Article

Examining Firms' Sustainability Frontier: Efficiency in Reaching the Triple Bottom Line

Yiming Zhuang 1,*, Meltem Denizel 2 and Frank Montabon 2

1 College of Business, Frostburg State University, Frostburg, MD 21532, USA
2 Debbie and Jerry Ivy College of Business, Iowa State University, Ames, IA 50011, USA; mdenizel@iastate.edu (M.D.); montabon@iastate.edu (F.M.)
* Correspondence: yzhuang@frostburg.edu

Abstract: Sustainability has become a significant concern worldwide in recent decades. There seems to be implicit competition among firms for better sustainability performance. Like any other firm activity, sustainability undertakings require resources and their efficient use to achieve the desired performance. Firms may hesitate to undertake sustainability initiatives due to the underlying costs, leading to the question of how efficient they are in their sustainability practices. Relying on data from CSRHub and COMPUSTAT, we employed data envelopment analysis to evaluate the sustainability efficiency of 1141 large U.S. manufacturing firms from 2009 to 2018. We measured the sustainability efficiency of each firm relative to those on the efficient frontier for all the firms in our sample and also separately for each industry. The analysis results indicate that firms’ sustainability efficiency varies across years and industries. Furthermore, we show a quadratic relationship between sustainability performance and sustainability efficiency. This finding implies a process that begins with firms struggling to streamline their sustainability efforts and decreasing their efficiency as sustainability performance increases. Sustainability efficiency starts increasing only after a certain threshold is reached in sustainability performance. Our findings offer valuable insights for firms and stakeholders in their efforts to achieve desired levels of sustainability efficiency.

Keywords: data envelopment analysis; sustainability efficiency; maturity theory; CSRHub

1. Introduction

The issue of sustainability has received much attention from both practitioners and scholars [1,2]. This can be attributed to increased regulations [3], customer awareness [4], and competitive pressures [5]. One crucial aspect of sustainability is actively engaging in sustainable activities to improve sustainability performance. While the benefits of achieving high sustainability performance are acknowledged in the existing literature, some firms display hesitancy in engaging in sustainable activities [6]. One reason behind this may be that some firms assume that high sustainability performance is costly because of limited firm resources [1]. According to Bhattacharya and Sen [7], millions of dollars have been spent by Fortune 500 companies each year on CSR-related issues. There is no doubt that improving sustainability performance would require the investment of various firm resources, including financial, physical, and human resources [8]. Consequently, optimizing investments for improving sustainability performances is essential for firms.

The objective of this study is to examine the relationship between the sustainability efficiency of each firm relative to those on the efficient frontier for all the firms in our sample and separately for each industry based on samples from two database: CSRHub and COMPUSTAT. We subscribe to the triple bottom line (TBL) viewpoint of sustainability without prioritizing any one of its three pillars: economic, environmental, and social [9,10]. We measured a firm’s sustainability performance in terms of these three components. Obviously, generating this output requires resources, which are the inputs the firms

have to invest in. Sustainability efficiency is the efficiency of a company in using resources to achieve not only the desired economic outcome (profit) but also the environmental (planet) and social (people) outcomes. We aim to explore the relationship between firms’ sustainability performance and their efficiency in achieving this performance, which we call sustainability efficiency. In production literature, efficiency has been a central construct [11]. It has, however, mostly been regarded in terms of only the economic bottom line [12]. The widespread acknowledgment of the negative impacts of this activity on the environment and society now leads companies to pay attention to environmental and social outcomes as well [13]. A company that is cost efficient, i.e., successful with respect to the economic aspect, may not be so efficient when environmental and social aspects of manufacturing are considered [12]. In this regard, efficiency needs to be defined in wider terms and measured differently, including social and environmental impacts of manufacturing. We relate sustainability performance to the resources necessary for creating it in a new efficiency measure. This research is a pioneering attempt to understand how efficient firms are in their sustainability efforts. Consequently, the contributions of this study can be divided into two main aspects. First, our research comprehensively evaluates sustainability efficiency by integrating all three pillars and utilizing an aggregated score derived from multiple indicators, thereby addressing the existing research gap. Second, our investigation into the relationship between sustainability performance and sustainability efficiency shows that the relationship is not linear. Sustainability efficiency decreases until a certain threshold is reached in sustainability performance as a result of increased maturity in implementing sustainability initiatives. This implies that firms must stay adaptable and strive for superior sustainability efficiency, despite a potential initial loss of efficiency, which can be shortened by effective resource allocation and utilization.

Sustainability performance defined in terms of the TBL is a multi-dimensional variable with different units of measurement that makes using traditional efficiency measures challenging. We address this by employing data envelopment analysis (DEA) [14], a nonparametric method used to measure the relative efficiency of decision-making units and has been commonly used to study operational efficiency. The results provide the relative sustainability efficiency of the firms in our sample, which includes 1141 U.S. manufacturing firms from 2009 to 2018. Based on the results, we investigated how sustainability efficiency changes with regards to sustainability performance. We hypothesize that the relationship between sustainability efficiency and sustainability performance is not linear. We expected an initial decrease in sustainability efficiency as firms started undertaking sustainability initiatives to increase their sustainability performance due to the resetting the liability-of-newness clock [15,16]. However, as firms continued adopting sustainability practices, they were expected to gain maturity by developing sustainable operation capabilities [17], and we expected to see a turning point after which sustainability efficiency increased with sustainability performance. Our results verify these expectations.

The organization of this paper is as follows: Section 2 consists of a review of related literature, divided into Section 2.1 Sustainability, Section 2.2 DEA in Sustainability, and Section 2.3 Hypothesis Development. In Section 3, the methodology is detailed, including Section 3.1 Research Design, Section 3.2 Data Collection, Section 3.3 Data Analysis, Section 3.4 Results, Section 3.5 Discussions, and Section 3.6 Implications for both theory and practice. Finally, Section 4 concludes the paper with a summary, giving the study’s limitations and providing recommendations for future research.

2. Literature Review

Section 2 provides a comprehensive literature review, which is divided into three subsections. Section 2.1 focuses on sustainability, examining the key concepts and empirical studies related to sustainability in the context of our research. Section 2.2 offers a description of the DEA method in sustainability research. Finally, Section 2.3 presents the hypothesis development, outlining the theoretical foundations and rationale behind our research hypotheses.
2.1. Sustainability

Sustainability emerged as an explicit social, environmental, and economic ideal in the late 1970s and early 1980s [18]. This is reflected in many useful literature review papers, such as Jiang et al. [19], who looked at global sourcing and sustainability. We refer the reader to the most recent survey by Lis et al. [20], who took a bibliometric approach and mapped the sustainable supply chain management research into thematic clusters. This research indicates that efficiency is one of the contemporary topics in scientific inquiry regarding sustainability in supply chains. Efficiency is an organizational capability that dynamically changes via structural, infrastructural, and integration choices [21]. Machado et al. [13] use a maturity framework, “... to organize capabilities development in an evolutionary path as maturity is being developed over time through sustainability practices adoption”.

As we shift the focus to sustainability efficiency, we will first examine the existing literature on sustainability performance. Measuring sustainability performance has been evolving in the literature [22]. In sustainable supply chain management research, previous studies that consider all three aspects of sustainability are relatively scarce [23,24]. This is seen in the literature review by Touboulc and Walker [25]. As they show, only 39.9% of articles considered a mix of social and environmental factors in sustainable supply chain management research. Focusing on only one pillar in measuring sustainable supply chain performance leads to limitations [12]. Recent studies have shifted from examining only one or two pillars of sustainability [22] to considering all three pillars in measuring sustainable performance. For instance, Said et al. [26] proposed a comprehensive disclosure checklist designed for evaluating corporate sustainability performance, incorporating the environmental and social pillars of the TBL. Following this, Wang et al. [27] presented an input–output modeling approach that assesses global supply chain sustainability performance. However, their model did not include the social pillar. Meanwhile, Malesios et al. [28] focused on creating a sustainable supply chain performance measurement model for SMEs, including all three pillars. Similarly, Pachar et al. [29] explored a two-stage DEA model that investigates the impact of sustainable operations on retail performance. Qorri et al. [30] introduced a novel method for evaluating sustainability aspects throughout the entire supply chain. Finally, Rajesh [31] demonstrated a two-stage prediction model that employs gray and rough set theories to assess and predict supply chain sustainability performance across various dimensions. All of these studies have taken the three pillars of sustainability into consideration. Meanwhile, aiming to propose a novel set of key sustainability performance indicators, Neri et al. [22] offered an extensive review of the diverse measurements for evaluating sustainability performance. Among the 69 papers they reviewed, 27 of them incorporated all pillars of sustainability into the measures. Readers can refer to Table 2 in their paper for a detailed summary of the existing literature. Their review also revealed an increasing trend, with more studies considering all three pillars in recent years. In line with recent trends in the literature, our study incorporates all three pillars to comprehensively measure sustainability performance.

2.2. DEA in Sustainability

Although DEA has been used in the sustainability context, there have not been any studies addressing the efficiency and performance relationship in terms of TBL. For a detailed literature review of DEA applications in sustainability research between 1996 and 2015, readers can consult Zhou et al. [32]. Table A1 in Appendix A summarizes the representative studies that use DEA in sustainability literature. An increasing tendency has been noted in combining the three pillars for gauging sustainability efficiency, though this approach is not as prevalent as measuring sustainability performance. Additionally, studies employing DEA in the context of sustainability have focused on specific environmental or economic outcomes such as waste reduction, carbon emissions, GDP, or some combination of these or similar factors. To address this gap, our study incorporates all three pillars in assessing sustainability efficiency holistically. Instead of focusing on specific sustainability
outcomes, our approach to measuring sustainability efficiency is based on an aggregated score of multiple indicators of sustainability outcomes. Building on this measurement of sustainability efficiency, the primary aim of this study is to explore the relationship between sustainability performance and sustainability efficiency, an area that remains under-investigated in the existing literature. This study differs from the literature in providing a macro-level understanding of how companies use their resources with respect to those on the frontiers of sustainability efficiency.

2.3. Hypothesis Development

Sustainability undertakings may be challenging for companies and require non-trivial changes that encompass all departments within an organization [33]. Organizational change literature suggests that such organizational changes can reset the liability-of-newness clock [34]. Liability-of-newness theory [35] argues that “emerging organizations face complex challenges limiting their viability, including managing relationships among strangers, assembling resources quickly, and coping with difficult environments”. Amburgey et al. [36] states “A changed organization that survives long enough can rebuild internal processes and external relationships. In this way, change can be thought of as “resetting” the liability-of-newness clock” [15,16]. Likewise, Haveman [34] states “The task facing an organization that undertakes change is similar to that facing a new organization. The effort involved in developing a structure and system of activities de novo or in restructuring an existing organization lowers the efficiency of operations, which leads to poor performance in the short term and lower survival chances in the long term”.

Similar observations regarding the impact of change on performance have been reported in the innovations literature. Bourke and Roper [37] show a short-term disruption effect on performance but longer-term positive benefits of quality improvement on product innovation performance. McAdam and Bannister [38] state “Often there is a discrepancy between short-term and long-term business results, and it is difficult to determine when results should be analyzed, following TQM type interventions. The longer the time scale, the more opportunity the TQM process has to realize its impact on business results”. Maturity based models rooted in quality management research and first formulated by Shewhart in the 1930s provide a useful lens for understanding process improvement and change management in multifaceted situations. It has been used in the literature to “… describe and determine the state of perfection or completeness (maturity) of certain capabilities” [39]. The main goal is to outline conditions when certain capabilities reach the best state for its purpose. The general maturity framework also delineates the stages or levels for certain capabilities to reach the best state. These stages or levels reflect a capability’s evolution from being less mature to more mature [40,41]. This view also applies to a firm’s sustainability efficiency as an organizational capability. Machado et al. [13] discuss “… the challenges of developing and integrating sustainability to business operations” and try to answer the question of “how (do) capabilities of sustainable operations evolve?” Using a maturity modeling framework, they show that maturity is reached through “sustainable operations capabilities adoption and development”. In other words, as companies develop and adopt sustainable practices, they are expected to increase their maturity through sustainable operations capabilities. Similarly, we argue that through adoption of sustainability practices, firms are expected to go through a path of increased maturity and improve their capability in sustainability efficiency.

In 2021, the proportion of S&P 500 companies that routinely released reports with an ESG focus had increased to 86%, compared to 35% of publicly traded corporations in 2010 [42]. Threlfall et al. [43] state that 80% of companies in the world report on sustainability, and North America has the highest regional sustainability reporting rate by 90%. The same source also states that Global Reporting Initiative (GRI) Standards remain the dominant standards for sustainability reporting. The reports provide performance on several metrics related to environment, society, and governance and have been identified a major catalyst for sustainability performance [44,45]. Reporting for sustainability pro-
vides a starting point for planning changes in organizational processes, and such changes improve the reporting process [46]. In other words, sustainability reporting leads to organizational changes in companies towards sustainability goals, and sustainability reporting and organizational change reinforce each other. The periodicity of sustainability reports (GRI reports are yearly, for instance) indicates a continuity in undertaking sustainability initiatives. As such, companies are expected to improve their sustainability performance as they continue to undertake new initiatives.

GRI reports make clear that sustainability initiatives require significant changes in existing organizational processes [33]. These changes can be either structural or infrastructural and most likely both. In terms of sustainability efficiency in achieving the triple bottom line, firms with lower levels of sustainability performance will not reap the full benefits of their efforts. They would lose some efficiency due to the liability of newness [47]. Their goals need to be well aligned between departments, and implementations of sustainable practices need to be well established. As their maturity increases as reflected by their sustainability performance, their efficiency will increase. Therefore, we expect to observe a decrease in sustainability efficiency of companies at the start of their efforts towards sustainability. Furthermore, as companies continue undertaking more sustainability initiatives and increase their sustainability performance, we expect to see an increase in sustainability efficiency.

As above discussions suggest, we use both the liability of newness and maturity theories as the basis to establish the relationship between sustainable performance and sustainability efficiency. Below, we state these as a formal hypothesis.

**Hypothesis 1.** At lower levels of sustainability performance, we expect to see a decrease in sustainability efficiency, which will start increasing after a certain threshold is reached in sustainability performance.

This describes a U-shaped relationship between sustainability efficiency and sustainability performance.

3. Methods

3.1. Research Design

DEA provides a relative measure that specifies the efficiency of a company with respect to the frontier companies in the sample by consolidating multiple inputs and multiple outputs into a single output/input ratio and optimizing their weighted averages [48,49]. Alternatively, DEA can be employed to analyze inefficient configurations [50]. As discussed in our literature review, the method has been used widely in sustainability studies. It considers the ratio of a weighted sum of multiple outputs to a weighted sum of multiple inputs as a measure of the relative efficiency for each unit [51]. In this paper, a unit is one specific company, and the data are from two sources: the CSRHub database and the COMPUSTAT database via Wharton Research Data Services (WRDS). Thus, DEA maximizes each company’s efficiency separately by determining the best set of weights such that the efficiencies for all other companies are less than or equal to one. These attributes make DEA a very suitable tool to determine firm sustainability performance and sustainability efficiency. Our research requires a multiple-measure analysis technique, and DEA “helps to obviate many of the conceptual problems surrounding single-measure studies” [52]. We adopted the input-oriented variable returns to scale (VRS) DEA model. Our focus was to calculate efficiency scores assuming constant outputs similar to Jacobs et al. [41]. The input-oriented model can determine how firms adjust their resource investments to achieve the desired sustainability performance. Due to the heterogeneous nature of our sample, outputs will change in different proportions as inputs are changed in the VRS analysis.
3.2. Data Collection

We use data from two sources. We first obtained the CSRHub score of each firm from the CSRHub database. CSRHub provides twelve aggregated indicators of more than 54,062 firms’ environmental and social sustainability performance in 155 countries [53]. The database combines a wide variety of data sources such as ASSET4, Carbon Disclosure Project (CDP), and MSCI (formerly KLD and GMI). It normalizes the data and provides scores from 0 to 100 for a firm’s overall sustainability performance and individual scores in the community, employees, environment, and governance dimensions of sustainability performance [54]. The overall score in CSRHub is based on the combination of the category ratings (i.e., community, employees, environment, and governance), which consist of twelve indicators (i.e., community development and philanthropy, human rights and supply chain, product, compensation and benefits, diversity and labor rights, training and safety and health, energy and climate change, environment policy and reporting, resource management, board, leadership ethics, and transparency and reporting) [54]. The default is a simple average, and we used the default.

We would like to clarify that the overall CSRHub score is not just a simple aggregation of environmental performance and social performance but rather a weighted score of various subcategories in both environmental and social performance. The computation of the CSRHub score also requires more information about the companies, as described in the CSRHub rating rules (https://www.csrhub.com/csrhub-esg-rating-rules, accessed on 27 May 2020). Considering these factors, we believe that the overall CSRHub score provides a more comprehensive representation of a company’s overall performance in environmental and social efforts, compared to individual scores for environmental and social performance. Relying solely on individual scores may introduce bias, as it does not consider the weighting assigned to each subcategory.

The CSRHub database has several major advantages over other CSR-related databases. First, it is relatively objective as it combines data from several leading ESG analyses (e.g., EIRIS, Carbon Disclosure Project (CDP), ASSET4 from Thomson Reuters) and over 250 premier influential NGOs, instead of solely relying on self-reported measures [55]. Second, the database is updated monthly, which is more frequent than other databases. Third, while CSRHub has not been used as widely as the KLD databases, it has recently been used by more scholars [55–57]. Bu and Wagner [58] found a significant and positive correlation between six KLD measures and CSRHub rating for 290 firms.

We matched the firms in CSRHub to financial information (i.e., assets, employees, COGS, and ROA) from the COMPUSTAT database via WRDS based on ticker symbols. We limited our sample to manufacturing firms in North America (SIC 20–30). The average CSRHub score in our sample is 52/100, and the maximum is 66/100 (see Table 1 for industry averages over the years), indicating that the manufacturing industry does not show a high performance in terms of environmental and social pillars of sustainability. Nevertheless, the question of their efficiency in attaining this performance still remains.

An important part of DEA is identifying the inputs and outputs with which the companies’ efficiencies in the sample will be determined. The TBL perspective of sustainability asserts that in addition to profit (economic impact), companies must also work for the people (social impact) and for the planet (environmental impact). In addition to its shareholders, society and the environment are also a firm’s stakeholders, which means firm resources must be used in a fashion that leads to superior performance not only for profits but also for the people and the planet. At the fundamental level, firms use three resources, capital, labor, and material, to produce goods and services. From the TBL perspective, a firm is expected to put these resources to use to achieve at least a satisfactory performance in all three bottom lines. We consider these three resources as the inputs to achieve the desired sustainability performance and determine the firm’s sustainability efficiency. By sustainability efficiency, we refer to the efficiency with which firms use these resources to attain sustainable outcomes. For this purpose, we employed input-oriented DEA. We operationalize capital by total assets because a firm’s cost of capital refers to the funds that
are used to acquire assets [59]. Labor is measured by the number of employees. Labor provides the resources such as expertise, staffing, and service to convert the raw materials to finished products [60]. The U.S. Bureau of Labor Statistics measures labor as the labor force [61]. Employees are the major sources of labor. We measured material by the cost of goods sold (COGS), which is “the costs that can be directly attributed to the sale, e.g., the purchasing cost of the raw materials and the components that go into the finished goods” [62].

Table 1. Average CSRHub score based on industry–year.

| Year | 20  | 23  | 24  | 25  | 26  | 27  | 28  | 29  | 30  | 31  | 32  | 33  | 34  | 35  | 36  | 37  | 38  | Mean |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 2010 | 52.1| NA  | NA  | NA  | NA  | 52.3| NA  | NA  | NA  | 47.2| 50.2| 48.7| 52.8| 47.1| 50.1|
| 2011 | 52.4| NA  | NA  | NA  | NA  | 51.3| NA  | NA  | NA  | 48.3| 49.5| 48.0| 50.8| 48.6| 49.8|
| 2012 | 49.8| 51.2| NA  | NA  | NA  | 49.4| NA  | NA  | NA  | 46.3| 46.6| 48.4| 46.4| 49.9| 46.7| 48.3|
| 2013 | 52.3| 52.9| NA  | NA  | NA  | 52.7| NA  | NA  | NA  | 48.5| 49.5| 51.6| 51.1| 52.5| 50.5| 51.4|
| 2014 | 55.1| 55.3| 56.6| 55.3| 57.8| 56.2| 57.5| 54.2| NA  | 53.6| 54.2| 55.2| 54.9| 54.9| 53.8| 55.3|
| 2015 | 55.5| 55.9| 57.5| 56.0| 57.6| 55.2| 56.5| 54.4| 56.8| 55.0| 55.0| 55.9| 54.9| 55.3| 54.8| 55.8|
| 2016 | 53.0| 51.8| 52.8| 51.5| 54.5| 50.5| 51.6| 52.2| 52.7| 51.2| 51.0| 52.5| 51.4| 51.3| 51.9| 52.0|
| 2017 | 52.3| 49.5| 49.2| 50.6| 53.1| 46.9| 49.7| 52.2| 51.3| 49.7| 48.9| 50.8| 50.3| 50.3| 49.6| 50.3|
| 2018 | 51.5| 49.2| NA  | 48.2| 51.6| 47.1| 48.2| 51.5| 49.4| 47.3| 48.6| 49.8| 49.5| 49.1| 48.9| 49.3|
| Mean | 52.7| 52.3| 54.0| 52.3| 54.6| 51.2| 52.1| 52.7| 52.6| 50.2| 49.9| 51.6| 50.6| 51.9| 50.2|

Note: NA is for two reasons: 1. There is no single firm in the specific industry of the given year. 2. There are less than 15 firms in the specific industry of the given year.

The output we are interested in is the firm’s sustainability performance, as defined by its three pillars (profit, people, and planet). While Bendheim et al. [40] used data from Kinder, Lydenberg, Domini (KLD), Soytas et al. [47] used the measurements provided by the CSRHub for the environment and social pillars of sustainability performance, and we follow their lead. Specifically, the aggregated score of four dimensions (community, environment, employees, and governance) was used for a combined measure of environmental and social sustainability performance. ROA was used as a measure of economic sustainability performance, which is in line with prior sustainability research [22,63]. Thus, we incorporate all the pillars of sustainability in our analysis. In our analysis, sustainability performance indicates the maturity level of the firms in implementing sustainable practices. Figure 1 describes the constructs we use as inputs and outputs for DEA, and Table 2 provides the operationalization of these constructs.

Figure 1. Inputs and outputs considered in DEA analysis.
### Table 2. Definitions of inputs and outputs of DEA model.

<table>
<thead>
<tr>
<th>Inputs and Outputs</th>
<th>Definition</th>
<th>Types of Firm Resources (for Input Variables)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total assets</td>
<td>Total amount of assets in the firm’s balance sheet</td>
<td>Capital resources</td>
</tr>
<tr>
<td>Employees</td>
<td>Numbers of employees.</td>
<td>Labor resources</td>
</tr>
<tr>
<td>COGS</td>
<td>COGS includes the direct costs that could be trackable to the production of the goods.</td>
<td>Material resources</td>
</tr>
<tr>
<td>CSRHub score</td>
<td>The aggregated score of four dimensions including community, environment, employees, and governance.</td>
<td>-</td>
</tr>
<tr>
<td>ROA</td>
<td>Return on assets.</td>
<td>-</td>
</tr>
</tbody>
</table>

Based on the beforementioned discussion, the DEA used in this study can be formulated as follows:

\[
\theta^* = \min_{\lambda_j} \theta^t
\]

subject to

\[
\sum_{j=1}^{n_t} \lambda_j x_{ij}^t \leq \theta^t x_{iy0}^t \quad \text{for } i = 1, 2, 3
\]

\[
\sum_{j=1}^{n_t} \lambda_j y_{jr}^t \geq y_{ry0}^t \quad \text{for } r = 1, 2
\]

\[
\sum_{j=1}^{n_t} \lambda_j = 1, \quad \text{for } j = 1, \ldots, n_t
\]

\[
\lambda_j \geq 0, \quad \text{for } j = 1, \ldots, n_t
\]

where \( \theta^t \) denotes the efficiency score in year \( t \) of the firm. \( x_{ij}^t \) and \( y_{jr}^t \) denote the \( i \)-th input and \( r \)-th output of firm \( j \) in year \( t \). In our case, \( m \) equals three and \( s \) equals two, given we have three inputs (i.e., assets, employees, and COGS) and two inputs (i.e., CSRHub score and ROA) in the DEA model. Therefore, \( x_{1j}^t \) denotes the assets of firm \( j \) at year \( t \), \( x_{2j}^t \) denotes the number of employees of firm \( j \) at year \( t \), and \( x_{3j}^t \) denotes the COGS of firm \( j \) at year \( t \). \( y_{1j}^t \) denotes the CSRHub score of firm \( j \) at year \( t \). \( y_{2j}^t \) denotes the ROA of firm \( j \) at year \( t \). \( \lambda_j \) denotes the variable weights determined by the solution to this model. \( n_t \) denotes the number of decision-making units (DMUs) (i.e., number of firms) in year \( t \).

In terms of our hypothesis, we expected that a firm’s sustainability efficiency first decreases as CSRHub score increases but then increase as the CSRHub score continues to increase. A similar pattern can be observed for the relationship between sustainability efficiency and ROA.

#### 3.3. Data Analysis

We are interested in understanding how efficient the firms are in achieving sustainability performance as measured by individually optimized weighted averages of the three indicators of sustainability: ROA and the CSRHub score, which combines both social and environmental sustainability.

It should be noted that our data include firms from different industries across time. Most studies [64, 65] with a data structure like ours conduct one DEA analysis containing all the observations. However, firms’ DEA scores may not be comparable if we include all firms in one DEA analysis because this approach does not take the heterogeneous characteristics of the firms across the different industries and years.

Instead, given the panel structure of our data, we ran the DEA analysis by following the approach in Jacobs et al. [41]. Specifically, we grouped the firms based on the industry–year and ran a DEA analysis for each group. We used 2-digit SIC as the basis for industry. In total, our original dataset consists of 20 industries and 9 years, which gives 180 groups. However, following Bowlin [66], we dropped the groups with less than 15 companies from
our analysis because the minimum number of DMUs to run a DEA analysis is suggested to be three times the total number of inputs and outputs. We finally have 107 groups with sample sizes (i.e., number of DMUs) from 15 to 355. Please note that the 109 groups are indeed derived from the nine-year period but not through a simple multiplication because we have a varying number of industries over the nine years. Some industries may have more than 15 companies in specific years but fewer than 15 companies in other years. In such cases, the industries in the years with fewer than 15 companies were dropped from the final sample.

Table 3 presents the sustainability efficiency scores by industry and year. When we consider industry averages over the years (average over each column in Table 3), the industry with the lowest sustainability efficiency score is Industrial and Commercial Machinery and Computer Equipment (SIC code 35). The top three industries with the highest average sustainability efficiency are SIC 30—Rubber and Miscellaneous Plastics Products, SIC 26—Paper and Allied Products, and SIC 27—Printing, Publishing, and Allied Industries. These three industries share several common features. The nature of the products manufactured in these industries may promote the adoption of sustainable practices. For example, the paper industry faces growing pressure to reduce deforestation and embrace more sustainable raw material sourcing methods. Similarly, the rubber and plastics industry is subject to scrutiny concerning waste management and the environmental impact of non-biodegradable materials. These industries may have already undergone significant technological advancements and innovations, allowing them to operate more sustainably. For instance, progress in recycling technologies has enabled the paper industry to recycle and reuse materials more efficiently. Likewise, innovations within the rubber and plastics industry have led to the creation of more environmentally friendly materials and production processes.

Table 3. Average sustainability efficiency based on industry–year.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.35</td>
<td>0.56</td>
<td>0.53</td>
<td>0.57</td>
<td>0.60</td>
<td>0.58</td>
<td>0.30</td>
<td>0.45</td>
<td>0.67</td>
<td>0.50</td>
</tr>
<tr>
<td>Note: NA is for two reasons: 1. There is no single firm in the specific industry of the given year. 2. There are less than 15 firms in in the specific industry of the given year.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, we utilized a one-way analysis of variance (ANOVA) with repeated measures to assess the sustainability efficiency scores across different industries over several years. This approach allowed us to measure the same industries at multiple points in time, providing a more nuanced view of the changes and trends within each sector. By using ANOVA with repeated measures, we accounted for within-industry variations over time, creating a more robust and comprehensive analysis. This method is superior to simply comparing the mean scores of different industries at a single point in time, as it captures the inherent variations and trends within each industry over the years. This approach also gave us the ability to better understand the dynamics of sustainability efficiency scores.
within industries and their progression over time. The result shows significant differences across industries ($p < 0.001$). Several industry characteristics could potentially account for the differences in sustainability efficiency scores. These factors include the level of environmental regulation and policy affecting each industry, the extent of technological innovation adopted, the types and amounts of resources used, and the age and maturity of the industry. Public pressure and consumer demand for sustainable practices could also play a significant role. Economic factors, including the financial stability of each industry, can impact the resources devoted to sustainable practices. Finally, the geographical location of industries, particularly in regions with strict environmental laws or heightened public awareness about sustainability, may influence these scores.

Furthermore, we specifically look at the firms whose sustainability efficiency scores are on the frontier (i.e., efficiency score equals one). We observed that 409 firms are on the efficient frontier in the different years, representing 35.85% of all firms. Moreover, these 409 firms are from 15 industries, with chemicals and allied products taking the largest proportion (i.e., 100 firms). The primary reason for chemicals and allied products representing the largest proportion is that firms from this sector comprise a significant portion of the observations in the database, accounting for 1838 out of the 6483 observations. Meanwhile, the chemicals and allied products industry is often subject to stringent environmental regulations due to the potential environmental impacts associated with the production, transportation, and disposal of chemicals. This regulatory pressure may drive firms in the industry to prioritize sustainability and implement more efficient practices to comply with regulations and avoid penalties.

Our main interest is the relationship between sustainability efficiency and sustainability performance, which indicates the firms’ maturity levels in implementing sustainable practices. In Figure 2, we provide a scatterplot of CSRHub scores and sustainability efficiency (DEA scores) of individual firms. Most of the companies are clustered in the region where sustainability efficiency scores are between 0 and 0.3, and sustainability performance scores are between 40 and 60. The blue line on each graph is fitted based on the locally weighted scatterplot smoothing (LOWESS). As recommended by Haans et al. [67], using a nonparametric method such as LOWESS is an effective strategy to identify the existence of a U-shaped relationship. The plot in Figure 2 indicates a quadratic relationship (U-shaped) between sustainability performance and sustainability efficiency. In the next section, we verify this relationship.

**Figure 2.** Scatter plot of CSRHub scores, ROA and sustainability efficiency scores (raw); The plotted data are after winsorization.
3.4. Results

DEA calculates the efficiency score of a firm by optimizing that firm’s individual ratio of weighted averaged inputs and outputs subject to the constraints that the corresponding ratio of all other firms in the sample is less than or equal to one. Therefore, for the 6483 firm-year observations in our sample, we solved 6483 separate linear optimization problems to obtain each firm’s efficiency score. The parameters of these linear optimization problems are the input and output values that are available for each firm. Of particular managerial importance is the impact of these parameters (inputs or outputs) on efficiency. Rather than using a one-parameter-at-a-time sensitivity analysis as usually performed in linear programming, we performed a multiple regression analysis. The dependent variable is the linear program’s objective function, which is the sustainability efficiency score, and the independent variables are the parameters (inputs or outputs or both). In this manner, we performed a form of global sensitivity analysis, where all inputs or outputs are varied at the same time [68]. This is an approach that has been successfully used in the literature before [69,70].

It is important to emphasize that the regression models presented in this section are not second-stage regressions that are customary in the literature after DEA efficiency results are obtained [65,71]. As mentioned in the previous paragraph, our regressions provide a means of sensitivity analysis to identify each variable’s significance (both input and output variables) used in the DEA to measure sustainability efficiency.

3.4.1. Impact of Inputs and Outputs on Sustainability Efficiency

Regression with Two-Way Clustering

We performed a regression analysis for sensitivity analysis as discussed above. This regression relates the calculated efficiency scores to the inputs and outputs used in the DEA model. It should be clear that we are regressing the efficiency scores on the same variables we used to determine them. It is therefore expected and desired [68] that the resulting regression will show a high $R^2$ value. To ensure that the regression residuals follow a Gaussian distribution, we took the natural logarithm of the sustainability efficiency scores [64] as well as three inputs to meet the assumptions of OLS. The industry-fixed effects based on 2-digit SIC codes were included to control the industry effects; in particular, it can be argued that the ratio of labor to capital can be different among industries. Given that this study involves resource efficiency, the differences have to be controlled. We also include the year-fixed effects controlling for the factors that vary over time [72]. All continuous variables have been winsorized at the 1% and 99% levels.

Due to the nature of the DEA method, an issue that needs to be considered is the serial correlation in the DEA efficiency score, which is the dependent variable in the regression analysis. The non-dependence of the dependent variable violates the assumptions of the OLS estimator [72]. To tackle this issue, we used OLS regression with clustered standard errors. Specifically, we ran the OLS with clustering industry and year. However, this approach could have issues because the year and industry fixed effects have already been included in the regression. Having industry and year both in the clustering and fixed effect gives a double penalty for including the fixed effects in the regression. The reason is that a penalty is already applied using cluster–robust standard errors at the same level [73]. Accordingly, we used the approach that Correia (2019) [73] proposed, which imposes a small sample adjustment for the estimator covariance matrix. The adjustment is based on the degree of freedom lost, including the fixed effects.

Additionally, a second approach, known as the generalized estimating equation (GEE), was used to ensure the robustness of the results. The GEE is a method that accommodates non-independent observations [74]. We found the GEE results are very similar to those from the OLS with two-way clustering in terms of coefficients and $p$-values as seen in the detailed discussions below.

Multicollinearity has been checked based on the variance inflation factor (VIF). The mean VIF is 4.13, which is well below the conventional cut-off of 10 [75]. Therefore, multicollinearity should not be a concern for this study. The summary statistics and correlations matrix are
reported in Table 4, and the OLS regression results are shown in Table 5 (Model 1). According to the correlation matrix, sustainability efficiency has a significant negative correlation with assets, employees, COGS, and ROA but a positive correlation with CSRHub score. Assets, employees, and COGS are all strongly positively correlated with each other, which makes sense as larger companies (more assets and employees) would also have higher costs of goods sold. CSRHub score is positively correlated with all other variables except sustainability efficiency and ROA. The negative correlation with sustainability efficiency might suggest that companies with higher CSRHub scores (indicating better environmental and social responsibility performance) tend to have lower sustainability efficiency scores. ROA is positively correlated with all variables except sustainability efficiency. This negative correlation suggests that companies with higher returns on assets tend to have lower sustainability efficiency scores. The adjusted $R^2$ of the OLS model is 0.701, which shows a good fit. The results using the GEE are also reported in Table 5.

Table 4. Summary statistics and correlations table (N = 6483).

<table>
<thead>
<tr>
<th></th>
<th>SE</th>
<th>Assets</th>
<th>Employees</th>
<th>COGS</th>
<th>CSRHub Score</th>
<th>ROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets (log)</td>
<td>−0.558 ***</td>
<td>−0.461 ***</td>
<td>0.882 ***</td>
<td>−0.543 ***</td>
<td>0.868 ***</td>
<td>0.896 ***</td>
</tr>
<tr>
<td>Employees (log)</td>
<td>−0.461 ***</td>
<td>0.882 ***</td>
<td>0.227 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
</tr>
<tr>
<td>COGS (log)</td>
<td>0.164 ***</td>
<td>0.227 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
</tr>
<tr>
<td>CSRHub score (log)</td>
<td>0.164 ***</td>
<td>0.227 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
<td>0.207 ***</td>
</tr>
<tr>
<td>ROA</td>
<td>−0.119 ***</td>
<td>0.491 ***</td>
<td>0.563 ***</td>
<td>0.514 ***</td>
<td>0.064 ***</td>
<td>0.064 ***</td>
</tr>
<tr>
<td>Mean</td>
<td>−1.991</td>
<td>7.288</td>
<td>1.031</td>
<td>6.336</td>
<td>51.582</td>
<td>−0.030</td>
</tr>
<tr>
<td>S.D.</td>
<td>1.516</td>
<td>1.788</td>
<td>1.985</td>
<td>2.119</td>
<td>6.146</td>
<td>0.242</td>
</tr>
</tbody>
</table>

Notes: SE refers to sustainability efficiency; $p$-values in brackets; All continuous variables have been winsorized at 1% and 99% level; *** $p < 0.01$.

Table 5. Regression results.

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS with Two-Way Clustering</th>
<th>GEE</th>
<th>OLS with Two-Way Clustering (Quadratic)</th>
<th>GEE (Quadratic)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>−0.360 *** (0.044)</td>
<td>−0.404 *** (0.022)</td>
<td>−1.006 *** (0.128)</td>
<td>−0.990 *** (0.069)</td>
</tr>
<tr>
<td>Assets$^2$</td>
<td></td>
<td>0.043 *** (0.006)</td>
<td></td>
<td>0.041 *** (0.005)</td>
</tr>
<tr>
<td>Employees</td>
<td>−0.263 *** (0.049)</td>
<td>−0.268 *** (0.023)</td>
<td>−0.245 *** (0.036)</td>
<td>−0.257 *** (0.020)</td>
</tr>
<tr>
<td>Employees$^2$</td>
<td></td>
<td>−0.005 (0.011)</td>
<td></td>
<td>−0.004 (0.004)</td>
</tr>
<tr>
<td>COGS</td>
<td>−0.146 *** (0.016)</td>
<td>−0.116 *** (0.016)</td>
<td>−0.062 *** (0.021)</td>
<td>−0.081 *** (0.026)</td>
</tr>
<tr>
<td>COGS$^2$</td>
<td></td>
<td>−0.010 ** (0.004)</td>
<td></td>
<td>−0.006 ** (0.003)</td>
</tr>
<tr>
<td>ROA</td>
<td>0.983 *** (0.223)</td>
<td>0.946 *** (0.061)</td>
<td>2.317 *** (0.259)</td>
<td>2.229 *** (0.095)</td>
</tr>
<tr>
<td>ROA$^2$</td>
<td></td>
<td>1.499 *** (0.338)</td>
<td></td>
<td>1.399 *** (0.100)</td>
</tr>
<tr>
<td>CSRHub score</td>
<td>0.107 *** (0.016)</td>
<td>0.096 *** (0.002)</td>
<td>−0.556 *** (0.131)</td>
<td>−0.489 *** (0.021)</td>
</tr>
<tr>
<td>CSRHub score$^2$</td>
<td></td>
<td>0.006 *** (0.001)</td>
<td></td>
<td>0.006 *** (0.000)</td>
</tr>
<tr>
<td>Constant</td>
<td>−3.653 *** (1.000)</td>
<td>−0.963 *** (0.198)</td>
<td>15.846 *** (3.047)</td>
<td>15.687 *** (0.596)</td>
</tr>
<tr>
<td>Industry-fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year-fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># of observations</td>
<td>6483</td>
<td>6483</td>
<td>6483</td>
<td>6483</td>
</tr>
<tr>
<td>$N$</td>
<td>0.702</td>
<td>0.764</td>
<td>0.762</td>
<td>14,267 ***</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.701</td>
<td>0.701</td>
<td>0.701</td>
<td>0.701</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. 
Table 5 (Model 1) shows that all three inputs are significantly related to sustainability efficiency such that an increase in a firm’s level of investments in these three inputs leads to a decrease in its sustainability efficiency. The significant results also offer support to the selection of the three variables as the inputs of the DEA model. The two output variables (i.e., CSRHub score measuring social and environmental performance and ROA measuring the financial performance), which collectively measure sustainability performance, show positive relationships with sustainability efficiency. OLS results verify that sustainability efficiency increases with the CSRHub score and ROA. OLS regression, however, may not be the best regression model to represent the pertinent relationship. We investigate this further in the following two sections.

Regression with Quadratic Terms

The OLS regression results suggest that firms with higher CSRHub scores (environmental and social sustainability performance) and ROA values have higher sustainability efficiency. We, however, hypothesized a U-shaped relationship between sustainability efficiency and sustainability performance. Prior studies have identified a U-shaped relationship between investment (i.e., inputs) and outcomes (i.e., outputs) [76]. Considering the quadratic fit on the scatterplots (Figure 3), consistent with our hypothesis, we also explored a curvilinear relationship between the input and output variables and sustainability efficiency. If the quadratic term is significant, this validates the liability of newness that we expect to observe at lower levels of sustainability performance and maturity. The regression results with quadratic terms are presented in Table 5 in the Model 3 column (OLS with two-way clustering) and in the Model 4 column (GEE). It shows that the quadratic terms are significant for two (out of three) of the input variables and for both output variables. We believe quadratic regression provides a more detailed picture and a better fit than OLS regression in terms of adjusted $R^2$ (0.762). Since it may be difficult to interpret the relationships in quadratic regression based on the regression coefficients, we provide the relevant graphical plots in Figure 3 for the significant terms. The graph with employee variable is dropped due to its large $p$-value. The shaded areas represent the 95% confidence intervals. We observe that our findings with the OLS model for all three input variables remain the same. Those firms with lower input levels tend to be more efficient on average. The impact of the quadratic term is negative but not significant for employees while being significant for assets and COGS. As firms’ assets increase, we observe that sustainability efficiency decreases at a decreasing rate. Conversely, as COGS gets larger, sustainability efficiency decreases at an increasing rate.

In terms of the output variables, the picture is more interesting. At lower levels of the CSRHub score, we observe a decrease in the sustainability efficiency, which reaches a minimum around 44 for the CSRHub score (out of a possible score of 100) and then makes an upward turn, suggesting that an increase in the CSRHub score leads to better sustainability efficiency. Thus, until the CSRHub score reaches about 44, an increase in sustainability performance leads to a decrease in sustainability efficiency. We see a similar result with ROA. Note that the CSRHub score and ROA provide our measure for the maturity levels in implementing sustainable practices. Their quadratic relationship with sustainability efficiency may indicate that the firms with CSRHub scores below 44 are just beginning to undertake sustainability initiatives and have not yet established efficient processes to excel in what they are doing. In addition, their goals may not be well aligned between departments, which may hurt their efficiency. As they perform better in undertaking sustainability, they also become more efficient. This is in line with the theory that maturity is reached through “sustainable operations capabilities adoption and development” [17].

For a robustness check, we also conducted the regression analysis using the efficiency scores derived from the DEA-based Malmquist productivity index [77], which is a dynamic DEA approach [78]. The results were similar to the original analysis.
Figure 3. Effects of assets, COGS, ROA, and CSRHub on sustainability efficiency (log). The shaded area represents the 95% confidence interval.

3.5. Discussion

Much of the previous research on sustainability is instrumental, i.e., it looks to see how adjusting one aspect of sustainability affects another aspect. As Montabon et al. [17] argue, this approach is simplistic and not helpful to advancing sustainability research in the supply chain management context. The idea of sustainability efficiency is not instrumental, as it simultaneously measures all aspects of sustainability, which is a more integrative approach. We believe this integrative lens is more useful for advancing sustainability research and potentially being more useful to practitioners.

Our DEA found that most firms are not near the efficient frontier. Much of the argumentation in the literature using stakeholder theory to study sustainability is based on the idea that as stakeholder pressure increases, the firm will effectively be forced to adopt more stakeholder-desired initiatives. While this may be happening, firms seem to be struggling with the efficiency of their sustainability efforts. Accordingly, companies should be cognizant of any existing efficiency gaps in their sustainability efforts and make concerted efforts to close them. This entails a commitment to continuously enhancing their internal processes and systems to optimize the efficiency of their sustainability efforts. Simultaneously, companies need to prioritize the allocation of resources to sustainability initiatives that hold the greatest potential for significant impact. Moreover, companies should take into account industry-specific factors and regulations when developing their sustainability strategies. This will help them better align their efforts with industry standards and stakeholder expectations, ultimately leading to more effective outcomes.

We see that as firms begin adopting sustainability practices, the liability of newness takes effect in the form of a decrease in their sustainability efficiency. As firms’ sustainability performance increases, however, they become more mature, and their sustainability efficiency also starts increasing. We therefore observe a U-shaped pattern in the relationship between sustainability performance in terms of the TBL and sustainability efficiency as measured by DEA. The varying levels of appreciation within companies may be indicative of their different stages in the sustainability journey. Initially, firms might prioritize performance-related aspects, recognizing the potential for cost savings and enhanced oper-
ational performance. As companies progress in their sustainability maturity, they become more efficient in achieving superior sustainability performance.

Specifically, we observe a decrease in sustainability efficiency until the CSRHub score reaches a threshold of around 44. The decrease might be attributed to a learning period during which firms try to align their objectives and streamline their processes. Only after that threshold sustainability efficiency starts increasing does CSRHub score increase. We could argue that as firms continue increasing their environmental performance, they also learn how to streamline their processes, incorporating precautions to reduce negative environmental impacts. Precautions such as using less energy, using recycled material or remanufactured parts, and using recycled water (all of which are captured in the CSRHub data) increase their environmental performance and help reduce their operating costs improving their sustainability efficiency. In a similar vein, social sustainability initiatives such as improving workplace safety to reduce accidents, offering better worker training, and improving worker welfare via better work hours (also captured by CSRHub data) are known to increase employee morale and motivation leading to increased efficiency, as well attracting job applicants [79,80]. Therefore, companies should recognize that their sustainability journey is an ongoing process. They should be adaptable and prepared to evolve their strategies to ensure continuous improvement in sustainability performance, ultimately striving for superior sustainability efficiency. Firms should not be discouraged by the loss of efficiency at the beginning of their sustainability efforts. As they gain more experience and mature in implementing sustainable practices, their efficiency will also increase. However, firms may be able to shorten the initial phase of efficiency loss by allocating and utilizing resources more effectively.

In this study, we present maturity theory as the primary framework to guide our discussion. Our findings are also consistent with legitimacy theory, which serves as a complementary perspective to maturity theory in clarifying the U-shaped relationship between sustainability performance and sustainability efficiency. According to legitimacy theory, companies aim to enhance their sustainability performance to maintain their legitimacy in the eyes of stakeholders and the broader society [81]. In the initial stages of improving sustainability performance, firms may prioritize visibility over efficiency. This is because they are more focused on establishing legitimacy by showcasing their commitment to sustainability. As a result, companies may invest in sustainability projects that generate positive publicity but have lower efficiency. However, once a company reaches a certain level of sustainability performance, it is more likely to have acquired the necessary knowledge and resources to implement highly efficient sustainability initiatives. This allows firms to achieve both high performance and high efficiency, further solidifying their legitimacy in the eyes of stakeholders. The U-shaped pattern relationship between sustainability performance and sustainability efficiency implies a potential trade-off at early maturity levels. Companies that focus on identifying and closing efficiency gaps in their sustainability efforts may allocate resources strategically. By assessing areas of improvement and optimizing internal processes and systems, they can allocate resources efficiently to achieve sustainability goals. Companies that solely focus on sustainability performance may primarily measure and track the outcomes and improvements achieved without explicitly considering the resources consumed or inputs required to achieve those outcomes. Stakeholder engagement can differ when focusing on sustainability performance versus sustainability efficiency. When a company emphasizes sustainability performance, stakeholder engagement typically involves sharing and communicating sustainability goals, targets, and achievements. In the context of sustainability efficiency, stakeholder engagement often revolves around optimizing resource allocation, operational processes, and systems to enhance sustainability performance.

We note that the median value of the CSRHub score in our sample is 51, which is above the threshold of 44. That means most firms in our sample have opportunities to boost their sustainability efficiency by increasing their CSRHub score. In other words, investments in improving the CSRHub score through implementing sustainability initiatives are worth-
while. Additionally, based on Figure 3, we observe the returns in terms of sustainability efficiency from such investments are not linear. Firms with higher CSRHub scores can obtain more sustainability efficiency improvements compared to firms with lower CSRHub scores, given the same level of investment.

3.6. Implications

Our study has both theoretical and practical implications. First, we contribute to the sustainability literature by defining sustainability efficiency as a function of sustainability performance considering the investment requirements as inputs to achieve a given level of sustainability performance. There has been a long debate regarding different dimensions of sustainability performance (i.e., economic performance, social performance, and environmental performance). With DEA, we combine the three dimensions (TBL) of each firm’s sustainability performance when calculating its sustainability efficiency. Second, our study contributes to maturity theory by empirically showing its relevance in sustainable operations. While maturity modeling has been adopted into various business research areas, Machado et al. [13] points to a lack of studies in sustainable operations. Their maturity model offers a framework for sustainable operations capability evolution and shows that firms gradually gain maturity for their sustainable operations capabilities, which help them achieve superior sustainability performance by adopting more sustainable practices. Meanwhile, firms can obtain better efficiency when they have more mature capabilities [82]. This study provides empirical evidence to these arguments by investigating the relationship between sustainability performance and sustainability efficiency. Third, our empirical results show an interesting relationship between sustainability performance and sustainability efficiency. Specifically, we observe a decrease in sustainability efficiency at lower levels of sustainability performance as sustainability performance increases. However, after a certain threshold, an increase in sustainability performance leads to an increase in sustainability efficiency. This initial decrease in efficiency is consistent with the liability of newness theory and offers significant theoretical and managerial implications for both academic scholars and practitioners.

Our study also has several implications for policymakers. We suggest that policies need to be flexible and adaptable to accommodate the diverse needs and contexts of different industries and firms. One-size-fits-all approaches may not be effective, as the U-shaped relationship between sustainability performance and efficiency can vary across sectors. Policymakers should consider tailoring interventions to specific industry characteristics and encourage experimentation and innovation. In addition, policymakers can provide targeted support to firms at different levels of sustainability performance. Firms experiencing low sustainability performance can benefit from incentives and assistance programs to help them improve their sustainability practices. Similarly, firms at the moderate level of sustainability performance should be encouraged to improve their performance, which leads to efficiency improvements. Furthermore, policies should promote knowledge sharing and collaboration among firms to facilitate learning and exchange of best practices. Encouraging industry-wide sustainability initiatives, networks, and partnerships can help firms navigate the complexities of achieving both sustainability performance and efficiency, fostering innovation and progress.

4. Conclusions

Using data from 1141 U.S. manufacturing firms, we employed a DEA approach to determine efficiency in attaining sustainability and identify the industries on the frontier of sustainability efficiency. This study pioneers the development of a measure for overarching sustainability efficiency of a firm as opposed to being restricted to a specific outcome, such as carbon emissions. Furthermore, our study is distinguished from the conventional sustainability performance studies by considering the TBL via integrating economic outputs in addition to environmental and social outputs.
Our results reveal significant differences in sustainability efficiency across industries, warranting further investigation into industry characteristics causing these variations. We also confirm a quadratic relationship between sustainability efficiency and performance, aligning with the liability-of-newness theory. Firms initially struggle to improve sustainability, but after reaching a threshold, they become more efficient in adopting sustainable practices. This promising outcome benefits stakeholders such as shareholders, the environment, and society. A recent McKinsey article [83] highlights the potential of operational efficiency and environmental advantages working together, as companies become more efficient in implementing sustainability improvements after a learning process and gaining maturity.

The scope of our study is limited to manufacturing firms in the United States. Therefore, the results may change because of the difference in economic development and social norms. Investigating the differences between developed and developing or emerging countries would be particularly interesting. Firms in developed countries have access to more resources such as state-of-the-art green technology to achieve superior sustainability efficiency than in developing countries. Similarly, future studies could examine how efficiency scores vary in different-sized firms. Although most studies have only used a single database, adopting multiple databases in one study can enhance the validity of the results. Future studies may adopt alternative databases for robustness checks. Table A2 in Appendix A lists the major databases that assess firms’ sustainability performance.

Author Contributions: Conceptualization, Y.Z., M.D. and F.M.; methodology, Y.Z. and M.D.; software, Y.Z.; validation, Y.Z. and M.D.; formal analysis, Y.Z.; investigation, Y.Z. and M.D.; resources, M.D.; data curation, Y.Z.; writing—original draft preparation, Y.Z., M.D. and F.M.; writing—review and editing, Y.Z., M.D. and F.M.; visualization, Y.Z.; supervision, M.D.; project administration, M.D. 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: Data were obtained from CSRHub and Wharton Research Data Services (WRDS) and are available from www.csrhub.com and wrds—www.wharton.upenn.edu respectively with the permission of CSRHub and WRDS.

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

Appendix A

Table A1. The table below reviews the use of DEA models in sustainability research.

<table>
<thead>
<tr>
<th>Article</th>
<th>Summary</th>
<th>Input</th>
<th>Output</th>
<th>Types of DEA Modes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhou et al. [84]</td>
<td>The study measures eight countries’ (regions’) carbon emission performance.</td>
<td>The consumption of total energy</td>
<td>GDP and CO₂ emissions</td>
<td>Output-oriented models</td>
</tr>
<tr>
<td>Belu [85]</td>
<td>This study rates public firms based on sustainable achievements as compared to financial results.</td>
<td>Return on assets; return on equity; yearly stock return</td>
<td>Sustainability scores based on a survey</td>
<td>Output-oriented models</td>
</tr>
<tr>
<td>Chen and Delmas [86]</td>
<td>This study measures a firm’s corporate social performance index for 2190 firms using DEA approach.</td>
<td>CSP concerns from KLD database</td>
<td>CSP strengths from KLD database</td>
<td>Input-oriented DEA model</td>
</tr>
<tr>
<td>Schoenherr and Talluri [87]</td>
<td>This study compares the influence of environmental sustainability initiatives on plant efficiency for 402 plants in Europe and the U.S.</td>
<td>Total plant employees; % invested in new equipment; % machines grouped by families</td>
<td>Cost performance index</td>
<td>Rejection rate (%)</td>
</tr>
</tbody>
</table>


Table A1. Cont.

<table>
<thead>
<tr>
<th>Article</th>
<th>Summary</th>
<th>Input</th>
<th>Output</th>
<th>Types of DEA Modes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chen et al. [88]</td>
<td>The authors employ DEA to estimate the environmental efficiency in China among 30 provinces based on the data from 2001 to 2010.</td>
<td>Energy consumption; social fixed assets investment</td>
<td>Desirable outputs: GDP; undesirable outputs: wastewater, solid, and gas</td>
<td>Output-oriented DEA model</td>
</tr>
<tr>
<td>Wang et al. [89]</td>
<td>This study assesses the environmental performance of S&amp;P 500 companies during the period of 2012 to 2013.</td>
<td>Firms’ investment in CO₂ abatement and R&amp;D expense; working capital; number of employees; total assets</td>
<td>Desirable outputs: CO₂ savings and return on assets; undesirable outputs: emission levels</td>
<td>Not specified</td>
</tr>
<tr>
<td>Liu and Wang [90]</td>
<td>This study evaluates the regional energy efficiency of 30 provinces in China in 2008.</td>
<td>Numbers of employees; capital assets; tons of coal used</td>
<td>The gross industrial output value</td>
<td>Network DEA model</td>
</tr>
<tr>
<td>Jacobs et al. [71]</td>
<td>The authors examine the relationship between operational productivity; corporate social performance, financial performance, and risk based on data from 476 US manufacturing firms.</td>
<td>CSP concerns from KLD database</td>
<td>CSP strengths from KLD database</td>
<td>Ordinal DEA</td>
</tr>
<tr>
<td>Wu et al. [91]</td>
<td>The study measures the sustainable performance among 30 manufacturing firms in China.</td>
<td>Multiple inputs (see Table 1 in their paper)</td>
<td>Multiple outputs (see Table 1 in their paper)</td>
<td>Two-stage network DEA model</td>
</tr>
<tr>
<td>Jiang et al. [92]</td>
<td>The study conducted an assessment of sustainability efficiency in wastewater treatment plants in China.</td>
<td>Operating cost; electricity consumption; number of laborers</td>
<td>Chemical oxygen demand removal rate; ammonia nitrogen removal rate; reclaimed water yield; undesirable outputs: dry sludge yield</td>
<td>Slacked-based DEA model based on cluster benchmarking</td>
</tr>
<tr>
<td>Jiang et al. [93]</td>
<td>The study assesses the sustainability efficiency of list companies in China from 2017 to 2019.</td>
<td>Total freshwater consumption; Comprehensive energy consumption; Total assets; Total number of employees</td>
<td>Operating income; net profit; taxa payable income; total emission of greenhouse gas</td>
<td>Super-efficiency slacks-based measure DEA</td>
</tr>
<tr>
<td>Lozano-Ramírez et al. [94]</td>
<td>This study assesses the sustainable efficacy of tourism in 27 European Union nations from 2015 to 2019.</td>
<td>Number of bed-places</td>
<td>International tourism receipts; female employment; male employment; undesirable outputs: greenhouse gas emissions</td>
<td>Non-oriented, slacks-based inefficiency DEA model</td>
</tr>
</tbody>
</table>

Table A2. The table below summarizes sustainability databases and representative studies.

<table>
<thead>
<tr>
<th>Database</th>
<th>Evaluation Composition</th>
<th>Firm Coverage</th>
<th>Representative Studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>KLD (MSCI)</td>
<td>Environmental indicator (positive and negative); social indicator (positive and negative); governance indicator (positive and negative)</td>
<td>2600 companies worldwide (in 2015)</td>
<td>Sharfman [95]; Harrison and Freeman [96]; McWilliams and Siegel [97]</td>
</tr>
<tr>
<td>CSRHub</td>
<td>CSR performance in four dimensions: community, employee, environment, and governance</td>
<td>17,334 companies from 141 countries</td>
<td>Bu et al. [98]; Soytas et al. [57]</td>
</tr>
<tr>
<td>ASSET4</td>
<td>250+ key performance indicators from three dimensions including environmental, social, and governance</td>
<td>More than 3400 public firms from 38 countries</td>
<td>Cheng et al. [99]; Khatri [100]</td>
</tr>
<tr>
<td>Sustainalytics</td>
<td>Environmental, social, and governance</td>
<td>Not specified</td>
<td>Cohen et al. [101]; Sancha et al. [102]</td>
</tr>
</tbody>
</table>

References


9. Burksiene, V.; Dvorak, J.; Burbulyte-Tsiskarishvili, G. Sustainability and Sustainability Marketing in Competing for the Title of European Capital of Culture. Organizacija 2018, 51, 66–78. [CrossRef]


20. Lis, A.; Sudolska, A.; Tomaneke, M. Mapping Research on Sustainable Supply-Chain Management. Sustainability 2020, 12, 3987. [CrossRef]


42. Layne, R. Are Companies Actually Greener—Or Are They All Talk? Available online: http://hbswk.hbs.edu/item/are-companies-actually-greener-or-are-they-all-talk-esg-greenwashing (accessed on 2 May 2023).


89. Liu, Y.; Wang, K. Energy Efficiency of China’s Industry Sector: An Adjusted Network DEA (Data Envelopment Analysis)-Based Decomposition Analysis. *Energy* 2015, 93, 1328–1337. [CrossRef]


102. Sancha, C.; Gutierrez-Gutierrez, L.; Tamayo-Torres, I.; Gimenez Thomsen, C. From Corporate Governance to Sustainability Outcomes: The Key Role of Operations Management. *Int. J. Oper. Prod. Manag.* 2022, 43, 27–49. [CrossRef]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.