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Article

Did New Retail Enhance Enterprise Competition during the COVID-19 Pandemic? An Empirical Analysis of Operating Efficiency

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Abstract: The question concerning how digital consumption demand has been adapted and how matching business models have been built has become an important practical problem in the digital development of the retail industry. Considering the effects of COVID-19, whether new retail enterprises can maintain adequate competitiveness and risk resilience in the post-pandemic era deserves in-depth study. In comparing the development of traditional retail and new retail enterprises, we extracted and evaluated key factors of enterprise operating efficiency. Then, we measured the transformation efficiency of 65 enterprises in China listed in 2016 and 2020 by establishing a DEA model and the Malmquist index method. Finally, based on an empirical analysis demonstrating the necessity of traditional retail transformation, we analyzed retail enterprises' efficiency and dynamic efficiency changes. The results show that the operating efficiency of enterprises using the new retail model was higher than those using the traditional retail model. The technical efficiency and total factor productivity were significantly improved after the new retail model was applied. Both technological progress and improved technological efficiency contributed to the improvement in total factor productivity during the COVID-19 pandemic.

Keywords: new retail enterprises; digital transformation; operating efficiency; retail innovation; enterprise competition

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1. Introduction

The global traditional retail industry is facing unprecedented challenges and tests. Business performance is seriously deteriorating in this confusing period of transformation and upgrading. Traditional retail enterprises are looking to transform themselves. By comparing the characteristics of store retail and online retail, we can see that the latter's advantages, in terms of the convenience of transactions, store expansion, and price selection adaptability, are more prominent [1]. Traditional retail has been affected by practical reasons, such as the rising operating costs of physical stores, the decline in comprehensive performance, and the sharp decrease in customer flow [2]. The successful transformation of Walmart to an online platform provides a reference for large retail enterprises.

Digital technologies have transformed consumers' shopping behaviors and business operation models [3,4]. Different scholars have different views on the next stage of retail development [5–12]. Bart J. Bronnenberg and Ellickson hypothesize that a variety of modern new retail technologies will significantly change the retail environment [13]. Bradlow et al. believe that in future retail development, customer, product, time, location, and channel data will be given increased attention and that effective prediction and analysis can drive market progress and social change [14]. Piskunova found that the COVID-19 (coronavirus disease 2019) crisis drove the omnichannel development of new retail [15]. Dyason et al. examined the combined impact of the disaster and the COVID-19 pandemic on traditional retail sales by analyzing consumer payment and transaction data in Christchurch and New

Zealand. They showed how enterprises can cope with different types of external shocks through transitioning from the traditional offline retail model to an online platform to cope with changing retail patterns [6,16].

At present, China's digital economy is developing rapidly, and disruptive scientific and technological innovations are emerging. The new generation of digital technology, represented by cloud computing, big data, the Internet of Things, blockchain, etc., promotes the development of industrial digitalization [3,4,10,17]. The butterfly effect brought about by digital technology has spawned new consumption phenomena in the field of consumption, such as non-contact consumption, targeted advertising, and multi-scene consumption, and has promoted the transformation of traditional consumption to digital consumption. COVID-19 accelerated the development of the digital economy and promoted the diversified transformation of the consumer market [18–20]. The digital transformation of business models has become important for enterprises seeking to adapt and obtain competitive advantages. In addition, after the emergence of COVID-19, even relatively mature e-commerce and new retail enterprises experienced a significant decline in performance. The crisis brought on by COVID-19 also presented good opportunities for development. The retail industry must seize the opportunity to transform their business models against the backdrop of consumption reform driven by COVID-19.

This paper used the annual reports of listed retail enterprises as the source of measurement data, combined with the DEA (data envelopment analysis) model and the Malmquist index method, to conduct a quantitative comparative analysis of their efficiency before and after the transformation of their retail business model. Then, we explored the favorable and adverse factors affecting the business efficiency of enterprises under the new retail model, provide a reference for the development of related enterprises and the future trend of the whole industry, and promote the rapid transformation and development of China's retail industry. One of the objectives of this study was to analyze the differences between the new retail model and the traditional retail model from the perspective of enterprise operation efficiency. The second goal of this study was to highlight that under the influence of the COVID-19 pandemic, new retail enterprises showed better risk responses.

The remainder of this paper is organized as follows. In Section 2, we review the progress of new retail research. ln Section 3, we describe the proposed model in detail. In Section 4, the DEA and Malmquist methods are used to calculate and analyze the efficiency values of 65 retail enterprises listed in 2016 and 2020. Finally, the conclusions and suggestions for the future are given in Section 5. This commentary offers the following research contributions. First, we use the DEA method and the Malmquist index method to analyze retail enterprises' efficiency and dynamic efficiency changes. The efficiency factors of new retail are identified to provide a decision-making basis for the digital transformation of retail enterprises. Second, an evaluation index is established to evaluate the operating efficiency of enterprises. Through empirical research on the impact of technological progress, pure technical efficiency, and scale efficiency on enterprise operating efficiency, the feasibility and necessity of enterprises' transformation to the new retail model is put forward through comparative study.

2. Literature Review

2.1. Retail Enterprise Transformation

Traditional retail enterprises face many difficulties. First of all, consumer loyalty has declined, product homogeneity has increased, brand value and differentiation are at historically low points, and brand switching and re-selection have become common occurrences. Secondly, the numerous channel data have not been well integrated and used, making it difficult to carry out refined management and operation. The more serious problem, however, is the economic environment. At present, the global economy and China's economy lack stability. The impact on consumer goods is that the upstream and downstream have become unstable. For example, the price of packaging has fluctuated sharply in the past, which creates a lot of uncertainty about cost control and profit and puts pressure on the operations of retail enterprises. Many scholars have begun to pay attention to the changes in the retail industry [21–23]. They have noted the transformation from a store form to a no-store form, focusing on the Internet transformation mode of traditional retail [2,24,25]. Chesbrough believes that the retail industry is being impacted by traditional concepts, business models, and Internet technology, and the traditional retail industry supported by physical stores is facing an unprecedented crisis [26]. Guimarães, through a survey of retail sales in major urban centers worldwide, found that consumer groups and the market demand from different age groups have changed significantly, reducing the business scale and profit in the region significantly [21]. Therefore, many companies immediately and actively sought the help of the Internet. However, some experts have pointed out that online retail cannot completely replace the role of brick-and-mortar stores, and only through full complementarity can the two create the maximum economic value [27].

The traditional retail industry of China has been struggling under the bottleneck of its mechanism and the multiple shocks of the Internet economy, which has inspired scholars to consider how retail enterprises can transform and upgrade [28,29]. Chinese scholars' transformation and upgrading challenges mainly come from external investment pressure, internal operation resistance, and online retail impact. First, Li contended that external competition, internal controversy, and other factors triggered the urgent need for a complete reform in the traditional retail industry of China [30]. Gu believes that, with increasing international trade dependence, investment and export pressure has gradually spread from abroad to China in recent years, so that the retail market of China constantly squeezed by competition from the external environment [31]. Secondly, Peng Jing and Peng and Lin pointed out that the size of demand disturbance and consumers' acceptance of electronic channels have an important impact on the optimal decision-making and coordination contract of the two-channel supply chain system [32]. Gao states that, in the "Internet+" business environment, traditional entities suffer from online retail impact due to the advantages of e-commerce in terms of price, category, region, and other aspects, transferring a large number of consumer groups from offline to online [25].

2.2. New Retail Enterprises and e-Commerce Platforms

All enterprises, especially retail enterprises, are facing a dilemma, which is the difficulty of product innovation and digital innovation [33]. For example, traditional retail enterprises have a large number of systems in stock. These systems have been running for many years and have accumulated a large amount of data. It is impossible to develop an Internet architecture overnight. In the digital era, the flexible retail business, especially the flexibility of front-end marketing, creates higher requirements for the robustness of the middle and back office. Through an overall review of the research status of related fields of scholars, we found that both traditional physical retail enterprises and pure e-commerce platforms have encountered many difficulties and challenges on the development path. The current business model is increasingly less suitable for the needs of the business environment and industry transformation background. Currently, most Chinese foreign scholars focus on traditional retail transformation, mostly on the process of simple Internet transformation. On the one hand, it is difficult to base this on the real needs of consumers. In reality, it is often challenging to reflect the value of "people, goods, and field." On the other hand, due to the inability to account for the role of big data, cloud computing, and artificial intelligence in the digital economy in the transformation, the overall innovation of enterprises is insufficient, highlighting that the reform of China's traditional retail industry has a long way to go [34].

In the new round of business model innovation, the new retail model of "online + offline + new logistics" has received attention from Chinese and foreign scholars due to its creative product form, deeply integrated shopping channels, and efficient and flexible operation mode, and has become an important research direction for the next stage of transformation of traditional retail enterprises in China [25,35–39]. The "new retail" concept is widely discussed as a new thing introduced into the academic field by the business environment. Most of the related literature is a theoretical analysis and case elaboration; there have been no articles verifying the necessity of the new retail model through empirical research. Based on this, relevant research has a very important frontier value. Therefore, this paper studies the transformation of traditional retail to the new retail model and assesses the feasibility and necessity of new retail model transformation for the enterprise's high-term strategic planning. This will help enterprises improve management efficiency and complete the transformation and upgrading of the Retail 4.0 era [7,40].

2.3. Operating Efficiency of Retail Enterprises

Global scholars started studying the business efficiency of retail enterprises early on. Most of their primary research methods use DEA, MPI (Malmquist Productivity Index), and Tobit models, among which the DEA model is the most widely used and mature for measuring retail efficiency. Farrell was the first to study operational efficiency, proposing the concept of extending productivity to production efficiency, including enterprise technology and price efficiency [41]. Caves first introduced the empirical method of Malmquist based on the DEA concept [42], which is based on the evaluation system of the total factor productivity of the enterprise decision making unit (DMU). Based on expanding the working principle of Chames and other C2R-DEA, Banker et al. proposed a BC2-DEA model for measuring the relationship between input and output, which was gradually implemented in the calculation and evaluation of enterprise efficiency [24]. Kato, Yu and Ramanathan, and other retail companies selected many retail enterprises in different countries and used DEA and MPI models to study the relationship between retail efficiency and the economy of scale, operating area, and number of employees [43,44].

In the empirical study based on Malmquist, Ray and Ray used the Malmquist index to study the technical and productivity changes of TFP values in India in 1992, 1993, 2007, and 2008 and showed that the improved technical level could improve the total factor productivity of the industry [22]. Scholars also studied the expansion activities of retail enterprises based on panel data and calculated results by DEA and the Malmquist index [22,45,46]. The results showed that the general retail enterprises would intensify competition among enterprises due to market demand and structural changes. Baviera-Puig et al. used DEA and GIS to analyze retail supermarket management efficiency and conducted a principal component analysis and classification analysis on a series of internal management variables in retail supermarkets in 61 locations revealing that loyalty membership is a key element affecting efficiency [47]. Lu et al. adopted the improved DEA game cross-efficiency evaluation method to select the annual observation sample data of 414 listed retail enterprises given by Forbes 2000 from 2013 to 2018 [48]. The results showed that the environmental dimension in corporate social responsibility was significantly correlated with corporate efficiency.

2.4. Opportunities and Challenges for China's New Retail Development

China has been one of the world's most significant online retail markets for many years [25,31,32,40,49]. However, due to the influence of the new normal reform of the economy [50,51], the segmentation of the online retail market [49], and the surge in-store operating costs [52], traditional Chinese retail enterprises suffered an unprecedented decline in business from 2010 to 2015 [53–56]. On 11 November 2016, the General Office of the State Council of China issued "Opinions on Promoting the innovation and transformation of physical retail," encouraging the integration of physical and online retail and accelerating the search for innovation and transformation [55,57]. In recent years, a large number of traditional retail enterprises have expanded their online channels, combined with the advantages of e-commerce, and e-commerce platforms have developed high-quality services [14,57–59]. Large groups such as Alibaba.com, JD.com, and Suning Corporation cooperated with traditional entities to make significant and bold reforms. Alibaba strategically staked in Suning, Yintai, and Bailian, taking the lead in Sanjiang Shopping, Lianhua supermarket, Auchan supermarket, and another old supermarket, making a new retail transformation. Jingdong, together with Walmart, acquired Yihaodian, took out a stake in Yonghui Supermarket, integrated Jingdong Home and Dada, and plans to open more than 1 million Jingdong convenience stores nationwide within five years. Suning plans to build a "Cloud Business" Group, open Suning Tesco stores and cloud stores, build a Red Child Maternal and Child life hall, provide customized V-purchase services, and implement the "smart retail" strategy.

From the perspective of operations, the decline in performance and sharp decline in profits have caused major global retail companies to encounter operational crises [2,60]. The total retail sales of the top 100 retailers in China have been declining year on year. In 2015, the growth rate was lower than 5% for the first time; in 2016, it was only 3.5% [25,32,61–66]. At the same time, due to the dual pressure of labor costs and rising housing prices, physical stores were forced to be involved in the "bankruptcy wave collectively." Wanda closed 56 stores in a year, and Walmart closed 269 physical stores. The tide of store closures is intensifying; supermarkets, department stores, stores, and so on are not spared. Industry data disclosed that retail enterprise profits declined seriously from 2010 to 2015, with negative growth in recent years, and the overall operating situation is not optimistic [35,46,67,68]. In 2016, the Internet shopping crowd in China continued to increase, with the annual online retail transaction volume reaching RMB 515 million, up 26.2% on the previous year. China's annual online retail sales reached RMB 7.18 trillion in 2017, up 39.1 percent over 2016. At the beginning of 2020, due to the COVID-19 pandemic, the scale of most network applications increased substantially [40,48]. In 2020, online retail sales in China reached RMB 11.76 trillion, up 10.9% from 2019. Among them, online retail sales of physical goods reached RMB 9.76 trillion, accounting for 24.9% of the total retail sales of social consumer goods. By December 2020, the number of online shopping users in China reached 782 million, an increase of 72.15 million over March 2020, accounting for 79.1% of total Internet users.

The whole social consumer goods retail industry is experiencing an unprecedented comprehensive business Internet transformation [1,15,28]. With the increase in consumption, every retail enterprise must cater to the needs of consumer groups in the new era [14,69], embrace the Omni-channel integration of online and offline [50,51], and pay attention to big data mining and the construction of new consumption scenarios. This represents the important trend of taking the initiative to seek development in the business environment [54], whether in traditional entities or e-commerce platforms [70–73]. Only deepening reform can absorb China's retail market of more than 30 trillion RMB. Therefore, it is of great significance to study the influence mechanism of operating efficiency before and after the new retail model to promote the rapid development of China's retail industry.

China's offline businesses have been under great pressure during the Covid-19 pandemic, but a turnaround has also occurred. The depletion of passenger flow leads to serious pressure on offline business. The pressure of inventory will affect the continuous operation of offline stores. Brands and distributors are already rebuilding the Omni-channel system of users. To reduce losses during the COVID-19 pandemic, various types of offline commercial companies tried to use online channels to expand their business. Some stores started to open online stores, and even mobilized employees to use social e-commerce platforms and communities to promote and sell. At the same time, many brands have also moved from offline to online, opening up a new way of selling goods. From founders and executives to store managers and clerks, they have promoted brands and goods live. In addition, the brand will reassess the launch of marketing content and the choice of marketing channels, and put some offline marketing resources online.

3. Materials and Methods

The necessity of transforming and upgrading Chinese traditional retail enterprises to a new retail model needs to be analyzed effectively. We selected the Shanghai and Shenzhen two market retail plate samples from the retail enterprise annual report data, and through a factor analysis selected reliable input–output indicators. Through the DEA and Malmquist model for scientific business efficiency and total factor productivity measurement [22,47,48], we analyzed the differences between the new retail model and the traditional retail model from the perspective of enterprise operating efficiency, and we selected two time nodes in 2016 and 2020 to compare the changes in enterprise operating efficiency of the two models before and during the COVID-19 pandemic.

3.1. Model Design

3.1.1. The C^2R Model and BC^2 Model

C^2R model: If the reward of scale is unchanged, assume n decision-making units, denoted as DMU_i, $i = 1, 2, \ldots, n$, with comparable requirements between DMU_i. Each DMU has m inputs and s outputs, and the indicator set can be scored as $I = \{1, 2, \ldots, m\}$ and $R = \{1, 2, \ldots, s\}$. This is specifically expressed as the evaluated object: $DMU_1, DMU_2, \ldots$, DMU_n; input indicators: $x_1, x, \ldots, x_n$; output indicators: $y_1, y, \ldots, y_n$; where $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$, $y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$ are the input and output data of the decision-making unit DMU_i, respectively. $v = (v_1, v_2, \ldots, v_m)^T$ and $u = (u_1, u_2, \ldots, u_s)^T$ are the measurement weight coefficients. For the weight coefficients $v \in E_m$ and $u \in E_s$, the efficiency evaluation index of the decision-making unit j can be expressed as follows:

$$hj = \frac{\sum\limits_{r=1}^{s} u_r y_{rj}}{\sum\limits_{i=1}^{m} v_i x_{ij}} \tag{1}$$

When evaluating the DMU $j_0 (1 \leq j_0 \leq n)$, the weight coefficients v and u are variables, and the efficiency index of the DMU j_0 is the target. The efficiency index of all DMUs is the constraint. Through a Charnes–Cooper transformation, its dual model is obtained, namely, the C^2R model:

$$\begin{cases} \min\theta \\ \sum\limits_{j=1}^{n} x_j \lambda_j \leq \theta x_{j0} \\ \sum\limits_{j=1}^{n} y_j \lambda_j \geq y_{j0} \\ \lambda j \geq 0, j = 1, 2, \cdots, n \end{cases} \tag{2}$$

The optimal value, θ, obtained by solving the above plan is the technical efficiency value of the corresponding decision-making unit. If $\theta < 1$, it shows that the DMU is inefficient, and also that the multiple input to the unit is a waste phenomenon, which requires enterprises to improve the output efficiency by reducing the input. The proportion of the reduction is $1 - \theta$; if $\theta = 1$, this shows that the DMU is efficient. This analysis shows that, if the θ values of all DMU can be solved, the technical efficiency of the whole system can be clearly understood. To further verify the effectiveness of DEA, the non-Archimedes infinitesimal size in mathematics is introduced to judge the effectiveness of DEA. The dual model can be expressed as follows:

$$\begin{cases} \min\left[\theta - \varepsilon\left(\hat{e}^{T} s^- + e^T s^+\right)\right] \\ s.t. \sum\limits_{j=1}^{n} xj\lambda j + s^- = \theta x_0 \\ \sum\limits_{j=1}^{n} yj\lambda j - s^+ = y_0 \\ \lambda \geq 0, j = 1, 2, \cdots, n, s^- \geq 0, s^+ \geq 0 \text{ s.t} \end{cases} \quad \begin{array}{l} \hat{e}^{T} = \text{s.t}\,(1, 1, \cdots, 1) \in E^m \\ e^T = (1, \theta 1, \ldots, 1) \in E^s \\ \varepsilon s^-, s^+ \\ \theta \leq 1 \end{array} \tag{3}$$

where θ, s^-, and s^+ are often used as the main indicators of a benefits evaluation: θ is the efficiency evaluation index, and s^- and s^+ are the relaxation variables. If $\theta < 1$, s^- and s^+ are not zero, the decision-making unit DEA is invalid, which indicates that the existing investment amount is just right. The C^2R model is built from the perspective of "constant output and least input." The DEA effective under the C^2R model is technically practical and scales effectively. To further discuss pure technical efficiency and scale efficiency, the BC^2 model is extended, which yields the technical efficiency of each unit. This paper combines the C^2R model and the BC^2 model to measure the technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) of the enterprise.

$$\begin{cases} \min\theta \\ \sum\limits_{j=1}^{n} x_j\lambda_j \leq \theta x_0 \\ \sum\limits_{j=1}^{n} y_j\lambda_j \geq y_0 \\ \lambda_j \geq 0, j = 1,2,\cdots,n \end{cases} \tag{4}$$

3.1.2. The Malmquist Index Model

The Swedish economist Malmquist first proposed the Malmquist index in 1953. In 1982, Caves was the first to incorporate Malmquist models in DEA into the evaluation method of productivity. This divides total factor productivity into technological efficiency and progress changes and can dynamically measure them. The input-based comprehensive factor productivity index can be expressed as follows:

$$M_i^t = \frac{D_i^t(\mathrm{x}^t, y^t)}{D_i^t(\mathrm{x}^{t+1}, y^{t+1})} \quad M_i^t = \frac{D_i^{t+1}(\mathrm{x}^t, y^t)}{D_i^{t+1}(\mathrm{x}^{t+1}, y^{t+1})} \tag{5}$$

Based on the input representation, under a certain combination of input, the technical efficiency is calculated by the ratio of the minimum input to the actual input, where x^t, x^{t+1}, y^t, and y^{t+1} represent the input and output data of periods t and $t+1$, respectively. $D_i^t(x_t, y_t)$, $D_i^t(x^{t+1}, y^{t+1})$, $D_i^{t+1}(x^t, y^t)$, and $D_i^{t+1}(x^{t+1}, y^{t+1})$ are distance function.M_i^t, M_i^{t+1} represent changes in total factor productivity from t to $t+1$, respectively.

The Malmquist Index (TFP) can be decomposed into changes in technical efficiency (EFFCH) and changes in technological progress (TECH).

$$M_\mathrm{i} = TFP = \left(\mathrm{x}^{t+1}, y^{t+1}, x^t, y^t\right) = \left[\frac{D_i^{t+1}(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} * \frac{D_i^t(x^t, y^t)}{D_i^t(x^{t+1}, y^{t+1})}\right]^{\frac{1}{2}} \tag{6}$$

Equation (6) may be further expressed as:

$$M_\mathrm{i} = \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} * \left[\frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^{t+1}, y^{t+1})} * \frac{D_i^{t+1}(x^t, y^t)}{D_i^t(x^t, y^t)}\right]^{\frac{1}{2}} \tag{7}$$

In Equation (7), the first part, EFFCH, is the technical efficiency change index, and the second part, TECH, is the technical progress index, which represents the technical efficiency and production technology changes from period t to period $t+1$, respectively. Therefore, total factor productivity can be expressed as TFP = EFFCH $*$ TECH.

The assumption condition of fixed scale reward is relaxed, and the technical efficiency change can be decomposed into pure technical efficiency change (PECH) and scale efficiency change (SECH). The Malmquist index can be expressed as follows:

$$M_\mathrm{i} = \frac{D_v^{t+1}\left(x_1^{t+1}, y_1^{t+1}\right)}{D_i^{t+1}(x_1^t, y_1^t)} * \left[\frac{\dfrac{D_v^{t+1}(x_1^t, y_1^t)}{D_c^t(x_1^t, y_1^t)}}{\dfrac{D_v^{t+1}\left(x_1^{t+1}, y_1^{t+1}\right)}{D_c^{t+1}\left(x_1^{t+1}, y_1^{t+1}\right)}}\right] * \left[\frac{\dfrac{D_c^t(x_1^t, y_1^t)}{D_1^{t+1}(x_1^t, y_1^t)}}{\dfrac{D_c^t\left(x_1^{t+1}, y_1^{t+1}\right)}{D_c^{t+1}\left(x_1^{t+1}, y_1^{t+1}\right)}}\right] \tag{8}$$

Therefore, the individual variable relationship is TFP = EFFCH $*$ TECH + (PECH $*$ SECH) $*$ TECH. We used the Malmquist index to measure and analyze the change in enterprise efficiency. We thereby obtained the changes in enterprise technical efficiency (EFFCH), technology progress (TECHCH), pure technical efficiency (PECH), scale efficiency (SECH), and total factor productivity (TFPCH).

3.2. Data Description

The sample selection process started with examining whether the types of enterprise were consistent, whether the enterprise operation was regular, and whether the sample enterprise annual report data were complete for the purposes of screening and judgment. The selected samples must be of the same retail business type but in different categories. The selected sample enterprises should operate normally during the reporting period and generally we did not select ST grade sample enterprises on the inside; the selected sample enterprises should have a certain market strength and representativeness. Finally, the annual report data of the selected sample enterprises should be complete, and incomplete annual report data in a similar index system should be excluded. Therefore, we selected 74 listed retail enterprises in the Shanghai and Shenzhen sectors (see Appendix A Table A1).

We used the WIND database to collect statements from the annual reports of listed enterprises. After listing, enterprises must disclose their quarterly report, semi-annual report, and annual report data according to national regulations, and these should be checked by relevant institutions. The authenticity and stability of the data can be guaranteed. At the same time, since all of the data are open to the public, they are relatively easy to obtain. Therefore, we selected annual report data from retail listed enterprises for the next stage of research. However, due to incomplete data, nine enterprises from Wuhan, ZHONG SHANG (New name: Easyhome New Retail, 000785.SZ), Wuhan NEWHUADU (002264.SZ), Shenyang COMMERCIAL CITY (600306.SH), Beijing HUALIAN (600361.SH), Nanning Department Store (600712.SH), Xinjiang YOUHAO (600778.SH), QUANYE (New name: NYOCOR, 600821.SH), INZONE (600858.SH), Dalian FRIENDSHIP (000679.SZ), were excluded, and the final number was 65 (see Table A2). All of the input and output data established in the following index system were derived from the annual reports of the 65 sample enterprises, which are extracted from the WIND database.

3.3. Index System

3.3.1. Primary Input-Output Index System

Retail enterprises are a production system with more input and more output. Evaluating enterprises' operating efficiency evaluates which enterprises can use the fewest resources to obtain the greatest output. In establishing the index system, we comprehensively considered the following factors for the preliminary primary election. First, the comparability, hierarchy, and representativeness of the evaluation indicators were fully considered in the process of establishing the index system. Secondly, the selected indicators were intended to cover human, financial, and material resources. Finally, the enterprise's operations, management, income, and other aspects were included to ensure the scientific integrity of the selected index system. The primary selection index system is shown in Table 1.

3.3.2. Input and Output Indicators

In the DEA model, there cannot be a linear relationship between input and output indicators. In order to optimize the shortcomings of the DEA model, we conducted a factor analysis of the input and output data of 65 sample listed retail enterprises based on SPSS22.0 software. The KMO values obtained from the data test of Input indicators and Output indicators were 0.848 and 0.629 (see Appendix A Tables A3 and A4), indicating that there is a strong correlation between variables, which can be extracted by factor analysis. Through the extraction method of principal component analysis and the rotation method of Kaiser's standardized maximum variance method, we ascertained that the owner's equity, main business cost, and total number of employees are the input variables of the DEA model, while the return on equity, inventory turnover, and net profit are the output variables.

Table 1. Primary Input-output Index System.

Input Indicators	Unit	Type	Description
Number of employees	Person	Input	An important indicator to measure the operation scale of retail enterprises
Owner's equities	10,000	Input	Measure the long-term and sustainable capital sources of retail enterprises
Principle business cost	10,000	Input	Measure the total direct costs of all inputs to products or services related to the main business
Total Worth	10,000	Input	Measure the total amount of all assets held by retail enterprises that can bring economic benefits
Circulating assets	10,000	Input	Measure the assets that can be converted into cash in the operating period of retail enterprises for one year or more
Administrative expense	10,000	Input	Measure the total expenses incurred by retail enterprises in organizing relevant business activities in the office
Selling expenses	10,000	Input	Measure the total expenses incurred by retail enterprises when selling products and services at the business premises
Production quota	/	Output	Measure the use efficiency of capital injected by shareholders of listed retail enterprises
Basic earnings per share	RMB	Output	Measure the profitability of the shares issued by listed retail enterprises
Return on Equity	%	Output	Measure enterprise income and output results
Net profit	10,000	Output	Measure the revenue generated by developing products or services related to the main business
Main operating revenue	10,000	Output	Measure the revenue generated by developing products or services related to the main business
Operating profit	Ten thousand	Output	Measure the results of daily operation activities of retail enterprises
Inventory turnover	%	Output	Measure the purchasing and marketing balance ability of retail enterprises

Through KMO and Bartlett tests, we screened out objective and accurate indicators, so that the efficiency measurement below was more scientific and rigorous. The input–output variables we selected for the DEA evaluation model are shown in Table 2.

Table 2. List of input and output indicators.

Input Indicators	Output Indicators
Main operating revenue	Net profit
Owner's equities	Return on Equity
Number of employees	Inventory turnover

4. Empirical Analysis and Discussion

In this paper, the filtered input and output indicators were analyzed by the data envelope analysis software DEAP2.1. DEA and Malmquist methods were used to calculate and analyze the efficiency values of 65 listed retail enterprises in 2016 and 2020. At the same time, 45 sample listed enterprises that did not use the new retail model and 20 sample listed enterprises that used the new retail model were separately calculated and analyzed. In this way, the differences and impact of operating efficiency before and after the transformation were analyzed from both horizontal and vertical perspectives.

4.1. Efficiency Positive Results Based on DEA Method

In the DEA method, the input–output data of technical efficiency (TE), pure TE (PTE), and scale efficiency (SE) were calculated using the C^2R model and BC^2 model (see Figure 1).

Table 3 shows that the overall operating efficiency of the listed retail enterprises in China in 2016 and 2020 is not high, among which the average technical efficiency in 2016 and 2020 was 0.522 and 0.473, respectively, which is a large gap in terms of the effectiveness of DEA. This is also consistent with the operating situation of the entire retail industry in recent years, which reflects increases in cost and expenditure, a decline in operating profit, and an increasing burden on enterprises. In addition, the average efficiency in 2020 showed a large decrease compared with 2016 (down by nearly 5%), indicating that it has become urgent to address the declining efficiency and sustainable operation of retail enterprises.

The suspension of some Chinese retail enterprises during the COVID-19 pandemic is another important reason.

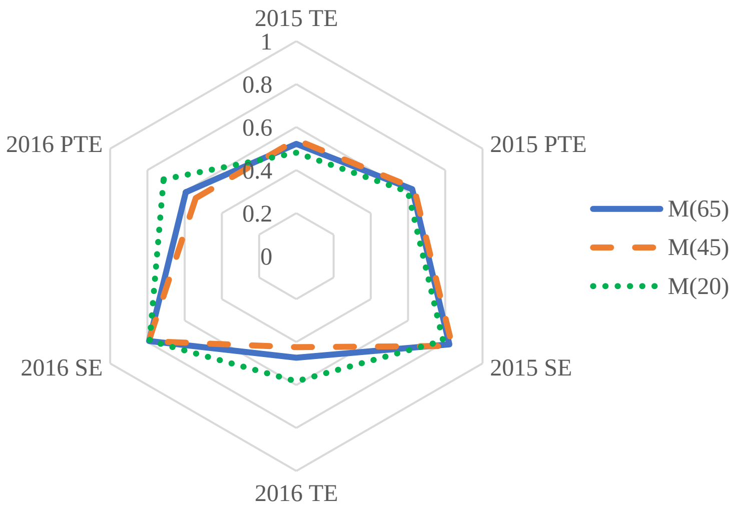

Figure 1. Average efficiency of the retail enterprises.

Table 3. Average efficiency of the retail enterprises.

	2016			2020		
Mean Value	**TE**	**PTE**	**SE**	**TE**	**PTE**	**SE**
M (65)	0.522	0.622	0.822	0.473	0.594	0.791
M (45)	0.541	0.633	0.837	0.424	0.540	0.793
M (20)	0.481	0.599	0.788	0.583	0.713	0.788

In 2020, the average efficiency of 45 traditional retail enterprises that did not use the new retail model was 0.424, down 0.117 from the average efficiency of 0.541 in 2016. The average efficiency of 45 enterprises in 2020 was 0.424, which was lower than the overall efficiency of 65. This indicates that the business performance of traditional retail enterprises was worse. The average efficiency of the 20 new retail enterprises using the new retail model was 0.583, significantly higher than the average efficiency of 65 enterprises (0.473) and of 45 enterprises (0.424). Compared with 2016 and 2020, the enterprise efficiency improved from 0.481 to 0.583. This indicates that enterprises adopting the transformation and exploration of the new retail model performed well, and their operating efficiency improved.

At the same time, in order to compare the advantages of the new retail enterprises, the average efficiency of 45 enterprises not using the new retail model and 20 enterprises using the new retail model was calculated.

- Efficiency measurement results of 45 companies that did not use the new retail model as shown in Appendix A Table A5.

As seen from the individual company efficiency changes of 45 sample enterprises, the top three enterprises in the efficiency value in 2020 were Doctor Glass, Zhejiang Winter, and Liqun Shares. The last three were the supply and marketing market, agricultural products, and Zhongbai Group. From 2016 to 2020, 31 companies saw their technology efficiency decline, and about 69% of traditional retail companies had poor operating efficiency. Of the 31 declining enterprises, in 24 the reduction in technical efficiency was attributed to a decrease in pure technical efficiency, accounting for 77.4%. The decline in technical efficiency of the other seven listed enterprises was attributed to a reduction in scale efficiency, accounting for 22.6%. This indicates that pure technical efficiency is the main reason for the decline in operating efficiency of traditional retail enterprises. From 2016 to 2020, there were only 12 enterprises with an upward trend of technical efficiency, accounting for

27%. The increase in pure technical efficiency caused a 66.7% efficiency increase for these 12 listed enterprises, and the remaining 33.3% was caused by scale efficiency, which further demonstrates the importance of pure technical efficiency.

Combined with the overall and individual efficiency changes, this shows that, at present, the traditional business model relying on manpower, business area, and "commodity delivery and real estate expansion" is increasingly unable to meet the needs of the business environment. Homogeneous goods will only lead to market saturation, making the scale efficiency of enterprises decrease. Therefore, on the one hand, enterprises must change their management concept, and further optimize the internal and external management level by, for example, flat operation, reducing the operation cycle, and improving the quality of management. On the other hand, companies need to respect the technological content, and practical value of their products: big data, cloud computing, and other technologies help stores to realize intelligent production and diversified operations improve the input and output efficiency of enterprises through a series of measures to improve management and technology.

- The efficiency measurement results of 20 enterprises using the new retail model are shown in Appendix A Table A6.

As can be seen from the empirical results of 20 enterprises, the average technical efficiency of enterprises using the new retail model was 0.583. The mean value of pure technical efficiency and scale efficiency was 0.713 and 0.788, respectively, which are greater than the average efficiency of the sample enterprises in 2016. In addition, the average efficiency of 20 enterprises using the new retail model was 0.583, much higher than the average efficiency of 45 traditional retail models (0.424), and the average efficiency of 65 retail enterprises was 0.473, so the operating efficiency was significantly improved.

As can be seen from the 20 sampled companies with efficiency changes, the technical efficiency of 14 out of the 20 listed companies improved after using the new retail model, accounting for 70% of the sample listed enterprises, such as Yonghui Supermarket, Nanjing Xinbai, Sanjiang Shopping, etc. The list includes Maoye Commercial, Ewushang A, and Zhejiang China Commodities City Group, with the pure technical efficiency enhanced in 2020. The pure technical efficiency was 1, indicating that the enterprise improved management and technology applications within a year, which significantly contributed to the technical efficiency. After the introduction of the new retail model, the technical efficiency of Sanjiang Shopping, Nanjing Xinbai, Fujian Dongbai Group, and Shanghai New World improved significantly compared with 2016, with an efficiency increase of more than 14%, indicating that they performed well in the exploration of the new retail model. Their business status is developing along a good trend. Suning Commerce, Xujiahui, Rainbow Holdings, and Bailian Holdings enterprises reduced their efficiency after using the new retail model, but the overall decrease was not significant.

The operating efficiency of enterprises is affected by pure technical efficiency to varying degrees, indicating that there may be some restrictions and obstacles in management and technology preventing the new retail model's implementation. In the early stage of the new business model, a change in traditional business projects requires significant human resources, material resources, and financial resources in the early stages, and it is not easy to obtain the expected high returns in a short period. At the same time, due to the lack of a mature reform mode and precise strategic planning in the internal management of the enterprise, the efficiency value of the new retail model may be reduced.

4.2. Efficiency Changes Based on the Malmquist Index Method

The DEA method above measures and analyzes the efficiency of each listed sample enterprise from the static efficiency level, but cannot dynamically analyze the specific progress and regression of enterprise efficiency. Therefore, the Malmquist index continues to be used to measure and analyze the change in enterprise efficiency. It enables us to quantify changes in enterprise technical efficiency (EFFCH), technological progress (TECHCH), pure technical efficiency (PECH), scale efficiency (SECH), and total factor productivity (TFPCH).

The Malmquist method was used to obtain the change value of total factor productivity and its decomposition index of 65 enterprises. Meanwhile, the mean change values of 45 sample enterprises that did not apply the new retail model, and the mean change values of 20 sample enterprises that applied the new retail mode, are shown in Figure 2.

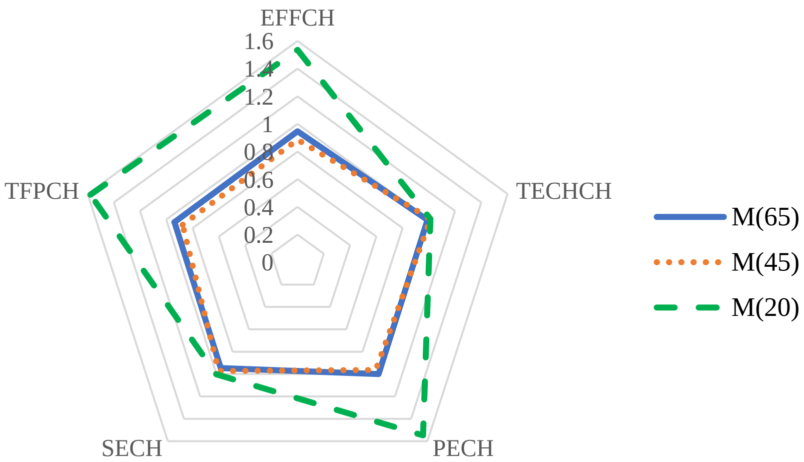

Figure 2. Decomposition mean table of enterprise total factor productivity.

As can be seen from the calculation results in Table 4, the mean change in total factor productivity of 65 Chinese enterprises from 2016 to 2020 was 0.938, an overall decrease of 0.62%. From the perspective of decomposition indicators, both technological efficiency and technological progress change indicators show a declining trend, among which the decrease in scale efficiency mainly causes a decrease in technological efficiency. This suggests that in the Chinese retail market, after struggling to realize the importance of the transformation, many enterprises began to close poor-performing stores. Paying less attention to the supply chain system and third-party payment technology, but not overall investment, management, and technology, it is still necessary to strengthen innovation, especially in terms of big data management, intelligent operations, and other aspects, to further appreciate "people, goods, and field".

Table 4. Decomposition mean table of enterprise total factor productivity.

Mean Value	EFFCH	TECHCH	PECH	SECH	TFPCH
M (65)	0.947	0.990	1.000	0.947	0.938
M (45)	0.886	1.014	0.963	0.972	0.876
M (20)	1.536	1.012	1.548	1.002	1.578

The mean change in total factor productivity of 45 traditional retail enterprises that did not use the new retail model was only 0.876, a decrease of 12.4%, showing an apparent downward trend. According to the Malmquist decomposition index, although the change index of technological progress was greater than 1, the total factor productivity did not improve. The main reason for the decrease is a decrease in technical efficiency of 11.4%. Further decomposition of technical efficiency shows that the inefficiency was mainly reflected in the substantial reduction of pure technical efficiency, indicating that traditional retail enterprises that have not explored new retail models have a small investment range in technology and management. Therefore, their operating efficiency has not been effectively improved.

From 2016 to 2020, the mean change in total factor productivity of the 20 listed retail enterprises using the new retail model was 1.578, an increase of 57.8%. The overall operation status of the sample listed retail enterprises improved and developed rapidly after the new retail model was applied. It can be observed from the Malmquist decomposition index that the change indexes of technological progress and technological efficiency were both greater than 1, and the mean change of technological efficiency was 1.536, an increase of more than 50%. Further decomposition of technical efficiency indicates that, when the scale efficiency remains basically unchanged, the growth of pure technical efficiency index directly determines the significant improvement of the technical efficiency index. Twenty listed enterprises using the new retail model actively utilized technologies such as facial recognition, intelligent terminals, mobile payment, etc. This allowed them to improve the store layout, commodity supply, and overall shopping experience, which made an outstanding contribution to total factor productivity.

- Efficiency changes results of 45 companies that did not use the new retail model are shown in Appendix A Table A7.

According to the empirical results of 45 sample enterprises, there were 9 enterprises with a total factor productivity greater than 1 from 2016 to 2020, accounting for 20% of the sample enterprises. There were 35 enterprises with a total factor productivity of less than 1, accounting for 77.8% of the sample enterprises. Among the 35 enterprises with a total factor productivity less than 1, the decrease in total factor productivity of 28 enterprises was caused by a decrease in the technical efficiency index. Further subdividing technical efficiency, it can be seen that the reduction in efficiency index of 20 enterprises was attributed to a reduction in pure technical efficiency, and the reduction in efficiency index of the other five enterprises was attributed to a reduction in scale efficiency index. At the same time, the reduction of total factor productivity of 10 enterprises was caused by a reduction in the technological progress index.

To sum up: The total factor productivity of the 45 enterprises that did not use the new retail mode declined from 2016 to 2020. Although traditional retail enterprises achieved better technological progress results in the same period, productivity did not improve the total factor. It is still necessary to further improve the technology and management level. Enterprises should pay particular attention to the role of big data in future operations and management, and try out the new retail model. Enterprises should also strengthen internal and external management, coordinate the relationship between upstream and downstream suppliers and customers, and realize the improvement of operational efficiency.

- The efficiency change results of 20 enterprises using the new retail model are shown in Appendix A Table A8.

According to the empirical results of 20 sample enterprises, there were 14 enterprises with a total factor productivity greater than 1 from 2016 to 2020 (accounting for 70% of the sample enterprises), and only six enterprises with a total factor productivity less than 1. This indicates that sample enterprises transforming from the traditional retail mode to the new retail mode performed well on the whole, and total factor productivity improved. Among the 14 enterprises with an improvement in total factor productivity, the improvement in total factor productivity of Baida Group, Shanghai Join Buy, and Zhejiang China Commodities City Group could be attributed to technological progress. After the application of the new retail model, these three enterprises showed outstanding performance in terms of the improvement in technical efficiency, and made remarkable achievements in the application of new retail technology.

The total factor productivity change value in the top three enterprises were Fujian Dongbai Group, Kunming Sinobright Group (5I5J Holding Group) and Shanghai New World. Compared with the previous year's total factor productivity, five enterprises (Shanghai Join Buy, Maoye Business, Sanjiang Supermarket Shopping, Yong Hui and Zhejiang China Commodities City Group) increased rapidly in technical efficiency, with an increase of more than 40%, especially for e-commerce companies and online business development. The level of management technology saw great progress, with timely adjustment of production scale and good prospects for development. At the same time, although the change value of the total factor productivity of traditional department stores Xujiahui and Nanjing Xinbai was less than 1, they were both greater than 0.9, indicating that the operation of physical stores has declined in recent years. Still, they made positive adjustments after the new retail layout, and the overall performance was developing in a good direction. Enterprises must invest a lot of money early on in switching to a new retail model. After the transformation, it takes time to find the management method most suitable for the enterprise. In the early stage of applying the new retail model, these enterprises will face problems such as inappropriate input–output distribution, improper management means to adapt to the new model, and immature application of new technology. Enterprises should improve the above aspects to improve efficiency.

5. Discussion and Conclusions

Based on an empirical analysis of the necessity of traditional retail transformation, we calculated the efficiency and dynamic efficiency changes of 65 listed retail enterprises in the Shanghai and Shenzhen Stock markets. We calculated the technical efficiency, the pure technical efficiency, and the scale efficiency of 65 listed retail enterprises in 2016 and 2020 using the DEA model. It showed that the operating efficiency of enterprises using the new retail model was higher than that of the others. The overall operating efficiency of 45 traditional retail enterprises that did not use the new retail model declined from 2016 to 2020: 69% of the 45 sample enterprises showed a downward trend in efficiency, while 27% of them improved their efficiency. From 2016 to 2020, the overall operating efficiency of the 20 traditional retail enterprises using the new retail model increased. Among the 20 sample enterprises, 70% improved their operating efficiency, while only 20% showed a downward trend, with a small decrease. We calculated the change in total factor productivity of 65 listed retail enterprises from 2016 to 2020 using the DEA-Malmquist model. The total factor productivity of 45 traditional retail enterprises without the new retail model decreased by 12.4%; the reduction in pure technical efficiency mainly caused a reduction in productivity. Among them, 77.8% experienced a decrease in total factor productivity, while only 20% improved.

From the experimental results and analysis, we can draw the following conclusions: (1) The efficiency of traditional retail enterprises in China is generally low. The mean efficiency of the 45 enterprises that did not use the new retail model was lower than the overall mean. In comparison, the mean efficiency of 20 enterprises that used the new retail model was higher than the overall mean. (3) The total factor productivity of 45 enterprises without the new retail mode decreased by 12.4%. The total factor productivity of the 20 enterprises using the new retail mode increased by 57.8%. Technological progress, pure technical efficiency, and scale efficiency all contributed to the improvement in total factor productivity. This shows that the efficiency of enterprises significantly improves after the application of the new retail model. Enterprises should focus on setting their future business strategy by adopting new retail technologies and enterprise management models, and enterprise-scale adjustments.

Our research shows that, for the sample companies, compared with the traditional retail model, the operating efficiency of enterprises engaging with the new retail model significantly improved, which brought about significant improvements in technical efficiency and scale efficiency. The representativeness of the new retail enterprises is highlighted in the empirical measurement results, which together provide strong support for traditional retail enterprises adopting the new retail model. Traditional retail enterprises should, therefore, change their business model as soon as possible to reverse trends of low efficiency and poor performance, and should focus on technology and management, etc., at the same time. The development of the new retail model is crucial for the transformation of traditional retail enterprises. "New retail" makes consumers the center, focuses on driving production and transactions through big data technology, and better meets consumers' all-around needs for shopping, entertainment, social interaction, and other comprehensive retail formats in the form of pan-retail.

For traditional retail enterprises, in order to reverse the decline in business performance, overall low efficiency must be addressed through innovation, specifically by adopting the new retail business model. On the one hand, enterprises must attach importance to consumer feedback; actively seek opportunities for strategic cooperation; attempt full-channel integration of offline stores, online e-commerce, and other forms; produce goods that meet the market demand; and expand the scale of operations. On the other hand, enterprises must improve their own management level and technical capability; integrate innovation capacity into production and manufacturing, supply chain circulation, daily management, and other aspects; and transform from commodity sales to smart service enterprises in order to realize the transformation and growth of the industry.

6. Implications

COVID-19 and subsequent periods of isolation have disrupted normal life of for people, affecting their access to and use of food, clothing, housing, and transportation. For example, physical stores have shortened their business hours, entertainment venues and catering establishments have at least temporarily closed their doors, and theaters and exhibitions have closed down or postponed showings. In the post-pandemic and digital economy era, the connotations of consumption have changed due to digital technology. Changes in terms of the personalized, virtual consumption of content and digital, platform-based consumption patterns have led to the large-scale replacement of traditional consumption with digital consumption.

While COVID-19 has brought many challenges, it has also promoted people's self-examination and social reflection in many ways, thus triggering a series of commercial and economic changes. COVID-19 has also represented an opportunity for many industries, including new retail. China's retail industry is embracing opportunities for transformation, namely, "new retail" with the deep integration of "online + offline + big data + logistics." Compared with the traditional retail model, "new retail" incorporates obvious innovations in terms of consumer group positioning, product and service characteristics, the production and manufacturing mode, marketing channel selection, relationship network management, etc. Macroeconomic growth and upgrading of consumption behavior, changes in information technology, and the e-commerce impact of many factors such as joint drive, have led to the necessity of retail transformation. We hope to provide timely guidance to enterprises shifting to the new retail model during the COVID-19 pandemic.

New economic formats will accelerate the development of digital consumption, which forces various economic entities to accelerate their digital innovation. Digital technology has led to new consumer experiences such as "contactless shopping," "contactless ordering," and "contactless distribution." During the COVID-19 pandemic, delivery people could not always deliver goods to a user's door; users were required to go downstairs or ask for help, but were sometimes reluctant to go out since they feared "contact with people" and face masks were a scarce resource. The number of delivery personnel during the COVID-19 pandemic was obviously insufficient, and the timeliness of distribution has been greatly reduced. Considering the intensification of demand, the improvement of user experience, human costs, and the difficulty of meeting the terminal distribution demand in some remote areas and special environments, the upgrading of traditional logistics has become a general trend, and the prospect of unmanned distribution is ever closer. Community commerce, fresh food e-commerce, and other retail formats have developed rapidly. For example, Dingdong, Alibaba, JD, and other enterprises have vigorously developed online and community group buying businesses, expanded marketing channels, accelerated the layout of front warehouses, and coordinated the supply chain to ensure the supply of goods, which has undoubtedly greatly improved retailers' digital capabilities.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The calculation data used in this paper comes from the WIND database.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The 74 initial retail companies in China.

1	SZAP	000061.SZ	26	MINBAI	600738.SH	51	SUNING.COM	002024.SZ
2	HUAQIANG	000062.SZ	27	LBX	603883.SH	52	ZHONGBAI	000759.SZ
3	AISIDI	002416.SZ	28	YIMIN	600824.SH	53	XUJIAHUI	002561.SZ
4	DOCTORGLASSES	300622.SZ	29	BAIDA	600865.SH	54	CCOOP	000564.SZ
5	SEG	000058.SZ	30	DDF	600327.SH	55	HONGQI CHAIN	002697.SZ
6	KM SINOBRIGHT	000560.SZ	31	HUALIAN	600361.SH	56	BETTER LIFE	002251.SZ
7	HIGHSUN	000861.SZ	32	DONGBAI	600693.SH	57	RAINBOW	002419.SZ
8	HAINING LEATHER	002344.SZ	33	NNDS	600712.SH	58	HF DS	000417.SZ
9	TONGCHENG	000419.SZ	34	CAPITAL RETAILING	600723.SH	59	FRIENDSHIP	000679.SZ
10	IMIC	000516.SZ	35	CQDS	600729.SH	60	WUSHANG	000501.SZ
11	HONG SHANG	000785.SZ	36	HANSHANG	600774.SH	61	ZHONGXINGSY	000715.SZ
12	YUEXIU	000987.SZ	37	YOUHAO	600778.SH	62	WANGFUJING	600859.SH
13	GRANDBUY	002187.SZ	38	XINHUA	600785.SH	63	SANJIANG	601116.SH
14	NEWHUADU	002264.SZ	39	QUANYE	600821.SH	64	YONGHUI	601933.SH
15	FRIENDSHIP&APOLLO	002277.SZ	40	MAOYE	600828.SH	65	YUYUAN	600655.SH
16	HAPPIGO	300413.SZ	41	JOIN BUY	600838.SH	66	NJ DS	600682.SH
17	PANGDA	601258.SH	42	INZONE	600858.SH	67	CENTRALEMPORIUM	600280.SH
18	SUNNY LOAN	600830.SH	43	BJ URBAN-RURAL	600861.SH	68	BAILIAN	600827.SH
19	HONGTU HT	600122.SH	44	CHURIN	600891.SH	69	JIEBAI	600814.SH
20	ZHONGDA	600704.SH	45	WENFENG	601010.SH	70	CCCGROUP	600415.SH
21	SLSS	600898.SH	46	LIQUN	601366.SH	71	LAIYIFEN	603777.SH
22	LEYSEN	603900.SH	47	ANDRE	603031.SH	72	NEWWORLD	600628.SH
23	MARKOR	600337.SH	48	WINKATIMES	603101.SH	73	EURASIA	600697.SH
24	DONGRI	600113.SH	49	CUIWEI	603123.SH	74	DASHANG	600694.SH
25	COMMERCIAL CITY	600306.SH	50	JIAJIAYUE	603708.SH			

Table A2. The 65 retail companies in China.

1	SZAP	000061.SZ	23	MINBAI	600738.SH	45	XUJIAHUI	002561.SZ
2	HUAQIANG	000062.SZ	24	LBX	603883.SH	46	CCOOP	000564.SZ
3	AISIDI	002416.SZ	25	YIMIN	600824.SH	47	HONGQI CHAIN	002697.SZ
4	DOCTORGLASSES	300622.SZ	26	BAIDA	600865.SH	48	BETTER LIFE	002251.SZ
5	SEG	000058.SZ	27	DDF	600327.SH	49	RAINBOW	002419.SZ
6	KM SINOBRIGHT	000560.SZ	28	DONGBAI	600693.SH	50	HFDS	000417.SZ
7	HIGHSUN	000861.SZ	29	CAPITAL RETAILING	600723.SH	51	WUSHANG	000501.SZ
8	HAINING LEATHER	002344.SZ	30	CQDS	600729.SH	52	ZHONGXINGSY	000715.SZ
9	TONGCHENG	000419.SZ	31	HANSHANG	600774.SH	53	WANGFUJING	600859.SH
10	IMIC	000516.SZ	32	XINHUA	600785.SH	54	SANJIANG	601116.SH
11	YUEXIU	000987.SZ	33	MAOYE	600828.SH	55	YONGHUI	601933.SH
12	GRANDBUY	002187.SZ	34	JOIN BUY	600838.SH	56	YUYUAN	600655.SH
13	FRIENDSHIP&APOLLO	002277.SZ	35	BJ URBAN-RURAL	600861.SH	57	NJDS	600682.SH
14	HAPPIGO	300413.SZ	36	CHURIN	600891.SH	58	CENTRALEMPORIUM	600280.SH
15	PANGDA	601258.SH	37	WENFENG	601010.SH	59	BAILIAN	600827.SH
16	SUNNY LOAN	600830.SH	38	LIQUN	601366.SH	60	JIEBAI	600814.SH
17	HONGTU HT	600122.SH	39	ANDRE	603031.SH	61	CCCGROUP	600415.SH
18	ZHONGDA	600704.SH	40	WINKATIMES	603101.SH	62	LAIYIFEN	603777.SH
19	SLSS	600898.SH	41	CUIWEI	603123.SH	63	NEWWORLD	600628.SH
20	LEYSEN	603900.SH	42	JIAJIAYUE	603708.SH	64	EURASIA	600697.SH
21	MARKOR	600337.SH	43	SUNING.COM	002024.SZ	65	DASHANG	600694.SH
22	DONGRI	600113.SH	44	ZHONGBAI	000759.SZ			

KMO and Bartlett Test. The KMO value obtained from the data test of Input indicators and Output indicators is 0.848 and 0.629 (see Tables A3 and A4), indicating that there is a strong correlation between variables, which can be extracted by factor analysis.

Table A3. KMO and Bartlett Test on Input Index.

KMO Sampling Suitability Quantity		**0.848**
Bartlett's Test of Sphericity	chi-square	670.36
	free degree	21
	significance	0.000

Table A4. KMO and Bartlett Test on Output Index.

KMO Sampling Suitability Quantity		**0.629**
Bartlett's Test of Sphericity	chi-square	417.74
	free degree	15
	significance	0.000

Through the extraction method of principal component analysis and the rotation method of Kaiser's standardized maximum variance method, we obtained that the owner's equity, main business cost and total number of employees are the input variables of the DEA model, while the return on equity, inventory turnover and net profit are the output variables of the DEA model.

Table A5. Efficiency measurement results of 45 companies that did not use the new retail model.

		2016			**2020**	
Firm	**TE**	**PTE**	**SE**	**TE**	**PTE**	**SE**
SZAP	0.063	0.081	0.785	0.092	0.168	0.549
HUAQIANG	0.799	0.896	0.892	0.711	1.000	0.711
AISIDI	0.214	0.246	0.871	0.242	0.351	0.690
...	...	...	...	...	...	...
LAIYIFEN	0.559	0.675	0.827	0.408	0.483	0.845
EURASIA	0.734	0.920	0.798	0.731	0.783	0.932
DASHANG	0.425	0.521	0.816	0.528	0.611	0.864
Mean Value	0.541	0.633	0.837	0.424	0.540	0.793

Table A6. The efficiency measurement results of 20 enterprises using the new retail model.

		2016			**2020**	
Firm	**TE**	**PTE**	**SE**	**TE**	**PTE**	**SE**
YONGHUI	0.219	0.467	0.469	0.360	0.920	0.392
NJ DS	0.753	0.886	0.850	0.945	0.988	0.956
SANJIANG	0.199	0.220	0.905	0.362	0.377	0.959
...	...	...	...	...	...	...
JOIN BUY	1.000	1.000	1.000	1.000	1.000	1.000
CCCGROUP	0.521	0.938	0.555	0.623	1.000	0.623
NEWWORLD	0.187	0.191	0.982	0.427	0.665	0.642
Mean Value	0.481	0.599	0.788	0.583	0.713	0.788

Table A7. MPI of 45 Enterprises not using the new retail model.

Firm	**EFFCH**	**TECHCH**	**PECH**	**SECH**	**TFPCH**
SZAP	1.459	1.378	2.087	0.699	2.010
HUAQIANG	0.890	1.216	1.116	0.797	1.082

Table A7. *Cont.*

Firm	EFFCH	TECHCH	PECH	SECH	TFPCH
AISIDI	1.132	1.114	1.429	0.792	1.261
...	...	...	...	...	...
LAIYIFEN	0.731	0.826	0.715	1.022	0.604
EURASIA	0.995	0.801	0.851	1.169	0.797
DASHANG	1.242	0.798	1.173	1.059	0.991
Mean Value	0.886	1.014	0.963	0.972	0.876

Table A8. MPI of 20 enterprises using the new retail model.

Firm	EFFCH	TECHCH	PECH	SECH	TFPCH
KM SINOBRIGHT	3.330	1.295	3.036	1.097	4.312
SUNING.COM	0.302	1.160	0.523	0.578	0.350
XUJIAHUI	0.828	1.111	0.951	0.870	0.919
...	...	...	...	...	...
SANJIANG	1.817	0.809	1.715	1.060	1.471
YONGHUI	1.645	0.792	1.971	0.834	1.302
CCCGROUP	1.196	1.201	1.066	1.122	1.436
NEWWORLD	2.282	1.238	3.489	0.654	2.825
Mean Value	1.5355	1.0118	1.5481	1.0015	1.5783

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