

Article

Meta-Frontier Analysis of Disclosing Sustainable Development Information: Evidence from China's AI Industry

An-Chi Liu ¹, Junyi Wang ², Yiting Zhan ², Chien-Jung Li ³ and Yang Li ^{4,*}

- ¹ College of Business Administration, Fujian Business University, Fuzhou 350016, China; angela@fjbu.edu.cn
² New Huadu Business School, Minjiang University, Fuzhou 350108, China; wangjunyi_2018@nbs.edu.cn (J.W.); zhan yiting_2018@nbs.edu.cn (Y.Z.)
³ Department of Finance, Tunghai University, Taichung 407224, Taiwan; s07440131@thu.edu.tw
⁴ Department of International Business, National Taiwan University, Taipei 10617, Taiwan
* Correspondence: isu.yangli@gmail.com

Abstract: China currently adopts voluntary principles to disclose sustainable development information, and so considerable numbers of listed companies have chosen not to disclose such information. Since disclosure and non-disclosure groups face different production opportunities, this research uses the meta-frontier framework to completely analyze sustainable development practices of China's artificial intelligence (AI) industry. Empirical results show that the disclosure group outperforms the non-disclosure group in operating scales, efficiencies, and technologies, while the superior efficiency of state-owned enterprises (SOEs) comes entirely from the non-disclosure group. Hence, the government should mandate or actively encourage capable corporations, especially SOEs, to disclose sustainable development information, as doing so improves the overall sustainable development of society and also enhances these firms' performance. Finally, the authority can formulate a nationwide disclosure policy regardless of the existing differences in regional development.

Keywords: disclosing sustainable development information; meta-frontier approach; AI industry; reputation effect; state-owned enterprises



Citation: Liu, A.-C.; Wang, J.; Zhan, Y.; Li, C.-J.; Li, Y. Meta-Frontier Analysis of Disclosing Sustainable Development Information: Evidence from China's AI Industry. *Energies* **2021**, *14*, 6139. <https://doi.org/10.3390/en14196139>

Academic Editors: Jin-Li Hu and Edmundas Kazimieras Zavadskas

Received: 29 August 2021
Accepted: 23 September 2021
Published: 27 September 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Sustainable development, especially firms' environmental, social, and governance (ESG) behaviors, has attracted considerable attention in recent years, with even the United Nations recommending that corporations disclose their ESG practices [1]. As the world's largest emerging economy, China actively encourages domestic corporations to disclose their sustainable development information, e.g., in 2018 the "China Securities Regulatory Commission" revised and issued the "Code of Corporate Governance for Listed Companies in China," clarifying the basic framework for sustainable development disclosures and mainly focusing on ESG practices. However, disclosing sustainable development information in China is currently voluntary, and the end result still appears to not be good enough, e.g., the China Stock Market and Accounting Research Database shows that only 36 out of 134 (26.8%) listed artificial intelligence (AI) companies chose to disclose their sustainable development information. Most studies' analysis on the relationship between sustainable development and economic and/or environmental performance, including research samples of developed and emerging economies, focuses only on disclosing companies [2]. Given the low proportion of corporate sustainability disclosure and that full disclosure of sustainability information is the future trend, any sub-sample that only includes disclosing corporations is not very representative and also faces the problem of non-random selection bias. In addition, environmental adaptability, resource sufficiency, technology and cost adjustment capabilities, social visibility, and so on also influence whether companies disclose sustainable development information [3–5]. Therefore, disclosure and non-disclosure groups should face different production opportunities. Because the meta-frontier approach

is able to estimate separate production frontiers for different groups of firms, this research applies it to analyze disclosing sustainable development information of China's AI firms to complement our knowledge about this burgeoning topic.

Although the Industrial Revolution has promoted rapid economic development, the world has also paid considerable environmental and social costs. While the global economy achieved rapid growth during the 20th century, the problems of excessive energy consumption, environmental pollution, and greenhouse effect have become too serious to be ignored. Therefore, since the 1970s the international community has advocated a green and circular economy, encouraging companies to undertake social responsibilities and promote sustainable development. In 1972, the United Nations' declaration of the human environment [6], also known as the Stockholm Declaration, initially proposed the concept of sustainable development. By 1987, the World Commission for Environment and Development (WCED) published the report *Our Common Future* [7], stating that sustainable development is "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" and is also committed to achieving a balanced development between human beings and nature.

According to the theory of externalities, companies only care about their own private cost and do not bear external social costs; in other words, with regard to corporate social responsibility (CSR) or ESG, firms have no incentive to promote and/or invest in it. However, recognizing that corporate reputation is a valuable intangible asset contributing to their competitive advantage, many enterprises engage in sustainable development activities in order to gain or enhance their image [8–12]. The World Bank [13] stated that "CSR is the commitment of business to contribute to sustainable economic development." In addition, Verbin [14] and Sætra [15] suggested that ESG is increasingly replacing CSR. Hence, many scholars used the value of CSR or ESG to measure sustainable development practices. Some studies have supported a positive contribution of CSR or ESG on firms' performance [16–20], mainly from lower systematic market risks and idiosyncratic risks due to a smaller likelihood of litigation or negative market reaction [21].

The literature has generally found a positive relationship between corporate social activities and performance in developed markets, but findings are mixed in emerging markets [2]. One possible reason is that the lack of financial institutions' recognition of a firm's CSR and/or ESG activities may result in its ineffectiveness in allocating resources toward sustainable development [2,22–24], implying that disclosing sustainable development information is very important for improving future sustainability. Hence, the United Nations advises firms to disclose their ESG practices before 2030 [1].

Ever since China's reform and opening up in 1979, the country's annual average growth rate was about 9.5% up until 2018, which the World Bank described as "the fastest sustained expansion of major economies in history" [25]. However, fast development comes with damage to the environment and society. To solve domestic environmental and social problems, China has positively pushed forward sustainable development and promoted ecological and environmental protection requirements into corporations' governance structure by clarifying the basic framework for sustainable development. Firms disclosing sustainability development information signal trust in their ability to generate superior performance in comparison to their competitors [26], may be recognized as the leading and most admired firms in the market [24], and can generate positive effects on long-term performance through positive feedback on their reputation [12]. However, even if firms want to engage in sustainable development disclosures, insufficient resources may hinder small and growing companies to divulge them [3]. Hence, under the "voluntary disclosure" principle in China, each listed company decides whether or not to disclose sustainable development information based on its own resources and the external environment it faces.

Artificial intelligence (AI) is leading a new round of technological revolution and industrial transformation in the 21st century. Presently, countries around the world are seizing the opportunity to become leaders in the AI field and are formulating nationwide

strategies or plans. McKinsey Global Institute [27] suggested that about 70% of enterprises will have adopted at least one AI technology by 2030; in addition, it is expected by 2030 that AI could potentially contribute to USD 13 trillion in output, enhancing global GDP by 1.2% a year. As one of the first countries to propose a strategic plan for developing AI, China has established a complete AI development system. According to the “Big data analysis report of China’s new infrastructure in 2020,” the total fundraising of Chinese enterprises in the AI field reached CNY 311.294 billion in 2020. At the same time, the “2020 AI China patent technology analysis report” pointed out that the total number of AI technology patent applications in China surpassed the United States for the first time in 2019, allowing the country to own the most applications in the world. In October 2020, the number of AI patent applications in China reached 694,000, or an increase of 56.3% compared to 2019. According to China’s artificial intelligence development report 2018 [28], the largest share of China’s AI market covers the computer vision industry, including biometrics, image recognition, and video recognition, achieving 34.9% of the total market share, followed by speech processing (24.8%) and natural language processing (21%). China aims to create a domestic AI market of USD 150 billion by 2020 and become a world-leading AI center by 2030 [29]. The AI industry now plays an important role in China’s future development, and so core sustainable development strategies should be included when evaluating its performance.

Data envelopment analysis (DEA), proposed by Charnes et al. [30], is a data-driven tool for performance evaluation. Because it can conduct multiple-output and multiple-input analysis without specifying any particular functional form, it has been widely employed in many different fields [31–37]. However, given the low percentage of sustainability disclosures (26.8%) in China and with full mandatory disclosure of sustainable development to be the mainstream trend in the future, if we only conduct research on AI firms with sustainability disclosures, then the sample lacks representativeness and faces a problem of non-random selection bias. Furthermore, environmental adaptability, resource sufficiency, and the degree of social visibility to gain a reputation all affect whether or not firms engage in sustainability disclosures. Therefore, disclosure and non-disclosure groups should have distinctive production probability sets, but they violate the convexity assumption of conventional DEA models. This study thus uses the meta-frontier approach, proposed by O’Donnell et al. [38], by allowing each group to have its own group-frontier so as to completely analyze sustainable development practices of China’s AI industry. We further investigate the efficiency of disclosure and non-disclosure groups by different owner-types and regions.

This rest of the paper is organized as follows. Section 2 examines the related literature. Section 3 describes the methodology. Section 4 offers a description of the data and empirical analyses. The final section is concluding remarks.

2. Literature Review

The basic concept of sustainable development must not only meet the needs of contemporary people without compromising the ability of future generations, but also strive to achieve balanced development between human beings and nature. Since the 1970s, international society has encouraged corporations to engage in sustainable development, and the externality theory suggests that by only caring about their own private cost, firms have no incentive to promote sustainable development [39,40]. Studies have argued that investors anticipate enhancing their wealth from a firm without a sustainable policy, thus meaning any such policy should be carried out by non-profit organizations. However, many studies have indeed found that being sustainable can benefit firms’ performance [16–20]. Some scholars have proposed that corporations engaging in social activities can gain a positive reputation that contributes to their sustainable competitive advantage, thereby improving performance [8–12].

The signaling theory suggests that when there exists information asymmetry, the party with the information advantage can actively pass the information to the party with the

information disadvantage or disclose the information through a certain system or policy, which can subsequently reduce information asymmetry, thus improving the allocation of resources [41]. Some studies suggested that disclosing CSR or ESG contributes positively to firms' performance [2,5,42,43]. Pham and Tran [42] found that disclosing CSR has a positive effect on a firm's reputation and can improve its financial performance tremendously. Mohammad and Wasiuzzaman [2] took Malaysian firms as the research sample and showed a positive relationship between ESG disclosure and performance. However, several scholars hold different opinions. Worokinasih and Zaini [44] used listed mining companies in Indonesia as the research sample and noted that CSR disclosure has no significant impact on corporate value. Xie et al. [45] indicated that a high level of ESG disclosure has a negative correlation with corporate efficiency.

Several research studies have focused on voluntary and mandatory sustainable development disclosures [46,47] and how environmental factors affect such disclosures [4,5]. Charumathi and Ramesh [47] suggested that voluntary disclosure positively relates to corporate value, and that the market recognizes that companies disclosing ESG information have higher values. Liu and Tian [46] argued that mandatory CSR disclosure reduces investment efficiency, but when corporations have serious agency problems, mandatory disclosure helps improve the supervision of Chinese firms. Ting [5] indicated that corporate size has a positive impact on CSR disclosures. Acar et al. [4] found that firms with greater state-owned ownership have higher ESG disclosures. The above studies are only based on sample firms engaged in sustainable development disclosures and cannot be extended to infer anything about non-disclosure firms. Therefore, a complete study on disclosing sustainable development information requires appropriate methods to analyze research samples that include both disclosed and non-disclosed companies.

Traditional DEA models assume that different groups of firms share the similar technology level, but ignoring group heterogeneity may lead to estimation bias [48,49]. The concept of meta-frontier, initially proposed by Hayami [50] and Hayami and Ruttan [51], emphasizes group heterogeneity of production opportunities. O'Donnell et al. [38] incorporated the meta-frontier into DEA, allowing each group to have its own group frontier, and decomposing meta efficiency into group efficiency and technological gap. Since then, many scholars have applied the meta-frontier approach to evaluate efficiency in various fields, such as the cable TV industry [52], CO₂ emissions [49,53], water companies [54], hospitals [55], airports [56], banks [57], hotels [58,59], and more.

3. Methodology

3.1. Meta-Frontier Approach

Suppose that there are N decision-making units (DMUs). Each DMU employs k inputs $\underline{x} = (x_1, \dots, x_k)' \in \mathbb{R}_+^k$ to produce r outputs $\underline{y} = (y_1, \dots, y_r)' \in \mathbb{R}_+^r$. The production possibility set is given by the closed set:

$$\Omega = \left\{ (x, y) \mid x \text{ can produce } y \right\} \subset \mathbb{R}_+^{k+r} \quad (1)$$

Since Ω is unknown, we have to first estimate Ω from the observed input–output set. Charnes et al. [23] recommended the estimator of Ω , known as the CCR model, as follows:

$$\hat{\Omega} = \left\{ (x, y) \mid x \geq \mathbf{X}\lambda, y \leq \mathbf{Y}\lambda, \lambda \geq 0 \right\} \subset \mathbb{R}_+^{k+r} \quad (2)$$

where $\mathbf{X} = (x_1, \dots, x_N)$, $\mathbf{Y} = (y_1, \dots, y_N)$, λ is an $(N \times 1)$ vector of intensity variables, and 0 is an $(N \times 1)$ vector of zeros. Equation (2) reveals that $\hat{\Omega}$ is the smallest free disposal

convex set containing all the data. The output-oriented technical efficiency of the CCR model for DMU n , TE_n , is defined as:

$$(TE_n)^{-1} = \sup_{\delta, \lambda} \{ \delta | (x_n, \delta y_n) \in \hat{\Omega} \} \quad (3)$$

The CCR model assumes that production exhibits constant returns to scale (CRS), which is only appropriate when all DMUs are operating at an optimal scale. Banker et al. [60] extended the CCR model to account for variable returns to scale (VRS), calling it the BCC model. Mathematically, the BCC model is modified easily from the CCR model by adding the convexity constraint $\sum \lambda = 1$ in Equation (2), where $\mathbf{1}$ is an $(N \times 1)$ vector of ones.

The production possibility set estimators in both the CCR and BCC models are assumed to be convex. However, because of different resource constraints, managerial modes, technology flexibilities, and/or social visibilities to gain reputation, different groups of firms generally face different technology opportunities, and thus the assumption of convexity may not be valid. To overcome this problem, O'Donnell et al. [38] proposed the meta-frontier approach to allow each group to have its own group frontier.

Let $\hat{\Omega}^m$ be the corresponding meta-technology set estimator that envelopes the G group frontiers such that $\hat{\Omega}^m = \hat{\Omega}^1 \cup \dots \cup \hat{\Omega}^G$, where $\hat{\Omega}^g$ is the corresponding technology set estimator of group g , $g = 1, \dots, G$. The corresponding output-oriented technical efficiency relative to the meta-technology set can be expressed as:

$$(TE^m)^{-1} = \sup_{\delta, \lambda} \{ \delta | (x, \delta y) \in \hat{\Omega}^m \} \quad (4)$$

The corresponding output-oriented technical efficiency relative to the technology set of group g can be defined as:

$$(TE^g)^{-1} = \sup_{\delta, \lambda} \{ \delta | (x, \delta y) \in \hat{\Omega}^g \} \quad (5)$$

Additionally, O'Donnell et al. [38] defined the meta-technology ratio (*MTR*) as follows:

$$MTR = TE^m / TE^g \quad (6)$$

The output-oriented TE^m (TE^g) measures the ratio of the distance from the origin to the observed output y relative to the distance from the origin to the potential output, along the y direction, located on the meta-frontier y^{m*} (located on group-frontier y^{g*}). Hence, *MTR* measures the distance between the group-frontier and the meta-frontier.

3.2. The Wilcoxon Test

Suppose that there are two independent samples, $(u_1, u_2, \dots, u_{n1})$ and $(v_1, v_2, \dots, v_{n2})$, with sample sizes $n1$ and $n2$, respectively. We combine these two samples and rank the combined samples in ascending order. Under the null hypothesis H_0 : two population means are equal, any arrangement of the u 's and v 's is equally likely to occur. Replacing the observations with their combined sample ranks, the Wilcoxon W statistics are defined as the sum of the ranks of the u 's.

$$W = \sum rank(u's) \quad (7)$$

We reject the null hypothesis H_0 if W is large enough or small enough, or if the p -value is less than the specified level.

4. Empirical Analysis

4.1. Data and Input–Output Variables

The dataset, obtained from the China Stock Market and Accounting Research Database, consists of 134 listed AI companies and 372 observations from 2017 to 2019. We conduct cluster processing according to whether a firm discloses sustainable development. Among them, 36 AI companies (88 observations) disclosed their sustainable development, and the other 98 firms (284 observations) chose not to disclose. All nominal variables are deflated by the GDP deflator with 2015 as the base year.

One of the critical works for applying DEA models is to select appropriate input and output variables. Since the AI industry is a high-tech industry, innovation activities play a key role in the operation and future development of AI companies. Therefore, in addition to considering the general input variables, number of employees (*Labor*), and fixed assets (*FA*), we also include number of research and development employees (*R&Dp*) and research and development intensity (*R&DI*). The output variables are main revenue (*Rev*) and other revenue (*ORev*). The total income of an enterprise consists of operating income and non-operating income, but the importance of these two to a firm is clearly different, and so they need to be treated separately.

4.2. Empirical Specifications and Results

In addition to the statistical data of the entire sample, Table 1 also classifies them according to disclosure and non-disclosure and presents the descriptive statistics of their grouped data, respectively. It is apparent that all average values of the disclosure group are much larger than those of the non-disclosure group, except for R&D intensity (*R&DI*), with the average R&D expenditure of the disclosure group much greater at about 7.6 times that of the non-disclosure group (CNY 1.336 billion vs. CNY 175 million). In addition, the average R&D personnel of the disclosure group is approximately 5.6 times greater than the non-disclosure group (4262 vs. 756). Since the R&D investment of the disclosure group is much more than that of the non-disclosure group, both groups should have distinctive technological frontiers. Furthermore, the average number of employees and fixed assets of the disclosure group are approximately 3.7 times (10,736 vs. 2883) and 5.2 times (2517 vs. 489) that of the non-disclosure group, respectively, indicating during the 2017–2019 period that the size of the disclosure group was larger than that of the non-disclosure group. This may suggest that even if firms want to participate in sustainable development disclosures that insufficient resources may impede small and growing companies from doing so. We thus conclude that disclosure and non-disclosure AI firms own different technology opportunities. Hence, this study uses the meta-frontier approach to analyze the operational efficiency of China's AI industry.

Balk [61] suggested that it is better to regard actual technology as VRS, because even though a DMU is technically efficient under VRS, one can also augment its productivity by increasing its operating scale along the VRS frontier. Therefore, this study applies the BCC model to estimate the meta-frontier and group-frontier. Furthermore, the input-oriented approach of contracting innovation activities (input variables) contradicts the objective of sustainable development. Hence, we use the output-oriented approach, proportionally maximizing the expansion of outputs by holding inputs constant, to evaluate the operation efficiency of China's AI industry. Table 2 presents the descriptive statistics of meta efficiency TE^m , group efficiency TE^g , and meta-technology ratio MTR .

Table 1. Descriptive Statistics of Inputs and Outputs.

Variables	Mean	Std. Dev.	Min	Max
Inputs				
<i>R&Dp</i> : Number of R&D employees (persons)				
Overall	1585.11	3293.61	6.00	28,942.00
Disclosure	4262.361	5812.74	52.00	28,942.00
Non-Disclosure	755.54	956.31	6.00	6185.00
<i>R&DI</i> : R&D intensity (%), 100*R&D Expenditure/Sales				
Overall	11.39	9.62	0.06	83.23
Disclosure	11.01	9.43	0.06	83.23
Non-Disclosure	12.61	10.19	1.78	56.67
<i>Labor</i> : Number of employees (persons)				
Overall	4740.61	8919.88	175.00	74,773.00
Disclosure	10,736.31	14,501.33	200.00	74,773.00
Non-Disclosure	2882.79	5001.61	175.00	57,463.00
<i>FA</i> : Fixed assets (CNY million)				
Overall	967.03	2690.09	3.64	24,006.73
Disclosure	2517.36	5003.92	13.17	24,006.73
Non-Disclosure	486.65	900.19	3.64	7589.39
Outputs				
<i>Rev</i> : Main revenue (CNY million)				
Overall	5644.51	12,982.62	77.15	103,810.91
Disclosure	15,837.92	22,063.81	318.72	103,810.91
Non-Disclosure	2485.99	5383.48	77.15	73,936.68
<i>ORev</i> : Other revenue (CNY million)				
Overall	15.69	60.15	0.00004	847.74
Disclosure	44.76	116.38	0.05420	847.74
Non-Disclosure	6.68	15.33	0.00004	202.98

Note: All nominal variables, including *FA*, *Rev*, and *ORev*, are deflated by the GDP deflator with 2015 as the base year.

Table 2. Descriptive Statistics of TE^m , TE^g , and *MTR*.

		Mean	Std. Dev.	Min	Max
TE^m	Overall	0.2793	0.2829	0.0238	1.0000
	Disclosure	0.4142	0.3516	0.0398	1.0000
	Non-Disclosure	0.2375	0.2439	0.0238	1.0000
TE^g	Overall	0.3459	0.3096	0.0408	1.0000
	Disclosure	0.4864	0.3809	0.0408	1.0000
	Non-Disclosure	0.3024	0.2702	0.0434	1.0000
<i>MTR</i>	Overall	0.8028	0.1931	0.0956	1.0000
	Disclosure	0.8931	0.2015	0.0956	1.0000
	Non-Disclosure	0.7748	0.1818	0.3703	1.0000

4.3. General Analysis

Table 2 shows that both mean efficiencies, meta efficiency TE^m and group efficiency TE^g , of the disclosure group (0.4142 and 0.4864, respectively) are larger than those of the non-disclosure group (0.2375 and 0.3024, respectively). This may indicate compared to the non-disclosure group that the performances of the inefficient AI firms in the disclosure group are relatively similar to the efficient ones operating on the frontier. In other words, homogeneity among corporations of the disclosure group is relatively high, while the DMUs of the non-disclosure group are relatively heterogeneous. Meta-technology ratio *MTR* measures the distance between the group-frontier and meta-frontier. The average value of the disclosure group is 0.8931, which is better than the non-disclosure group's 0.7748. It suggests that the disclosure group-frontier is closer to the meta-frontier, offering potential technology opportunities for the AI industry and implying that the disclosure group may hold better operation technology. In addition, Table 3 shows that the efficient

DMUs located on the frontiers of the disclosure group fall on the meta-frontier and the group frontier and are, respectively, 14.77 and 25%, which are greater than 4.93 and 8.1% of the non-disclosure group. This advocates further that on average the disclosure group outperforms the non-disclosure group.

Table 3. Summary of Efficient DMUs Located on the Frontiers.

	Disclosure		Non-Disclosure	
	Number of Efficient DMUs	Percentage	Number of Efficient DMUs	Percentage
TE^m	13	14.77% (13/88)	14	4.93% (14/284)
TE^s	22	25.00% (22/88)	23	8.10% (23/284)
Number of DMUs	88		284	

Although Table 2 points out that the three performance indicators of the disclosure group are greater than those of the non-disclosure group, whether they are significantly different requires further statistical analysis. In addition, the group efficiency TE^s measures the distance from a DMU's operating point to the group-frontier that it belongs, indicating that group efficiencies obtained from different groups are not comparable, and thus we cannot perform the hypothesis test between groups. Hence, we apply the non-parametric test only to investigate whether average values of meta efficiency TE^m and/or meta-technology ratio MTR are significantly different between the disclosure and non-disclosure groups. The Wilcoxon rank sum tests in Table 4 show at the 0.1% level that there is indeed a significant difference in TE^m and MTR between the two groups. In other words, the disclosure group significantly outperforms the non-disclosure group.

Table 4. Wilcoxon Rank Sum Tests of Disclosure vs. Non-Disclosure.

	Mean Values		W Statistics	p-Value
	Disclosure	Disclosure		
TE^m	0.4142	0.2375	15,944	<0.001
MTR	0.8931	0.7748	18,005	<0.001

4.4. Analysis by Different Locations and/or Owner-Types

Since its reform and opening up, China's economic development and related policies have gradually extended from the east coast to the west inland, presenting clear regional differences. In addition, state-owned enterprises (SOEs) still have a pivotal position in China. In contrast to non-state-owned enterprises (NSOEs) maximizing their own profit, SOEs focus more so on raising social welfare. As different goals may lead to different operating and production modes of SOEs and NSOEs, we further divide the AI enterprise sample into coast and inland sub-samples according to location as well as into SOE and NSOE sub-samples according to owner-type.

Table 5 displays the mean values of TE^m , TE^s , and MTR by owner type and location. In terms of ownership, no matter in the overall sample or the disclosure and non-disclosure groups, the three performance indicators of SOEs are almost always larger than those of NSOEs, except for the disclosure group's MTR , which are also very close (0.8909 vs. 0.8952). As for location, there is no obvious regional advantage, and all indicators between regions appear very close, regardless of disclosures. We further apply the non-parametric test to examine location and/or owner-type effects.

The Wilcoxon rank sum tests in Table 6 show for the overall sample that TE^m and MTR of SOEs are significantly greater than those of NSOEs at the 0.1% level. For the disclosure group, there is no significant difference between SOEs and NSOEs for all three indicators. In the non-disclosure group, SOEs are better than NSOEs in both efficiencies at the 2% level of significance, while there is no significant difference in MTR with a p -value of 0.8037. Hence, SOEs' efficiency advantage mainly comes from the non-disclosure group, while

technological superiority is due to the difference in technical opportunities between groups. In terms of locations, whether it is a disclosure group or non-disclosure group, coast and inland AI firms do not exhibit significances in all three performance values, except *MTR* in the disclosure group at the 5% level of significance. In other words, under the 10% level of significance, coast and inland DMUs are insignificantly different in efficiencies and *MTR*, regardless of disclosures.

Table 5. Mean Values of TE^m , TE^s , and *MTR* by Owner-Types and/or Locations.

		Owner-Types		Locations	
		SOEs	NSOEs	SOEs	NSOEs
TE^m	Overall	0.4294	0.2481	0.2804	0.2729
	Disclosure	0.4523	0.3778	0.4059	0.5103
	Non-Disclosure	0.3825	0.2259	0.2374	0.2375
TE^s	Overall	0.5175	0.3103	0.3426	0.3654
	Disclosure	0.5454	0.4300	0.4732	0.6395
	Non-Disclosure	0.4603	0.2898	0.2980	0.3246
<i>MTR</i>	Overall	0.8589	0.7911	0.8019	0.8074
	Disclosure	0.8909	0.8952	0.8950	0.8708
	Non-Disclosure	0.7934	0.7733	0.7702	0.7980

Table 6. Wilcoxon Rank Sum Tests of Different Owner Types and/or Locations.

		SOEs vs. NSOEs		Coast vs. Inland	
		W Statistics	<i>p</i> -Value	W Statistics	<i>p</i> -Value
TE^m	Overall	6778.5	<0.001	8000.5	0.4233
	Disclosure	875	0.4425	336	0.4226
	Non-Disclosure	1839	0.0109	5099	0.3608
TE^s	Overall	–	–	–	–
	Disclosure	826	0.2392	363	0.2231
	Non-Disclosure	1881	0.0151	4984	0.2554
<i>MTR</i>	Overall	7069	0.0004	8903	0.6649
	Disclosure	806	0.1789	406.5	0.0589
	Non-Disclosure	2671	0.8037	6032	0.3691

5. Discussion

Tables 2 and 3 indicate that AI firms which voluntarily disclose sustainability information outperform those that do not disclose in terms of efficiency and production technology. In addition, the homogeneity of the disclosure group is better than that of the non-disclosure group. These empirical results suggest that after engaging in sustainable development disclosures, AI firms gain efficiency and/or productivity enhancement through signaling and reputation effects, as empirically supported by various studies [2,12,17,22,26,42,43]. This finding indicates that disclosing sustainability information can promote a sustainable future and increase the productivity of the disclosure company.

We also see that firm size of the disclosure group in the research sample is on average larger than that of the non-disclosure group, which might reflect that some small- and medium-sized enterprises (SMEs) and/or growing companies, constrained by insufficient resources, are willing yet unable to invest in sustainable development activities [3]. Conversely, large and/or respected corporations can easily signal messages to support environmental and social improvement through sustainable development activities, thereby gaining reputational effects [24] and suggesting that they are most likely to obtain the net benefit of investing in environment and social activities, at least in the long run. Therefore, these eligible companies should give priority to disclosing their sustainable development information.

Tables 5 and 6 show in terms of owner type that there is no significant difference between SOEs and NSOEs for all three performance values of the disclosure group. Additionally, SOEs are superior to NSOEs in efficiency, which come completely from the non-disclosure group, while both present insignificant differences in *MRT*, suggesting that the superior technology of SOEs arises from distinct technological opportunities between disclosure and non-disclosure groups. Therefore, SOEs are clearly qualified for sustainability disclosures, which can help achieve the goal of maximizing social welfare and promote sustainable development. Furthermore, regardless of the disclosure and non-disclosure groups, coastal and inland AI companies exhibit no significant differences in terms of technological opportunities and/or efficiency at the 10% level of significance. Hence, when formulating related policies of sustainable development disclosures, there is no need to consider the differences in the degree of regional development.

Based on the above discussion, we provide the following policy suggestions. First, the government should force qualified companies, especially SOEs, to engage in sustainable development disclosures. Corporations that reach a certain scale or possess superior technology and operation efficiency can realize long-term benefits from investing in sustainable development activities more than the costs they pay for them [5,24,26]. Perhaps due to resource crowding effects and/or a focus on short-term benefits and market value, these qualified companies have not yet participated in environmental and/or social activities. For example, Table 3 shows that 14 efficient DMUs (4.93%) of the non-disclosure group operate on the meta-frontier, which is more than the 13 efficient DMUs of the disclosure group. Hence, mandating these qualified corporations to disclose sustainable development information will not only help the overall society to upgrade its future sustainability, but also correctly guide firms to improve their future performance through enhancing their reputation and competitive advantage.

Second, some SMEs and growing companies cannot invest in environmental and/or social activities due to insufficient resources. The authority can provide tax incentives and/or supportive policies (e.g., tax concessions and/or setting stringent environmental protection standards) to guide them toward voluntarily disclosing sustainable development information. In other words, suitable actions can be deployed ahead of time in response to the trend of comprehensive disclosure and sustainable development in the future. Finally, when formulating sustainable development disclosure policies, the government can disregard any existing variations in regional development and simply design nationwide policies.

6. Conclusions

China currently adopts the voluntary principle for corporations to disclose sustainable development information, resulting in a low disclosure ratio for the AI enterprise sample (26.8%, 36 out of 134) herein. Previous studies on sustainable development mainly take a sample of disclosing enterprises [2,44–46], but with the low disclosure rate of our sample firms and because full mandatory disclosure is the future trend, conducting research only on AI firms that disclose sustainability information not only lacks representativeness, but also faces a problem of non-random selection bias. Furthermore, the average operating scale of the disclosure group is much larger than that of the non-disclosure group, suggesting that both groups should own different distinctive production probability sets. Hence, this study employed the meta-frontier approach, allowing each group to have its own group-frontier, to fully evaluate sustainable development disclosures in China's AI industry and to supplement our knowledge about this topic in emerging markets.

Empirical results showed on average that the disclosure group is superior to the non-disclosure group in operating scale, efficiencies, and production opportunities. In addition, SOEs outperform NSOEs in both efficiencies and technologies. Therefore, if enterprises with a certain scale and/or good reputation, especially SOEs, have not disclosed their sustainability information, then the government should mandate that they engage in such disclosure. Doing so not only improves the sustainable development of society, but also

guides corporations to correctly accelerate their future performance by improving their reputation and competitive advantage. Regardless of the disclosure, there is no significant difference in efficiency and technology between coastal and inland AI firms. Hence, the government can simply formulate national policies while ignoring the existing differences in regional development.

One of key limitations of this study is only taking into account output expansion. Therefore, future research can apply the hyperbolic distance function and/or directional distance function by simultaneously expanding the output and shrinking the input to further study the characteristics of disclosing sustainability information. Despite this limitation, our study finds that the disclosure group outperforms the non-disclosure group in terms of efficiency and production technology, and further analysis is carried out by location and owner type, thus providing some useful policy implications. The same methodology can also be used in other countries and/or other industries to supplement our knowledge of sustainable development.

Author Contributions: Conceptualization, A.-C.L. and Y.L.; methodology, Y.L.; software, Y.L.; validation, Y.L., Y.Z. and C.-J.L.; formal analysis, Y.L., J.W. and A.-C.L.; investigation, J.W., Y.Z. and C.-J.L.; resources, A.-C.L.; data curation, J.W. and Y.Z.; writing—original draft preparation, A.-C.L., J.W. and Y.L.; writing—review and editing, A.-C.L. and Y.L.; visualization, Y.Z. and C.-J.L.; supervision, A.-C.L. and Y.L.; project administration, A.-C.L.; funding acquisition, A.-C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

References

1. Sustainable Stock Exchanges (SSE). Sustainable Stock Exchanges Initiative: Model Guidance on Reporting ESG Information to Investors. 2015. Available online: www.sseinitiative.org/wp-content/uploads/2015/09/SSE-Model-Guidance-on-Reporting-ESG.pdf (accessed on 29 February 2020).
2. Mohammad, W.M.W.; Wasiuzzaman, S. Environmental, Social and Governance (ESG) Disclosure, Competitive Advantage and Performance of Firms in Malaysia. *Clean. Environ. Syst.* **2021**, *2*, 100015. [\[CrossRef\]](#)
3. Ren, S.; Wei, W.; Sun, H.; Xu, Q.; Hu, Y.; Chen, X. Can mandatory environmental information disclosure achieve a win-win for a firm's environmental and economic performance? *J. Clean. Prod.* **2020**, *250*, 119530. [\[CrossRef\]](#)
4. Acar, E.; Çaluyurt, K.T.; Zengin-Karabrahimoglu, Y. Does ownership type affect environmental disclosure? *Int. J. Clim. Chang. Strat. Manag.* **2021**, *13*, 120–141. [\[CrossRef\]](#)
5. Ting, P.-H. Do large firms just talk corporate social responsibility?—The evidence from CSR report disclosure. *Financ. Res. Lett.* **2021**, *38*, 101476. [\[CrossRef\]](#)
6. United Nations. Report of the United Nations Conference on the Human Environment; United Nations Publication 1972. Sales No. E.73.II.A.14. Available online: <https://digitallibrary.un.org/record/523249#record-files-collapse-header> (accessed on 10 August 2021).
7. Brundtland, G.H. Report of the World Commission on Environment and Development: Our Common Future. 20 March 1987. Available online: <https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf> (accessed on 18 July 2020).
8. Hall, R. A framework Linking Intangible Resources and Capabilities to Sustainable Competitive Advantage. *Strateg. Manag. J.* **1993**, *14*, 607–618. [\[CrossRef\]](#)
9. Eberl, M.; Schwaiger, M. Corporate reputation: Disentangling the effects on financial performance. *Eur. J. Mark.* **2005**, *39*, 838–854. [\[CrossRef\]](#)
10. Galbreath, J.; Shum, P. Do customer satisfaction and reputation mediate the CSR–FP link? Evidence from Australia. *Aust. J. Manag.* **2012**, *37*, 211–229. [\[CrossRef\]](#)
11. Saeidi, S.P.; Sofian, S.; Saeidi, P.; Saeidi, S.P.; Saeidi, S.A. How does corporate social responsibility contribute to firm financial performance? The mediating role of competitive advantage, reputation, and customer satisfaction. *J. Bus. Res.* **2015**, *68*, 341–350. [\[CrossRef\]](#)

12. Park, S. Corporate social responsibility, visibility, reputation and financial performance: Empirical analysis on the moderating and mediating variables from Korea. *Soc. Responsib. J.* **2017**, *13*, 856–871. [CrossRef]
13. World Bank. Corporate Social Responsibility Diamond: Main Elements of CSR. 2008. Available online: https://web.worldbank.org/archive/website00818/WEB/PDF/CSR_DIAM.PDF (accessed on 17 September 2021).
14. Verbin, I. *Corporate Responsibility in the Digital Age: A Practitioner's Roadmap for Corporate Responsibility in the Digital Age*, 1st ed.; Routledge: London, UK, 2020.
15. Sætra, H. A Framework for Evaluating and Disclosing the ESG Related Impacts of AI with the SDGs. *Sustainability* **2021**, *13*, 8503. [CrossRef]
16. Cai, L.; He, C. Corporate Environmental Responsibility and Equity Prices. *J. Bus. Ethic* **2014**, *125*, 617–635. [CrossRef]
17. Friede, G.; Busch, T.; Bassen, A. ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *J. Sustain. Financ. Invest.* **2015**, *5*, 210–233. [CrossRef]
18. Sherwood, M.W.; Pollard, J.L. The risk-adjusted return potential of integrating ESG strategies into emerging market equities. *J. Sustain. Financ. Invest.* **2018**, *8*, 26–44. [CrossRef]
19. Porter, M.; Serafeim, G.; Kramer, M. Where ESG fails. Institutional Investor. 2019. Available online: <https://www.institutionalinvestor.com/article/b1hm5ghqtxj9s7/Where-ESG-Fails> (accessed on 13 March 2021).
20. Buallay, A.; Fadel, S.M.; Al-Ajmi, J.Y.; Saudagaran, S. Sustainability Reporting and Performance of MENA Banks: Is There a Trade-off? *Meas. Bus. Excell.* **2020**, *24*, 197–221. [CrossRef]
21. Sassen, R.; Hinze, A.-K.; Hardeck, I. Impact of ESG factors on firm risk in Europe. *J. Bus. Econ.* **2016**, *86*, 867–904. [CrossRef]
22. Wu, S.-W.; Lin, F.; Wu, C.-M. Corporate Social Responsibility and Cost of Capital: An Empirical Study of the Taiwan Stock Market. *Emerg. Mark. Financ. Trade* **2014**, *50*, 107–120. [CrossRef]
23. Atan, R.; Alam, M.; Said, J.; Zamri, M. The impacts of environmental, social, and governance factors on firm performance. *Manag. Environ. Qual. Int. J.* **2018**, *29*, 182–194. [CrossRef]
24. Jeffrey, S.; Rosenberg, S.; McCabe, B. Corporate social responsibility behaviors and corporate reputation. *Soc. Responsib. J.* **2019**, *15*, 395–408. [CrossRef]
25. Morrison, W.M. China's Economic Rise: History, Trends, Challenges, and Implications for the United States. The Congressional Research Service. 2019. Available online: https://www.everycrsreport.com/files/20190625_RL33534_088c5467dd11365dd4ab5f72133db289fa10030f.pdf (accessed on 1 August 2021).
26. Li, Y.; Gong, M.; Zhang, X.-Y.; Koh, L. The impact of environmental, social, and governance disclosure on firm value: The role of CEO power. *Br. Account. Rev.* **2018**, *50*, 60–75. [CrossRef]
27. Bughin, J.; Seong, J.; Manyika, J.; Chui, M.; Joshi, R. *Notes from the AI frontier: Modeling the Impact of AI on the World Economy*; McKinsey Global Institute: New York, NY, USA, 2018.
28. China Institute for Science and Technology Policy at Tsinghua University. *China's Artificial Intelligence Development Report 2018*; Tsinghua University: Beijing, China, 2018.
29. Wan, G. China to publish guideline on AI development: Minister, The State Council of the People's Republic of China 2018. 2018. Available online: http://www.xinhuanet.com/english/2018-03/10/c_137029724.htm (accessed on 11 March 2020).
30. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
31. Anderson, R.I.; Robert, F.; Scott, J. Hotel Industry Efficiency: An Advanced Linear Programming Examination. *Am. Bus. Rev.* **2000**, *18*, 40–48.
32. Hwang, S.-N.; Chang, T.-Y. Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan. *Tour. Manag.* **2003**, *24*, 357–369. [CrossRef]
33. Barros, C.P.; Alves, P. Productivity in the Tourism Industry. *Int. Adv. Econ. Res.* **2004**, *10*, 215–225. [CrossRef]
34. Yang, C.; Lu, W.-M. Performance Benchmarking for Taiwan's International Tourist Hotels. *INFOR Inf. Syst. Oper. Res.* **2006**, *44*, 229–245. [CrossRef]
35. Li, Y.; Chen, Y.-K.; Chien, F.S.; Lee, W.C.; Hsu, Y.C. Study of optimal capital adequacy ratios. *J. Prod. Anal.* **2016**, *45*, 261–274. [CrossRef]
36. Guo, X.; Wei, W.; Li, Y.; Wang, L.-Y. A Study of Different Types of Air Pollutants on the Efficiency of China's Hotel Industry. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4319. [CrossRef] [PubMed]
37. Li, Y. Analyzing efficiencies of city commercial banks in China: An application of the bootstrapped DEA approach. *Pac. Basin Financ. J.* **2020**, *62*, 101372. [CrossRef]
38. O'Donnell, C.J.; Rao, D.S.P.; Battese, G.E. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empir. Econ.* **2008**, *34*, 231–255. [CrossRef]
39. Zivin, J.G.; Small, A. A Modigliani-Miller Theory of Altruistic Corporate Social Responsibility. *BE J. Econ. Anal. Policy* **2005**, *5*, 1–21.
40. Mackey, A.; Mackey, T.B.; Barney, J.B. Corporate social responsibility and firm performance: Investor preferences and corporate strategies. *Acad. Manag. Rev.* **2007**, *32*, 817–835. [CrossRef]
41. Spence, M. Job Market Signaling. *Q. J. Econ.* **1973**, *87*, 355–374. [CrossRef]
42. Pham, H.S.T.; Tran, H. CSR disclosure and firm performance: The mediating role of corporate reputation and moderating role of CEO integrity. *J. Bus. Res.* **2020**, *120*, 127–136. [CrossRef]

43. Chaudhry, A.A.; Ramakrishnan, S.; Sulimany, H.G.H.; Sharif, A. Enhancing Shareholder Value through Corporate Social Responsibility Disclosure in a Developing Country. *Stud. Appl. Econ.* **2021**, *39*. [[CrossRef](#)]
44. Worokinasih, S.; Zaini, M.L.Z.B.M. The Mediating Role of Corporate Social Responsibility (CSR) Disclosure on Good Corporate Governance (GCG) and Firm Value. A Technical Note. *Australas. Account. Bus. Financ. J.* **2020**, *14*, 88–96. [[CrossRef](#)]
45. Xie, J.; Nozawa, W.; Yagi, M.; Fujii, H.; Managi, S. Do environmental, social, and governance activities improve corporate financial performance? *Bus. Strat. Environ.* **2019**, *28*, 286–300. [[CrossRef](#)]
46. Liu, L.; Tian, G.G. Mandatory CSR disclosure, monitoring and investment efficiency: Evidence from China. *Account. Financ.* **2021**, *61*, 595–644. [[CrossRef](#)]
47. Charumathi, B.; Ramesh, L. Impact of Voluntary Disclosure on Valuation of Firms: Evidence from Indian Companies. *Vis. J. Bus. Perspect.* **2020**, *24*, 194–203. [[CrossRef](#)]
48. Wang, Q.; Zhao, Z.; Zhou, P.; Zhou, D. Energy efficiency and production technology heterogeneity in China: A meta-frontier DEA approach. *Econ. Model.* **2013**, *35*, 283–289. [[CrossRef](#)]
49. Du, K.; Lu, H.; Yu, K. Sources of the potential CO2 emission reduction in China: A nonparametric metafrontier approach. *Appl. Energy* **2014**, *115*, 491–501. [[CrossRef](#)]
50. Hayami, Y. Sources of Agricultural Productivity Gap Among Selected Countries. *Am. J. Agric. Econ.* **1969**, *51*, 564–575. [[CrossRef](#)]
51. Hayami, Y.; Ruttan, V. Agricultural Development: An International Perspective. *J. Econ. Hist.* **1973**, *33*, 484–487.
52. Hong, A.; Lee, D.; Hwang, J. Metafrontier Production Function Analysis of Horizontal and Vertical Integration in Korea's Cable TV Industry. *J. Media Econ.* **2011**, *24*, 221–236. [[CrossRef](#)]
53. Wang, Q.; Zhou, P.; Ge, S.; Zhao, Z. An International Comparison of Carbon Dioxide Emission Performance Using the Nonparametric Metafrontier Approach. *Pol. J. Environ. Stud.* **2014**, *23*, 923–931.
54. Molinos-Senante, M.; Maziotis, A.; Sala-Garrido, R. Assessing the relative efficiency of water companies in the English and Welsh water industry: A metafrontier approach. *Environ. Sci. Pollut. Res.* **2015**, *22*, 16987–16996. [[CrossRef](#)] [[PubMed](#)]
55. Tunca, H.; Yesilyurt, F. Hospital Efficiency in Turkey: Metafrontier Analysis. *Eur. Sci. J.* **2016**, *12*, 165–172.
56. Chen, Y.H.; Lai, P.L.; Piboonrungraj, P. The Relationship between Airport Performance and Privatization Policy: A Nonparametric Metafrontier Approach. *J. Transp. Geogr.* **2017**, *62*, 229–235. [[CrossRef](#)]
57. Chao, C.-M.; Yu, M.-M.; Hsiung, N.-H.; Chen, L.-H. Profitability efficiency, marketability efficiency and technology gaps in Taiwan's banking industry: Meta-frontier network data envelopment analysis. *Appl. Econ.* **2017**, *50*, 233–250. [[CrossRef](#)]
58. Assaf, A.; Barros, C.; Josiassen, A. Hotel efficiency: A bootstrapped metafrontier approach. *Int. J. Hosp. Manag.* **2010**, *29*, 468–475. [[CrossRef](#)]
59. Huang, C.-W.; Ting, C.-T.; Lin, C.-H.; Lin, C.-T. Measuring non-convex metafrontier efficiency in international tourist hotels. *J. Oper. Res. Soc.* **2013**, *64*, 250–259. [[CrossRef](#)]
60. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [[CrossRef](#)]
61. Balk, B.M. Scale Efficiency and Productivity Change. *J. Prod. Anal.* **2001**, *15*, 159–183. [[CrossRef](#)]