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A Study on the Policy Effects of the Establishment of Guangdong–Hong Kong–Macao Greater Bay Area on Logistics Efficiency

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Abstract: Logistics efficiency is an important indicator when measuring the level of development of the logistics industry, and policy factors are the most difficult to measure among the factors affecting logistics efficiency. This study aimed to construct a new empirical model by combining a three-stage data envelopment analysis (DEA) model and the econometric method propensity score matching and difference-in-differences (PSM–DID) to measure and analyze the net change in logistics efficiency in the Guangdong–Hong Kong–Macao Greater Bay Area under the influence of this policy factor. The empirical evidence shows that different amounts of change occurred in the two time periods after the establishment of the Greater Bay Area and a significant increase in logistics efficiency occurred in the second period, further demonstrating that the economic policy of the Greater Bay Area is effective in improving logistics efficiency and providing a case reference for other countries or regions with similar conditions.

Keywords: PSM–DID; policy effects; Greater Bay Area; logistics efficiency; three-stage DEA model

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1. Introduction

The logistics industry has become a new engine of growth for the world economy and an important support industry for the development of major industries and is therefore highly valued by countries around the world, attracting a large number of scholars to research it. As one of the fastest-growing economies in the world, China's logistics industry is growing rapidly along with the size of the economy, and, naturally, the Chinese government attaches great importance to the development and research of the logistics industry. The economic region under study in this paper is the Pearl River Delta Economic Zone (PRD), one of China's three core economic regions, which was also the earliest area of early reform and development in China's economic development. Its economic performance is an important barometer of China's economic development as well as a directional indicator of the development of China's logistics industry. However, there remain endogenous problems in the development of the cities in the PRD economic zone, such as large economic differences, significant homogeneity, overcapacity, unbalanced supply and demand structures as well as differences and coordination problems between Hong Kong and Macau, such as different social systems, legal systems, and tariff zones, which prevent the efficient integration of the region's trade and logistics networks, thus limiting the economic development of the region and likewise affecting the improvement of the region's logistics efficiency. Scholars who have studied the regional development of logistics believe that there are various indicators that can be used to measure the level of logistics development in a region. Among these, logistics efficiency, which is one of the important indicators to measure the development of the logistics industry, is influenced by a variety of complex factors, such as cost factors, customer service quality, etc. One of the most difficult to measure and most easily ignored factors is the policy factor, and the degree of influence of policy factors on logistics efficiency also varies depending on the implementation of different policies in different regions, resulting in different impact effects. Due to its unique political system, China's promulgated economic policies and efficient policy implementation are one of the key assets of its rapid development. As a result, the policies enacted and implemented in China have had a tremendous impact on the development of the regional economy. The Chinese government is also aware that the various problems in terms of disparities among cities in the PRD Economic Zone mentioned above have led to stagnant economic growth in the region and hindered further improvement in logistics efficiency, and it is for this reason that the Chinese government promulgated the Framework Agreement on Deepening Cooperation among Guangdong, Hong Kong, and Macao to Promote the Development of the Greater Bay Area 2017 (hereinafter referred to as "the Framework Agreement") on 1 July 2017 [1]. The framework agreement integrates the two special administrative regions of Hong Kong and Macau and the nine cities of the Pearl River Delta Economic Zone in Guangdong Province, namely Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing, into a mega economic region named the Guangdong–Hong Kong–Macao Greater Bay Area (hereinafter referred to as the Greater Bay Area). Although the Greater Bay Area had already been established, the framework agreement was a directional guidance document and there were still coordination problems in many aspects of economic, trade, and logistics integration among the 11 cities. Therefore, two years later, i.e., on 18 February 2019, the State Council of the Central Committee of the Communist Party of China issued the Outline of the Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area (2019) (hereinafter referred to as the Outline of the Plan) [2]. The plan specifically provides comprehensive guidance on the synergistic development of trade, transport, and logistics in the Greater Bay Area. It is intended that the promulgation and implementation of the plan will further accelerate the integration of trade, commerce, and logistics in the region, break through bottlenecks in the economic development of the region, and further promote economic development in the Greater Bay Area.

According to the latest figures for 2021 provided by the governments of Guangdong Province, Hong Kong, and Macau, the Guangdong–Hong Kong–Macao Greater Bay Area covers a total area of about 56,000 square kilometers and has a total population of over 86 million, a gross regional product of US $1668.8 billion, over 150 logistics parks, and over 160,000 logistics enterprises and features important ports such as Hong Kong, Guangzhou, and Shenzhen, which rank among the top five in the world in terms of throughput, and several international shipping centers. It is clear that the scale of logistics output in the Greater Bay Area has increased tremendously since its establishment, but has the efficiency of logistics also increased as a result? If so, how much of an impact has policy had on the many factors that have contributed to this increase? To clarify the above issues, this study firstly analyzed and selected a model for measuring logistics efficiency and then selected a three-stage DEA model to measure the efficiency of the logistics industry in the Greater Bay Area through an analysis of the literature. However, the measurements were the result of a combination of factors, so it was also necessary to use the difference-in-differences method (DID) to remove the impact effects of the policy factors while using the PSM method for accuracy matching. The methodology used the introduction of the Framework Agreement in 2017 as a marker for the establishment of the Greater Bay Area, the changes in logistics efficiency before and after the establishment of the Greater Bay Area as a quasi-natural experiment, and the PSM–DID econometric analysis method to finally derive and analyze the policy shock effect on logistics efficiency in the region after the establishment of the Greater Bay Area.

The rest of the text is structured as follows: the second part conducts the literature review and the analysis of the study hypotheses; the third part presents the research methodology and model; the fourth part conducts the empirical analysis; and the fifth part draws conclusions and policy recommendations.

2. Literature Review and Research Hypotheses

2.1. Literature Review and Research Motivation

Logistics efficiency, as an important indicator for evaluating the logistics industry, has been adopted by several scholars and studied for different logistics areas. Among the measures of logistics efficiency are the extensive use of DEA models based on input–output ratios and other synthetic methods. For example, Zhang and Cui analyzed the synergy of the urban logistics industry based on the results of the DEA model to measure the logistics efficiency of 17 cities in Shandong Province and constructed a spatial network model to analyze the development of the inter-city logistics industry [3]. However, the traditional DEA model has a single measurement and does not meet the needs of other aspects of research, so many scholars have used the "DEA+" model to conduct research. For example, Cao argues that the logistics efficiency values measured by traditional DEA models cannot predict the pollution caused by the logistics industry in advance, with this problem being effectively solves by combining DEA models and Bayesian methods [4]. On the other hand, Tao et al. used a combination of principal component analysis (PCA) and DEA models to empirically analyze a variety of key factors in 18 smart logistics parks in the Yangtze River Economic Zone and determined the impact of collaborative innovation on logistics efficiency [5]. Quan et al. used a combination of a DEA model and Malmquist model to calculate the TFP production index to analyze the inputs and outputs of listed logistics enterprises in China [6]. With recent developments in the field of machine learning, a new risk management approach consisting of the DEA model and machine learning was used as a case study to improve the identification of decision units and contribute to the sustainable development of a company's logistics business [7]. On the other hand, certain scholars have studied output indicators and proposed the SBM-DEA model based on non-expected outputs as indicators. For example, Choi used the SBM-DEA model to measure logistics efficiency using non-expected outputs, such as the use of ineffective operations in Chinese logistics parks as output indicators, to discover the importance of non-expected output factors for the purpose logistics efficiency improvement and to draw on the development of improved logistics parks in Korea [8]. In contrast, Deng et al. used the logistics industry carbon emission indicator as a non-desired output indicator to measure and analyze 30 Chinese provinces using both PCA and SBM-DEA [9,10]. Meanwhile, a number of scholars conducted a phased DEA to address specific issues, for example, in the case of Wohlgemuth et al. to conduct a technical efficiency analysis of logistics service operators in Brazil based on a two-stage DEA model, leading to the conclusion that there are different effects associated with logistics service package provision and logistics technical efficiency [11]. Cavaignac analyzed 3PLs in France through a two-stage DEA analysis and concluded that only a portion of the 3PLs in this market improved their efficiency [12]. As the DEA model continues to be studied in depth, it has been found that the three-stage DEA model can effectively remove the influence of environmental variables on efficiency and refine a more pure efficiency value. Therefore, the scholar Gan measured the green logistics efficiency of 11 cities in Jiangxi Province, China from the perspective of green logistics efficiency and analyzed its evolutionary characteristics using a three-stage DEA model [13]. While different "DEA+" and different stage DEA models have been used for different specific problems, the three-stage DEA model can yield pure logistics efficiency values, which is why this study used this model for research purposes.

However, the logistics efficiency values measured using the three-stage DEA model reflect the pure efficiency values resulting from the combined influence of several factors, and the policy factors underlying changes in efficiency values cannot be measured. The difference-in-differences method (DID) is an effective tool for measuring the impact of a policy on the subject of study before and after its implementation, and the logistics industry, as the global bloodline, is naturally affected by policy shocks. Therefore, according to our analysis of the domestic and international literature, one of the first scholars to use the DID analysis method used it to empirically analyze whether the tax burden on logistics enterprises has been significantly reduced following the enactment and implementation of the "National Article 9" policy on the logistics industry in China [14]. Additionally, in the context of the global concern surrounding carbon emissions, scholars applied the DID method to empirically analyze whether the implementation of smart logistics policies can effectively curb carbon emissions [15]. Li et al. used the National Distribution Node City Layout Plan (2015–2020) issued by the Ministry of Commerce and other departments as a policy evaluation node and used the DID model to analyze the impact of distribution node cities on urban logistics production efficiency and its mechanism of action [16]. He used the DID method to empirically test the positive impact of the establishment of innovative cities on the efficiency of the urban logistics industry [17]. Zhou and Zhang used the DID model to empirically analyze the rapid growth of China's product imports and exports after the opening of the China–Europe Class Train (CEB) [18].

The above analyses were based on the common traditional DID method. However, to make DID experimental data more reasonable, certain scholars have used the PSM method, which can be a more effective matching method in terms of treatment and control groups, in combination with the DID model for combined analysis. For example, Sun et al. used the PSM–DID method to effectively match and empirically analyze treatment and experimental groups, and it was found that the implementation of China's Belt and Road Program increased the GDP of participating countries [19]. Dong used the "Logistics Industry Adjustment and Revitalization Plan" promulgated by the State Council in March 2009 as the policy evaluation node, and a double-difference propensity score matching model (PSM–DID) was constructed to test the effectiveness of the policy and its mechanism of action [20]. Zhang used the new urbanization policy as the evaluation node, and a difference-in-differences and propensity score matching method (PSM–DID) was constructed to analyze and study whether the new urbanization had an impact on the development of the logistics industry [21]. Based on the above, to make the DID experiment more effective, this study used the PSM–DID model to analyze the Greater Bay Area.

Since the establishment of the Guangdong–Hong Kong–Macao Greater Bay Area in 2017, research on it has been extensive and fruitful, but there is a lack of high-quality research results in the field of logistics. An earlier article combining the national strategy of Guangdong–Hong Kong–Macao Greater Bay Area and the high-quality development of the logistics industry as the research hotspot analyzed the main problems faced by the high-quality development of logistics industry in the Guangdong–Hong Kong–Macao Greater Bay Area, conducting an in-depth analysis [22,23]. In the same year, Xiao proposed that to improve the quality of logistics development in the Guangdong–Hong Kong–Macao Greater Bay Area, it was necessary to analyze the reform of the ecosystem, technological innovation, the deepening of industrial development, and the acceleration the agglomeration of the logistics industry to promote the high-quality development of the logistics industry in the Greater Bay Area [24]. Liu and Liu used the improved AHP algorithm and the expert scoring method to analyze various indicators and improve the calculation of the service level of port logistics in the Greater Bay Area [25]. The only recent study on logistics efficiency in the Greater Bay Area is a study by Qin, which used a three-stage DEA model to empirically study the efficiency of the logistics industry in the Guangdong–Hong Kong–Macao Greater Bay Area city cluster and analyzed it in terms of both time and space dimensions [26].

According to the above review, although the research on logistics efficiency and the DEA+ model, PSM–DID+ logistics, and the Greater Bay Area and the logistics industry has achieved fruitful results, there is still room for further research, mainly in the following three areas. First, according to the literature analysis, although there are various "DEA +" models that can be used, there are few studies that use the three-stage DEA model for measurements, and the use of the three-stage DEA for the Greater Bay Area is rarer. Secondly, in recent years, DID methods have been widely used in academic research, but the matching of treatment and control groups, which is the basis of experimental DID studies, has not been subjected to rigorous scientific analysis. The propensity score matching method (PSM) can be an effective solution to this problem, but there is no literature on the use of the PSM approach for the purpose of match analysis in the Greater Bay Area. Thirdly, there is also no relevant literature that combines the PSM and DID methods and conducts research and analysis on the logistics efficiency of the Greater Bay Area. Therefore, for the purpose of further analysis on the above problems and to obtain the following marginal contribution, this study consisted of the following: First, through an analysis of the literature and a comparison and PSM equilibrium test, it was scientifically proven that the Guangdong–Hong Kong–Macao Greater Bay Area and the Yangtze River Delta urban agglomeration are highly similar and exhibit the basic conditions necessary to be used as a DID experiment, providing a scientific research basis for other related academic studies that need to compare urban agglomerations; second, through the use of the PSM–DID method, the effect of policy on the Greater Bay Area was empirically analyzed to improve the logistics efficiency of the region and fill a policy-based research gap concerning the logistics efficiency of the Greater Bay Area.

2.2. Research Hypothesis

This paper uses the three-stage DEA model and the propensity score matching—difference-in-differences method (PSM–DID) to empirically study the policy impact of the Greater Bay Area establishment on regional logistics efficiency. According to the detailed user instructions of the difference-in-differences method [27], the DID experimental basis shall have two basic conditions Condition 1 is that it must meet the parallel trend assumption, also known as the common trend assumption. This means that if the individual in the treatment group does not receive the intervention or impact, the changing trend of the results is the same as that of the individual results in the control group, with the trend varying after the impact of policy and the experimental group and the control group following the principle of "randomization". Condition 2 is the stable unit treatment values assumption (SUTVA), which measures whether the different individuals impacted by the policy are independent of each other and whether one individual being affected under policy impact (treatment status) does not affect the results of any other individual, in other words, it determined whether the treatment group and the control group are strictly separated and do not interfere with each other. Both of the above conditions involve a core problem, namely the "randomization grouping" problem, which makes it difficult to make the experimental group and the control group reach condition 2 and not interfere with each other, with the reality being that it is difficult to achieve strict non-interference between the two groups, especially in today's tightly linked global economic landscape. However, the idea of a 'quasi-natural experiment' is implicit in the difference-in-differences method and does not strictly require that the randomization conditions between the treatment and control groups are met.

Based on the above analysis, this study took the establishment of the Greater Bay Area as the research object. The ideal grouping would be that the nine cities in the Greater Bay Area were the treatment group, and the random urban agglomeration not affected by the policy of the Greater Bay Area would be set up as the control group. However, this grouping would be unrealistic and unreasonable. Taking into account the current 265 cities in China, the control group would be too large, and it is difficult for the cities near the Greater Bay Area not to be affected by the Greater Bay Area, so the analysis would be more biased. Therefore, to increase the scientific comparable evidence of the two groups, this study adopted the PSM–DID method proposed by Heckman et al. [28]. The basic logic of this method is to find the control group with similar characteristics to the treatment group through the PSM method and then use the DID method under the requirement of a balance test, which can effectively avoid endogenous interference and isolate the policy effect as purely as possible. The PSM idea stems from the matching estimator proposed by Rosenbaum and Rubin [29]. The basic idea of this paper was to use Logit regression to calculate the propensity score of the experimental group and the control group, to use the kernel matching method according to the propensity score, and finally to conduct the propensity matching balance test. If the balance test is passed, the grouping of the treatment and control groups can be proved credible, so that the DID analysis can be continued, and, finally, the robustness test can be conducted to verify its reliability again.

Based on the above analysis, we searched for the keyword "urban agglomerations comparison" in several Chinese academic databases based on various indicators of Chinese urban agglomerations (population, GDP, land area, development system model, scientific research, etc.), and found 8920 relevant papers which contain the keywords. When we further selected the keywords "Yangtze River Delta, Pearl River Delta, population, economy, urbanization", the literature search reached 1151 articles. However, a search of the Web of Science for this keyword revealed only a dozen or so relevant articles, suggesting that comparative analysis of the two regions in China is still restricted to Chinese scholarship. Among the relevant scholars, Li undertook a comparative analysis of the Yangtze River Delta and the Pearl River Delta urban agglomeration from the perspective of environmental technology efficiency, green productivity, and sustainable development [30]. Wei and Wang conducted a comparative study on the technical isomorphism of the Yangtze River Delta and Pearl River Delta regions [31]. Ma and Zhu provided a comparative analysis of the Yangtze River Delta and the Pearl River Delta clusters from the perspective of the business environment and R&D behavior of enterprises [32]. Zhang and Ma made a comparative analysis of the Yangtze River Delta and the Pearl River Delta urban agglomeration from the perspective of regional innovation model research [33,34]. Pi and Yang analyzed the comparison system of the development model of the Yangtze River Delta and Pearl River Delta [35]. Zhang and Sun undertook a comparative study on the relationship between R&D investment and investor return in enterprises in the Yangtze River Delta and Pearl River Delta [36]. Xie et al. undertooks comparative study on the spatial and temporal changes in population aging in the Yangtze River Delta and Pearl River Delta regions [37]. Zhong and Qin conducted comparative research on the service industry collaborative agglomeration in China's urban agglomeration [38], etc. The large number of studies mentioned above, which make use of a variety of data and almost comprehensive comparative analysis, are enough to show that although there are differences between the two core regions in China, the comparability is very strong. If the PSM balance test was to be continued in the following analysis, the hypothesis of the Yangtze River Delta as a control group would be fully proved. Therefore, we proposed the following hypothesis:

Hypothesis 1. *Through PSM matching and its balance test, experimental analysis with the Yangtze River Delta city cluster as the control group and the Guangdong–Hong Kong–Macao Greater Bay Area as the treatment group is scientifically comparable, which is in line with the experimental basis of DID.*

With the establishment of the Guangdong–Hong Kong–Macao Greater Bay Area, the governments in the region will inevitably introduce a series of complementary policies to promote the development of the logistics industry in the Greater Bay Area under the general policy of the Outline of the Plan, which has been analyzed by researchers at different levels. Analyzed from the perspective of talent strategy, the talent policy of the Greater Bay Area helps to attract more service talents, and the logistics industry, which is a production service industry, will naturally also be attractive to logistics talents, thus stimulating the vitality of logistics innovation and driving the development of other related industries in the region, illustrating the importance of the talent policy in enhancing the level of the logistics industry [39]. In terms of industrial coordination policy, using MATLAB for simulation analysis, Wan et al. found that the urban logistics efficiency with the best synergy degree in the Greater Bay Area is higher than the other cities with low coordination degrees [40], and through an analysis of the political system, economic system, and internal links of the Greater Bay Area, Yang found that the coordinated construction of the circulation system of the Greater Bay Area through a top-level design would greatly improve the logistics efficiency in the region, indicating that regional coordination policies can significantly affect improvements in logistics efficiency [41]. Concerning the analysis of industrial policy, through an in-depth analysis of the comparative advantages of the high-quality development of the logistics industry in the Greater Bay Area, Huang found that the rapid transformation and upgrading of the logistics industry is conducive to the effective improvement of logistics efficiency [22]. Meanwhile, by making use of 2007–2019 big bay nine cities basic data, based on the modified gravity model and social network analysis of a large bay area urban agglomeration logistics network structure evolution, Shi and Hu found that an urban agglomeration logistics network can promote regional industrial structural upgrades and improve the efficiency of regional comprehensive logistics [42]. From the perspective of logistics trade and technology policy, by building a trade logistics competitiveness evaluation system and using factor analysis of the nine core cities in Guangdong province, Li found that the trade logistics integration degree will greatly improve logistics efficiency [43], while by exploring the application of blockchain technology in Guangdong, Li et al. found that the technology helps to greatly improve logistics efficiency [44]. To sum up, the governments the Greater Bay Area at all levels will be under the guidance of the planning outline in terms of talent, industrial structure, government coordination, trade, science, and technology, and various aspects of the development of logistics industry policies and measures will greatly integrate and optimize logistical resources, further promoting logistics enterprise operation optimization, which, as it continues to improve, directly or indirectly promotes logistics efficiency. Based on the above analysis, we proposed hypothesis 2:

Hypothesis 2. *The establishment of the Guangdong–Hong Kong–Macao Greater Bay Area has had significant policy effects in terms of improving the logistics efficiency of the logistics industry in the Bay Area.*

3. Methodology

3.1. Research Method

This study was mainly divided into three stages. The first stage refers to the existing literature research methods. Based on the panel data of 9 cities in the Greater Bay Area and 27 cities in the Yangtze River Delta from 2000 to 2020, the three-stage DEA model was used to measure the logistics efficiency of the logistics industry in 36 cities, and the final calculation results were taken as the dependent variable of the DID model. In the second stage, according to the experimental principle of PSM, the treatment group and the control group were matched and balanced. After passing the balance experience, the invalid data were eliminated, and the final matching data results were used as DID analysis data. In the third stage, the PSM–DID of the natural experiment evaluation method was used to empires and analyze the changes in the logistics efficiency in the region before and after the establishment of the Greater Bay Area to prove whether the establishment of the Greater Bay Area has had a significant policy impact on the logistics efficiency. The use of the PSM–DID method helps to reduce the endogenous problems caused by missing variables and can effectively isolate the net impact of the policy effect, with the use of various methods for the robustness test making the research conclusions more reliable.

3.2. Model

3.2.1. Three-Stage DEA Model

The traditional DEA model measures the logistics efficiency value via an analysis of the literature, but this paper uses the three-stage DEA because, as Fried pointed out, the traditional DEA model does not consider the impact of environmental factors and random noise on the efficiency evaluation of the decision unit, with two published articles discussing how to introduce environmental factors and random noise into the DEA model [45,46]. Among them, the first paper only excluded environmental factors, while the later paper considered both environmental factors and random noise, which is known as the three-stage DEA model in China. Therefore, to measure the logistics efficiency relatively accurately, the Fried three-stage DEA model was selected to calculate the treatment group and the control group. The obtained logistics DEA logistics efficiency was used as the explained variable, where Le stands for logistics efficiency and specifically comprehensive logistics efficiency (hereafter abbreviated as logistics efficiency). The specific models and methods are as follows:

Stage I: The traditional DEA model (BCC mode). According to the research from Charnes et al., this model is mainly used to analyze the relative effectiveness of the decision unit (DMU) in the multi-input and multi-output mode of variable returns scales (VRS). The BCC model is represented by the formula [47]:

$$\min_{\theta,\lambda}\left[\theta-\varepsilon\left(e^t s^- + e^t s^+\right)\right]$$
$$\text{s.t.}\begin{cases}\sum\limits_{i=1}^{n}\lambda_i y_{ir}-s^+=y_{or}\\ \sum\limits_{i=1}^{n}\lambda_i x_{ij}+s^-=\theta x_{oj}\\ \sum\limits_{i=1}^{n}\lambda_i=1\\ \lambda_i\geqslant 0; s^+\geqslant 0; s^-\geqslant 0\end{cases} \tag{1}$$

In Equation (1), n is the number of DMU; m and s represent the number of input and output variables; $i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, m$; $r = 1, 2, \ldots, s$; x_{ij} ($j = 1, 2, \ldots, m$) represents the j th input element of the i th decision unit; and y_{ir} ($r = 1, 2, \ldots, s$) is the s th output element of the i th decision unit and is the valid value of the decision unit DMU.

Stage II: Environmental factors and random factors are eliminated. First, we construct the following functions, which are similar to the SFA regression function:

$$S_{ij}=f\left(Z_j;\beta_j\right)+v_{ij}+\mu_{ij}; i=1,2,\cdots,m; j=1,2,\cdots,n \tag{2}$$

In Equation (2), S_{ij} is the relaxation variable of the j th decision unit; $f\left(Z_j;\beta_j\right)$ is the environment function of the j th decision unit; v_{ij} ~N (0, σ_v^2) represents a random error; and $\mu_{ij}\sim N^+$ (0,σ_μ^2) is representative of management inefficiency items.

Estimating m similar SFA equations after separating management efficiency terms, the separation formula using [48,49] is as follows (Equation (3)):

$$E(\mu|\varepsilon)=\sigma^*\left[\frac{\phi\left(\lambda\frac{\varepsilon}{\sigma}\right)}{\Phi\left(\lambda\frac{\varepsilon}{\sigma}\right)}+\lambda\frac{\varepsilon}{\sigma}\right];$$
$$\text{where}\quad \sigma^*=\frac{\sigma_\mu\sigma_v}{\sigma};\sigma=\sqrt{\sigma_\mu^2+\sigma_v^2};\lambda=\frac{\sigma_\mu}{\sigma};\varepsilon=\mu+v \tag{3}$$

Then, an adjusted random error term is obtained with the following formula (4):

$$E\left(v_{ij}\mid v_{ij}+\mu_{ij}\right)=S_{ij}f\left(Z_j;\hat{\beta}_j\right)-E\left(\mu_{ij}\mid v_{ij}+\mu_{ij}\right) \tag{4}$$

Finally, both environmental and random factors are eliminated so that all decision units are adjusted to the same external environment. The adjustment formula of input vector X is as follows (Equation (5)):

$$x_{ij}^f=x_{ij}+\left[max\left(f\left(Z_j;\hat{\beta}_j\right)\right)-f\left(Z_j;\hat{\beta}_j\right)\right]+\left[max\left(v_{ij}\right)-v_{ij}\right] \tag{5}$$

where $i = 1, 2, \cdots, m; j = 1, 2, \cdots, n$. Then, x_{ij}^{f} is the adjusted investment; x_{ij} is the investment before the adjustment; v_{ij} is the adjusted random error term; $\left[max\left(f\left(Z_j; \hat{\beta}_j\right)\right) - f\left(Z_j; \hat{\beta}_j\right)\right]$ is used to adjust to the external environmental factors; and $\left[max\left(v_{ij}\right) - v_{ij}\right]$ moves all the decision units down to the same operation level.

Stage III: Adjusted DEA model. The efficiency of each decision unit is measured again by using the adjusted input–output variables. At this time, the DEA efficiency value is already a relatively real efficiency evaluation value after excluding environmental factors and random errors.

3.2.2. PSM–DID Method

The difference-in-differences method was first proposed by Ashenfelter and Card in 1985 [50]. This model effectively solves the systematic difference between the treatment group and the control group through the group difference and the successive group difference and then extracts the policy effect. The basic formula is as follows (formula (6)):

$$\hat{\beta}_{\text{ols}} = \Delta\overline{Y}_{\text{treat}} - \triangle\overline{Y}_{\text{control}} = \left(\overline{Y}_{\text{treat},2} - \overline{Y}_{\text{treat},1}\right) - \left(\overline{Y}_{\text{control},2} - \overline{Y}_{\text{control},1}\right) \tag{6}$$

The PSM method, when used on the selected aspects of the treatment group and the control groups, is undoubtedly a scientific matching method. The PSM method is a feasible method that was established to improve the efficiency and accuracy of post-hoc policy assessment. The basic idea is to find one or more matched or similar individuals from the control group for each individual in the treatment group and then calculate the average of the difference between policy implementation and non-implementation. A lower difference means a proven low difference between the two groups, namely high matching, and vice versa. Therefore, the combination of PSM and DID can better solve the accuracy problem of the DID model in relation to matching to achieve more accurate reaction experimental results.

Since the establishment of the Greater Bay Area, changes in logistics efficiency have mainly come about as a result of three aspects: First, the "individual effect" formed by the regional differences in terms of the logistics industry itself; second, the "time effect" caused by changes in the logistics industry over time; and third, the "policy treatment effect" caused by the establishment of logistics efficiency in the Bay Area. Thus, the following model was constructed to examine the net effect of the logistics efficiency established in the Greater Bay Area:

$$\text{Le}_{i,t} = \alpha + \beta(\text{Post} \times \text{Treat})_{i,t} + \beta_1 \text{ ControlVariables}_{i,t} + \gamma_{\text{city}} + \gamma_{\text{year}} + \varepsilon_{i,t} \tag{7}$$

In formula (7), $\text{Le}_{i,t}$ stands for the dependent variable representing the logistics efficiency; γ_{year} represents a time-fixed effect; γ_{city} represents urban individual fixed effects; $\varepsilon_{i,t}$ represents a random interference term; Treat is the treatment group dummy variable, and if a city belongs to the treatment group, then Treat = 1, otherwise Treat = 0; Post is a time dummy variable, i.e., municipalities had Post = 1 after the 2017 time period and Post = 0 for the previous year; DID = Post $\times$ Treat and is representative of policy variables, with the significance, size, and positive and negative of its coefficients, which represent the degree and direction of the policy effect on the change in logistics production efficiency, being the focus of this paper; and $\text{ControlVariables}_{i,t}$ represents other control variables, including transportation infrastructure, the level of science and technology investment, foreign capital proportion, labor investment, urbanization, and government intervention, etc.

3.3. Variable and Data

3.3.1. Variable Selection

1. Dependent variable. For the measure of logistics efficiency, the three-stage DEA calculation and the logarithm were chosen as the dependent variable.

2. Independent variables. The post represents the time variable, Treat represents the treatment group variable, and the coefficient of DID = (Post $\times$ Treat) represents the net effect after the establishment of the Greater Bay Area, with this being the main observation object of this paper.
3. Control variables. Regarding the choice of control variables, this study considered them from the following perspectives.

The first is the level of transportation infrastructure (Transport). The amount of investment in transportation infrastructure resources and the density of the transportation network can affect logistics production efficiency. This paper draws on [16], taking the proportion of road mileage in each city in land area as the variable for transportation infrastructure.

The second is the level of scientific research investment (R&D). China's modern logistics industry has paid more and more attention to investment in scientific research, and unmanned warehouses, automatic sorting, unmanned distribution, and other logistics technologies also promote the efficient development of the logistics industry. This paper measures the level of scientific research investment by taking the logarithm of urban R&D investment and science and technology investment.

The third is the level of external openness (FDI). Both the Greater Bay Area and the Yangtze River Delta are important areas of foreign investment. The level of opening up indirectly affects the capital and technical resources of the logistics industry, which is conducive to improving the market level of the regional logistics industry. This paper uses the dependence of foreign capital (the ratio of FDI to GDP) to measure the level of openness of each city.

The fourth is the urbanization level (Urban-level). The status of cities has an important impact on the attraction of the industry and the efficiency of resource allocation and indirectly attracts logistics industry investment and allocation. The ratio of the urban population to the total regional population was used to measure the urbanization level.

The fifth is the level of local government intervention (Gov). Shi found that whereas effective government intervention in industry and enterprise investment increased the integration of a large bay area, fragmented government effectively suppressed it, making government intervention effective when it comes to strengthening cooperation between regional logistics industries and creating positive macro environment conditions for logistics industry development. This paper uses the proportion of local public financial expenditure in local GDP to indicate the intervention of local governments [51].

The sixth is the level of regional economic development (PGDP). The logistics industry will develop along with improvements in economic development. This paper uses the logarithm of regional per capita GDP to indicate the level of economic development.

The seventh is the labor force input level (Employee). Labor input was directly measured by the number of transportation, storage, and postal services employed in the statistical yearbook.

The eighth is the industrial structure (Industrial). Goe found that a change in industrial structure will increase the market proportion of producer services [52], and logistics belongs to the producer service industry, so this paper draws on the practice of [17] concerning the proportion of the secondary industry, and measures the added value of the urban secondary industry to the proportion of GDP.

The interpretation of the main variables and the specific calculation methods are shown in Table 1.

Table 1. Main Variables and Calculation Methods.

Variable Name	Variable Meaning	Computational Method
Le	Logistics efficiency	The three-stage DEA comprehensive efficiency values were taken as the log
DID	Treat × Post	Virtual variables (0,1)
Transport	Transportation infrastructure level	The proportion of urban highway mileage in the land area
R&D	Research investment level	Urban R&D inputs were taken logarithmically
FDI	Opening up level	The ratio of FDI to GDP
Urban-level	Urbanization level	The ratio of the urban population to the total population of the region
Gov	Local government intervention level	Local public finance expenditure accounts for a share of local GDP
PGDP	Regional economic development level	The logarithm of regional per capita GDP
Employee	Labor input level	People working in transportation, storage, and postal services
Industrial	Industrial structure	The proportion of the added value of the urban secondary industry in the GDP

3.3.2. Data

The Greater Bay Area was established in 2017, refers to nine cities in the Pearl River Delta and two cities in Hong Kong and Macao. However, due to the fact that the statistical indicators of Hong Kong and Macao differ greatly from those of the mainland and even lack relevant key indicators, for the reliability and robustness of the experiments, this study eliminated the two cities of Hong Kong and Macao, and only the nine Pearl River Delta cities, namely Guangzhou, Shenzhen, Dongguan, Foshan, Huizhou, Zhuhai, Zhongshan, Jiangmen, and Zhaoqing, were selected as the treatment group. The control group was 27 cities in the Yangtze River Delta: Shanghai, Nanjing, Wuxi, Changzhou, Taizhou, Yancheng, Suzhou, Nantong, Zhenjiang, Yangzhou, Hangzhou, Zhoushan, Ningbo, Shaoxing, Jinhua, Huzhou, Taizhou, Wenzhou, Jiaxing, Tongling, Hefei, Wuhu, Chuzhou, Maanshan, Chizhou, Anqing, and Yicheng. The data sample was the panel data from 9 cities in the Pearl River Delta and 27 cities in the Yangtze River Delta from 2000 to 2020, with missing data being completed using the interpolation method and the year selection including the policy impact year of 2017. The data at the city level were from the EPS Data Statistics Network, the China Statistical Yearbook, the China Urban Statistical Yearbook, and the official websites of the provincial Statistics Bureau of Guangdong, Shanghai, Jiangsu, Zhejiang, and Anhui provinces. Table 2 shows the statistical description before the PSM matching:

Table 2. Descriptive statistics of the main variables before the PSM.

Variable	N	Mean	p50	SD	Min	Max
Transport	756	0.900	0.915	0.518	0.002	2.438
R&D	756	3.270	3.295	1.567	0.028	7.388
FDI	756	0.801	0.270	1.649	0.000	16.160
Urban-level	756	0.735	0.883	0.301	0.148	1.012
Gov	756	0.107	0.099	0.052	0.004	0.283
PGDP	756	7.581	7.633	1.216	4.063	10.560
Employee	756	4.361	1.652	8.377	0.080	66.920
Industrial	756	0.586	0.511	2.177	0.252	60.310

4. Empirical Results and Analysis

4.1. Three-Stage DEA Measurement

Referring to the practice of [53,54] and adjusting the evaluation indicators appropriately according to the changes in the logistics industry, we selected the "number of employees in transportation, storage, and postal services", the total investment in fixed assets, and the investment in scientific research and technology as the logistics efficiency input indicators, transportation, storage, and post and telecommunications GDP, freight volume, and regional GDP were the output indicators. Then, Deap2.1 and Frontier4.1 software were used to calculate the 36 prefecture-level cities in the experimental group and the control group from 2000–2020. However, due to the space limitations of this paper, the specific calculation process is not described here. The following table captures the data from 2012–2020, and only the comprehensive efficiency is intercepted in this test, as shown in Table 3.

Table 3. Treatment group and control group 36 city logistics efficiency value.

Le	2012	2013	2014	2015	2016	2017	2018	2019	2020
Guangzhou	0.983	0.966	0.954	0.964	0.975	1.000	1.000	1.000	1.000
Shenzhen	0.999	1.000	1.000	1.000	0.997	0.996	1.000	1.000	1.000
Zhuhai	0.677	0.656	0.781	0.831	0.796	0.825	0.861	0.917	0.845
Foshan	1.000	0.906	0.919	0.931	0.957	0.989	1.000	1.000	1.000
Huizhou	1.000	0.842	0.878	0.917	0.922	0.932	1.000	1.000	0.775
Dongguan	1.000	0.939	0.964	0.997	0.989	1.000	1.000	1.000	1.000
Zhongshan	0.977	0.953	1.000	0.994	1.000	1.000	1.000	0.890	0.851
Jiangmen	0.865	0.576	0.719	0.848	0.750	0.769	0.777	0.846	0.859
Zhaoqing	0.694	0.615	0.723	0.806	0.731	0.764	0.854	1.000	1.000
Shanghai	0.765	0.690	0.732	0.750	0.835	0.863	0.981	1.000	1.000
Nanjing	0.623	0.456	0.416	0.436	0.462	0.595	0.638	0.800	0.853
Wuxi	0.875	0.735	0.712	0.709	0.769	0.867	1.000	1.000	1.000
Changzhou	1.000	0.898	0.889	0.886	0.865	0.974	1.000	1.000	1.000
Taizhou	0.993	1.000	0.697	0.674	0.636	0.652	0.666	0.781	1.000
Yancheng	1.000	1.000	0.861	0.754	0.748	0.815	0.863	0.923	1.000
Suzhou	1.000	0.816	0.814	0.834	0.861	0.946	1.000	1.000	1.000
Nantong	1.000	0.844	0.773	0.772	0.811	0.924	1.000	1.000	1.000
Zhenjiang	1.000	0.999	0.988	0.962	0.995	1.000	0.985	1.000	1.000
Yangzhou	1.000	0.637	0.635	0.611	0.607	0.675	0.891	0.834	0.792
Hangzhou	0.631	0.587	0.566	0.563	0.570	0.591	0.637	0.792	1.000
Zhoushan	0.969	0.918	0.748	0.749	0.779	0.954	1.000	1.000	1.000
Ningpo	0.773	0.763	0.742	0.713	0.781	0.853	0.895	0.950	1.000
Shaoxing	0.968	0.979	0.930	0.878	0.876	0.925	1.000	0.974	0.931
Jinhua	0.856	0.798	0.771	0.749	0.739	0.750	0.804	0.875	1.000
Huzhou	0.871	0.682	0.633	0.795	0.800	0.864	0.947	1.000	0.931
Taizhou	0.892	0.877	0.837	0.833	0.879	0.941	1.000	0.979	0.894
Wenzhou	0.905	0.881	0.893	0.901	0.948	0.954	1.000	0.751	0.779
Jiaxing	0.821	0.782	0.754	0.747	0.806	0.885	1.000	1.000	1.000
Tongling	1.000	0.896	0.723	0.840	0.595	0.672	0.694	0.804	1.000
Hefei	0.730	0.712	0.726	0.767	0.760	0.789	0.837	0.920	1.000
Wuhu	0.820	0.832	0.836	0.724	0.702	0.716	0.724	0.798	0.808
Chuzhou	0.939	0.901	1.000	1.000	0.961	0.796	0.816	1.000	0.999
Maanshan	1.000	0.728	0.719	0.721	0.769	0.876	0.859	0.999	1.000
Chizhou	0.940	0.646	0.593	0.578	0.618	0.671	0.689	0.853	0.845
Anqing	1.000	1.000	1.000	0.816	0.878	0.911	0.798	0.941	0.964
Yicheng	0.716	0.681	1.000	0.938	0.879	1.000	0.917	1.000	1.000

4.2. PSM Results and Analysis

4.2.1. PSM Kernel Density Function Graph

The kernel density function graph was used to test the quality of the PSM matching of the treatment and control groups, and the more overlapping there is regarding the kernel density curves of the treatment and control groups, the better the matching effect. This study matched all the control variables, and Figure 1 shows the kernel density matching before and after PSM. Figure 1 shows large deviations in skewness and kurtosis in the kernel density maps for both treatment and control groups, with less overlap before the PSM. After the PSM, the overlap of the kernel density function between the control group and the treatment group increased substantially, indicating a better match quality. This lays a good data foundation for the further use of DID methods to explore the impact of the establishment of the Greater Bay Area on the logistics efficiency in the area.

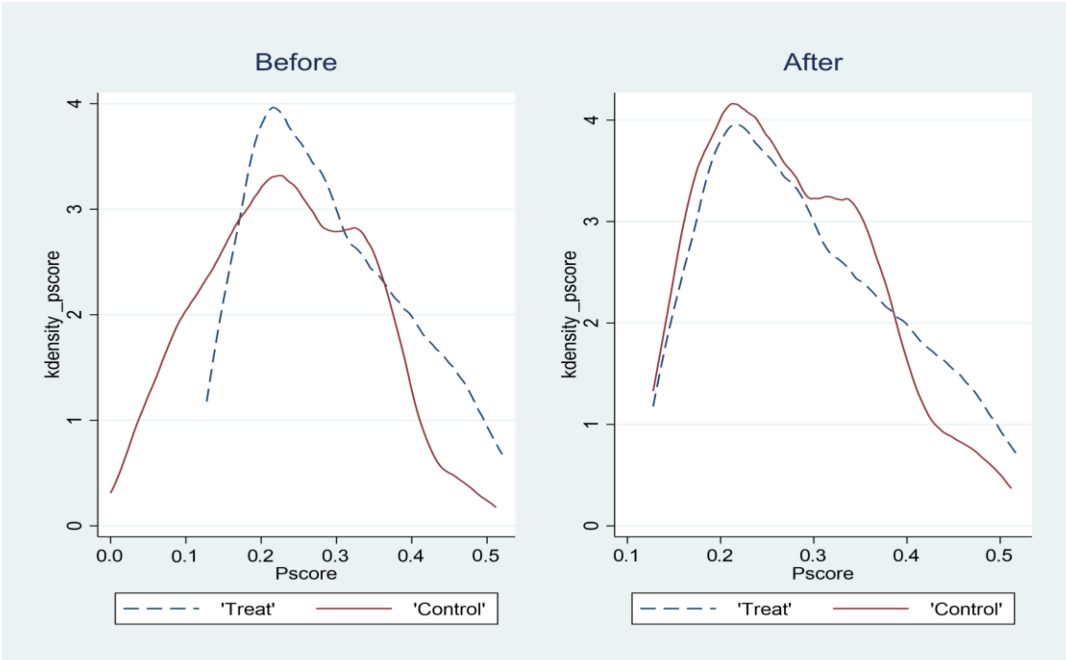

Figure 1. The plot of the kernel density function before and after PSM matching.

4.2.2. PSM Balance Test

The reliability test of the PSM results needed to meet the hypothesis that there is no significant difference between the treatment group and the control group in the matching variables. The general practice when determining whether the PSM is effective is to check the size of the standard bias (%bias) before and after the matching and to judge the significance of the *p*-value, both of which, when they meet the relevant test standards, are regarded as good matching. Regarding the standard bias value (%bias), Rosenbaum and Rubin considered that the absolute deviation value after the matching value to be less than 20 [29], and Smith and Todd argued that the smaller the deviation value, the better the matching effect [55]. The second criterion is that the *p* worth significance is mainly significant before the match and not significant after the match. In this study, kernel matching was selected in multiple PSM matching methods. The results are shown in Table 4. With transportation infrastructure being used as an example, the bias between the treatment group and the control group before matching is 31.9%, and the bias after matching is only 7.8%. At the same time, the t-statistic of the observed difference is 3.54. The *p*-value of the significant difference between the treatment group and the control group in terms of traffic infrastructure is 0.000. It is found that there is a significant difference before matching. However, the matching *p*-value is 0.470, which overall indicates that for the individuals between the control and treatment groups, there is no significant difference in the construction of transportation facilities after matching. The results show that the construction of transportation facilities also conforms to PSM matching judgment and approval, so this factor has passed the PSM matching balance test. According to the results of Table 4, the level of urbanization and industrial structure is not significant before and after matching, indicating that there is no significant difference between the control variable before and after matching, that is, both factors are highly similar. The remaining control variables all met the two requirements of the balance test, that is, they passed the PSM balance test, indicating that the treatment and control groups are highly comparable and verifying hypothesis 1.

Table 4. Results of the PSM balance test.

Variable	Unmatched Matched	Mean Treated	Mean Control	%Reduct %bias	%Reduct ∣bias∣	t-Test t	t-Test $p > \mid t \mid$	V(T)/V(C)
Transport	U	1.0144	0.86152	31.9		3.54	0.000	0.53
	M	1.0084	0.97106	7.8	75.6	0.72	0.470	0.44
Urban-level	U	0.76129	0.72586	13.2		1.40	0.162	0.31
	M	0.76056	0.73261	10.4	21.1	1.02	0.309	0.31
R&D	U	3.6635	3.1394	34.7		4.02	0.000	0.81
	M	3.6543	3.5687	5.7	83.7	0.55	0.583	0.81
FDI	U	1.0255	0.72558	17.7		2.17	0.030	1.24
	M	1.0192	0.99396	1.5	91.6	0.14	0.890	1.02
Employee	U	5.4761	3.9889	17.8		2.12	0.034	0.99
	M	5.4885	4.9994	5.9	67.1	0.53	0.596	0.78
PGDP	U	7.8329	7.4977	28.4		3.30	0.001	0.82
	M	7.8266	7.7268	8.5	70.2	0.82	0.414	0.80
Gov	U	0.09982	0.10987	−20.8		−2.30	0.022	0.52
	M	0.09988	0.09808	3.7	82.1	0.42	0.672	0.90
Industrial	U	0.50005	0.61418	−6.4		−0.62	0.533	0.00
	M	0.50012	0.50247	−0.1	97.9	−0.27	0.791	1.20

4.2.3. Data after the PSM

Table 5 shows the descriptive statistical results for the main variables of the total sample after PSM. As can be seen from Table 5, the total amount of samples, and Table 2 before matching, the total amount is 106 less, indicating that the data that did not meet the match criteria were eliminated in the PSM process. The excluded total sample was used for DID regression analysis to provide a more accurate data basis for the analysis results of this paper.

Table 5. The statistical description of the data after PSM matching.

Variable	N	Mean	p50	SD	Min	Max
Le	650	0.873	0.927	0.144	0.389	1.000
Transport	650	0.937	0.946	0.519	0.002	2.438
Urban-level	650	0.726	0.871	0.297	0.148	1.011
R&D	650	3.464	3.560	1.534	0.028	7.388
FDI	650	0.906	0.351	1.753	0.000	16.160
Employee	650	4.841	1.752	8.925	0.080	66.920
PGDP	650	7.674	7.745	1.209	4.063	10.560
Gov	650	0.0990	0.096	0.043	0.004	0.246
Industrial	650	0.507	0.516	0.085	0.252	0.747

4.3. PSM–DID Empirical Results and Analysis

Table 6 reports the empirical PSM–DID results concerning the impact of the establishment of the Greater Bay Area on the logistics efficiency in the region. The results showed that the DID coefficient of model (1) and model (3) was still significantly positive at 1%, whether the city fixed effect was controlled or not, indicating that the establishment of the Greater Bay Area improved logistics efficiency in the Greater Bay Area. When model (2) and model (4) reported the uncontrolled and controlled fixed effects of cities, respectively, with the addition of control variables, the DID coefficient was also significantly positive, at the level of 1%, once again proving that the policy established in the Greater Bay Area had significantly improved the logistics efficiency of the Greater Bay Area. According to model (4), while simultaneously controlling for time-fixed effects and city-fixed effects, after adding the control variable, the DID coefficient was significantly positive, at the level of 1%, with a value of 0.376. In other words, under the control of time difference, urban regional difference, and control variables, the establishment of the Greater Bay Area has improved the logistics efficiency of the region by 37.6%, and the improvement effect is very prominent. The preliminarily results verify hypothesis 2.

Table 6. Results of logistics efficiency (Le) in Greater Bay Area Establishment.

	(1)	**(2)**	**(3)**	**(4)**
	Le	**Le**	**Le**	**Le**
DID	0.442 ***	0.271 ***	0.542 ***	0.376 ***
	(0.097)	(0.096)	(0.095)	(0.100)
Industrial		−0.110		−0.348
		(0.313)		(0.554)
Transport		−0.251 ***		0.062
		(0.045)		(0.074)
Urban-level		−0.282 **		−0.595 ***
		(0.134)		(0.111)
R&D		0.019		0.018
		(0.047)		(0.054)
FDI		−0.048 ***		−0.068 ***
		(0.014)		(0.019)
Employee		0.036 ***		0.037 ***
		(0.005)		(0.011)
PGDP		−0.101 *		−0.251 *
		(0.059)		(0.129)
Gov		4.367 ***		1.919 **
		(0.846)		(0.921)
Control	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	NO	NO	YES	YES
_cons	−3.738 ***	−2.680 ***	−3.064 ***	−1.434
	(0.028)	(0.419)	(0.097)	(1.067)
N	650.000	650.000	650.000	650.000
r2	0.096	0.455	0.711	0.747
r2_a	0.093	0.430	0.683	0.720

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Robust Analysis

4.4.1. Parallel Trend Assumption Test

In the research hypothesis, it was explained that a DID experiment needs to meet two conditions, with one of these being to meet the parallel trend assumption. The parallel trend assumption is that the treatment group and control group will have the same development trend before the event, while the treatment group and control group will have exhibit an obvious trend difference after the event. Therefore, to verify the robustness of the DID model used in this paper, parallel trend maps were drawn according to the time nodes established in the Greater Bay Area to verify whether the impact of the establishment of the Greater Bay Area on logistics efficiency meets the parallel trend assumption. Figure 2 shows that the Greater Bay Area set up in 2017. According to the strict requirements of the parallel trend assumption test, a parallel trend significant difference should be visible in 2017 and later years, but Figure 2 shows a parallel trend significant difference in 2019, the reason for this being policy delay, i.e., the fact that most policy implementation effects are not apparent in the same year and need a period to become apparent. The establishment of large-scale urban agglomerations such as the Guangdong–Hong Kong–Macao Greater Bay Area, in particular, require the joint integration of resources from multiple cities, meaning that the time taken to integrate is longer. In 2019, the CPC Central Committee and the State Council issued the Outline of the Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area [2], which made the Greater Bay Area further supported by the state and thus significantly increased the logistics efficiency of the Greater Bay Area, which had been integrated for two years. Thus, Figure 2 shows that the logistics efficiency levels of the treatment and control groups maintain roughly the same growth trend without significant differences until 2019. Meanwhile, in 2019 and 2020, after the establishment of the Greater Bay Area, the growth trends in terms of the logistics efficiency of the treatment and control groups appear to be significantly different, which indicates that the DID model in this paper passes the parallel trend hypothesis test.

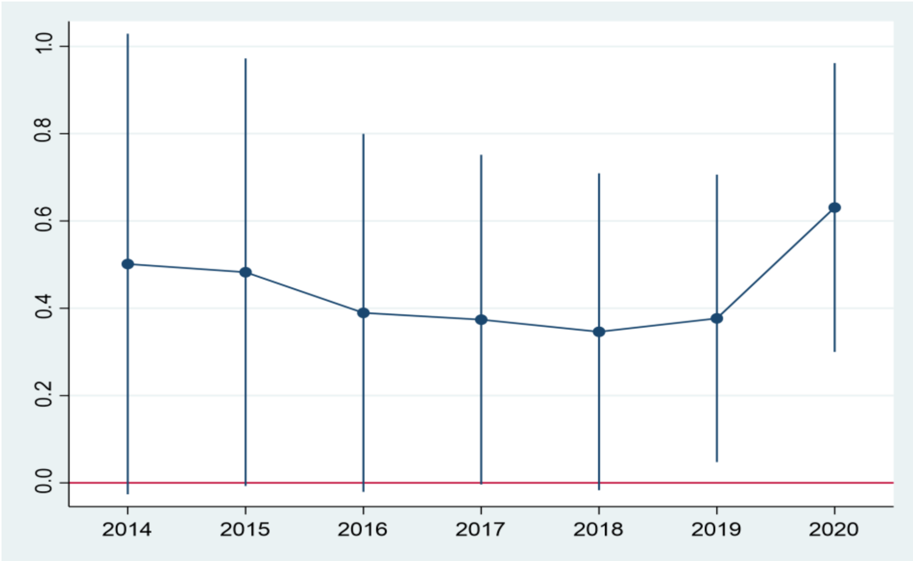

Figure 2. DID the parallel trend assumption test.

4.4.2. Placebo Test

To test the extent to which the above results were influenced by missing variables and random factors, etc., a placebo test was utilized by referring to the practices of [56,57].

The method used randomly "screens" other urban agglomerations in China and randomly produces the bay Area establishment time, thus constructing two two-level random experiments: reform time and urban agglomeration. Next, according to column (4) of Table 6, a placebo test was utilized to determine the reliability of the conclusion based on the probability of obtaining the benchmark regression estimation coefficient from the false experiment. To further enhance the efficacy of the placebo test, the above process was repeated 800 times, and, finally, the estimated coefficient distribution map of the coefficient DID was drawn. Based on this, another test was utilized to verify whether the improvement in logistics efficiency was significantly affected by other factors except for the "Greater Bay Area establishment" factor. If the estimated coefficient of DID under random treatment was around 0, this meant that enough important impact factors were not missed in the model set. In other words, the impact effect in the benchmark analysis was indeed the result of this paper. As can be seen in the estimation coefficient distribution map reported in Figure 3, the estimated coefficient of the false double difference terms is distributed around 0, indicating that there is no serious missing variable problem in the model set and the core conclusion is still robust.

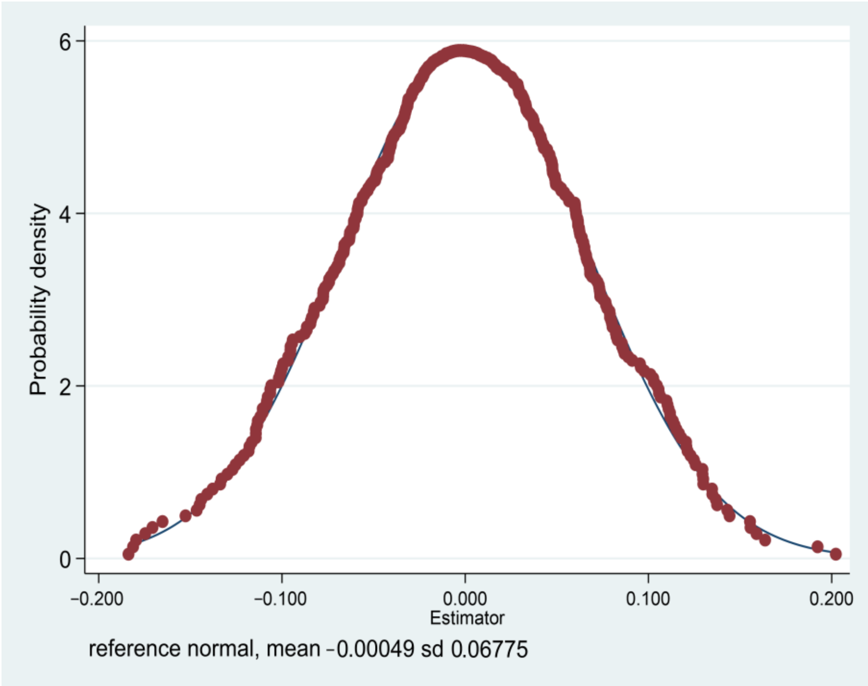

Figure 3. Placebo Test.

4.4.3. Change PSM Test

The above studies were based on sample matching between treatment and control groups using kernel matching methods in the PSM method. To make the estimation results more reliable, the matching method to was changed to rematch using Mahalanobis distance matching, k order (k = 2) nearest neighbor matching, caliper (radius) matching, local linear regression matching, and spline matching, etc. Then, the DID estimation was performed, and if the DID estimation results of the six matching methods were not significantly different, then the estimation results were robust. The results of the DID estimates for applying the five matching methods described above are shown in Table 7. The results showed that after changing the five PSM matching methods, the DID estimation results were not significantly different from the benchmark regression results of Table 6 model (4), indicating that the results were very robust, and all the above tests fully verified hypothesis 2.

Table 7. Results of DID estimation for the five PSM matching methods.

	Mahalanobis	Neighbor	Radius Caliper	LLR	Spline
DID	0.373 ***	0.357 ***	0.389 ***	0.372 ***	0.363 ***
	(0.100)	(0.106)	(0.097)	(0.100)	(0.098)
Control	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
_cons	−1.222	−1.521	−1.314	−1.392	−1.422
	(0.127)	(1.023)	(0.997)	(1.047)	(0.981)
N	756.000	663.000	684.000	662.000	656.000
r2	0.721	0.743	0.717	0.755	0.741

Standard errors in parentheses. *** $p < 0.01$.

5. Conclusions and Trends

This paper, which took as its research object 9 cities in the Pearl River Delta and Yangtze River Delta, for a total of 36 cities, based on the 36 cities in 2000–2020 city panel data, empirically tested the impact of the establishment of the Greater Bay Area and the outline of the Guangdong Large Bay Area on logistics efficiency in the area using the three-stage DEA model and the PSM–DID experiment method. The study found that: (1) Through an analysis of the literature and PSM balance verification, the Pearl River Delta and Yangtze River Delta urban clusters have similar characteristics and are highly comparable, verifying hypothesis 1; (2) based on the establishment of hypothesis 1 and a DID empirical analysis, although the changes in logistics efficiency in the first two years of the Greater Bay Area establishment did not differ significantly from the control group comparison, in 2019, the State Council issued the Outline of the Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area, which resulted in significant positive changes compared with the control logistics efficiency, i.e., logistics efficiency in the area increased 37.6%, proving hypothesis 2. In the two years after the establishment of the Greater Bay Area, the logistics efficiency in the area has not changed significantly compared with the control group, which is due to the fact that large collaborative policies have an obvious lag. In the early stage of the policy implementation, various urban government departments and the logistics industry chain in the Greater Bay Area are constantly carrying out policy coordination and industrial coordination, so that the logistics efficiency does not change significantly. In 2019, the State Council issued the Greater Bay Area Development Planning Outline, which has become a Greater Bay Area logistics efficiency booster after two years of regional integration and coordination. This, plus a further policy drive, means that the Greater Bay Area logistics efficiency has improved significantly, further illustrating the policy effect on logistics efficiency. The above conclusions were further verified through a series of robustness tests on the reliability of our conclusions, including parallel trend tests, placebo tests, and change matching method tests.

This study shows that the overall efficiency of logistics in the nine cities in the region has indeed improved after the establishment of the Greater Bay Area. However, according to the results of the data analysis in Table 6, the improvement in logistics efficiency is significantly positive in the case of the input of the logistics labor force but not for the input of R&D. This indirectly indicates that the improvement in the efficiency of the logistics industry in the region is still influenced by labor force input, with this being one of the main factors. This result was unexpected, as the Greater Bay Area is home to logistics technology talent from all over China and the world and continues to develop, with the latest technologies such as unmanned intelligent docks, unmanned intelligent warehouses, drone delivery, etc. all being seen in the Greater Bay Area, with unremarkable results. The reasons for this could be manifold—is it possible that the widespread use of these technologies is an illusion and that they are actually only used on a small scale? It is also possible that not much of the R$D investment has gone into logistics technology. A similarly insignificant transport facility input is also a major question mark, and the fact that none of the above hypotheses have been empirically proven in further research in this paper is one of the limitations of this paper. The research was conducted in 2020, before the epidemic, and the situation after the epidemic is also worthy of study [58], with this being a direction for future research.

Finally, even though there are still many issues that can be studied at the micro level, this paper has argued that the establishment of the Guangdong–Hong Kong–Macao Greater Bay Area has had a significant policy effect on the efficiency of logistics in the region, showing that with strong policy support, the synergistic development of city clusters can effectively promote the efficiency of the logistics industry. As for the huge size of China's economy, the large number of cities and the uneven distribution of logistics industries, it is entirely possible to refer to this model for the further integration of other economic zones in China based on the empirical results regarding logistics efficiency improvement in the Guangdong–Hong Kong–Macao Greater Bay Area. Based on China's policy development pattern over the years, it is inferred that China's economic regional integration will accelerate in the future and the establishment of medium and large economic regions similar to the Great Bay Area will also accelerate. Therefore, it will be the authors' future research direction to study regional integration with the logistics industry and other forms of diversified industrial integration in the future.

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