



# Assessing the implementation effect of Shanghai's compulsory municipal solid waste classification policy

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## Abstract

Waste treatment is a problem faced by cities all over the world. In recent years, China, as a developing country, regards the municipal solid waste (MSW) classification as one of the important strategies to deal with the MSW problem. The previous MSW classification policies in China were all only advocacy in nature. It was not until January 2019 that the “Regulations on the Management of MSW in Shanghai” was officially promulgated as China's first compulsory MSW classification policy, marking the beginning of an era of compulsory MSW classification in China. How effective is the implementation of Shanghai's compulsory MSW classification policy 18 months after its implementation and can developing countries continuously and effectively implement compulsory MSW classification policies? These are important issues of concern to the government, academia, and the public. This paper establishes a three-stage DEA model to evaluate the implementation effect of the compulsory MSW classification policies in Shanghai during the period of February 2019 and July 2020. The study found that the average efficiency of the compulsory MSW classification policy in Shanghai reached 0.906 during the study period, indicating that the policy was executed reasonably well. However, there are only 5 months in 18 months that the policy was fully effective (reaching efficiency level 1), suggesting that there is still room for improvement. The main reason for not being able to achieve full effectiveness in some months is attributed to scale efficiency. At the same time, the general public budget revenue and expenditure of environmental variables have positive and negative impacts on the policy implementation effect in Shanghai. The research results can provide experience for China to comprehensively implement the compulsory MSW classification policy in the future and can also provide valuable case study information for cities in other developing countries to implement the compulsory MSW classification policy.

**Keywords** Compulsory MSW classification policy · Policy effect · Three-stage DEA · Developing country

## Introduction

The rapid economic development, urbanization, and improvement of living standards in China have led to a continuous increase in the amount of waste generated. Municipal solid waste (MSW) is the main source of waste, accounting for the vast majority of urban environmental sanitation expenditure, and seriously hinders the harmonious development of society and the environment. The existing capacity and means of MSW treatment can no longer keep up with its growth rate [1]. It is well known that the fundamental solution to the MSW problem lies in "reduction" and "recycling" [2], in which the source classification of waste is both a prerequisite and a key strategy. Source classification not only can greatly improve the recycling rate of MSW but also reduce the transportation cost of MSW and the difficulty of terminal disposal. In developed countries, the disposal

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of MSW has been effectively practiced, and the production of MSW in some areas has not increased even with the increase in population [3]. The Chinese government has also increasingly realized the importance of waste classification in recent years.

In June 2000, Shanghai and seven other cities were identified as the first pilot cities for separate waste collection in China [4, 5]. In 2003, the state established the “Signs for classification of MSW” [6], according to which MSW is divided into three categories: recyclables, hazardous waste, and other waste. In 2004, the Ministry of Construction approved the “Classification and Evaluation Standard of MSW” as the industry standard [7]. In April 2007, the Ministry of Construction issued the “Measures for the Management of MSW” [8], which clearly stipulated that the areas under the MSW classification policy are to place the MSW into specific containers or collection sites according to the classification requirements. However, in the eight years from 2000 to 2008, the MSW classification rate in Shenzhen, Hangzhou, Nanjing, Guilin, Guangzhou, and Xiamen did not reach 15%. Since then, the pilot cities have attempted to learn from the successful waste classification experience at home and abroad. The year 2016 ushered in a new era of waste classification in China, when the state issued the “Plan for the Compulsory Classification System of Garbage (Draft for Comments)” [9], which put forward the concept of mandatory classification of MSW for the first time. In March 2017, the State issued the “Implementation Plan for the MSW Classification System” [10] and launched 46 pilot cities to implement mandatory MSW classification. Although the state has made 17 years effort to promote MSW classification, there has not been significant breakthrough and progress in MSW classification practices.

Until January 2019, when “Regulations on the Management of MSW in Shanghai” was officially promulgated, which was marked as China’s first compulsory MSW classification policy [11, 12]. Considered the strictest MSW classification policy in history, “Regulations on the Management of MSW in Shanghai” divides MSW into four categories: recyclable waste, hazardous waste, food waste, and residual waste [13, 60]. This policy requires that Shanghai’s front-end waste disposal, mid-end waste transportation, and end-end waste treatment all strictly adhere to the waste separation policy standards. To this end, the Shanghai Municipal Government has set up a two-way supervision mechanism between the five links of classified delivery, transportation, transit, and disposal. Through measures such as “no classification, no collection, no classification, no disposal” and quantitative assessment, the responsibilities of all parties have been implemented, efforts have been made to eliminate mixed loading and transportation, and law enforcement has been strengthened with the respective urban management and law enforcement departments. Punitive measures were

to be taken against individuals and collectives in violation of the regulations. This marks that China has officially entered a new era to legislatively enforce the compulsory classification policy of MSW. What has been the effect of the policy and whether it can be effectively implemented in the future are of common concern to the government, researchers, and society, and warrant empirical study.

The MSW classification policy is a “complex process” [14], and the effect of policy implementation is influenced by many factors, including macro-level policy factors [15] and social environmental factors [16], as well as micro-level individual factors, such as values [17], awareness and knowledge of MSW classification [18], and so on. Since the developed countries started the process of urbanization earlier and have achieved a higher degree of urbanization, their researchers began to pay attention to the problem of MSW classification relatively early and have accumulated more in-depth research findings. Wertz first discussed the problem of MSW classification among residents [19]. Linderhof et al. [20], Dijkgraaf and Gradus [21], and others expanded Wertz’s research, revealing that incentive and punitive measures have a direct and significant impact on the implementation of MSW classification policies. Iyer and Kashyap [22] further demonstrated the timeliness of the incentive policy and argued that the incentive effect would disappear with the end of the MSW classification policy. More research emerged later that explored the impact of policy factors such as the government’s MSW management policy [23], laws and regulations [24], the government’s investment in MSW classification and recycling hardware facilities [25], and the relevant departments’ investment in education and enhancement of residents’ MSW classification knowledge [26].

Researchers have also made strides in the methodology of investigating policy implementation effect. Based on the population data of a few areas in France, Kirakozian [27] used the Probit model to test the significance of six categories of public factors on classification behavior. Starr and Nicolson [28] examined the cumulative effects of different policies based on Panel Data from a 13-year follow-up study, Pakpour et al. [26] also applied a time series model in their study of factors affecting the classification of DSW in Qazvin, Iran. In recent years, more and more scholars use Data Envelope Analysis (DEA) to evaluate the effect of policy implementation. Li Yun and Guan Qiao [29] used the DEA method to analyze rice production performance before and after the implementation of the direct grain subsidy policy. Zhang et al. [30] used the DEA method to evaluate the emission reduction effect of China’s carbon emissions trading policy. However, the above articles did not consider comprehensively the impact of other factors on the policy implementation effect. The three-stage DEA model is an extension of the original DEA model, which was first proposed by Fried et al. [31] Combined

with the application of Stochastic Frontier Analysis (SFA), this model can filter out the impact of environment and random factors on the evaluation object in the traditional DEA model [32], so as to make a more accurate evaluation. Tingley, et al., Liu, Wang, and Bi [32–34] adopted a three-stage DEA model in their research. For example, Liu used the CCR model, BCC model, and three-stage DEA model to compare the evaluation efficiency of 10 ports in Asia–Pacific region from 1998 to 2001. The results show that, on average, the 3-stage DEA method has the highest evaluation efficiency and the CCR method has the lowest evaluation efficiency. The CCR and BCC models are not as effective as the three-stage DEA method in policy evaluation because they do not take into account environmental factors and low management efficiency.

The previous literature provides a useful reference for this paper to select proper influencing factors and research methods. However, there is still some room for improvement. First, most of the domestic studies on the impact of factors affecting waste classification are theoretical explorations. Few studies have set up and investigated the input and output indicators from the front-end classification, middle-end transportation, and end-of-pipe treatment of the waste classification policy implementation process. Their results are more theoretical and lack practical relevance and support of empirical evidence. Second, many studies of foreign countries are based on panel data accumulated over a long period of time. In contrast, China Shanghai's period of implementing the compulsory MSW classification policy is relatively short, with limited data from 2019 to now. Third, there are virtually no articles that evaluate the effect of China's MSW classification policy on a monthly basis. In an attempt to advance research in this area, first of all, when specifying the influencing factors, this paper starts from the input and output of the actual implementation of the policy. The indicators clearly proposed in the policy are selected to make the evaluation results more realistic. Second, this paper uses the DEA method which is more applicable to the data volume at hand in this paper and also takes into account the environmental and random factors that may affect the evaluation results, so that the results are more accurate and scientific. More importantly, this paper uses the higher frequency monthly data, which allows a more timely and accurate quantitative evaluation of China's first compulsory MSW classification policy. As a leading representative city in developing countries, Shanghai's experience and performance in implementing the compulsory MSW classification policy can be used as a reference for all prefecture-level cities in China to comprehensively implement the MSW classification policy and can also provide useful case references for other cities in developing countries

considering implementing the compulsory classification policy of MSW.

## Data, variable specification, and methods

Considering the characteristics of Shanghai's compulsory MSW classification policy, we measure output variable by the amount of MSW classifications and specify 5 input variables: the number of social organizations, the number of renovated waste classification stations, the number of recycling service stations, the number of waste transfer stations, and the number of waste transport vehicles. In addition, we designate two environmental factor variables: revenue in the general public budgets and expenditure in the general public budgets.

### Data source

In consideration of data integrity and availability, the number of social organizations is obtained from the official website of the Shanghai Social Organization Announcement Service Platform. The data of recycling service stations, renovated waste classification stations, waste transfer stations, waste transport vehicles and the amount of MSW classifications come from official data released by Shanghai Landscaping and City Appearance Administrative Bureau. Revenue in the general public budgets and expenditure in the general public budgets are from the Shanghai Statistical Yearbooks (Monthly data).

### Variable specification

An accurate study of the implementation performance of the MSW classification policy calls for proper specification of dependent and independent variables [35]. Conforming to characteristics of the input–output system in the context of MSW classification, the personnel/organizational input is generally measured by the number of social organizations, and the material/resources input is measured by the number of vehicles and equipment for MSW processing, whereas the output variable is commonly measured by the amount of MSW classifications. Meanwhile, we also take into account the possible impact of the external environment on the effect of policy implementation and specify two environmental variables that affect the efficiency of waste classification but are beyond the control of production entities: revenue in the general public budgets and expenditure in the general public budgets. The definition and measurement of variables in MSW classification policy implementation are presented in Table 1. Table 2 displays the descriptive statistics of variables.

**Table 1** Definition and measurement of variables

Variable name	Variable meaning	Unit
<b>Input</b>		
The number of social organizations	Social organizations engaged in MSW classification, including social groups, private non-profits, and foundations	Unit
The number of renovated waste classification stations	Rebuilt waste classification stations that previously did not meet the standards of compulsory classification policy	Unit
The number of recycling service stations	Service stations for recycling recyclable waste	Unit
The number of waste transfer stations	Service stations for compressing and transferring waste	Unit
The number of waste transport vehicles	Waste transport vehicles used to transport MSW that has been classified	Unit
<b>Output</b>		
The amount of MSW classifications	The total amount of MSW being classified following implementation of the compulsory policy	Ton
<b>Environment</b>		
Revenue in the general public budgets	Planned, organized and state-controlled funds included in the budget management	Ten thousand yuan
Expenditure in the general public budgets	Expenditure appropriated by the state for planned distribution and use of centralized budget revenue	Ten thousand yuan

**Table 2** Descriptive statistics

Variable name	Maximum value	Minimum value	Mean value	Standard deviation
<b>Input variable</b>				
The number of social organizations	31.00	4.00	14.33	6.02
The number of renovated waste classification stations	2.10	1.00	1.73	0.47
The number of recycling service stations	15,000.00	1167.00	11,167.33	4488.51
The number of waste transfer stations	201.00	94.00	165.44	38.62
The number of MSW vehicles	4952.00	3659.00	3746.28	988.00
<b>Output variable</b>				
The amount of MSW classifications	1,042,267.00	505,230.00	875,094.52	125,830.93
<b>Environment factor</b>				
Revenue in the general public budgets	1070.60	363.90	599.54	189.22
Expenditure in the general public budgets	1026.40	385.90	651.33	204.44

## Input and output variables

### (1) Input variables

Shanghai's compulsory MSW classification policy explicitly states that volunteers and voluntary service organizations are encouraged to carry out activities such as publicity and demonstration of MSW classification, and a large number of social organizations are employed to facilitate, promote, review and supervise residents' waste classification behavior. The government actively enlists third-party social organizations to engage the community and guide residents to carry out MSW classification. Therefore, the number of social organizations involved is used as an input variable.

Classification facilities are the prerequisite and basis for the implementation of the MSW classification policy [36]. The whole process of MSW classification policy includes three links: source classification, mid-end collection and transportation, and end treatment. The facilities used in the three links are expected to impact the outcome of the MSW classification policy. First, the convenient access and availability of waste disposal facilities would positively impact the residents' waste classification behavior [37, 38], because the setting of waste classification bins and classification stations can hint to residents that the waste needs to be classified at the source and induce them to do so. Second, in the middle-end cleaning and transportation link after waste classifi-

cation at the source, the transportation efficiency of MSW vehicles also affects the effect of policy implementation [39–41]. Finally, in the end processing link, the recyclable waste is sent to the recycling service stations, and the non-recyclable waste is temporarily transferred to the waste transfer station. Therefore, considering the three links process, we specify several input variables including the number of renovated classification stations, the number of recycling service stations, the number of waste transfer stations, and the number of waste transport vehicles.

## (2) Output variable

The MSW classification standards in Shanghai have been adjusted several times, and the final policy has determined four types of waste classification: recyclable waste, hazardous waste, household food waste, and residual waste. The amount of MSW classifications is chosen as the output variable, because currently the main purpose of MSW policy in developing countries like China is to increase the amount of MSW classification for recycling and centralized harmless treatment [42, 43].

## Environment variables

### (1) Revenue in the general public budgets

Revenue in the general public budgets is a major source of fiscal revenue [44]. It is the fund that is planned, organized, and controlled by the state. On one hand, the revenue in a city's general public budgets reflects its level of economic development, and a higher level of economic development makes the city more capable and affordable to implement public policies. On the other hand, the revenue in the general public budgets will affect the degree of development and establishment of social organizations, which will further enhance the implementation of public policies.

### (2) Expenditure in the general public budgets

From the perspective of the single administrative system of developing countries, the policies issued by the state play a decisive role to dictate the behavior of local governments. Expenditure in the general public budgets is the planned distribution and spending of revenue by the state, reflecting the direction of state support and the choice of policy targets. State-supported policies are expected to induce local governments to invest more energy and resources to implement such policies.

## Methodology

The three-stage DEA model was first introduced by Fried et al. [31]. It is applicable to evaluating the relative

effectiveness and returns to scale in the case of multiple inputs and outputs [45–48] and has been widely used to evaluate the effects of various policies [49]. Combined with the application of Stochastic Frontier Analysis (SFA), the three-stage DEA model can filter out the impact of environment and random factors on the evaluation object in the traditional DEA model [32], so as to make a more accurate evaluation. The three-stage DEA model is fully suitable for the research on the implementation effect of the compulsory MSW classification policy in Shanghai.

The three-stage DEA model proceeds in three stages [50]. In the first stage, the traditional DEA-BCC model is used for preliminary measurement [51]. In the second stage, the input and output were adjusted with the SFA method, the relationship between slack variables and environmental variables was established, the random errors were separated, and the factors that might affect the model operation results were removed [52]. In the third stage, the adjusted input and output data of each decision-making unit are combined with the traditional DEA model for the final calculation, and the conclusion is more scientific and accurate [53].

## The first stage: traditional DEA model

As a standard practice [54], the DEA-BCC model decomposes the technical efficiency (TE) in the CCR model into pure technical efficiency (PTE) and scale efficiency (SE), i.e.,  $TE = PTE \times SE$ . To evaluate the implementation effect of the MSW classification policy in Shanghai, the following model is constructed. We take the 18 months of policy implementation as 18 decision-making units (DMU), each with  $m$  input and  $s$  output. Then, the calculation of the total efficiency of the  $p^{th}$  DMU is converted into a linear programming problem. The model is built as follows:

$$Max\theta = \theta_0 - \varepsilon \left( \sum_{i=1}^s S_i^+ + \sum_{i=1}^m S_i^- \right) \quad (1)$$

$$s.t. = \begin{cases} \sum_{j=1}^n \lambda_j x_{ij} + S_i^- = \theta_0 x_{i0} \\ \sum_{j=1}^n \lambda_j y_{rj} + \lambda_j x_{ij} = y_{r0} \\ \lambda_j, S_i^+, S_i^- \geq 0, i = 1, 2, \dots, m \\ j = 1, 2, 3, \dots, n; r = 1, 2, \dots, s \end{cases} \quad (2)$$

where each DMU with  $m$  input and  $s$  output;  $x_{ij}(i = 1, 2, \dots, m)$  is the  $i$ th input variable of the  $j$ th DMU;  $y_{rj}(r = 1, 2, \dots, s)$  is the  $r$ th output variable of the  $j$ th DMU. Efficiency is the ratio of the weighted sum of output to the weighted sum of inputs. Then, taking efficiency as the objective function, calculation of total efficiency

of the 18 DMU is converted into a linear programming problem, where  $X_1(x_{11}, x_{21}, \dots, x_{m1}), Y_1(y_{11}, y_{21}, \dots, y_{n1}), \theta$  is the total efficiency value of investigated DMU, and  $0 \leq \theta \leq 1$ . When  $\theta = 1$ , the investigated DMU is a point on an efficient frontier plane. When  $\theta < 1$ , it is a point on an inefficient frontier plane.  $1 - \theta$  is the proportion of redundant input related to the investigated DMU.

**The second stage: adjusting input indicator variable**

In this exercise, the slack variable is the dependent variable, whereas the random error, internal management, and environmental factors are the explanatory variables for SFA regression. Suppose the  $n$ th input value of the  $i$ th DMU is  $X_{ni}$  and the slack variable is  $S_{ni}$ , then  $S_{ni} = X_{ni} - X_{n\lambda} > 0$ . According to Battese and Coelli [55], the relation between the slack variable and environment variable can be expressed as Eq. (3):

$$S_{ni} = f_i(Z_i, \beta_n) + V_{ni} + U_{ni} \quad i = 1, 2, \dots, I; n = 1, 2, \dots, N \quad (3)$$

where  $S_{ni}$  is the slack variable of the  $n$ th input of the  $i$ th DMU;  $Z_{1k} = (Z_{1i}, Z_{2i}, \dots, Z_{ki})$  represents  $k$  environmental variables;  $f_i(Z_i, \beta_n)$  represents the influence of environmental variables on the input slack variable  $S_{ni}$ ; generally,  $f_i(Z_i, \beta_n) = V_{ni} + U_{ni}$  is the combined error term, where  $V_{ni} \sim N(0, \sigma_{vn}^2)$  reflects random error and  $U_{ni}$  reflects management inefficiency and exhibits a truncated normal distribution, i.e.,  $U_{ni} \sim N(\mu, \sigma_{un}^2)$  and  $V_{ni}$  is independent from and uncorrelated to  $U_{ni}$ . When  $\gamma = \sigma_{vn}^2 / (\sigma_{vn}^2 + \sigma_{un}^2)$  is close to 1, the influence of management factor dominates; when  $\gamma = \sigma_{vn}^2 / (\sigma_{vn}^2 + \sigma_{un}^2)$  is close to 0, the influence of random error dominates.

Through adjusting input variable data of the  $n$ th DMU with the result of SFA model regression and eliminating the influences of environmental factor and random error, an efficiency value purely reflecting management level can be calculated. The adjustment formula can be written as Eq. (4):

$$X_{ni}^A = X_{ni} + \{ [Max(f(Z_i, \beta_n) - (f(Z_i, \beta_n))] + [Max(V_{ni}) - V_{ni}] \} \quad i = 1, 2, \dots, I; n = 1, 2, \dots, N \quad (4)$$

where  $X_{ni}^A$  is input after adjustment;  $X_{ni}$  is the original input value. The first bracket in Eq. (4) indicates that all DMUs are adjusted to be under the same external environment and the second bracket indicates all DMUs are adjusted to the same random errors. These adjustments make all DMUs under the same external environment and fortune (random error).

**The third stage: DEA model after adjustment**

In this stage, we fit the input data after adjustment in the second stage and the original output data into the DEA model to calculate the relative efficiency value. The result obtained is the efficiency value presumably only reflecting the management factor after eliminating the influence of environmental factor and random factor.

**Results and discussion**

**Traditional DEA results (the first stage)**

According to Table 3, the average technical efficiency, average pure technical efficiency, and average scale efficiency of these months are 0.886, 0.925, and 0.959, respectively. It appears that in most months pure technical efficiencies are smaller than scale efficiencies, which means that the low technical efficiencies of most months have resulted more from pure technical inefficiency than scale inefficiency.

However, the first stage results did not net out the impact of environmental factors and random errors. Therefore, the next step is to identify and purge the influence and errors caused by environmental factors on the results. Through

**Table 3** Comparison of MSW classification efficiency over 18 months (the first stage results before adjusting input)

Time	TE	PTE	SE	RTS
2019. 02	1.0000	1.0000	1.0000	–
2019. 03	1.0000	1.0000	1.0000	–
2019. 04	1.0000	1.0000	1.0000	–
2019. 05	1.0000	1.0000	1.0000	–
2019. 06	0.9662	1.0000	0.9662	Irs
2019. 07	0.8749	0.8928	0.9799	drs
2019. 08	0.9196	0.9985	0.9209	drs
2019. 09	1.0000	1.0000	1.0000	–
2019. 10	0.8705	0.8758	0.9939	Irs
2019. 11	0.7221	0.7547	0.9569	Irs
2019. 12	0.5824	0.6048	0.9630	Irs
2020. 01	0.8621	0.8837	0.9755	drs
2020. 02	0.7063	1.0000	0.7063	irs
2020. 03	1.0000	1.0000	1.0000	–
2020. 04	0.8697	0.8928	0.9742	drs
2020. 05	0.9378	1.0000	0.9378	drs
2020. 06	0.7269	0.7507	0.9683	drs
2020. 07	0.9171	1.0000	0.9171	drs
Average	0.8864	0.9252	0.9589	

TE technical efficiency, PTE pure technical efficiency, SE scale efficiency, TE = PTE × SE, RTS returns to scale, irs increasing returns to scale, drs decreasing returns to scale, ‘–’ means the returns to scale remain unchanged

**Table 4** SFA regression results

	The number of social organizations	The number of renovated classification stations	The number of recycling service stations	The number of waste transfer stations	The number of waste transport vehicles
Constant term	-0.1065 <sup>c</sup> (-12.8648)	-0.7976 <sup>c</sup> (-6.5761)	-6456.7475 <sup>a</sup> (-6456.7481)	-82.1237 <sup>a</sup> (-415.1204)	-2316.0237 <sup>a</sup> (-2316.0239)
Revenue in the general public budgets	-64.1633 <sup>a</sup> (-64.20734)	-6.9025 <sup>a</sup> (-6.3627)	-0.5437 <sup>c</sup> (-54,370.7530)	-385.3418 <sup>a</sup> (-516.2201)	-7177.8072 <sup>a</sup> (-7177.8072)
Expenditure in the general public budgets	45.9353 <sup>a</sup> (45.9611)	-0.3015 <sup>c</sup> (-0.3293)	18,652.7670 <sup>a</sup> (18,652.7670)	226.3312 <sup>a</sup> (360.0614)	5108.6716 <sup>a</sup> (5108.6716)
Sigma-squared ( $\sigma^2$ )	26.9882 <sup>a</sup> (26.9898)	0.1161 <sup>c</sup> (4.7062)	0.4657 <sup>c</sup> (0.4657)	475.7758 <sup>a</sup> (475.7769)	385,404.6700 <sup>a</sup> (385,404.6700)
Gamma ( $\gamma$ )	1.0000 (3.1270)	1.0000 (0.1033)	0.4292 (1.8202)	1.0000 (1,299,344.6000)	0.9996 (54.4202)
Log likelihood	-41.7081	-0.5081	-160.8377	-73.3327	-129.6323
LR test of the one-sided error	10.2787	4.2938	19.7603	34.8169	6.6240

<sup>a</sup>Significant at 1% level<sup>b</sup>Significant at 5% level<sup>c</sup>Significant at 10% level

further adjustment and calculation of the model, we can more accurately assess the implementation effect of Shanghai's compulsory MSW classification policy.

### SFA regression results (the second stage)

As can be seen from Table 4, the log-likelihood function values and likelihood ratio test statistics for each variable are significant, and the gamma values for all four input variables are close to 1, indicating that environmental variables and random factors do have a large impact on the implementation effect of MSW classification policy in Shanghai. In order to obtain more accurate efficiency measures, it is effective and necessary to use the SFA model to separate the effects of environmental variables and random factors.

As can be seen from Table 4, general public budget revenue shows a negative and significant (at 1% level) effect on all variables, indicating that the increase in general public budget revenue can improve the implementation effect of the compulsory MSW classification policy in Shanghai. The reason may be that the general public budget revenue is the fiscal revenue mainly collected from taxation, which is intended to be dispensed to protect and improve people's livelihood and promote economic and social development. Therefore, more general public budget revenue means that more funding is available for the government to carry out compulsory MSW classification policy. Cost and economic support are the cornerstones to guarantee the effectiveness of policy implementation, and the backing of general public budget revenue contributes to improving the implementation of Shanghai's compulsory MSW classification policy.

According to Table 4, the regression coefficients of general public budget expenditures are positive for four variables (number of social organizations, number of recycling service stations, number of waste transfer stations, and number of waste transportation vehicles), and negative for one variable (number of renovated waste classification stations), albeit with a smaller magnitude and weaker significance level. Overall, the general public budget expenditure appears to have a negative effect on the implementation of MSW classification policy in Shanghai. The possible reason is that general public budget expenditures are categorized by their economic nature into salary and welfare expenditures, goods and services expenditures, capital expenditures, and other expenditures. That means general public budget expenditures do not exclusively or entirely refer to the economic costs of public service operations. In addition to the various types of MSW classification facilities, the number of inputs from social organizations is also used here as an important measure to influence the implementation effectiveness of the compulsory MSW classification policy in Shanghai. As the first city in China to implement compulsory MSW classification, Shanghai is under pressure of the central government to improve the performance of MSW classification. It is possible that the municipal government acquired and established an unduly amount of social organizations to increase volunteers to guide and supervise residents' MSW classification behavior, which may have led to a large duplication or redundancy of resources and negatively affected the policy implementation effect.

**Table 5** Comparison of MSW classification efficiency over 18 months after adjusting input (the third stage)

Time	TE	PTE	SE	RTS
2019. 02	0.9354	1.0000	0.9354	irs
2019. 03	1.0000	1.0000	1.0000	–
2019. 04	0.9559	0.9912	0.9644	drs
2019. 05	1.0000	1.0000	1.0000	–
2019. 06	1.0000	1.0000	1.0000	–
2019. 07	0.9216	0.9529	0.9671	drs
2019. 08	0.9431	1.0000	0.9431	drs
2019. 09	1.0000	1.0000	1.0000	–
2019. 10	0.8372	0.8450	0.9907	drs
2019. 11	0.9229	0.9438	0.9778	irs
2019. 12	0.8741	0.8933	0.9785	irs
2020. 01	0.8180	0.8227	0.9944	drs
2020. 02	0.5289	0.8189	0.6458	irs
2020. 03	1.0000	1.0000	1.0000	–
2020. 04	0.8553	0.8604	0.9941	drs
2020. 05	0.9165	0.9897	0.9261	drs
2020. 06	0.9051	0.9888	0.9153	drs
2020. 07	0.9354	1.0000	0.9354	irs
Average	0.9063	0.9504	0.9518	–

**DEA results after adjusting inputs (the third stage)**

The third stage DEA results are presented in Table 5. Compared to the first stage results, it can be seen that the classification efficiency values before and after adjustment are different to some extent. The average technical efficiency increases from 0.886 to 0.906, pure technical efficiency grows from 0.925 to 0.95, and the scale efficiency value declines slightly from 0.959 to 0.952, indicating that the selected environmental variables had a significant influence on the implementation efficiency of the compulsory MSW classification policy in Shanghai. The results also show that using the three-stage DEA model can help accrue more accurate and scientific results. While these efficiency values, which are measured against the level of the benchmark efficiency, appear to show fairly good efficiency, yet not all months have been fully effective and there is still room for improvement.

February 2020 is the first month of the official promulgation of the compulsory MSW classification policy. The relatively low-efficiency level in that month may be because the infrastructure was not completely developed and the citizens were not fully prepared to do classification. Then, from March 2020 to June 2020, with continuous improvement of the MSW classification infrastructure, the efficiency of policy implementation stabilized in those months. By July 2020, the compulsory MSW classification policy was formally and strictly implemented. As China’s most strict MSW classification policy in history, its classification standards were very detailed. Despite the help of volunteers, the vast majority of citizens still cannot complete the classification task accurately. Therefore, there was still room for efficiency improvement in July and August 2020. Moving into September–November 2020, although the overall efficiency still fluctuated, it remained at a high value of 0.92 and continued on the rise. Nevertheless, when COVID-19 broke out, Shanghai was still subject to small fluctuations initially. With the continuous onslaught and widespread of the epidemic, the minimum efficiency of 0.53 was ushered in February 2020. Although there were fluctuations later, the overall effect was not optimistic. Conceivably, the strong pandemic risk minimization and containment measures inhibited the working of household publicity for waste classification, on-site guidance, and supervision of the MSW placement in the community, and interrupted regular and fixed point collection and transportation of MSW. Before December 2019, the average implementation effect of Shanghai’s compulsory MSW classification policy was 0.95, and after December 2019, the average efficiency was only 0.85. The COVID pandemic’s impact on the implementation of compulsory MSW classification policy in Shanghai can be clearly seen.

Looking further at Table 5, we find that in all those ineffective months, the reason for technical efficiency not reaching 1 is mostly due to scale efficiency not reaching 1. Table 6 shows the distribution of scale efficiency before and after SFA adjustment. It can be inferred that the redundancy and inadequacy of social organizations and various MSW classification infrastructure are the underlying reasons for the lack of scale efficiency of 1, causing the compulsory MSW classification policy in Shanghai not reaching the desired efficiency level. This suggests that there is some efficiency

**Table 6** Distribution of scale efficiency in each month before and after the SFA adjustment

Scale efficiency stage	Stage distribution of scale efficiency before SFA adjustment		Stage distribution of scale efficiency after SFA adjustment	
	Number	Percentage (%)	Number	Percentage (%)
Scale efficiency increasing stage	5	27.8	5	27.8
Scale efficiency unchanged stage	6	33.3	5	27.8
Scale efficiency declining stage	7	38.9	8	44.4



bias of MSW classification infrastructure construction, and also some room for improvement in the use and scheduling of all kinds of MSW trucks.

## Conclusions

This paper finds that after excluding environmental variables, the compulsory MSW classification policy in Shanghai reaches efficiency level 1 (fully effective) in only 5 out of 18 months, and scale efficiency may be an important reason for the policy being not fully effective. Although more months fail to reach 1, the average overall efficiency is 0.906, which still shows that the implementation effect of Shanghai's compulsory MSW classification policy is fairly good overall, and there is still room for improvement. Meanwhile, the analysis of the influence of two environmental factors on the implementation effect of the MSW classification policy in Shanghai reveals that they have different degrees of influence on the MSW policy. On the one hand, the general public budget revenue has a significant positive impact on the overall effect of policy implementation, with the greatest impact on the number of waste transportation vehicles. On the other hand, general public budget expenditures are found to have a negative effect on policy implementation.

Based on the conclusion of this paper and the practical experience of developed countries, there are ways for China and other developing countries to further improve the compulsory MSW classification policy. In Japan, the most stringent country for the MSW classification, more than 70% of the funds for MSW classification comes from government budgetary appropriations [56]. This is consistent with the conclusion of this paper. Sufficient funding support from the general public budget can guarantee the stable implementation of MSW classification. As a "Garden City", Singapore attaches great importance to MSW classification [57]. In Singapore, MSW sorting and recycling are done mainly by shipping vendors. Singapore's experience demonstrates that a stable recycling market and a recycling industry with reasonably good recycling technology will help MSW classification and enhance MSW classification policy. Many scholars that investigate why MSW classification and recycling works well in the United States have found that the US government attaches great importance to the construction of MSW classification infrastructure and that the collection and transportation time, place, and route of the MSW classification middle-end facilities are very scientific and standardized in the United States. This explains why the U. S. compulsory MSW classification policy exhibits high-scale efficiency [58]. Equally important, many cities in the United States do not just rely on social organizations to monitor their residents' MSW classification practices, but also invest a lot of effort in education and promotion, to subtly nudge

people's behavior and develop the habit of MSW classification. That way, the redundancy that may arise from investing too many human resources (such as the case in Shanghai) can be avoided.

Wen [59] and others point out that the biggest problem of MSW classification and recycling in China is that MSW removal is mainly handled through the sanitation system, while the disposal of recyclables rests with the commercial sector, and the former is not motivated to classify actively, while the latter makes more profits with the finer classification. Hence, there is a conflict of interest at the source between the two separate systems. In his opinion, the solution to the problem is not complicated. Local governments can design and plan the MSW classification, collection, transportation, and disposal in a unified manner, and ensure that the MSW is disposed in the corresponding facilities after classification. The best way to do this is to commission a large integrated service company to combine the two functions of MSW removal and recycling into one, and the government can just use the general public budget to purchase the service. That way, both the issues of conflict of interest and compatibility of MSW classification with the market, industry, and technology can be resolved, while ensuring pure technical efficiency and scale efficiency. In fact, this approach is currently undertaken in most of the US municipalities. In summary, the findings of this paper have some commonalities with previous studies in related fields. Through comparing and learning from previous successful research cases, this paper reveals relevant findings and proposes countermeasures to provide valuable reference information for other cities in China and other developing countries implementing mandatory classification policies.

The conclusion of this paper helps to complement and expand the theoretical research on compulsory MSW classification. At the same time, the case study in Shanghai can provide experience and reference for other provinces and cities in China to carry out compulsory MSW classification policy in the future. However, constrained by research time and resources, this paper also has some limitations. The short sample period using 18-month data of Shanghai from February 2019 to July 2020 awaits extension and updating in the future study. The number of cases, timeliness, and the richness of indicators still need to be improved, and the conclusions and suggested measures need more validation. Local governments should formulate policies on the treatment of MSW incorporating local conditions and characteristics. With the full implementation of compulsory MSW classification in all provinces and cities in China in the future, we will further expand the scope of sample data and incorporate more indicators into models in future research. We hope to be able to evaluate the implementation effect of the national compulsory MSW classification policy in real time. We also plan to collaborate with other researchers to

study the effect of compulsory MSW classification policy in more developing countries and help them improve their MSW management system.

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