands" and "low-tier brands" using consumer search volume as the primary criterion, defining brands with the highest search volumes as "high-quality brands" and those with the lowest search volumes as "low-tier brands." The advantage of this definition is that it relies as much as possible on consumers' proactive behaviors, thereby minimizing the interference caused by platform promotions and push activities. At the same time, this method ensures that "high-quality brands" are truly premium and "low-tier brands" are sufficiently low-tier, providing a cleaner and more reliable dataset for metric selection.

Specifically, for each industry and quarter, we selected the top 10 brands with the highest search volumes and calculated their average search volume. Using 1/10th of this average as the threshold, brands with search volumes exceeding the threshold were classified as "high-quality brands." For "low-tier brands," we randomly drew twice the number of premium brands from those with search volumes below 1/30th of the average of the top brands, ensuring their sales were non-zero. This method meets research needs in three ways: First, the selected premium brands have search volumes within the same magnitude, avoiding drastic disparities. Second, the low-tier brands have valid non-empty metrics and show significant differences compared to premium brands. Third, it accounts for structural differences across industries. For instance, in the household appliances industry, the top 10 brands by search volume typically encompass all major premium brands in that sector. In contrast, in the fashion industry, the top 10 brands only represent a portion of high-quality brands, as lower-ranked brands may have similar market influence. In such cases, using a threshold-based selection ensures that all major premium brands across industries are included in the sample, with comparable influence on the top brands.

Second, based on the above sample, we used the available metrics to build models predicting whether a brand is a "high-quality brand." Since metrics in non-durable goods industries are generally higher than those in durable goods industries, cross-industry comparisons required a certain degree of standardization. Metrics with strong cross-industry comparability, such as ratings-related metrics, were kept in their original form, while metrics with weaker comparability, such as sales and search volumes, were standardized. The modeling methods primarily included two approaches: Random Forest Analysis, which was used to predict whether a brand is a premium brand and to determine the relative importance of different metrics (feature importance), and Logit Regression Analysis, which assessed the explanatory power of different metrics on the likelihood of being classified as a premium brand, retaining only metrics with significant and positive regression coefficients.

Third, within each dimension, we selected three key metrics from all available options based on the following principles: We started by using Random Forest to identify the metric with the highest relative importance. Next, we incorporated insights from industry surveys and interviews to select a second metric which is widely recognized in industry practices. If the first two metrics overlapped, we combined the results from Random Forest and interview findings to determine the second most important metric. For the third metric, we conducted a correlation analysis to identify one that was distinct from the first two, had weak correlations with them, and was also recognized by industry experts. When metrics performed similarly in statistical evaluations, we prioritized those that ensure logical consistency with metrics in other dimensions. For example, if two dimensions had already selected variables related to the "number of buyers," and a third dimension presented a choice between "number of buyers" and "gross merchandise value," we prioritized the "number of buyers" metric for consistency. Finally, all selected metrics were tested using Logit Regression to confirm that their regression coefficients were positive. Metrics that failed this test were replaced by repeating the selection process.

Table 3 Brand Scoring Dimensions and Corresponding Indicators

Dimension	**Indicator**	**Definition**
Brand Awareness (32.5%)	Brand keyword search volume	The average daily number of unique visitors searching for brand keywords (during the quarter, excluding duplicate searches by the same users.
	Gross merchandise value	The average daily transaction value of the brand's products completed via e-commerce platforms during the quarter.
	Total buyers	The average daily number of buyers completing transactions for the brand's products on e-commerce platforms during the quarter.

Brand Novelty (27.5%)	Smoothed gross merchandise value of new products	The average daily transaction value of new products launched by the brand during the quarter, completed via e-commerce platforms. To reduce volatility caused by brands' varying quarterly launch preferences, this metric averages the current and previous quarter's data.
	Growth rate of buyers aged 18-24	The quarterly growth rate in the number of buyers aged 18–24 among the brand's transaction users.
	Growth rate of gross merchandise value	The quarterly growth rate of the brand's total transaction value.
Customer Loyalty (22.5%)	Price per customer	The average transaction value per customer for the brand during the quarter.
	Members' gross merchandise value	The average daily transaction value of the brand's store members during the quarter.
	Returning customers' gross merchandise value	The average daily transaction value during the quarter of customers who made purchases from the brand in the previous quarter.
Customer Satisfaction (17.5%)	Logistics rating	The average logistics rating for products sold in the brand's store during the quarter.
	Quality rating	The average rating for product quality (matching product description) in the brand's stores during the quarter.
	Store reviews	The positive review rate for the brand's stores during the quarter.

Based on modeling analysis and industry interviews, the final indicators included in the scoring system are shown in Table 3, and the selection process is as follows: (1) For the Awareness dimension, among the 8 available indicators, brand keyword search volume was identified as the most important through Random Forest analysis. At the same time, gross merchandise value (GMV) was recognized as the most critical indicator by the industry. On top of these two, the number of total buyers was selected as the third indicator based on its differentiation, weak correlation with the other two, and strong industry recognition. (2) For the Novelty dimension, out of 13 related indicators, Random Forest analysis showed that the smoothed gross merchandise value of new products was the most important predictor for premium brands. This smoothed value outperformed the raw value as it accounts for the seasonal nature of new product launches across brands. Additionally, industry interviews emphasized that younger users (aged 18–24) are more sensitive to emerging brands, making the growth rate of buyers aged 18–24 a key indicator. Among the remaining indicators, the growth rate of gross merchandise value and the growth rate of products showed the weakest correlations with the selected indicators and are both regarded as important in industry practices. However, both failed the Logit regression test, as emerging markets with higher growth rates generally do not represent well-established premium brands. To emphasize the growth dimension, one of these indicators needed to be included, and growth rate of gross merchandise value was ultimately chosen for its logical consistency with the previously selected dimensions. (3) For the Loyalty dimension, among 12 indicators, Random Forest analysis identified returning customers' gross merchandise value as the most important, as it reflects genuine repeat purchase behavior. Industry interviews emphasized members' gross merchandise value, which represents the effectiveness of a brand's active customer engagement strategies and consumer trust. Correlation analysis showed that both price per customer and price per order were weakly correlated with the selected indicators and provided additional insights. Considering industry preferences, price per customer was ultimately selected, as a higher value indicates that consumers are less price-sensitive toward the brand, meaning purchases are not driven by discounts or promotions. (4) For the Satisfaction dimension, among 12 potential indicators, Random Forest analysis highlighted store reviews as the most important. Industry interviews pointed to quality rating as another critical indicator. Correlation analysis showed that logistics rating was the least correlated with the above two indicators and also reflected key characteristics of online shopping. However, it is worth noting that the after-sales rating system on Taobao and Tmall platform has been in use for many years and is set to be updated within the year. While the current system ensures stable evaluations for cross-brand comparisons in the short term, its cross-period comparability may weaken after the upcoming updates.

The above scoring system, beyond the traditional brand equity model, fully takes into account emerging brands, younger customer groups, and a focus on brand innovation. In terms of Novelty, traditional brands do not hold a significant advantage, while rapidly growing emerging brands, brands that maintain strong innovation capabilities, and those that quickly attract younger audiences can achieve higher scores in this dimension.

3. Methodology Framework for Brand Scoring and Index

The calculation methodology is introduced in three parts: (1) Brand scoring within the industry, (2) Brand index, and (3) Brand rankings. In the following explanation, the following notations are used to represent different dimensions corresponding to the indicators or scores: i denotes the brand, j denotes the industry, r denotes the region, t denotes the quarter, h denotes the indicator.

3.1 Within-Industry Brand Scoring

To create objective brand scores across quarters and industries, this study involves normalizing indicators from different dimensions, aggregating them with assigned weights, and standardizing the results.

Dimensionless Processing and Weighting

In a multi-indicator evaluation system, it is essential to process indicators with different properties and measurement units to make them dimensionless. This step converts all indicators into values with the same scale, enabling comparison and aggregation. Considering the rapid growth and wide reach of online markets, this study adopts a logarithmic value function to map the original indicator values to a unified range [0, 1], while ensuring monotonicity and consistency in the results. The transformation equation is as follows:[7]

$$Z_{i,j,t}^{h} = \frac{ln(k_{i,j,t}^{h}) - ln(k_{min,j,t}^{h})}{ln(k_{max,j,t}^{h}) - ln(k_{min,j,t}^{h})} \quad (1)$$

Where:

$Z_{i,j,t}^{h}$: The dimensionless value of indicator h for brand i in industry j during quarter t.

$k_{i,j,t}^{h}$: The original value of indicator h for brand i in industry j during quarter t.

$k_{max,j,t}^{h}$: The maximum value of indicator h across all brands in industry j during quarter t.

$k_{min,j,t}^{h}$: The minimum value of indicator h across all brands in industry j during quarter t.

After dimensionless processing, the dimensionless values of each indicator are aggregated using the weights determined in the previous section. The weighted average is calculated to obtain the raw score for each brand. The equation is as follows:

$$S_{i,j,t}^{raw} = \sum_{h=1}^{H} Z_{i,j,t}^{h} \cdot W_h \quad (2)$$

Where:

$S_{i,j,t}^{raw}$: The raw score of brand i in industry j during quarter t.

$Z_{i,j,t}^{h}$: The dimensionless value of indicator h for brand i in industry j during quarter t.

[7] Since the store review data falls within the range of 0 to 1, it does not require transformation via a value function and is kept in its original form. For the rating data, which ranges from 0 to 5, it is not suitable to use a logarithmic efficacy function. Therefore, it is standardized by dividing by 5 to map its values to the range of 0 to 1.

W_h: The weight assigned to indicator h.

H: The total number of indicators.

Brand Score Standardization

As outlined earlier, this report recognizes the differences between industries and time periods. To ensure comparability within the same industry and quarter, the highest score in an industry is standardized to **100**, and the lowest score is standardized to **0**. This approach ensures that all evaluations and rankings are conducted **within the same industry and quarter**, with scores reflecting the relative performance of brands during that specific period.

The raw scores for brands in the same industry and quarter are standardized using the following equation:

$$S_{i,j,t} = 100 \cdot \frac{S_{i,j,t}^{raw} - S_{min,j,t}^{raw}}{S_{max,j,t}^{raw} - S_{min,j,t}^{raw}} \quad (3)$$

Where:

$S_{i,j,t}$: The final standardized score of brand i in industry j during quarter t.

$S_{i,j,t}^{raw}$: The raw score of brand i in industry j during quarter t.

$S_{max,j,t}^{raw}$: The highest raw score among all brands in in industry j during quarter t.

$S_{min,j,t}^{raw}$: The lowest raw score among all brands in in industry j during quarter t, which is calculated as the weighted average of the minimum values of all indicators within the industry, using this equation: $S_{min,j,t}^{raw} = \sum_{h=1}^{H} \min_i \{Z_{i,j,t}^{h}\} \cdot W_h$.

3.2 Brand Index Calculation

To provide a broader perspective on consumer "quality of consumption" across different regions, industries, and the overall market, this study develops two indices based on the previously calculated brand scores: The first is the Consumer Brand Index (CBI), which is a quarterly, industry-specific, and region-specific average metric that reflects the average brand score for a region's consumption. The second is the Brand Purchase Index (BPI), a total metric that measures the overall purchasing power of a region's consumers for high-scoring brands.

The inclusion of both CBI and BPI addresses the potential for Simpson's Paradox, where average and total metrics might lead to contradictory conclusions. Simpson's Paradox occurs when trends that appear in aggregated data contradict trends seen in subsets of the data. From an economic perspective, a region with higher average brand scores (CBI) usually indicates stronger purchasing power for high-scoring brands (BPI). However, due to differences in factors like total sales volume or population size, the two metrics may not always align. For example, consider Figure 1: Region A has a large population and a developed economy, leading to significantly higher brand sales across all categories compared to Region B. As a result, Region A shows stronger purchasing power for high-scoring brands (BPI). However, the average brand score (CBI) in Region A may be lower than in Region B if low-scoring brands dominate sales in Region A due to their broader appeal.

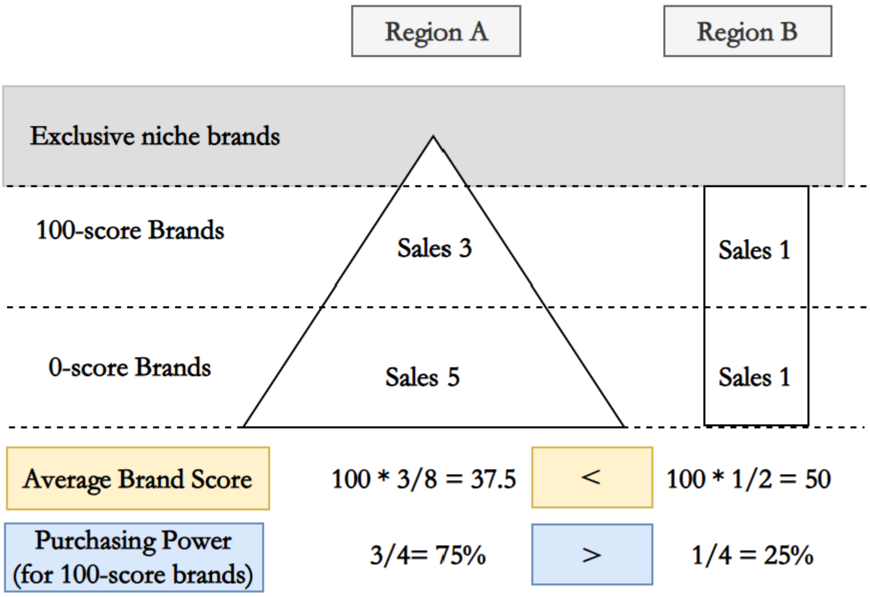

Figure 1 Simpson's Paradox

It is important to note that this study uses the delivery address (with all information anonymized and spatial precision limited to the prefecture-level city) to determine the regional attribution of sales. As a result, the calculation of sales accounts for both registered residents and the migrant workers. This approach differs significantly from traditional micro-level household surveys. In particular, first- and second-tier cities, which are more inclusive and attract a larger number of migrant workers, may exhibit brand sales distribution characteristics closer to Region A rather than Region B. This highlights the need to consider both average and total metrics, leading to the construction of the Consumer Brand Index (CBI) to represent the average quality of consumption and the Brand Purchase Index (BPI) to represent overall purchasing power. Additionally, since online consumption does not accurately represent niche, high-end, or luxury brands, the underlying data cannot capture the niche high-end brands illustrated at the top of the triangle in Figure 1 (corresponding to Region A). This means that these indices primarily focus on the quality characteristics of online consumption and mass-market consumption, compromising their precision and representativeness for the affluent population.

Quarter × Industry × Region Consumer Brand Index (CBI)

The Consumer Brand Index (CBI), with its English full name Chinese Online Consumer Brand Index, is designed to measure the average quality of consumption in a specific region for a particular industry. For industry j in quarter t and region r, the CBI index is calculated by taking a sales-weighted average of brand scores within the region. It reflects the average score of a basket of consumer brands in that region and industry during the quarter. The equation is as follows:

$$\mathrm{CBI}_{r,j,t} = \sum_i \left(S_{i,j,t} \times w_{i,r,j,t}\right) = \frac{\sum_i S_{i,j,t} \cdot sales_{i,r,j,t}}{\sum_i sales_{i,r,j,t}} \quad (4)$$

Where:

$S_{i,j,t}$ represent the standardized score of brand i in industry j during quarter t.

$w_{i,r,j,t}$ represents the sales share of brand i in region r within industry j during quarter t, calculated as $w_{i,r,j,t} = \frac{sales_{i,r,j,t}}{\sum_i sales_{i,r,j,t}}$. The denominator includes the total sales of all brands in the region and industry, including brands with a score of 0 and unbranded products.

The CBI index reflects the average “consumer brand score” for a particular region and industry over a quarter. A higher $\mathrm{CBI}_{r,j,t}$ indicates that local consumers purchase brands with higher average scores, thus measuring the average consumption quality of all consumers in the region.

From equation (4), we can further understand the differences between average (CBI) and total metrics (like Brand Purchase Index). First- and second-tier cities typically exhibit stronger purchasing power for high-scoring brands, meaning that the numerator $\sum_i S_{i,j,t} \cdot sales_{i,r,j,t}$ in these cities tends to be larger. At the same time, these cities also attract more migrant workers and have greater economic vitality, resulting in a denominator $\sum_i sales_{i,r,j,t}$that is significantly higher due to the larger resident population compared to the registered population. The CBI score for each region depends on the relative size of the numerator and denominator. Regions with stronger economic vitality and higher inflows of migrants may have a larger denominator, which could lead to a lower average score (CBI) despite higher total sales and stronger purchasing power.

To address this, we also calculate a **Brand Purchase Index (BPI)** focusing on the numerator (total purchase of high-scoring brands), enabling better inter-regional comparisons from different perspectives.

Quarter × Industry × Region Brand Purchase Index (BPI)

The Brand Purchase Index (BPI), with its English full name Chinese Online Brand Purchase Index, measures the overall purchasing power of consumers in a specific region and industry. It evaluates the purchasing power based on the sales revenue of high-scoring brands. For industry j in quarter t, the total sales of all brands in region r are aggregated, with adjustments made to account for differences in brand scores. The equation is as follows:

$$BP_{r,j,t} = \sum_i S_{i,j,t} \cdot sales_{i,r,j,t} \quad (5)$$

Where:

$BP_{r,j,t}$ represents the brand-weighted sales, calculated by multiplying the sales of each brand $sales_{i,r,j,t}$ by its corresponding score $S_{i,j,t}$, and then summing the products across all brands. Specifically: For a brand with a score of 100, if its sales increase by 1 unit, the brand-weighted sales $BP_{r,j,t}$ increases by 100; For a brand with a score of 0 or unbranded products, an increase of 1 unit in sales does not change the brand-weighted sales $BP_{r,j,t}$. The equation (5) for $BP_{r,j,t}$ corresponds to the numerator of the CBI index equation (4).

However, the original brand-weighted sales $BP_{r,j,t}$ is not directly comparable across different contexts. On one hand, within the same industry, brand-weighted sales can represent the purchasing power for branded products across different regions. For the same industry, a higher $BP_{r,j,t}$ in a region indicates stronger purchasing power for high-scoring brands in that region. On the other hand, due to differences in online penetration rates across industries, $BP_{r,j,t}$ is not directly comparable between different industries within the same region. For example, the online penetration rate of the fashion industry is relatively high, while that of the pet care industry is relatively low. Consequently, the sales of the fashion industry are bound to be higher than those of the pet care industry. However, this does not necessarily imply that local consumers have weaker purchasing power for branded pet care.

Therefore, to avoid misinterpreting the value of brand-weighted sales, we standardize it within each industry, transforming it into a comparable BPI index. The equation is as follows:

$$BPI_{r,j,t} = 100 \cdot \frac{BP_{r,j,t}}{\sum_r BP_{r,j,t}} \quad (6)$$

The numerator $BP_{r,j,t}$ represents the brand-weighted sales for region r and industry j. The denominator $\sum_r BP_{r,j,t}$ is the total brand-weighted sales across all regions for industry j. The multiplier 100 converts the proportion into a percentage value. Hence, a $\mathrm{BPI}_{r,j,t}$ value of 100 means that all brand-weighted sales in the industry come from region r. A $\mathrm{BPI}_{r,j,t}$ value of 0 means that region r has no brand-weighted sales in the industry or only purchases brands with a score of zero or unbranded products. A $\mathrm{BPI}_{r,j,t}$ value of 10 means that indicates that 10% of the industry's total brand-weighted sales come from region r. The Quarterly × Industry × Region Brand Purchase Index (BPI) thus represents the relative purchasing proportion of brand-weighted sales for each region within an industry.

Since BPI reflects the relative proportion of brand-weighted sales in a region, the provincial-level BPI is the sum of the BPI values for all prefecture-level cities within the province. The national-level BPI is the sum of the BPI values for all regions, which is always 100. This implies that the BPI indicator is highly comparable between regions, but the national-level BPI values for different industries do not hold significant analytical value for cross-industry comparisons.

Quarter × Region Brand Indices

This section calculates the Quarter × Region Brand Indices by weighting the indices of various industries within each region. Since industries differ in their levels of online consumption penetration and their significance in overall spending, the previous section introduced detailed industry indices that researchers can use to customize their analysis. By adjusting industry weights to align with their research focus, researchers can create region-level indices that better match their study objectives. Here, we propose an industry-weighting scheme that combines considerations for the importance of industry categories in CPI weights (as inferred from the China Household Survey Yearbook) and the representativeness of e-commerce data. The suggested weighting scheme, shown in Table 4, is provided as a reference for researchers.

Table 4 Industry Categories and Reference Weights

(1) Primary Categories	(2) Secondary Categories	(3) No.	(4) Original Weights in CPI	(5) Converted Industry Weights w_j^{CPI}

Food	Food	1	NA	0.00%
Fashion	Sports & Outdoors	2	2.00%	8.77%
	Fashion (Women's Wear) (Excluding Sports & Outdoors)	3	2.00%	11.70%
	Fashion (Men's Wear) (Excluding Sports & Outdoors)	4	1.00%	5.85%
	Fashion (Others) (Excluding Sports & Outdoors)	5	1.00%	5.85%
Housing	Renovation Materials	6	NA	0.00%
Household Essentials & Services	Home Furnishing & Home Decos	7	0.90%	5.26%
	Home Appliances	8	1.50%	8.77%
	Household Textiles	9	0.40%	2.34%
	Personal Care	10	0.70%	4.09%
	Cleaning Products	11	1.40%	8.19%
	Beauty	12	0.60%	3.51%
Transportation & Communications	Transportation	13	0.00%	0.00%
	3C Communications	14	3.00%	17.54%
Culture & Entertainment	3C Smart Devices	15	0.10%	0.58%
	3C Culture & Education	16	1.50%	8.77%
	Collectible	17	0.30%	1.75%
	Flowers & Gardening	18	0.30%	1.75%
	Office & School Supplies (Non-electronic)	19	0.60%	3.51%
	Pet Care	20	0.30%	1.75%
Medical & Healthcare	Medical & Healthcare	21	NA	0.00%
Others	Jewelry & Accessories	22	NA	0.00%

This report aims to align industry weights as closely as possible with CPI weights. However, it is important to note that online consumption has weaker representativeness for industries such as transportation, food (e.g., fresh produce), housing (e.g., imputed rent for owner-occupied housing and rental expenses), other goods and services, and healthcare (e.g., medical and pharmaceutical expenses). Therefore, as a precaution, this report sets the weights for these industries to zero when calculating the overall index. This adjustment makes it impossible to directly apply the original CPI and household survey weights. Hence, in column (4) of Table 4, the report lists the original CPI and household survey weights for other industries that remain relevant after this adjustment. These weights are then summed to obtain a total value of 17.1%. This total represents the sum of the original weights for the selected industries that are eligible for subsequent calculations. Next, the original weights for each industry are divided by the summed weight to derive the adjusted industry weights, w_j^{CPI}, which are presented in column (5) of Table 4.

For a given region r and quarter t, the quarter × region Consumer Brand Index (CBI) is calculated by weighting the industry indices using the CPI-adjusted industry weights w_j^{CPI}, as follows:

$$CBI_{r,t} = \sum_j \left(CBI_{r,j,t} \times w_j^{\text{CPI}}\right) \quad (7)$$

Similarly, the quarter × region Brand Purchase Index (BPI) is as follows:

$$BPI_{r,t} = \sum_j \left(BPI_{r,j,t} \times w_j^{\text{CPI}}\right) \quad (8)$$

Quarter × Industry and Quarter × National Consumer Brand Index

To compare the average consumption quality across industries, it is necessary to calculate the quarter × industry Consumer Brand Index (CBI) by further aggregating data. For a given industry j and quarter t, this requires calculating a weighted average of the CBI values across all regions. To avoid the influence of platform-specific sales proportions in certain regions on the index, we adopt regional GDP proportions as the weights for aggregation.

Let w_r^{GDP} represent the GDP weight of region r, which is the proportion of that region's GDP to the national GDP. This report uses the 2023 GDP data from the *China City Statistical Yearbook* and the Wind database for prefecture-level administrative units (including prefecture-level cities, leagues, autonomous prefectures, and regions) as the basis for weight calculations. Researchers may also choose other reasonable weights for aggregation. The equation is as follows:

$$CBI_{j,t} = \sum_r \left(CBI_{r,j,t} \times w_r^{\text{GDP}}\right) \quad (9)$$

Based on the previously defined indices, the equation for the national Consumer Brand Index is as follows:

$$CBI_t = \sum_r \sum_j \left(CBI_{r,j,t} \times w_r^{\text{GDP}} \times w_j^{\text{CPI}}\right) \quad (10)$$

This index allows for the comparison of changes in the National Consumer Brand Index over time. A higher index value indicates that the average rating of brands purchased by consumers nationwide is higher, reflecting an overall improvement in consumption quality.

Based on the series of indices introduced above, future research can explore several analytical directions. First, temporal comparisons can be made by analyzing the national CBI or the quarter ×

industry CBI across quarters to reveal changes in the average brand ratings for sales nationwide and within each industry. Similarly, comparing the BPI and the CBI within a region over time enables observation of the region's brand purchasing share and average consumption quality trends. Second, cross-sectional comparisons can be conducted by analyzing regional indices for the same period and industry to explore differences in purchasing power shares and average consumption quality across regions. Additionally, the CBI for different industries during the same period can be compared to examine whether consumers' brand purchases are concentrated in high-rating brands across industries. These analyses provide valuable insights into both temporal and spatial dimensions of brand purchasing behavior and consumption quality.

Table 5 summarizes the various granularities of the brand indices, as well as their temporal and cross-sectional comparability. Cross-sectional comparability refers to comparisons across regions or industries within the same period, while temporal comparability refers to comparisons across quarters within the same industry or region. The regional granularity includes prefecture-level cities and provinces.

Table 5 Granularity and Comparability of the Series of Indices

	Consumer Brand Index (CBI)	Brand Purchase Index (BPI)	Cross-sectional Comparability	Temporal Comparability
Quarter × Industry × Region	√	√	√	√
Quarter × Region	√	√	√	√
Quarter × Industry	√	NA	√	√
Quarter (national)	√	NA	×	√

3.3 Methodology for Brand Rankings

This report consolidates brand scores across industries, regions, and quarters to create the Top 500 Online Consumer Brands List (CBI500). The rankings encompass millions of brands; however, due to space constraints, only the top 500 brands with the highest scores are presented. The rankings do not distinguish between "brands excelling in channel distribution" and "brands leading in production of goods," meaning that both high quality in merchandise production and excellence in product selection during sales process can reflect a brand's influence.

To construct the CBI500, two key issues must be addressed: First, comparing brands with the same scores across industries. Within each industry, the top brand is assigned a standardized score of 100. When two brands receive a score of 100 in different industries, their positions in the rankings are determined by their total sales. The ranking score is calculated by multiplying the brand's standardized score by its gross merchandise value (GMV).[8] Second, determining the ranking score for multi-industry brands. For brands operating across multiple industries, total sales are calculated by summing their sales across all industries. The standardized score is determined by the highest score the brand achieves in any single industry. Additionally, the industry with the highest score and sales is identified as the brand's primary industry.[9] This approach assumes that a brand's success in one industry can influence its performance in others, which justifies using the highest score across industries for the same brand.

In summary, the ranking scores for all brands across industries are calculated using the following equation:

$$S_{i,t}^{all} = GMV_{i,t} \cdot \max_{j}\{S_{i,j,t}\} \quad (11)$$

Where:

$S_{i,t}^{all}$ represents the ranking score of brand i across all industries.

$S_{i,j,t}$ represents the standardized score of brand i in industry j.

$GMV_{i,t}$ is the log-standardized value of brand i's total sales across all industries, calculated by $GMV_{i,t} = \frac{ln(GMV_{i,t}^{raw})-ln(GMV_{min,t}^{raw})}{ln(GMV_{max,t}^{raw})-ln(GMV_{min,t}^{raw})}$, where the brand with the highest total sales across all industries has a $GMV_{i,t}$ value of 1, while the brand with the lowest total sales has a $GMV_{i,t}$ value of 0.

The final ranking is determined by the total score $S_{i,t}^{all}$, which reflects the comprehensive ranking of brands across all industries. Luxury brands, which primarily rely on offline channels, are excluded from the CBI 500 list. Additionally, counterfeit or substandard brands are not included,

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[8] Theoretically, within the same industry, discrepancies may arise between the rankings of standardized brand scores and the overall rankings on the CBI500 list. For instance, Brand A might have a higher standardized score but lower sales, while Brand B has a lower standardized score but higher sales. As a result, Brand A's standardized score is higher, but Brand B ranks higher on the CBI500 list. However, in practice, this theoretical possibility is extremely rare because sales are already considered in the standardized scoring. When the standardized score is multiplied by sales, the rankings within the industry remain largely unchanged.

[9] For brands operating across multiple industries, the industry with the highest GMV typically aligns with the industry where the brand achieves its highest score.

and brands that primarily operate through licensing are also excluded due to the complexity of evaluating their brand influence and the misalignment with the focus of this ranking. The CBI 500 list also provides detailed scores for individual indicators. To ensure comparability across industries, all dimensionless indicators are standardized using the same method as the total score and are further adjusted by multiplying with $GMV_{i,t}$ and their respective weights. The sum of the scores for all indicators equals the total score for the ranking.

The CBI500 is updated regularly, offering a clear and dynamic view of China's leading online consumer brands. It highlights the growth trajectories of both industry leaders and emerging brands. Through regional and industry comparisons, the ranking provides a comprehensive perspective on the ecosystem of high-quality online consumer brands in China. It also serves as a valuable resource for brand owners, investors, and government agencies, offering precise insights to support decision-making.

4. Brand Indices and Ranking Analysis

4.1 Trend Analysis

The Consumer Brand Index (CBI) across all quarters has shown a steady upward trend with minimal fluctuations. As shown in Figure 2, the CBI for 2024 is significantly higher than that of 2023, while the CBI for 2025 has also notably surpassed the same period in 2024. This indicates a stable and consistent improvement in the quality of consumption in China.

Consumer quality tends to evolve more gradually compared to consumption quantity or price. From the first quarter of 2023, when the Consumer Brand Index (CBI) stood at 59.42, to the first quarter of 2025, it climbed to 63.38—an increase of about 4 points in the average brand score nationwide.

To put it into perspective, this improvement is roughly equivalent to half of all consumers switching from brands ranked outside the top 1000 to newly emerging brands that have just broken into the top 500. This shift highlights a broad trend of consumers upgrading their choices across various categories, reflecting a growing preference for higher-quality brands.

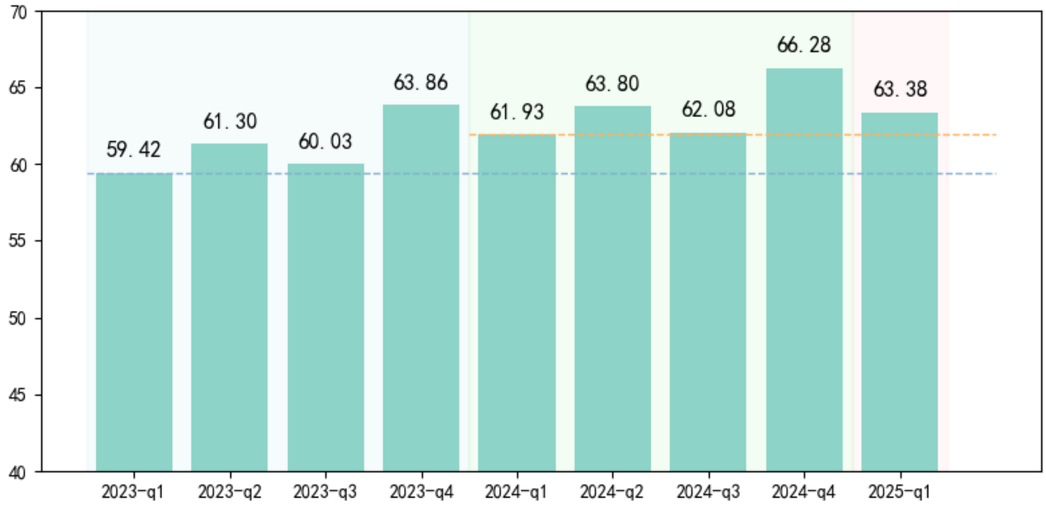

Figure 2 China’s Online Consumer Brand Index (CBI) (Q1 2023 – Q1 2025)

From a quarter-on-quarter perspective, as shown in Figure 3, the index demonstrates upward fluctuations in the second and fourth quarters, consistent with online consumption patterns. These increases are driven by major shopping events such as the “6.18 Shopping Festival” in Q2 and the “11.11 Global Shopping Festival” in Q4. The rise in the fourth quarter is significantly larger than in the second quarter, as the “11.11 Global Shopping Festival” has a relatively greater impact. This trend aligns well with economic intuition.

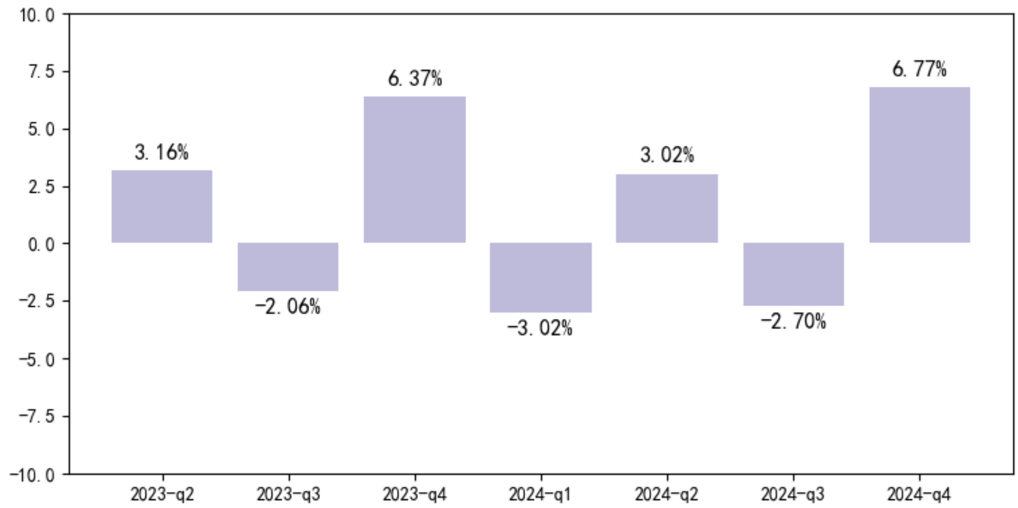

Figure 3 Quarter-on-Quarter Changes in China’s Online Consumer Brand Index (CBI)

To better illustrate the relative changes in China’s Online Consumer Brand Index (CBI), we set the starting period of the first report as the base period, with the base index value standardized to 100. Based on this adjustment, subsequent periods are calculated relative to the base index. As shown in Figure 4, the national CBI increased significantly compared to the base period, rising by

11.5% in Q4 2024 and 6.7% in Q1 2025.

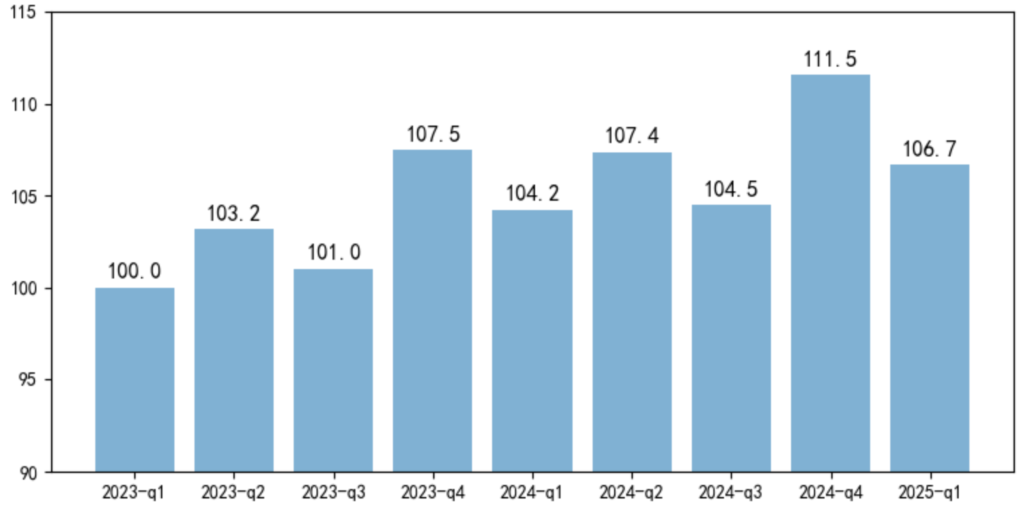

Figure 2 CBI (Using Q1 2023 as the Base Period, Base Index = 100)

4.2 Industry Comparison

The CBI shows significant differences across industry categories. A higher CBI indicates a greater concentration of sales among leading brands and fewer unbranded products, while a lower CBI suggests an opportunity for brands to enter and compete. When an industry's CBI shows an upward trend, it signals either the gradual formation of leading brands or sales consolidation among existing leading brands.

Consistent with public perception, the 3C (mobile phones, smart devices, and other digital products) industry exhibits the highest CBI values, with scores ranging between 75 and 85. This indicates that unbranded products in this sector are less competitive, and most consumers prefer leading brands. Traditional brands like Apple, Huawei, and Xiaomi dominate every subcategory, including 3C communication, 3C smart devices, and other 3C categories (primarily educational and entertainment products). However, unlike other 3C subcategories, the 3C smart devices category demonstrates a distinct growth trajectory, with the emergence of new and innovative brands such as iFLYTEK, imoo, DJI, and Unitree Robotics, showcasing the vitality of this emerging sub-industry. Among them, Unitree Robotics has shown particularly striking growth. Its sales growth rate ranks first in the category, and its total brand score has surpassed international competitors like Garmin and Samsung. This success is largely driven by its core product line of AI-powered robots, highlighting its strong innovation capabilities.

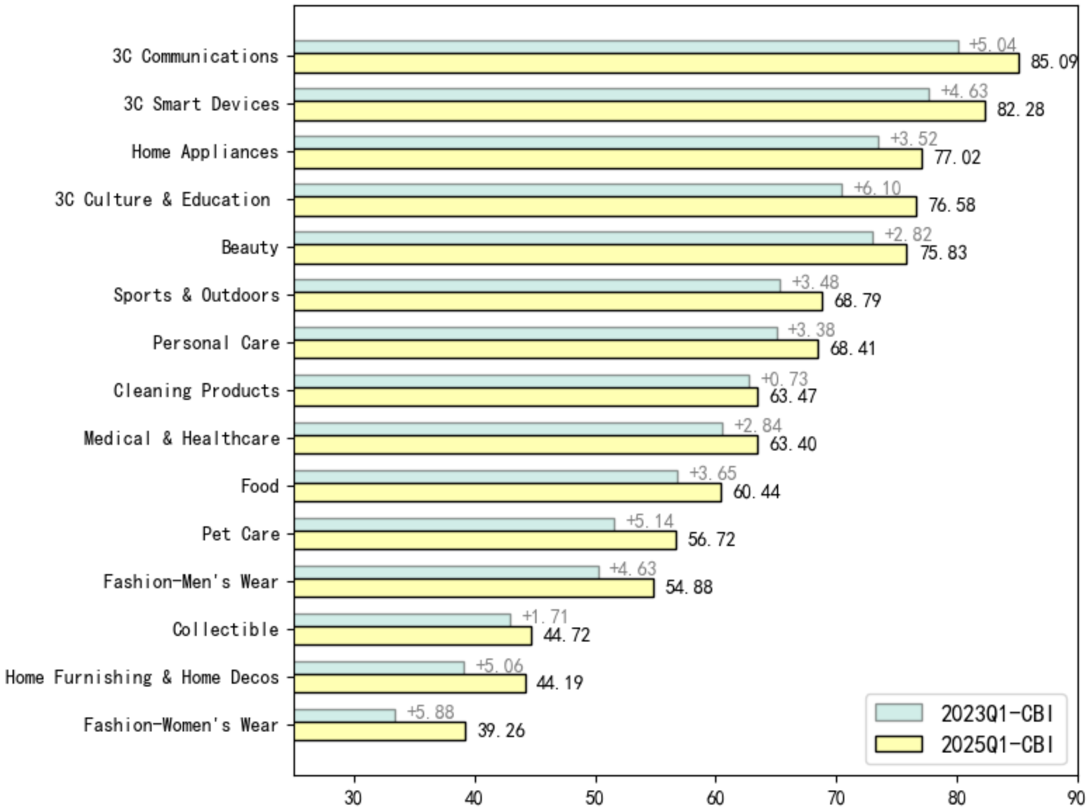

Figure 5 Comparison of CBI by Industry Category

The home appliances industry follows closely behind 3C digital products, with a Consumer Brand Index (CBI) consistently above 75. This category covers both major appliances, like refrigerators and washing machines, and small appliances, such as rice cookers and yogurt makers. While consumers in this sector tend to favor high-rated brands, the market is more fragmented compared to the 3C industry, with no single brand achieving absolute dominance. Emerging players like Bear and Dreame have managed to secure notable market positions, showcasing the competitive nature of the industry and its potential for further growth.

Beauty products rank highest in the daily necessities category in the CBI, with a score of 75.83 in Q1 2025. Other personal care products, such as facial cleansers and body washes, also achieve relatively high scores at 68.41, with a slightly higher growth rate since 2023 compared to the beauty category. In contrast, the household cleaning products category (e.g., laundry detergent, soap, dishwashing liquid) has a relatively stable market structure, and its CBI has shown little change since 2023.

The fashion industry is one of the most digitized sectors in terms of online penetration. Sports and outdoor apparel stand out with a relatively high CBI, driven by their functional nature, as consumers place significant importance on brand reputation in this segment. Men's wear also scores higher than women's wear in the CBI, largely due to the smaller number of leading brands in the men's market. In contrast, the women's wear segment is more competitive, with a wider variety of brands and more fragmented sales distribution. However, in terms of growth, women's wear has the highest CBI growth rate, while sports and outdoor apparel show the slowest growth among fashion categories.

Pet care has shown significant growth in the culture and entertainment category, reflecting a growing consumer preference for quality and branded products. Brands like Myfoodie and Royal Canin have achieved high brand scores, driven by increasing consumer brand awareness in pet-related purchases. Interestingly, the collectible category has a CBI score below 50, despite dominant brands like LEGO and Pop Mart leading the market. Since 2023, the sector has seen the emergence of new brands such as BLOKEES, Light and Night, and KAYOU, which have quickly gained consumer recognition and even entered the top 500 online consumption brands.

Home furnishing, while traditionally scoring low on the CBI, has experienced rapid growth since 2023, with its score increase approaching that of the pet care sector. Due to relatively high transportation and service costs, the furniture and home decoration industry characteristics remain regional, and national-scale leading brands have yet to dominate. However, with the rise of e-commerce and advancements in logistics, representative brands such as YESWOOD and LINSY have broken regional barriers, achieving significant success in the national online market.

Other industries, such as transportation, jewelry, and renovation materials have relatively low online consumption penetration. The CBI for these categories can be found in the appendix for further reference. For instance, in the jewelry category, standout brands include Chow Tai Fook and Laopu Gold, while Nippon Paint represents the renovation materials category. In the transportation category, brands like Yadea and Phoenix dominate the electric bike and bicycle markets. Though these industries have some online sales presence, they are still primarily driven by offline markets.

3.3 Regional Analysis

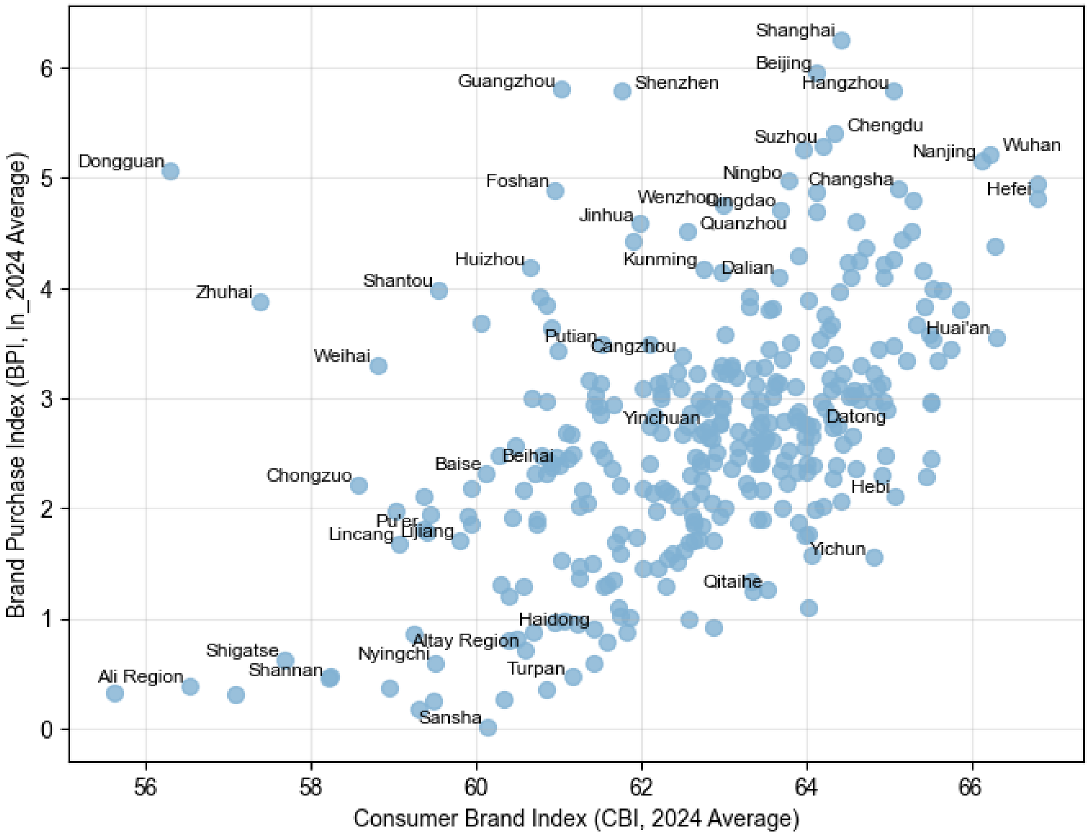

Figure 6 Brand Purchase Index (BPI) and Consumer Brand Index (CBI)

Regarding regional distribution, there are correlations and divergences between the CBI and the BPI. Figure 6 compares the two indices, with the horizontal axis representing the CBI and the vertical axis representing the BPI. Overall, the two indices exhibit similar trends, which aligns with economic intuition—regions with stronger purchasing power tend to have higher-quality consumption. However, there are deviations in specific cities between the two indices. Note that the CBI is based on data derived from the "delivery address," which includes purchases made by both local residents and migrant workers. In cities with a high proportion of migrant workers, the larger population and sales base can result in a slightly lower CBI. First-tier cities like Beijing, Shanghai, Guangzhou, and Shenzhen have some of the highest shares of migrant workers nationwide. Similarly, economically dynamic cities in Guangdong Province, such as Dongguan, Zhongshan, Foshan, and Zhuhai, also rank among the top in terms of migrant worker ratios. Regions with greater inflows of migrant workers tend to exhibit lower average consumption quality and greater inclusiveness toward brands at various levels.

As shown in Table 6, the top ten cities in CBI are all second and third-tier cities with significant potential, including Hefei in Anhui Province, Zhengzhou in Henan Province, Huai'an in Jiangsu Province, and Nanchang in Jiangxi Province. The BPI aligns closely with the distribution of China's population and GDP. First-tier cities, such as Shanghai, Beijing, Guangzhou, and Shenzhen, remain at the top of the list, while other top ten cities are mostly emerging first-tier cities, such as Hangzhou, Chengdu, Suzhou, and Wuhan.

Table 6 Top Ten Cities in the Brand Indices

CBI Top 10 (Q1 2025)	BPI Top 10 (Q1 2025)	CBI Top 10 (2024 Average)	BPI Top 10 (2024 Average)
Hefei	Shanghai	Zhengzhou	Shanghai
Zhengzhou	Beijing	Hefei	Beijing
Huai'an	Hangzhou	Huai'an	Guangzhou
Nanchang	Guangzhou	Nanchang	Shenzhen
Nanjing	Shenzhen	Wuhan	Hangzhou
Zhoukou	Chengdu	Nanjing	Chengdu
Huaibei	Suzhou	Yangzhou	Suzhou
Yancheng	Chongqing	Xinxiang	Chongqing
Kaifeng	Wuhan	Taiyuan	Wuhan
Linyi	Nanjing	Zhoukou	Nanjing

To better understand the sources of regional differences and the factors influencing both CBI and BPI, a simple cross-sectional regression analysis was conducted, using brand indices for each region as dependent variables and several key economic indicators from urban statistical yearbooks as explanatory variables. Table 7 highlights four indicators closely correlated with brand indices: per capita GDP, the proportion of migrant workers in the total population, [10] the share of the tertiary sector, and the number of non-private sector employees.

The first two columns of Table 7 present regression results for all prefecture-level cities. The findings indicate that per capita GDP, tertiary sector share, and non-private sector employment are positively correlated with both the Consumer Brand Index (CBI) and the Brand Purchase Index

[10] To account for data availability, this report calculates the proportion of the migrant workers as: (Residents - Registered Population) / Registered Population. Since data on the residents (including those without a local *Hukou*) is mostly available for 2020, values for per capita GDP, floating population proportion, tertiary industry proportion, and non-private employment numbers are all taken from the 2020 city statistical yearbook. The calculation for per capita regional GDP is the natural logarithm of per capita GDP plus one. The tertiary industry proportion is defined as the share of tertiary industry in the regional GDP. Non-private employment numbers refer to the year-end number of employees in urban non-private units, calculated as the natural logarithm of the number plus one. To align with the floating population proportion data, the dependent variable uses the 2023 average value.

(BPI). However, the proportion of migrant workers in the total population exhibits opposing effects on the two indices: regions with a higher proportion of migrant workers tend to have lower CBI scores, reflecting lower average consumption quality, while simultaneously showing higher BPI scores, which highlight stronger purchasing power for premium brands.

The last two columns of Table 7 focus on economically vibrant prefecture-level cities that attract a significant proportion of migrant populations, defined as cities where the resident population exceeds the registered population. In this subset, the regression models demonstrate improved explanatory power, with R^2 values of 0.531 for the CBI and 0.682 for the BPI. This indicates that four key variables—per capita GDP, proportion of migrant workers, tertiary sector share, and non-private employment—collectively have strong explanatory power for regional differences in both indices. Specifically: These variables explain approximately 53.1% of the regional variation in CBI, and account for about 68.2% of the regional differences in BPI. Additionally, other factors such as per capita savings, age structure, and housing prices also show some explanatory power. However, the mechanisms through which these variables influence the indices fall outside the scope of this report and warrant further investigation in future research based on the indices.

Table 7 CBI, BPI, and Key Economic Variables

	(1)	**(2)**	**(3)**	**(4)**
	Full sample		**Subsample (residents > registered)**	
	CBI	**BPI**	**CBI**	**BPI**
ln per capita GDP	1.600***	0.124**	1.701***	0.664***
	(0.22)	(0.06)	(0.48)	(0.21)
Proportion of migrant workers	-2.488***	0.363***	-2.703***	0.309**
	(0.31)	(0.08)	(0.35)	(0.15)
Tertiary sector share	2.455**	1.554***	4.321**	2.093***
	(1.10)	(0.30)	(1.67)	(0.72)
ln non-private employment	0.601***	0.328***	0.475**	0.424***
	(0.12)	(0.03)	(0.19)	(0.08)
Constant	34.12***	-5.967***	33.81***	-13.77***
	(2.32)	(0.63)	(4.97)	(2.14)
Observations	275	275	80	80
R-squared	0.354	0.658	0.531	0.682

Note: standard deviations in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

When looking at regional distribution and growth trends, the CBI has shown a clear upward trend, with most prefecture-level cities experiencing growth. Sansha City stood out with the fastest increase. The eastern (including northeastern) and western regions saw particularly strong growth in CBI, largely thanks to the certain free delivery campaigns launched by major e-commerce platforms in 2024. As for the BPI, its regional distribution closely mirrors China's population and GDP patterns.

4.4 Top Brands Analysis

We analyzed the top 1,000 brands based on brand origins, innovation characteristics, and others.

Looking at the founding year distribution of listed brands, as shown in Figure 7, over 20% of the top 1,000 highest-rated brands were founded between 2011 and 2019. The inclusion of so many brands created within the past 15 years highlights two key factors. First, the scoring system places a strong emphasis on identifying emerging brands and encouraging innovation, giving newer brands more opportunities to stand out. Second, this trend reflects the favorable entrepreneurial environment and business climate during the 2011–2019 period, which fostered quality competition and supported brand development. On the other hand, brands founded after 2020 have struggled to achieve high scores. This is largely due to the challenging macroeconomic environment, intensified price wars among platforms, and the time lag required for brand-building efforts to bear fruit.

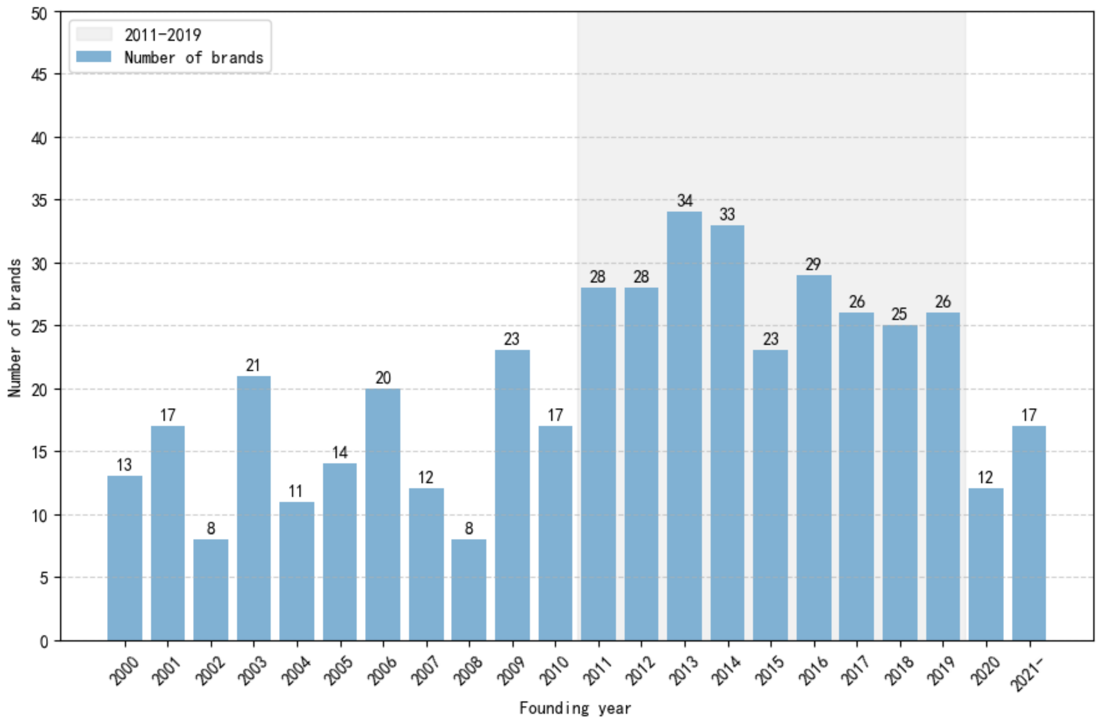

Figure 7 Founding Year Distribution of Listed Domestic Brands

Note: Ratings are based on Q1 2025 data, focusing on domestic brands within the top 1,000 ranking, with only those established after 2000 included.

Regarding the regional distribution of domestic brands, as shown in Figure 8, the number of ranked brands is influenced by regional GDP and industrial structure factors. Guangdong province ranked first nationwide by GDP in 2024 and had the most listed brands. The number of consumer brands founded in Zhejiang, Shanghai, and Beijing also ranked high. While Jiangsu province ranked second by GDP, the number of ranked brands was only fifth in the country. This is because Jiangsu's competitive industries are not in the consumer retail sector but upstream industries such as advanced equipment, electronic information, and biopharmaceuticals. At the city level, Shanghai, Hangzhou, Guangzhou, Shenzhen, and Beijing are home to the most ranked brands. Leveraging their advanced manufacturing industries, Foshan, Ningbo, Quanzhou, Jinhua, and Suzhou also ranked among the top ten cities by the number of brands listed.

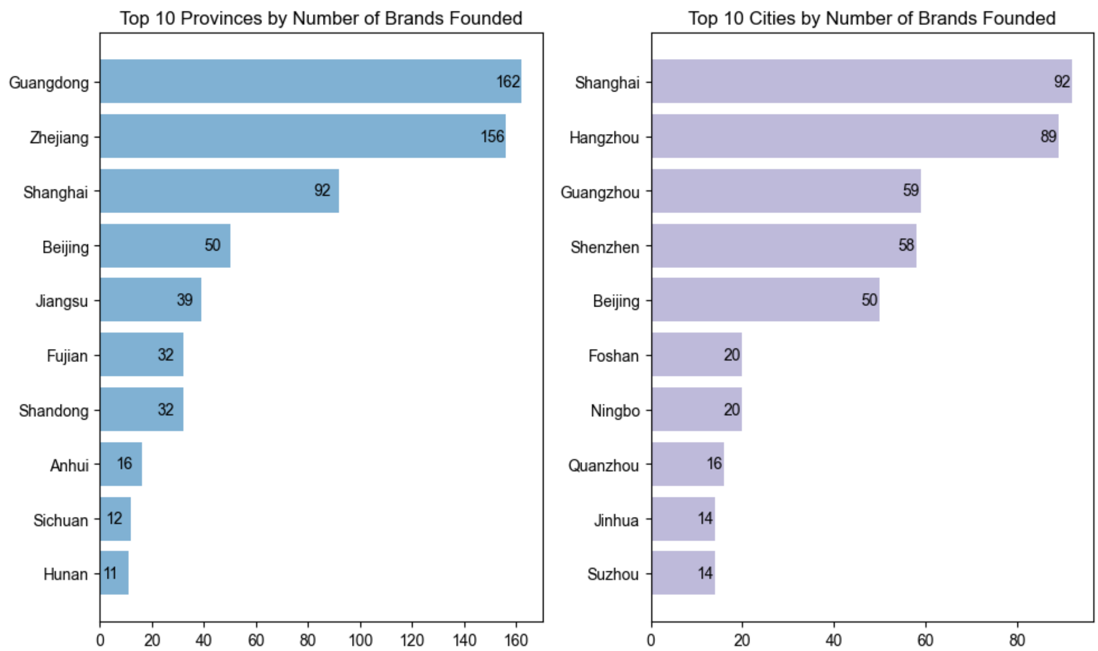

Figure 8 Regional Distribution of Listed Domestic Brands

Based on brand origins, 67.8% were founded in mainland China (excluding Hong Kong, Macau, and Taiwan) among the top 1,000 brands. However, in certain categories such as beauty and personal care, as well as sports and outdoor products, international brands still account for close to or more than 60%. This is due to the firm advantages international brands maintains in aspects like raw materials, manufacturing techniques, and technology, which present competitive barriers for domestic brands. The expertise and functionality of certain categories remain distinct advantages of international brands. The higher segments of the rankings feature a greater share of international brands: among the top 1000 brands, international brands account for 29.8%; in the top 500, this proportion rises to 31.2%; and among the top 100, the share further increases to 36%. This underscores the strong emphasis international brands place on the China's e-commerce market. With its advanced digital economy, China's e-commerce market not only offers immense growth potential but also provides a diverse range of opportunities for brands to engage consumers and innovate their business strategies. As such, effectively leveraging online channels and adapting to the digital ecosystem are crucial for international brands seeking to thrive in China's consumer market.

The top three ranked brands are Apple, Huawei, and Xiaomi, all leading players in 3C digital industry. Apple delivered strong performance across various metrics, with its gross merchandise value (GMV) standing out, earning the top spot in the overall rankings. This underscores Chinese consumers' recognition of international brands. China has also become a key market for the overseas expansion of international brands, thanks to its enormous market potential and commitment to high-level opening-up. At the same time, Huawei and Xiaomi have recorded significantly faster GMV growth. They have also excelled in areas like brand keyword search volume and membership programs, showcasing the rapid growth and rising competitiveness of Chinese brands in an open market environment.

Emerging brands on the list generally focus on niche market needs and show strong product innovation capabilities. Based on the top 1,000 brands in the Q1 2025 rankings, we identified the 100 fastest-growing brands by sales. Among these, 36 brands demonstrated a distinct focus on "product innovation + niche scenarios." For example, in the jewelry category, Laopu Gold (老铺黄金)specializes in premium craftsmanship gold jewelry; in the 3C category, iQOO (艾酷)focuses on mobile phones for gaming; and in the personal care category, Hi!papa(海龟爸爸)specializes in children's sunscreen. In the 3C smart devices category, Unitree Robotics (宇树科技), the fastest-growing brand, showcases strong product innovation by focusing on AI smart robots. Among the 100 fastest-growing brands in terms of gross merchandise value, 80 of them are domestic brands. These local brands thrive by addressing niche needs and focused on targeted product development, which gives them a distinct advantage.

5. Conclusion

This report, drawing on existing literature—particularly studies on brand equity models and online consumer price indices—develops a comprehensive series of indices and rankings for China's online consumer brands. Leveraging data from Alibaba’s Taobao and Tmall Group, the indices are designed to cover various regions, industries, and time periods, while accounting for the unique characteristics of the online consumer market.

We not only provide a list of the top 500 brands in China’s online consumer market along with their scores across multiple dimensions but also reference the top 1,000 brands as a benchmark for analysis. The index series includes the Consumer Brand Index (CBI), which measures the average scores of brands purchased by consumers in a specific region or industry, and the Brand Purchase Index (BPI), which evaluates a region’s relative purchasing power for high-scoring brands compared to others. These indices are broken down into over 300 prefecture-level administrative divisions, 22 industries, and multiple levels, including Quarter × Industry × Region, Quarter × Industry, Quarter × Region, and Quarter × National, allowing researchers to directly use the corresponding data or adapt the indices to their specific research needs by selecting appropriate weights for industry- or region-level aggregation. This flexibility enables the generation of custom indices tailored to specific research projects. Notably, when aggregating the industry × region indices into regional indices, the report does not use online sales revenue as the industry weight but instead adopts weights from the CPI or household survey data. This approach avoids distortions caused by fluctuations in the online sales share of specific industries, ensuring more stable and reliable results.

This index series reveals the following: From a trend perspective, Consumption quality of China’s e-commerce market has steadily improved. From a category perspective, the 3C digital and home appliance sectors have established consumption patterns dominated by leading brands. Meanwhile, categories such as pet care, collectibles, and personal care and beauty are still seeing the emergence of new brands. From a regional perspective, first-tier cities have an absolute advantage in brand purchasing power. However, due to their large migrant workers population and diverse consumption bases, the average consumption quality is not significantly higher than that of other cities. On the other hand, new first-tier or second-tier cities, such as Hefei, Zhengzhou, and Nanchang, demonstrate relatively high average consumption quality.

This study, however, has some limitations that leave room for improvement. First, while the data sample size from Taobao and Tmall is already quite significant by standard research practices, the research relies solely on data from Alibaba’s Taobao and Tmall platforms and therefore cannot capture the dynamics of other online platforms. Second, industries such as housing and automobiles, which are primarily driven by offline consumption, are not well-represented in the index. Third, even for the included industries, the indices are affected by the online penetration rates of leading brands in each sector. Fourth, the online consumer market primarily reflects the everyday consumption behavior of general consumers and does not fully capture overall consumer spending patterns. Fifth, in scoring brands, less emphasis is placed on niche, high-end, or luxury brands. Instead, more attention is given to emerging brands, reflecting a value orientation that encourages innovation, promotes healthy competition, and prioritizes mass consumers. However, this approach makes the index less representative of the highest-income demographic. Finally, due to the challenges in early-stage data cleaning, the first edition of the index only includes data from 2023 onward. In the future, as more data is added and updated, the index will expand its time span to provide a more comprehensive and dynamic view of the development of China’s online consumption market and brand quality.

Reference

[1] Liu, T., Tang, K. , Jiang, F. , Zhang, L.. (2019). Design and Application of Novel CPI Based on Online Big Data. *Journal of Quantitative & Technological Economics*,(9), 81-101. (刘涛雄、汤珂、姜婷凤、仉力：《一种基于在线大数据的高频 CPI 指数的设计及应用》，《数量经济技术经济研究》，2019 年第 9 期,81-101.)

[2] Jiang, F., Tang, K., Liu, T. (2020). The Stickiness of Online Prices in China. *Economic Research Journal*, (6): 56-72. (姜婷凤、汤珂、刘涛雄：《基于在线大数据的中国商品价格粘性研究》，《经济研究》,2020 年第 6 期，56-72.)

[3] Sun, Z., Liu, J., Liu, T. (2021). Cross-Platform Competition and Market Segmentation in China's Online Market——Evidence Based on Platform Prices and Price Dispersion. *China's Industrial Economics*, (6), 118-136. (孙震、刘健平、刘涛雄：《跨平台竞争与平台市场分割——基于中国线上市场价格离散的证据》，《中国工业经济》，2021 年第 6 期，118-136.)

[4] Aaker, D. A. (1991). Managing Brand Equity: Capitalizing on the Value of a Brand Name. New York: The Free Press.

[5] Armstrong, M. (2006). Competition in two-sided markets. *The RAND journal of economics*, 37(3), 668-691.

[6] Bils, M., & Klenow, P. J. (2001). Quantifying quality growth. *American Economic Review*, *91*(4), 1006-1030.

[7] Caillaud, B., & Jullien, B. (2003). Chicken & egg: Competition among intermediation service providers. *RAND journal of Economics*, 309-328.

[8] Cavallo, A. (2017). Are online and offline prices similar? Evidence from large multi-channel retailers. *American Economic Review*, *107*(1), 283-303.

[9] Chevalier, J. A. and Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3):345–354.

[10] Elfenbein, D. W., Fisman, R., and McManus, B. (2015). Market structure, reputation, and the value of quality certification. *American Economic Journal: Microeconomics*, 7(4):83–108.

[11] Horton, J. J. (2017). The effects of algorithmic labor market recommendations: Evidence from a field experiment. *Journal of Labor Economics*, 35(2):345–385.

[12] Jin, G. Z., & Kato, A. (2006). Price, quality, and reputation: Evidence from an online field experiment. *The RAND Journal of Economics*, 37(4), 983-1005.

[13] Linstone, H. A., & Turoff, M. (Eds.). (1975). The Delphi Method (Vol. 1975, pp. 3-12). Reading, MA: Addison-Wesley.

[14] Nelson, P. (1974). "Advertising as Information." *Journal of Political Economy*, 82(4), 729–754.

[15] Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, 51(10), 1494-1504.

[16] Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4), 990-1029.

[17] Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34-55.

[18] Ursu, R. M. (2018). The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Science*, 37(4):530–552.

[19] Sahni, N. S. and Nair, H. S. (2020). Does advertising serve as a signal? evidence from a

field experiment in mobile search. *The Review of Economic Studies*, 87(3):1529–1564.

Appendix 1: CBI500 Top 100 Brands

The table below shows the top 100 brands based on their overall scores. For the CBI500 list and detailed scores for each indicator, please refer to the attachment.

Rank	Brand		Category	Overall scores
1	苹果	Apple	3C Digital	100.00
2	华为	HUAWEI	3C Digital	95.30
3	小米	Xiaomi	3C Digital	95.13
4	美的	Midea	Home Appliances	94.08
5	海尔	Haier	Home Appliances	93.87
6	联想	Lenovo	3C Digital	93.14
7	茅台	Moutai	Food	92.62
8	耐克	NIKE	Sports & Outdoors + Fashion	91.25
9	李宁	LI-NING	Sports & Outdoors + Fashion	88.52
10	阿迪达斯	adidas	Sports & Outdoors + Fashion	87.46
11	优衣库	UNIQLO	Sports & Outdoors + Fashion	86.97
12	林氏家居	LINSY	Home Furnishing & Home Decos	86.97
13	欧莱雅	L'ORÉAL	Beauty	86.51
14	苏泊尔	SUPOR	Home Appliances	86.30
15	周大福	Chow Tai Fook	Jewelry & Accessories	85.62
16	维沃	vivo	3C Digital	85.12
17	斐乐	FILA	Sports & Outdoors + Fashion	85.12
18	安踏	ANTA	Sports & Outdoors + Fashion	85.01
19	五粮液	Wuliangye	Food	84.77
20	老铺黄金	Laopu Gold	Jewelry & Accessories	84.75
21	珀莱雅	PROYA	Beauty	84.57
22	源氏木语	YESWOOD	Home Furnishing & Home Decos	84.36
23	兰蔻	LANCÔME	Beauty	84.21
24	波司登	BOSIDENG	Sports & Outdoors + Fashion	83.67
25	索尼	SONY	3C Digital	83.66
26	得力	deli	Office & School Supplies	83.51
27	巴拉巴拉	balabala	Sports & Outdoors + Fashion	83.44
28	猫人	MiiOW	Sports & Outdoors + Fashion	83.41
29	无印良品	MUJI	Sports & Outdoors + Fashion	83.33
30	雅诗兰黛	ESTĒE LAUDER	Beauty	83.07
31	泡泡玛特	POP MART	Collectible	82.83
32	公牛	BULL	Home Furnishing & Home Decos	82.22
33	回力	Warrior	Sports & Outdoors + Fashion	82.13
34	荣耀	HONOR	3C Digital	82.08
35	三只松鼠	Three Squirrels	Food	81.96
36	/	OPPO	3C Digital	81.70
37	华硕	ASUS	3C Digital	81.65

38	斯维诗	Swisse	Medical/Healthcare/Nutritional Products	81.58
39	海蓝之谜	LA MER	Beauty	81.55
40	领丰金	LING FENG GOLD	Jewelry & Accessories	81.53
41	圣罗兰（美妆）	YSL	Beauty	81.44
42	维达	Vinda	Household Items	81.25
43	爱他美	Aptamil	Food	80.95
44	骆驼	CAMEL	Sports & Outdoors + Fashion	80.85
45	香奈儿（美妆）	CHANEL	Beauty	80.42
46	好奇	HUGGIES	Household Items	80.26
47	可复美	KOMFYMED	Beauty	79.86
48	卡诗	KÉRASTASE	Household Items	79.78
49	飞利浦	PHILIPS	Home Appliances	79.68
50	全棉时代	Purcotton	Household Items	79.50
51	雀巢	Nestle	Food	79.42
52	娇韵诗	CLARINS	Beauty	79.41
53	白贝壳	Babycare	Household Items	79.17
54	佳能	Canon	3C Digital	79.11
55	雅迪	Yadea	Transportation	79.06
56	戴森	dyson	Home Appliances	79.05
57	小天鹅	LittleSwan	Home Appliances	78.95
58	奥克斯	AUX	Home Appliances	78.74
59	中国黄金	China Gold	Jewelry & Accessories	78.67
60	乐高	LEGO	Collectible	78.58
61	追觅	Dreame	Home Appliances	78.57
62	海信	Hisense	Home Appliances	78.53
63	大疆	DJI	3C Digital	78.53
64	九阳	Joyoung	Home Appliances	78.50
65	周生生	Chow Sang Sang	Jewelry & Accessories	78.50
66	伊利	Yili	Food	78.47
67	森马	SEMIR	Sports & Outdoors + Fashion	78.43
68	始祖鸟	ARC'TERYX	Sports & Outdoors + Fashion	78.27
69	富士	Fujifilm	3C Digital	78.02
70	百丽	BELLE	Sports & Outdoors + Fashion	77.94
71	惠普	HP	3C Digital	77.88
72	斯凯奇	SKECHERS	Sports & Outdoors + Fashion	77.87
73	皇家	ROYAL CANIN	Pet Care	77.80
74	倍思	Baseus	3C Digital	77.75
75	蔻驰	COACH	Sports & Outdoors + Fashion	77.66
76	心相印	Xin Xiang Yin	Household Items	77.60
77	/	UR(URBAN REVIVO)	Sports & Outdoors + Fashion	77.56
78	鱼跃	yuwell	Medical/Healthcare/Nutritional Products	77.52
79	/	SK-II	Beauty	77.45

80	麦富迪	MYFOODIE	Pet Care	77.44
81	科颜氏	Kiehl´s	Beauty	77.37
82	修丽可	SKIN CEUTICALS	Beauty	77.37
83	罗蒙	ROMON	Sports & Outdoors + Fashion	77.13
84	万代	BANDAI	Collectible	77.11
85	晨光	M&G	Office & School Supplies	77.05
86	周大生	Chow Tai Seng	Jewelry & Accessories	76.96
87	迪士尼	Disney	Collectible	76.81
88	特步	XTEP	Sports & Outdoors + Fashion	76.66
89	帮宝适	Pampers	Household Items	76.64
90	资生堂	SHISEIDO	Beauty	76.38
91	一加	OnePlus	3C Digital	76.30
92	剑南春	JianNanChun	Food	76.29
93	全友	QUANU	Home Furnishing & Home Decos	76.26
94	小熊	Bear	Home Appliances	76.25
95	/	TCL	Home Appliances	76.17
96	闪魔	SmartDevil	3C Digital	76.16
97	薇诺娜	WINONA	Beauty	76.16
98	杰士邦	jissbon	Medical/Healthcare/Nutritional Products	76.11
99	蕉下	Beneunder	Sports & Outdoors + Fashion	76.02
100	蒙牛	MENGNIU	Food	76.01

Appendix 2：Quarter×Industry Consumer Brand Index (CBI)

Category	Year：2023				2024				2025
	Quarter：Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1
Food	56.78	56.92	58.01	61.94	60.25	61.72	60.90	63.85	60.44
Sports & Outdoors	65.31	65.74	62.63	71.03	67.40	66.65	64.66	72.86	68.79
Fashion (Women's Wear)	33.38	35.28	35.47	36.71	35.32	35.52	36.62	41.29	39.26
Fashion (Men's Wear)	50.25	49.08	47.35	52.37	50.86	50.28	50.06	57.69	54.88
Fashion (Others)	49.26	49.39	47.68	50.76	48.30	51.89	50.94	55.67	52.62
Renovation Materials	31.69	31.33	31.83	31.42	32.27	32.59	33.03	34.93	32.48
Home Furnishing & Home Decos	39.13	41.50	39.78	43.46	40.24	43.23	42.39	48.06	44.19
Home Appliances	73.51	78.15	74.67	78.41	76.00	81.15	75.81	80.04	77.02
Household Textiles	39.93	41.50	40.35	41.89	40.81	40.93	39.30	42.81	41.20
Personal Care	65.02	66.63	65.91	69.01	67.00	69.01	67.00	70.20	68.41
Cleaning Products	62.74	65.69	63.21	66.33	63.18	65.25	62.97	66.98	63.47
Beauty	73.01	74.97	71.92	77.99	74.90	75.61	73.16	78.82	75.83
Transportation	51.10	51.03	51.47	48.73	49.01	48.62	47.02	45.61	46.25
3C Communications	80.05	81.80	82.96	87.77	86.17	89.38	86.62	89.77	85.09
3C Smart Devices	77.64	82.03	78.77	81.19	80.88	86.33	83.51	85.92	82.28
3C Culture & Education	70.48	72.84	71.48	75.67	75.08	76.12	75.78	77.13	76.58
Office & School Supplies (Non-electronic)	35.74	38.71	37.42	39.26	37.19	39.06	37.90	40.89	37.79
Collectible	43.01	45.08	42.16	42.90	43.64	44.92	44.02	43.67	44.72
Flowers & Gardening	32.71	32.55	34.00	30.81	32.59	35.18	31.48	27.90	30.28
Pet Care	51.59	54.66	52.09	56.16	56.32	57.91	54.88	59.61	56.72
Medical & Healthcare	60.56	60.90	58.44	63.85	63.19	62.37	61.49	62.89	63.40
Jewelry & Accessories	34.62	38.56	33.93	40.12	34.37	38.52	33.33	40.20	42.21

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