Assessment of Proactive Environmental Initiatives: Evaluation of Efficiency Based on Interval-Scale Data

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***Abstract*—In recent years, firms have pursued a host of environmental operational practices to derive superior environmental and business performance. However, the relative effectiveness of these practices has not been explored adequately. Past empirical studies have mainly assessed the performance impact of various practices across firms without accounting for firm-specific considerations. Consequently, it is not clear how the costs and benefits of various practices compare across firms that may weigh the practices differently. We examine this issue by analyzing the financial and environmental performance impact of five commonly adopted operational practices of 30 firms across a diverse set of industries. The operational practices are measured in interval scale through content analysis. Subsequently, we apply a data envelopment analysis-based technique proposed by Dehnokhalaji *et al.* [22] that can incorporate both ratio and interval-scale data. We find that although the emphases on various environmental practices vary among firms, mainly two of the five practices (i.e., proactive waste reduction and remanufacturing) differentiate firms' business and environmental performance. The theoretical and managerial implications of the findings are also discussed.**

***Index Terms*—Content analysis, data envelopment analysis (DEA), environmental operations, financial performance, interval-scale data.**

I. Introduction

IN RECENT years, firms have increasingly engaged in actions to improve environmental performance [38], [68]. Yet only one third of business leaders believe their companies are prepared for the business consequences of environmental concerns, such as climate change [57]. While many firms pursue environmental initiatives to comply with regulatory requirements, several others such as Herman Miller and Xerox are carrying out environmental initiatives to improve products and operational processes for lower operational costs and higher reputation [58]. According to a recent global survey by McKinsey & Company,[1] about 30% of the business leaders consider cost cutting and reputation are two of the top three reasons to adopt sustainability initiatives. However, accomplishing a good balance between environmental and business performance is often difficult because of the potential *tradeoffs* between the two. The costs and benefits of different environmental initiatives over time can vary to a great extent [30], but companies making investments in environmental programs usually expect a payback in less than two years. The mismatch between the expectations for quick paybacks and long-term nature of environmental initiatives makes them challenging and results in lower environmental investments [15]. Consequently, appropriate evaluation and selection of the different types of environmental initiatives is crucial for their successful implementation. Our paper investigates into this topic.

Environmental initiatives can be categorized into "preventative" and "end-of-the pipe" types. Preventative practices refer to product and process improvement initiatives that aim to avert occurrence of pollution. Often they are pursued voluntarily well before the regulatory pressure is imposed. In contrast, "end-of-the pipe" initiatives aim to remediate the pollution problem (e.g., dilute the impacts of emissions, clean-up effluents, etc.) after the occurrence of pollution in the operational processes. In general, these are adopted to comply with regulatory requirements. Preventative initiatives, on the other hand, being voluntary in nature, usually do not force constraints and reportedly yield better environmental and financial performance than the "end-of-the pipe" counterparts [48], indicating a *complementary* relationship between environment and business performance.

Environmental initiatives are often explained in terms of a 3R (i.e., reduce, reuse, and recycle) framework [70]. "Reduce" refers to minimization of waste (i.e., resource consumption that does not create value) through product and process (re)designs, "reuse" (e.g., remanufacturing) refers to repeat use of materials/components until they are unusable, and "recycle" refers to recovery of ingredients from process wastes, such as scrap/effluents. Recycled materials are often of inferior quality with lesser economic value compared to virgin materials. Since "reduce" avoids wasteful resource consumption, and "reuse" restricts amount of virgin resource usage, the ecological and economic benefits of these two types of environmental practices are usually higher than "recycle." In general, preventative initiatives put relatively more emphasis on "reduce" and "reuse" than on "recycle."

Several survey-based empirical studies (e.g., [13], [50], [60]) have utilized the "natural-resource-based view" [41] to explain the relationship between preventative environmental operations and financial performance. While these studies provide insights into the general pattern of the relationship between practices and performance, they do not account for *firm-specific considerations* (e.g., preference and capabilities for different types of initiatives) that can influence the relative effectiveness

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of different practices adopted by firms. The difficulty in including the firm-specific considerations could be in part due to the regression type methods that most of the past empirical studies have adopted. Consequently, alternative analysis approaches should be utilized to include firm-specific considerations, while assessing the relative usefulness of environmental initiatives.

A few analytical studies (e.g., [26], [53], [72]) have analyzed the cost effectiveness of environmental initiatives using data envelopment analysis (DEA)-based models. In DEA, firms are compared based on the ratio of weighted sum of outputs (e.g., electricity generation, emission reduction) to weighted sum of inputs (i.e., CO_2 emissions, investments). The input and output weights for each firm are derived such that the firm emerges as efficient as possible. Thus, DEA-based studies can account for *firm-specific* considerations. However, the aforementioned DEA-based studies considered the magnitude of environmentally undesirable emissions as inputs and desirable economical and/or ecological outcomes as outputs, while evaluating the relative efficiency of firms. Because of the focus on amount of pollution and not the actions leading to the outcomes, these studies were unable to provide enough insights into the relative effectiveness of various operational practices.

Chen and Delmas [10] applied a DEA-based methodology to compare corporate social performance using the information available in the Kinder, Lydenberg, and Domini, Inc. (KLD) database. The KLD database reflects environmental and social actions on a binomial scale (i.e., yes/no type of data). Thus, their study does not account for the intensity of diverse environmental initiatives in the analysis. Our study aims to address these shortfalls in the extant literature.

A key challenge in analyzing the effectiveness of different operational initiatives is the difficulty in measuring their costs and benefits on a common scale. Preventative initiatives (e.g., elimination of occurrence of waste, reduction in material and energy consumption, substitution of ecologically sensitive materials with less sensitive ones), in general, involve product and processes improvement practices. Intensity of these practices is difficult to measure and compare objectively. However, emphasis on these practices can be measured based on subjective perceptions. It is, therefore, imperative to include both objective and subjective measures in ratio and interval scales, while assessing the effectiveness of various initiatives.

In this paper, we analyze the performance effectiveness of a set of environmental operational practices that are commonly adopted by firms across various industries. The aim is to identify a set of practices that is more effective than others with respect to a set of performance outcomes when firm-specific priorities for those practices and performance outcomes are considered. In our analysis, we apply Dehnokhalaji *et al.* [22] DEA-based technique to classify efficient and inefficient firms. Based on the efficiency scores, we propose a uniqueness measure for firms to characterize their distinctiveness. Subsequently, we compare the firms in terms of environmental practices and financial performance. The analysis is carried out using information from sustainability and annual reports. Content analysis was used to collect information from the sustainability reports. Annual reports were used to collect financial performance data. We utilize a set of environmental initiatives that have reportedly influenced firms' competitiveness and financial success. These initiatives are preventative practices, such as waste reduction, remanufacturing, energy reduction, material substitution, and environmentally responsible packaging that were measured on perceptual interval scale. To the best of our knowledge, this paper is the first application of DEA on interval-scale data in analyzing the benefits of environmental initiatives.

Our study makes two important contributions. First, it presents an approach that combines content analysis and DEA to evaluate the *relative* effectiveness of different environmental initiatives, while accounting for firm-specific considerations. Content analysis helps us to include "difficult-to-measure" variables in the analysis. Second, we shed light on the business and environmental benefits of different types of preventative environmental initiatives. This finding provides theoretical insights into why the effectiveness of different initiatives might differ across firms and provides managerial guidelines for selecting appropriate environmental initiatives. Although we focus on evaluation of environmental initiatives in this paper, the method of analysis used in this study can be utilized to assess usefulness of other operational initiatives that might be difficult to measure objectively.

The remaining sections of the paper articulate the relevance of preventative environmental practices, discuss the analysis method and its usefulness vis-à-vis others, explain the data collection process, present the data analysis results, discuss the findings, and suggest directions for future research. A schematic diagram of the steps followed for data collection and analysis is presented in Appendix A, which is available as an online supplement.

II. Literature Review

A. *Preventative Environmental Operations and Organizational Performance*

Over the past two decades, there has been a distinct shift in the environmental debate. Firms have moved beyond asking "whether or not it pays to be green" (e.g., [48]) to "how to accomplish superior environmental performance, while maintaining or improving competitive advantage" [52]. In general, firms adopt two distinct types of environmental strategies: cost reduction (i.e., ecoefficiency) and/or differentiation (i.e., beyond compliance or eco-branding) [65]. While cost advantages follow from reduced usage of ecologically sensitive resources, differentiation occurs due to distinctively superior processes and products compared to the prevailing standards. "Preventative" initiatives are more effective than "end-of-the pipe" initiatives in deriving competitive advantages.

Preventative operational initiatives involve elimination/ reduction of waste and hazardous byproducts during manufacturing, use of environmentally sound substitutes, used product recovery, use of recyclable packaging and remanufacturing, reuse/reduction of wasted energy [32], etc. These initiatives improve hazardous manufacturing processes, redesign existing products, and packaging to lower ecological damage, and improve production efficiency through lower wastes, material, and energy usages all contributing to better financial and market performance [51]. Environmentally friendly products are likely to be appreciated by "green" customers [28], leading to environmental reputation, higher demand, premium pricing, and increased sales [64]. Product recovery and remanufacturing strategies extend the useful life of products. Extension of the product life cycle helps in lowering resource consumption [55]. Many organizations including Caterpillar [2], Hewlett–Packard [83], and Xerox [79] have carried out remanufacturing and recycling operations to enhance profitability. Use of recycled and recyclable materials reduces waste and energy consumption [85]. Lower energy consumption [59], reuse of wasted energy [32], and higher energy efficiency [64] make significant positive impacts on the environment and bottom lines [65]. Preventative environmental initiatives necessitate implementation of process standards and of management control and audit systems that are similar to lean and TQM systems [49], [86]. Successful implementation of these systems helps achieve ISO 14 000 standards [18].

While the past studies have reported the usefulness of a diverse set of "preventative" environmental practices, to the best of our knowledge, no previous work has discussed whether a certain set of practices is more effective than the others. Making a distinction between more and less effective practices is important because the beneficial association between environmental initiatives and financial and environmental performance is not universal (e.g., [5], [34], [54], [63]). For example, Nga [63] and Link and Naveh [54] found a contradictory association between environmental certification and financial performance; Gilley *et al.* [34] noted that although high-profile coverage of environmental initiatives is often viewed positively by investors, environmental initiatives have no overall benefit on stock returns. Our investigation aims to clarify this inadequacy or ambiguity in the extant literature.

We believe that while evaluating the relevance of various practices, it is important to consider differences among firms' priorities and capabilities to adopt different environmental initiatives. Assessing the relationship between various environmental initiatives and firm performance without accounting for these *firm-specific considerations* would lead to confounding results. Past empirical studies on the relationship between various environmental initiatives and firm performance that used a regression type of analysis or event studies have not accounted for this issue. According to strategic choice theory tenets, firms pursue different strategies even under similar industry influences due to the unique dynamic relationship between external constraints and a firm's internal considerations [12], [75]. Thus, it is appropriate to account for firm-specific considerations, while evaluating the cost effectiveness of various practices adopted by firms.

B. Usefulness of DEA Vis-à-Vis Other Techniques in Assessing the Relevance of Alternate Environmental Initiatives

DEA allows analysis of the usefulness of different practices, while making the firm under consideration as efficient as possible compared to the other firms. DEA is a proven technique for comparing organizational operational performance among peers when multiple inputs and outputs are involved (e.g., [67]). The inputs and outputs in DEA refer to sets of antecedent and consequent variables that are of managerial relevance. Thus, the choice of inputs and outputs in a DEA is based on the problem on hand, and inputs and outputs need not be related in a strict physical sense (e.g., [53], [76]. DEA has some unique advantages over comparable techniques, such as regression, structural equation modeling (SEM), analytical hierarchy process, multicriteria decision making (MCDM), multiobjective programming, stochastic frontier analysis (SFA), etc., that are available to assess the practice–performance relationships. While regression-based models are useful in evaluating performance when just one output is considered, for comparisons involving multiple outputs DEA is a more suitable tool [11]. In the presence of multiple outputs, regression with one output holds a strong assumption regarding the independence of outputs [8], and reveals only partial information on the nature of associations between inputs and the chosen output. In addition, while regression and SEM estimate the average relationship across all units in the sample, DEA compares the optimal performance of each decision making unit (DMU) in the sample with the best combination of units in the same sample. Thus, DEA facilitates accounting for firm-specific considerations, provides deeper understanding of DMU's performance [9], and generates specific information to make recommendations regarding inputs and outputs for enhancing efficiency [78].

Unlike parametric statistical and econometric methods, DEA does not hold any distributional assumptions [67] and is less demanding on sample size. In DEA, the number of input and output variables should be well below the number of DMUs being evaluated for obtaining accurate results. The rule of thumb is $n \geq [\max\{m \times p, 3(m+p)\}$ or $2 \times m \times p]$, where n is the number of DMUs and m and p are the number of inputs and number of outputs, respectively, [17], [27]. Premachandra *et al.* [67] used DEA to determine weights of a classification function to separate default and nondefault firms in assessing corporate bankruptcy. They found DEA to outperform logistic regression because of the absence of an assumption regarding statistical distribution of the sample data. Unlike an econometric regression model, DEA does not require the analyst to specify the production function to link inputs and outputs [6]. There is no need to assign an *a priori* weight to each input and output in DEA, which is a requirement for several widely applied MCDM methods. Another methodology for measuring efficiency of organizational units is SFA [1]. While DEA assumes that data is essentially noise free, SFA allows for noise or random shock in the data and can make stochastic inferences. On the other hand, unlike SFA, DEA does not hold assumptions regarding distribution of the error terms and the functional form linking the outputs and inputs.

Despite the above advantages, the traditional DEA has some limitations. DEA is sensitive to the nature of data—the original formulation (i.e., Banker, Charnes, and Cooper (BCC) model [4]) requires data to be in ratio scale [20]; sometimes inputs and outputs are difficult to obtain in that format. Managers often describe the inputs/outputs using alternative scales (i.e., categorical, ordinal, or interval scales). Further, DEA requires an upper limit on the number of input and output variables for a given sample size [33] and does not allow negative data

[29]. Although these limitations restrict DEA's applicability to some extent, the limitations are fewer than other comparable methods and many of these limitations have been addressed in later extensions to DEA.

To illustrate, for dealing with negative data in DEA, a slack-based measure of superefficiency has been developed [56]. Another alternative approach for handling negative input and output variables in DEA is the "semioriented radial measure" [29]. Cook and Zhu [16] developed a framework to analyze rank order data using DEA. For dealing with the interval-scale data, Halme *et al*. [39] proposed decomposition of the interval-scale variable as the difference between two positive or negative ratio-scale variables such that one is treated as an input variable and the other one is treated as an output variable. While this is a novel approach, there is a possibility of inefficient units appearing efficient. Further, in situations where the variables are on interval scale with positive (or negative but not mixed) values, the efficiency scores of traditional DEA will not be useful since they are not invariant under the translation [22]. In conditions where the inputs and outputs are both negative and positive, the traditional/basic DEA models would not work. Dehnokhalaji *et al*. [22] suggest an improved approach that is robust against rescaling of inputs/outputs and can handle both positive and negative input/output data. The approach finds efficiency based on a hyperplane that separates the units better and worse than the DMU under consideration.

Our data have five inputs and one output in an interval scale. One other input variable and two other output variables are measured in ratio scale. The two ratio-scale output variables have a few negative values. Given the adequacy of Dehnokhalaji *et al*. 's [22] technique for our data, we use this approach in our analysis.

III. Model

As discussed in the previous section, Dehnokhalaji *et al*. [22] approach separates the units as better or worse than the unit under consideration (DMU_0) such that the number of better units is minimal. The approach can handle interval-scale data, as well as negative values in the variables. The main difference between this approach and the traditional DEA models is that it does not measure the distance from the efficient frontier to DMU_0, rather it finds the minimum number of units that need to be omitted from the set to make DMU_0 efficient. It has some of the salient features of the traditional DEA models including efficiency score, reference, or benchmarking unit, and the concept of each of the units taking a turn for being projected in the most positive way.

There are two types of DEA: input oriented and output oriented. In the input-oriented approach, the efficiency for the DMU under consideration is computed by maximizing the ratio of weighted outputs to weighted inputs, while enforcing the condition that similar ratios for all DMUs are not higher than one. The solution will find a set of efficiency scores less than or equal to one. This approach holds the output levels constant and evaluates how much the input levels should decrease for the DMU under consideration to be efficient. On the other hand, in the output-oriented approach, the efficiency of the DMU under consideration is computed by minimizing the ratio of weighted inputs to weighted outputs, and the solution finds a set of efficiency scores greater than or equal to one. The output-oriented approach holds input levels constant and assesses how much the output level needs to increase for the DMU under consideration to be efficient. Firms with proactive environmental initiatives would adjust different practices (inputs) optimally to accomplish business and environmental targets. An input-oriented model reflects this strategy; consequently, we use an input-oriented approach for our analysis. The main steps in the analysis are as follows.

Say we have *n* DMUs and each of the DMUs needs *m* inputs (denoted by vector $\mathbf{x} \in \boldsymbol{R}^m$) to generate *p* outputs (denoted by vector $\mathbf{y} \in \boldsymbol{R}^p$). The corresponding input and output information of all DMUs (i.e., *n* number of DMUs) can be presented by $\mathbf{X}(m \times n \text{ matrix})$ and $\mathbf{Y}(p \times n \text{ matrix})$, respectively. For the unit under consideration (DMU_0), the inputs and outputs are denoted by vectors $\mathbf{x_0}$ and $\mathbf{y_0}$, respectively,

$$\text{Let } \mathbf{U} = \begin{pmatrix} \mathbf{Y} \\ -\mathbf{X} \end{pmatrix} \text{ and } \mathbf{u_0} = \begin{pmatrix} \mathbf{y}_0 \\ -\mathbf{x_0} \end{pmatrix}.$$

Since ours is an input-oriented model, the input–output vector for the unit under consideration is $w = \begin{pmatrix} \mathbf{0} \\ \mathbf{x_0} \end{pmatrix}$.

Dehnokhalaji *et al*. [22] extended the basic BCC model [4] described in a general form [47]. The general form is provided as

$$\begin{aligned}
&\min \theta = -\boldsymbol{\rho}^T \boldsymbol{u_0} + \eta \\
&\text{s.t.} \\
&-(\boldsymbol{\rho}^T \boldsymbol{U})^T + \eta\, \mathbf{1} \geq \mathbf{0} \\
&-\boldsymbol{\rho}^T w = 1 \\
&\boldsymbol{\rho} \geq \varepsilon \mathbf{1} (\varepsilon > 0, \text{ is Non -Archimedian}) \\
&\eta \text{ is free.}
\end{aligned} \tag{1}$$

The weights are defined by vector $\boldsymbol{\rho}$. The parameter η determines the returns to scale property. For example, $\eta = 0$ enforces constant returns to scale. The objective of the formulation above is to minimize the difference between weighted inputs and outputs. This is equivalent to maximizing the difference between weighted outputs and inputs in a typical input-oriented model. The first set of constraints ensure all efficiency measures must be less than or equal to one. In order to avoid infinite number of solutions, the second constraint is imposed. The third set of constraints impose strictly positive lower limit to the weights used in the model so that all inputs and outputs can take some positive values, and weakly efficient units are not diagnosed to be efficient.

Dehnokhalaji *et al*. [22] model finds a maximal subset of *n* units, in which DMU_0 is efficient. If DMU_0 is not efficient, then some of the inequalities in $-\boldsymbol{\rho}^T \mathbf{U} + \eta\, \mathbf{1} \geq 0$ are not satisfied. Each of the inequalities is associated with one unit. Thus, violation of an inequality implies that the corresponding unit will need to be omitted from the set to make DMU_0 efficient. The Big M technique is employed to address the violations. Accordingly, the basic general form of DEA [47] is modified as follows:

$$
\begin{aligned}
&\min \mathbf{1}^T z \\
&\text{s.t.} \\
&-\boldsymbol{\rho}^T \mathbf{u_0} + \eta = 0 \\
&-(\boldsymbol{\rho}^T \mathbf{U})^T + \eta \mathbf{1} + M\mathbf{z} \geq \mathbf{0} \quad (M \gg 0) \\
&-\boldsymbol{\rho}^T \mathbf{w} = 1 \\
&\boldsymbol{\rho} \geq \varepsilon \mathbf{1} (\varepsilon > 0, \text{ is Non-Archimedian}) \\
&\eta \text{ is free} \\
&z_j \in \{0, 1\}, j = 1, \ldots, n. \qquad (2)
\end{aligned}
$$

For each unit under consideration (DMU_0), the model (2) finds the optimal solution. If z_j has value of 1, the second constraint in (2) becomes redundant indicating the corresponding unit (DMU_j) is excluded from the set in which DMU_0 is efficient. If no units are excluded from the set, then z_j will have value of zero for all of the units indicating not a single unit is better than DMU_0. This implies DMU_0 is efficient with respect to all units. In such scenario, DMU_0 will be considered to be fully efficient with an efficiency score of 1. On the other hand, if many units are excluded from the set (i.e., these units will have z_j value of 1) to make DMU_0 efficient then the efficiency score of DMU_0 will be much lower than one. Thus, the efficiency score of DMU_0 can be obtained as

$$\text{Efficiency score} = \frac{n - \sum_{j=1}^{n} z_j}{n}. \qquad (3)$$

Note that each of the *n* units takes a turn to become the unit under consideration (i.e., DMU_0). Thus, the above optimization model is solved *n* times. In these runs, it is of interest to see how many times a specific unit is excluded (i.e., has $z_j = 1$) from the sets of firms in which the other $n - 1$ DMU_0 are efficient. In light of the above results, we propose the more frequently a unit is excluded, the more distinctly superior the unit is compared to others. We refer to this characteristic as an index of uniqueness. Formally, we characterize the uniqueness measure of a unit as

$$\text{Uniqueness measure of unit } j = \frac{\sum_{i=1}^{n} z_{ji}}{n}$$

$$\text{where, } z_{ji} \text{ is value of } z_j \text{ in the } i\text{th optimization run.} \qquad (4)$$

IV. Data Collection

We use six input variables and three output variables to evaluate the usefulness of a set of preventative environmental practices. Five of the six input variables and all of the three output variables were adopted from Montabon *et al*. [62]. The five input variables are proactive waste reduction, remanufacturing, material substitution, packaging reduction, and energy reduction. Proactive waste reduction emphasizes use of improved inputs, manufacturing, and operational processes to prevent creation of waste in the first place. This is distinct from reactive waste reduction that deals with "end-of-the pipe" emission reduction through scrubbers, incinerators, and treatment of waste. Firms across industries emphasize these five practices to prevent/reduce generation of waste [62] although there are variations in details. For example, firms (e.g., HP, Xerox) in the electronics industry that usually emphasize remanufacturing have been improving products and processes to reduce energy consumption and GHG emission, eliminate/restrict hazardous chemicals, use ecoefficient inputs, and reduce/reuse packaging [44]. Similarly, firms (e.g., Dow, BASF) in the chemical industry that commonly focus on waste reduction, packaging optimization, and energy reduction are more recently emphasizing reuse (i.e., similar to remanufacturing) of chemicals (e.g., reusing millions of pounds of byproducts) and mechanical equipment, and use of reusable packaging (e.g., metal boxes being used multiple times) [3], [24]. Firms in machinery (e.g., Ford, Danfoss) and other miscellaneous sectors (e.g., Weyerhaeuser, IBM) have been emphasizing the aforesaid initiatives, as well to derive financial and environmental gains [19], [31], [45], [82].

We use two financial performance measures [i.e., return on assets (ROA) and compound annual sales growth rate (CAGR)] and one environmental performance measure (environmental certification such as ISO 14 000, EMAS, Green Seal, etc.) as outputs. We include environmental certifications as a performance outcome because such certifications reflect existence of robust processes, systems, and standards that lead to superior environmental performance and continued business from customers. Process-oriented capabilities improve operational efficiency resulting in lesser resource consumption and increased market distinctiveness [65], [71]. Further, environmental certification, enhances external stakeholder's confidence leading to market reputation and ecobranding [60], [65]. Corbett and Kirsch [18] discuss how absence of ISO 9000 certification led to loss of business for Japanese manufacturers in 1990s; this negative experience motivated Japanese firms to obtain ISO 14 000 certifications quickly.

The input and output variables used in this study have been utilized by a number of extant survey-based empirical studies examining the practice–performance linkages. For example, King and Lenox [50] used pollution reduction means/methods as the independent variables, and ROA as one of the dependent variables in their analysis of financial performance of environmental initiatives. Gonzalez-Benito and Gonzalez-Benito [35] included substitution of polluting materials, use of reusable packaging, process design for energy, and resource reduction as independent variables, and ROA as a dependent variable in their study of the relationship between environmental initiatives and business performance. Montabon *et al*. [62] considered proactive waste reduction and remanufacturing as independent variables and sales growth as a dependent variable in their analysis of the relationships between environmental initiatives and firm performance. Cervelini and Souza [7] argued that the existence of cleaner production system contributes to ISO 14001certification. Gonzalez-Benito and Gonzalez-Benito [36] noted that companies with preventative environmental management practices are more likely to obtain the ISO 14001 certification.

In empirical research, the "size of firm" variable is often used as a proxy for the available resources. We use the logarithm of total assets as the sixth input variable to represent the size of the firm [37], [40]. Inclusion of this variable controls for the effects of total assets. We group the output variables into two sets: 1) CAGR and environmental certification; and 2) ROA and environmental certification—and analyze the relationship between the inputs and outputs for the two sets. The two sets refer to improvements in revenue/sales and efficiency in asset utilization, respectively. Asset utilization efficiency and revenue growth are two distinct business objectives of firms. Inclusion of environmental certification along with the financial measures in both the output sets aims to provide a balanced perspective of environmental-responsible business [21], [80].

The data for the five environmental inputs and environmental certification were collected through content analysis of firms' sustainability reports. The sustainability reports were obtained from www.corporateregister.com, an independent, privately held, and self-funded UK-based organization that collects and disseminates corporate social responsibility reports and resources. The reports were on average 40–50 pages and had discussion of manufacturing/process characteristics, which were considered, while assigning scores to avoid the confounding effects of industry-specific practices. Content analysis has been recognized as a systematic, replicable technique to discover the organizational focus when the information is nonstandardized and too costly to collect [81]. In particular, content analysis allows conversion of qualitative/textual data into quantitative form to perform statistical analyses [84]. With a large amount of textual and qualitative data being publicly available from annual reports, industry news reports, trade magazines, and other relevant reports, content analysis has been emerging as an important research methodology [25], [77]. Further, for complex issues, the reliability/authenticity of information from publicly available published reports is likely to be higher than the subjective, perceptual data obtained through survey because these reports are available for public scrutiny. Environmental operational initiatives pursued by firms are difficult to compare using common objective metrics because the specific activities are quite diverse across firms due to the varied nature of products and technological processes. These factors make content analysis a more suitable technique than survey data collection for the problem in our study. For the financial variables ROA and CAGR, annual financial reports were used.

Environmental data were collected by three graduate students who had studied "environmental supply chain management" as an elective seminar course. Past studies (e.g., [61], [62], [86]) have used responses by graduate and senior undergraduate students in operation management research. The students participating in this study had 4–6 years of executive work experiences in the corporate sector. The students collected the data independently under the guidance of one of the coauthors, who also taught the elective course. Use of three knowledgeable data collectors is consistent with past content-analysis-based studies as well (e.g., [66]). The student used the information provided in the firms' sustainability reports for the year 2009 to assess the five environmental initiatives and environmental certification of products and processes on a 1–5 point Likert scale (1 representing a very low level of existence and 5 representing a very high level of existence). A description of the measurement instruments for the input and output variables is presented in Appendix B (available as an online supplement). The instrument used to collect the information and the approaches to distinguish different levels of environmental practice were explained by the instructor according to the guidelines provided in Montabon *et al*. [62]. Students were asked to make intercompany comparisons of their scores to ensure consistency of their ratings. On average, each student spent about 10–12 h on each report, adding up to 300–360 h to assess the environmental initiatives across 30 companies. Such intense involvement makes the scores highly reliable. Interrater reliabilities for each variable were computed based on the guidelines of James *et al*. [46]. The reliability scores were above the normative threshold of 0.7 for each variable [66]. Consequently, the averages of the three raters' scores for the five inputs and one output (i.e., environmental certification) were used in the analysis.

The financial impacts of the operational initiatives are likely to be experienced with some time lag. To the best of our knowledge, there is no formal guideline on how to choose the appropriate time lag in studies such as ours. However, some of the past studies (e.g., [42], [43]) have noted that the financial benefits can be realized in one to two years. Firms reportedly expect a payback in less than 18 months on their environmental investments [15]. Consequently, we used one to two year lags in our analysis. We used ROA for 2010, and CAGR over the averages of 2008–2009 and 2010–2011. The average sales were used to smooth out peaks and troughs in yearly data. For the sixth input variable, logarithm of total assets, we used the asset data for the year 2008.

In the interest of generalizability of findings, our sample included a diverse set of 30 companies which have been very active in environmental pursuits and are reportedly well known (i.e., discussed in published business case studies and research [62]) for their environmental initiatives. The sample size of 30 was considered adequate for our analysis because $n \geq [\max\{m \times p, 3(m+p)\}$ or $2 \times m \times p]$, where n is the number of DMUs and m and p are the number of inputs and number of outputs, respectively, [17], [27]; we have six inputs and two outputs in our DEA models, and DEA, being a nonparametric study, is less sensitive to sample size. We classified the firms according to first two digits of NAICS (i.e., North American Industry Classification System) codes. Five of the 30 firms could not fit into a common industry group; the firms represented a wide range of industry sectors, such as professional, scientific, and technical services; food products; nonmetallic mineral products, wood products, and utilities; consequently, we grouped them as "others." Thus, we had four industry groups. The firms and their industry groups are listed in Appendix C, which is available as an online supplement. The interval-scale data were collected in a standard scale (i.e., 1–5 point Likert scale). We conducted the Kruskal Wallis test to verify if there were significant differences among the distributions of inputs and outputs across the four industry groups. Lack of significant difference verified absence of industry effects.

V. Results and Discussion

We measured firms' performance in terms of the efficiency and uniqueness scores (refer to (3) and (4) in Section III). We classified the firms into groups of high performers (top 20 percentile of the units), medium performers (units between 40th percentile and 60th percentile), and low performers (bottom 20th percentile of the units) based on each of the efficiency and uniqueness scores. The numbers of units across the performance groups are comparable. The aim of our study is to assess if certain proactive environmental practices yield better business and environmental outcomes. Comparing the directional relationships in the means of the inputs and outputs across the performance groups using one-tailed *t*-tests reveals the relative cost effectiveness of different operational practices. The *t*-test is fairly robust for small sample sizes [74] and for moderately nonnormal population when the sample sizes are comparable [73]. We tested for the normality with respect to the inputs and outputs for the three performance levels across efficiency and uniqueness dimensions using Shapiro---Wilk's test. The Shapiro–Wilk's test is robust for small samples (i.e., $n \geq 3$) [69]. We had eight variables, for three levels of performance across efficiency and uniqueness dimensions, leading to 48 cases for normality test. The normality test results were satisfactory for 43 of the 48 cases. Consequently, application of *t*-tests to analyze the effectiveness of different practices across the performance groups was not a concern. The results of our *t*-tests are presented in Tables I–VI. Apparently, the three performance groups do not show bias for any specific industry. The details for variables that show statistically significant difference are presented in bold.

Tables I and II present the comparisons for efficiency score based performance for the two sets of outputs across the three performance levels. The results indicate that none of the operational practices are statistically lower for the high performers. However, the logarithm of total assets can be statistically lower for the high performers when CAGR and environmental certification are the outputs. While the lower assets of high performers are consistent with the DEA's efficiency maximization perspective of (relatively) lower inputs for a given amount of outputs, other operational inputs (e.g., proactive waste reduction etc.) do not seem to conform to this perspective. These results imply that the high performance group does not deemphasize preventative initiatives for obtaining higher efficiency because increased emphasis on preventative initiatives yield proportionately greater benefits than the costs. The nondecreasing inputs for the high-performance group suggest the existence of a *complementary* relationship between environmental practices and economic and environmental performance. The above complementary relationship is somewhat less noticed when the medium performers are compared with low performers for the ROA-based output set. Proactive waste reduction, remanufacturing, packaging reduction, and energy reduction are not statistically different across these two groups. However, consistent with DEA's efficiency maximization perspective medium performers have higher ROA and lesser emphasis on environmentally sensitive material substitution compared to low performers. The above result suggests that compared to low performers medium performers tend to benefit from a *tradeoff relationship* between environment and business. These findings are consistent with a recent Accenture's study that finds many companies are reluctant to invest heavily in sustainability programs because of the difficulty in deriving short-term payback [15].

Among the five operational practices, *proactive waste reduction* shows statistically significant difference for both sets of outputs for high performers. The higher emphasis on proactive waste reduction in the more efficient groups suggests that among the five initiatives proactive waste reduction is most effective in contributing to business and environmental performance. Although this finding is consistent with past large-scale survey-based research (e.g., [42], [48]), distinguishing proactive waste reduction from others provides clarity regarding the payoffs from alternate initiatives. The positive impact of the difference in the emphasis on proactive waste reduction is more apparent for ROA and environmental certification compared to CAGR and environmental certification when the high performers are compared with the low performers. Since proactive waste reduction involves process improvement initiatives, the above finding is consistent with the total quality environmental management perspective in sustainable operations literature (e.g., [23], [60]), which argues that preventative environmental initiatives are not only good for the environment but also lead to *cost efficiency and higher productivity* through increased process capability. The finding also lends supports to Orsato's [65] ecoefficiency-based competitive strategy that suggests that preventative environmental initiatives can lower operating costs by reducing resource consumption. Interestingly, ROA is not statistically different when high and medium performers are compared. This reflects the difficulty in deriving economic benefits after the low hanging fruits are harvested.

For efficiency score based-classification, our results do not indicate statistical difference for any other input variables except waste reduction, material substitution, and logarithm of total assets across the performance groups. Further, unlike ROA, the CAGR is not statistically different when high performers are compared against the low and medium performers. However, with lower assets medium performers exhibit greater CAGR than low performers; this indicates a *complementary* relationship between asset productivity and business performance.

Tables III and IV show the comparisons for uniqueness score-based performance. The results in Table III indicate that unlike the case of efficiency score-based classification, when the high-performance group is compared with the low-performance group, none of the inputs is statistically different but ROA and environmental certification are higher for the high-performance group. However, for other comparisons among the performance groups, some of the inputs are statistically different at 10% significance level. When the high-performance group is compared with the medium-performance group, ROA is higher, while remanufacturing initiatives are lower. The medium-performance group has greater waste reduction and remanufacturing initiatives and higher ROA and certifications compared to the low-performance group. These results imply that the complementary relationship between environmental initiatives and economic performance is less evident for the high-performance group; their uniqueness is primarily due to higher "ecoefficiency" resulting in high ROA. In contrast, the uniqueness of medium performers vis-a-vis low performers can be attributed to the *complementary* relationship between environmental initiatives and high ROA.

TABLE I
MEAN COMPARISON OF HIGH, MEDIUM, AND LOW PERFORMERS BASED ON EFFICIENCY SCORES (WITH ROA AND ENVIRONMENTAL CERTIFICATION AS THE OUTPUTS)

Item	Log (asset)	Waste reduction	Remanfg.	Substitution	Packaging	Energy	ROA	Env. Certif.
H	4.62	**3.48**	2.24	2.33	2.55	3.38	**0.076**	**3.71**
L	4.35	**2.83**	2.22	2.44	2.50	3.67	**0.037**	**2.33**
P(T$<=$t) one-tail	0.29	**0.06***	0.40	0.34	0.47	0.18	**0.060***	**0.003****
H	4.62	**3.48**	2.24	2.33	2.55	3.38	0.076	**3.71**
M	4.48	**2.67**	2.03	2.00	1.94	3.28	0.083	**2.72**
P(T$<=$t) one-tail	0.31	**0.02****	0.28	0.21	0.20	0.38	0.378	**0.03****
M	4.48	2.67	2.03	**2.00**	1.94	3.28	**0.083**	2.72
L	4.35	2.83	2.22	**2.44**	2.50	3.67	**0.037**	2.33
P(T$<=$t) one-tail	0.40	0.25	0.28	**0.098***	0.21	0.11	**0.048****	0.21

Notes *: weakly significant ($p<10\%$), **: significant ($p<5\%$).
H: high performers, M: medium performers, L: low performers (based on efficiency scores).
Sample size:
H: 7 (chemical: 1, computer and electronics: 3, others: 3).
M: 6 (chemical: 3, machinery manufacturing: 2, others: 1).
L: 6 (chemical: 2, computer and electronics: 3, machinery manufacturing: 1).

TABLE II
MEAN COMPARISON OF HIGH, MEDIUM, AND LOW PERFORMERS BASED ON EFFICIENCY SCORES (WITH CAGR AND ENVIRONMENTAL CERTIFICATION AS THE OUTPUTS)

Item	Log (asset)	Waste reduction	Remanfg.	Substitution	Packaging	Energy	CAGR	Env. Certif.
H	**4.70**	**3.38**	2.24	2.38	2.21	3.43	0.086	**3.38**
L	**5.16**	**2.72**	2.36	2.11	3.06	3.67	0.019	**2.28**
P(T$<=$t) one-tail	**0.03****	**0.06***	0.38	0.28	0.13	0.19	0.17	**0.02****
H	4.70	3.38	2.24	2.38	2.21	3.43	0.086	**3.38**
M	4.53	3.05	2.33	2.24	2.38	3.43	0.078	**2.38**
P(T$<=$t) one-tail	0.27	0.24	0.43	0.38	0.39	0.50	0.453	**0.054***
M	**4.53**	3.05	2.33	2.24	2.38	3.43	**0.078**	2.38
L	**5.16**	2.72	2.36	2.11	3.06	3.67	**0.019**	2.28
P(T$<=$t) one-tail	**0.02****	0.16	0.48	0.37	0.16	0.26	**0.022****	0.41

Notes *: weakly significant ($p<10\%$), **: significant ($p<5\%$).
H: high performers, M: medium performers, L: low performers (based on efficiency scores).
Sample size:
H: 7 (chemical: 1, computer & electronics: 3, others: 3).
M: 7 (chemical: 2, computer & electronics: 2, machinery manufacturing: 2, others: 1).
L: 6 (chemical: 3, computer & electronics: 2, others: 1).

TABLE III
MEAN COMPARISON OF HIGH, MEDIUM, AND LOW PERFORMERS BASED ON UNIQUENESS SCORES (WITH ROA AND ENVIRONMENTAL CERTIFICATION AS THE OUTPUTS)

Item	Log (asset)	Waste reduction	Remanfg.	Substitution	Packaging	Energy	ROA	Env. Certif.
H	4.61	3.17	1.89	2.22	2.11	3.17	**0.171**	**3.28**
L	4.25	2.94	1.89	2.33	1.75	3.44	**0.035**	**2.44**
P(T$<=$t) one-tail	0.22	0.33	0.50	0.40	0.25	0.15	**0.005****	**0.07***
H	4.61	3.17	**1.89**	2.22	2.11	3.17	**0.171**	3.28
M	4.79	3.44	**2.56**	2.33	2.33	3.44	**0.064**	3.11
P(T$<=$t) one-tail	0.30	0.30	**0.08***	0.41	0.39	0.28	**0.014****	0.39
M	4.79	**3.44**	**2.56**	2.33	2.33	3.44	**0.064**	**3.11**
L	4.25	**2.94**	**1.89**	2.33	1.75	3.44	**0.035**	**2.44**
P(T$<=$t) one-tail	0.14	**0.08***	**0.09***	0.5	0.21	0.5	**0.0999***	**0.097***

Notes *: weakly significant ($p<10\%$), **: significant ($p<5\%$).
H: high performers, M: medium performers, L: low performers (based on uniqueness scores).
Sample size:
H: 6 (chemical: 2, computer & electronics: 1, others: 3).
M: 6 (chemical: 2, computer & electronics: 2, machinery manufacturing: 2).
L: 6 (chemical: 3, computer & electronics: 1, machinery manufacturing: 1, others: 1).

TABLE IV
MEAN COMPARISON OF HIGH, MEDIUM, AND LOW PERFORMERS BASED ON UNIQUENESS SCORES (WITH CAGR AND ENVIRONMENTAL CERTIFICATION AS THE OUTPUTS)

Item	Log (asset)	Waste reduction	Remanfg.	Substitution	Packaging	Energy	CAGR	Env. Certif.
H	4.72	**3.67**	**2.90**	2.57	2.62	3.86	**0.119**	**3.62**
L	4.56	**2.61**	**2.25**	2.44	2.67	3.39	− **0.003**	**2.28**
P(T< = t) one-tail	0.36	**0.005****	**0.057***	0.36	0.48	0.11	**0.054***	**0.005****
H	**4.72**	**3.67**	**2.90**	2.57	2.62	3.86	0.119	**3.62**
M	**4.28**	**3.00**	**2.07**	2.27	2.00	3.53	0.056	**2.87**
P(T< = t) one-tail	**0.06***	**0.09***	**0.02****	0.27	0.16	0.15	0.184	**0.097***
M	4.28	3.00	2.07	2.27	2.00	3.53	**0.056**	2.87
L	4.56	2.61	2.25	2.44	2.67	3.39	− **0.003**	2.28
P(T< = t) one-tail	0.27	0.18	0.28	0.35	0.18	0.33	**0.086***	0.12

Notes *: weakly significant ($p < 10\%$), **: significant ($p < 5\%$).
H: high performers, M: medium performers, L: low performers (based on uniqueness scores).
Sample size:
H: 7 (chemical: 1, computer & electronics: 3, machinery manufacturing: 2, others: 1).
M: 5 (chemical: 2, computer & electronics: 1, machinery manufacturing: 1, others: 1).
L: 6 (chemical: 1, computer & electronics: 3, others: 2).

TABLE V
MEAN COMPARISON OF HIGH, MEDIUM, AND LOW PERFORMERS BASED ON BOTH EFFICIENCY AND UNIQUENESS SCORES (WITH ROA AND ENVIRONMENTAL CERTIFICATION AS THE OUTPUTS)

Item	Log (asset)	Waste reduction	Remanfg.	Substitution	Packaging	Energy	ROA	Env. Certif.
HH	4.63	**4.11**	2.11	2.67	2.11	3.44	**0.111**	**4.11**
LL	4.04	**3.00**	2.00	2.33	2.00	3.50	**0.027**	**2.42**
P(T< = t) one-tail	0.21	**0.02****	0.40	0.34	0.45	0.41	**0.017****	**0.006****

Notes *: weakly significant ($p < 10\%$), **: significant ($p < 5\%$).
HH: high performers, MM: medium performers, LL: low performers (based on efficiency and uniqueness scores, respectively).
Sample size:
HH: 3 (chemical: 1, others: 2).
LL: 4 (chemical: 2, computer and electronics: 1, machinery manufacturing: 1).
We did not have any sample in the MM category.

TABLE VI
MEAN COMPARISON OF HIGH, MEDIUM, AND LOW PERFORMERS BASED ON BOTH EFFICIENCY AND UNIQUENESS SCORES (WITH CAGR AND ENVIRONMENTAL CERTIFICATION AS THE OUTPUTS)

Item	Log (asset)	Waste reduction	Remanfg.	Substitution	Packaging	Energy	CAGR	Env. Certif.
HH	4.92	**3.67**	2.75	2.58	2.67	3.58	0.149	**3.58**
LL	5.00	**2.56**	2.61	2.56	3.67	3.78	−0.001	**2.11**
P(T< = t) one-tail	0.41	**0.06***	0.37	0.48	0.16	0.34	0.131	**0.053***

Notes *: weakly significant ($p < 10\%$), **: significant ($p < 5\%$).
HH: high performers, MM: medium performers, LL: low performers (based on efficiency and uniqueness scores, respectively).
Sample size:
HH: 4 (chemical: 1, computer and electronics: 2, others: 1).
LL: 3 (computer & electronics: 2, others: 1).
MM: 2 (chemical: 1, machinery manufacturing: 1).
We had only two samples in the MM category and, hence, did not have statistical comparison involving this category.

TABLE VII
DESCRIPTIVE STATISTICS OF THE INPUTS AND OUTPUTS

Item	Log (asset)	Waste reduction	Remanufacturing	Substitution	Packaging	Energy	ROA	CAGR	Env. Certif.
Max	5.50	4.67	4.33	3.33	4.33	4.67	0.31	0.47	4.33
Min	2.69	2.00	1.33	1.00	1.00	2.33	−0.01	−0.12	1.33
Mean	4.60	3.06	2.31	2.28	2.29	3.44	0.09	0.06	2.87
Std. Dev.	0.63	0.71	0.79	0.66	1.21	0.64	0.07	0.10	0.91

Table IV suggests that when CAGR and environmental certification are considered as outputs, the relationship between inputs and outputs is somewhat opposite to that between ROA and environmental certification. Proactive waste reduction and remanufacturing initiatives and outputs are significantly higher for the highly unique firms exhibiting the *complementary relationship* between environmental initiatives and business performance. Evidently, the complementary relationship is more pronounced for the CAGR-based uniqueness metric. This implies that when market reputation-based distinctiveness (i.e., high CAGR of sales and environmental certification) is pursued, the higher performance group puts higher emphasis on proactive waste reduction and remanufacturing. The finding is consistent with Orsato's [65] "differentiation" strategy that suggests that firms undertaking preventative initiatives beyond the legally mandated standards can successfully differentiate themselves in the marketplace. Proactive waste reduction and remanufacturing strategy being somewhat resource intensive, expensive, and difficult to implement, firms emphasizing these initiatives achieve distinctiveness in the competitive market. Such differentiation can potentially result in greater market growth.

To see the common practices among the efficient and unique performers, we regrouped the common firms across both dimensions of performance (i.e., efficiency and uniqueness) for the three performance groups and compared their inputs and outputs for the both sets of outputs. The number of common firms in the medium-performance category was less than 3, making it difficult to include those for *t*-tests. We therefore dropped them from the analysis, and just compared the performance of high and low performers across both dimensions of performance. The results are given in Tables V and VI. The results indicate proactive waste reduction is *the only differentiator* between high and low performers in both efficiency and uniqueness dimensions. However, proactive waste reduction does not impact CAGR significantly.

To summarize, among the five preventative environmental initiatives, proactive waste reduction and remanufacturing are the main performance differentiators when firm-specific strategic priorities are accounted for through DEA. Consistent with strategic choice theory, the results highlight the significance of focus on a fewer set of environmental practices to achieve the dual benefits of environmental and business excellence. Comparing these results with the descriptive statistics in Table VII and correlations in appendix D, it is apparent that although the patterns of emphasis on proactive waste reduction and remanufacturing are not quite different from those on energy, substitution, and packaging reduction initiatives, the latter ones do not seem to affect the business and environmental performance significantly. This counterintuitive finding regarding the input and output variables may be explained in the following way. Since firms have been pursuing preventative environmental practices for quite some time, the performance impact of most of these practices except proactive waste reduction and remanufacturing have become negligible across firms over time. We recognize that proactive waste reduction and remanufacturing may show both *complementary* and *tradeoff* relationships with business performance. In general, the most successful firms are more likely to experience the complementary relationship. Apparently, firms experiencing complementary relationships either pursue "ecoefficiency" (i.e., derive high ROA with strong environmental initiatives leading to high-efficiency scores) or "ecobranding" (derive high CAGR with strong environmental initiatives leading to high uniqueness scores) strategies.

Further, it is apparent from a uniqueness score-based classification that the most *distinct* firms with respect to ROA-oriented performance do not show significantly higher environmental initiatives *vis-a-vis* the less distinct firms (refer to Table III). Thus, it is plausible that these high-performing firms are operating at their efficiency frontiers [14] with respect to the input–output set used in this study. However, the moderately distinct firms (medium performers) are putting relatively higher emphasis than low performers on proactive waste reduction to derive high ROA and environmental certifications. They may not have reached their efficiency frontiers yet. Since each firm will have its own unique efficiency frontier, additional research for deeper understanding of the operational dynamics in firm- and industry-specific contexts would offer interesting insights. Finally, we find that firms with the highest efficiency and uniqueness scores have distinctly high ROA but not CAGR. These firms seemingly experience a *complementary* relationship between the proactive waste reduction and ROA.

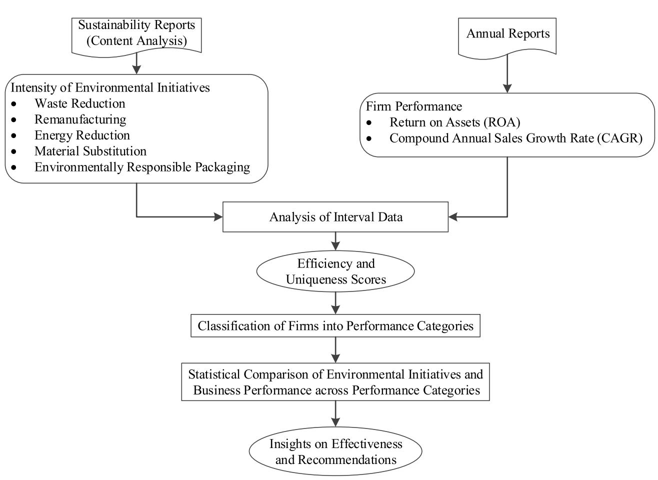
VI. Conclusion

In recent years, firms have been engaging in several practices to conduct business in an environmentally responsible manner. Broadly, these practices are either preventative or end-of-the pipe in nature. The motivation for such practices has been to derive competitive advantage. Given the unique business contexts and priorities of each firm, it is difficult to ascertain which practices would generate appropriate economic payoffs for a firm. Ascertaining their performance impacts is important for effective execution of the practices because environmental initiatives are expensive with relatively long-payback periods; however, firms usually expect a short-payback period. Both mathematical models and survey-based empirical research using parametric (e.g., regression type) methodologies have limitations to address these issues adequately. While mathematical models require objective data in ratio scales, empirical parametric studies mainly provide insights into the average relationships among the inputs and outputs across all firms. The proposed content analysis-based DEA approach allows accounting for specific firms' weightages for various environmental initiatives and performance outcomes, while utilizing interval-scaled data. Since objective data are difficult to obtain, an advantage of the proposed approach is the versatility to utilize both perceptual and objective data in the analysis. Further, the proposed methodology is less demanding than the parametric techniques in terms of sample size and assumptions regarding statistical distributions. Due to these advantages, our proposed approach can be used to evaluate the effectiveness of other important operations improvement initiatives, such as TQM, lean, flexible manufacturing, etc.

In this paper, we derived a new metric called the "uniqueness" score to characterize the distinctiveness of firms and illustrated how a firm can select the most useful practices from its unique perspective. Based on data from corporate sustainability and annual reports, we compared the preventative practices and performance of firms across a diverse set of industries. The findings provide nuanced insights into the relative usefulness of alternative preventative practices in accomplishing ecoefficiency and distinctiveness, leading to higher ROA and higher sales.

The preventative environmental initiatives included in this study are commonly followed across firms. Our selection of input and output variables in the DEA was motivated by extant theoretical frameworks and empirical studies that argue for a positive relationship between preventative initiatives and business performance. Although our choice of preventative variables is quite comprehensive, some "end-of-the pipe" initiatives might influence business performance. Future research can improve the analysis by considering a larger set of environmental initiatives. However, consideration for a larger set of practices will create missing values for the nonpracticing firms. The model used in this study cannot handle missing value-related challenges. We chose a select group of 30 firms, but expanding the analysis for a higher sample size could help enhance generalizability. Future research can be carried out to address these issues.

Appendix A
A Schematic Diagram of Data Collection and Analysis



Appendix B
Measurement Items for Inputs and Outputs [62]

Calibration for the interval scale: 1) not doing it, 2) eludes to doing it, 3) moderate level of implementation with minimal quantitative measures, 4) high level of implementation with some quantitative measures, and 5) extraordinary level of implementation with extensive quantitative measures, categories, and targets.

Inputs (operational practices).

1) Total fixed and current assets in use for the financial year 2008 (ratio scale).
2) Waste reduction (proactive): Pollution prevention, proactive talk in terms of proactive approaches to pollution prevention. Elimination of waste before it is produced. More specific to pollution prevention.
3) Remanufacturing: Rebuilding a product where some of the materials, parts or components are recovered or replaced.
4) Substitution: Replacing a material that can cause environmental problems with another material which is not problematic.
5) Packaging: Returnable packaging, reduced packaging, recyclable packaging, environmentally responsible packaging using packaging, and pallets that can be returned after they are finished being used. New alternative to packaging.
6) Energy: energy conservation, efficiency, recovery, fuel recovery capturing energy that was a previous emission in the form of steam, or heat. Installing energy-efficient equipment, or equipment that can capture previously released energy. Could also include proactive approaches to reduce fuel consumption for logistics activities.

Outputs (environmental and financial outcomes).

1) Return on total assets for the financial year 2010 (ratio scale).
2) Compound annual sales growth between 2008 and 2009 and 2010 and 2011 (ratio scale).
3) Environmental certification: The firm has specifically received certifications, such as ISO 14000, EMAS, Green Seal, etc.

Appendix C
List of Companies Included in the Study

Companies	**Industry Group**
3M	Others
American Electric Power	Others
Apple	Computer and Electronic Product Manufacturing
AT&T	Computer and Electronic Product Manufacturing
Bang and Olufsen A/S	Computer and Electronic Product Manufacturing
BASF	Chemical Manufacturing
Bristol–Myers Squibb	Chemical Manufacturing
Chevron	Chemical Manufacturing
DANFOSS A/S	Machinery Manufacturing
Dell	Computer and Electronic Product Manufacturing
Dow Chemical	Chemical Manufacturing
DuPont	Chemical Manufacturing
Eastman Kodak	Machinery Manufacturing
Exxon Mobil	Chemical Manufacturing
Ford	Machinery Manufacturing
General Motors	Machinery Manufacturing
Goodyear	Chemical Manufacturing
Hewlett-Packard	Computer and Electronic Product Manufacturing
IBM	Others
ITT	Machinery Manufacturing
Johnson & Johnson	Chemical Manufacturing
Motorola	Computer and Electronic Product Manufacturing
Nestle	Others
Novartis Pharmaceuticals	Chemical Manufacturing
Raytheon	Computer and Electronic Product Manufacturing
Rockwell Automation	Computer and Electronic Product Manufacturing
Shell	Chemical Manufacturing
Texas Instruments Inc.	Computer and Electronic Product Manufacturing
Weyerhaeuser	Others
Xerox	Computer and Electronic Product Manufacturing

APPENDIX D
CORRELATION STATISTICS OF INPUTS AND OUTPUTS

Correlations	1	2	3	4	5	6	7	8	9
1) log (asset)	1								
2) Waste Reduction (Proactive)	0.38	1							
3) Remanufacturing	0.121	0.565**	1						
4) Substitution	−0.179	0.541**	0.455*	1					
5) Packaging	0.277	0.274	0.607**	0.458*	1				
6) Energy	0.160	0.559**	0.651**	0.381*	0.409*	1			
7) ROA	0.247	−0.280	−0.227	−0.180	0.005	−0.329	1		
8) CAGR	0.167	−0.085	0.110	0.088	−0.075	−0.105	0.240	1	
9) Env. cert	−0.054	0.655**	0.359	0.263	0.222	0.388*	−0.298	−0.249	1

**Correlation is significant at the 0.01 level (two-tailed).
*Correlation is significant at the 0.05 level (two-tailed).

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REFERENCES

[1] D. J. Aigner, C. A. K. Lovell, and P. Schmidt, “Formulation and estimation of stochastic frontier production function models,” *J. Econometrics*, vol. 6, no. 1, pp. 21–37, 1977.
[2] M. Arndt, “Cat sink its claws into services,” *BusinessWeek*, Dec. 20, 2005, pp. 56–59.
[3] BASF Report. (2012). [Online]. Available: http://www.corporateregister.com
[4] R. D. Banker, A. Charnes, and W. W. Cooper, “Some models for estimating technical and scale inefficiencies in data envelopment analysis,” *Manage. Sci.*, vol. 30, no. 9, pp. 1078–1092, 1984.
[5] I. Bose and R. Pal, “Do green supply chain management initiatives impact stock prices of firms?” *Decision Support Syst.*, vol. 52, no. 3, pp. 624–634, 2012.
[6] A. Bussofiane, S. Martin, and D. Parker, “The impact of technical efficiency of the UK privatization programme,” *Appl. Econ.*, vol. 29, no. 3, pp. 297–310, 1997.
[7] F. M. Cervelini and M. T. S. Souza, “A contribution of cleaner production program to ISO 14001 management system: A case study in metal mechanic sector,” *J. Oper. Supply Chain Manage.*, vol. 2, no. 1, pp. 61–76, 2009.
[8] A. Charnes, W. Cooper, and E. Rhodes, “Evaluating program and managerial efficiency: An application of data envelopment analysis to program follow through,” *Manage. Sci.*, vol. 27, no. 6, pp. 668–697, 1981.
[9] A. Charnes, W. Cooper, A. Lewin, and L. Seiford, Eds., *Data Envelopment Analysis, Theory, Methodology and Applications*. Boston, MA, USA: Kluwer, 1994.
[10] C.-M. Chen and M. Delmas, “Measuring corporate social performance: An efficiency perspective,” *Prod. Oper. Manage.*, vol. 20, no. 6, pp. 789–804, 2011.
[11] Y. Chen and J. Zhu, “DEA models for identifying critical performance measures,” *Ann. Oper. Res.*, vol. 124, no. 1, pp. 225–244, 2003.
[12] J. Child, “Strategic choice in the analysis of action, structure, organizations and environment: Retrospect and prospect,” *Org. Stud.*, vol. 18, no. 1, pp. 43–76, 1997.
[13] P. Christmann, “Effects of best practices of environmental management on cost advantage: The role of complementary assets,” *Acad. Manage. J.*, vol. 43, no. 4, pp. 663–680, 2000.
[14] K. B. Clark, “Competing through manufacturing and the new manufacturing paradigm: Is manufacturing strategy passe?” *Prod. Oper. Manage.*, vol. 5, no. 1, pp. 42–58, 1996.
[15] J. A. Cook. (2014, Jan.–Mar.). Green supply chains are still too costly. *CSCM’s Supply Chain Quart*. [Online]. Available: www.SupplyChainQuarterly.com
[16] W. D. Cook and J. Zhu, “Rank order data in DEA: A general framework,” *Eur. J. Oper. Res.*, vol. 174, no. 2, pp. 1021–1038, 2006.
[17] W. Cooper, L. Seiford, and K. Tone, *Data Envelopment Analysis: A Comprehensive Text With Models, Application, References*. Boston, MA, USA: Kluwer, 2000.
[18] C. J. Corbett and D. A. Kirsch, “International diffusion of ISO 14000 certification,” *Prod. Oper. Manage.*, vol. 10, no. 3, pp. 327–342, 2001.
[19] Danfoss Sustainability Report. (2012). [Online]. Available: http://www.corporateregister.com
[20] P. de Lancer Julnes, “Decision-making tools for public productivity improvement: A comparison of DEA to cost-benefit and regression analyses,” *J. Public Budget., Account. Financial Manage.*, vol. 12, no. 4, pp. 625–646, 2000.
[21] J. J. de Vries, D. K. Bayramoglu, and T. van der Wiele, “Business and environmental impact of ISO 14001,” *Int. J. Quality Rel. Manage.*, vol. 29, no. 4, pp. 425–435, 2012.
[22] A. Dehnokhalaji, P. J. Korhonen, M. Köksalan, N. Nasrabadi, and J. Wallenius, “Efficiency analysis to incorporate interval-scale data,” *Eur. J. Oper. Res.*, vol. 207, no. 2, pp. 1116–1121, 2010.
[23] M. Delmas, “Stakeholders and competitive advantage: The case of ISO 14001,” *Prod. Oper. Manage.*, vol. 10, no. 3, pp. 343–358, 2001.
[24] Dow Chemical Company Annual Sustainability Report. (2012). [Online]. Available: http://www.corporateregister.com
[25] V. J. Duriau, R. K. Reger, and M. D. Pfarrer, “A content analysis of the content analysis literature in organization studies: Research themes, data sources, and methodological refinements,” *Org. Res. Methods*, vol. 10, no. 1, pp. 5–34, 2007.
[26] H. Dyckhoff and K. Allen, “Measuring ecological efficiency with data envelopment analysis (DEA),” *Eur. J. Oper. Res.*, vol. 132, no. 2, pp. 312–325, 2001.
[27] R. G. Dyson, R. Allen, A. S. Camano, V. V. Podinovski, C. S. Sarrico, and E. A. Shale, “Pitfalls and protocols in DEA,” *Eur. J. Oper. Res.*, vol. 132, no. 2, pp. 245–259, 2001.
[28] J. Elkington, “Towards the sustainable corporation: Win-win-win business strategies for sustainable development,” *California Manage. Rev.*, vol. 36, no. 2, pp. 90–100, 1994.
[29] A. Emrouznejad, A. L. Anouze, and E. Thanassoulis, “A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA,” *Eur. J. Oper. Res.*, vol. 200, no. 1, pp. 297–304, 2010.
[30] M. J. Epstein, “Improving environmental management with full environmental cost accounting,” *Environ. Quality Manage.*, vol. 6, no. 1, pp. 11–22, 1996.
[31] Ford Motor Company Sustainability. (2012, Dec.). [Online]. Available: http://www.corporateregister.com
[32] R. A. Frosch and N. E. Gallopoulos, “Strategies for manufacturing,” *Sci. Amer.*, vol. 261, no. 3, pp. 94–102, 1989.
[33] D. Galagedera and P. Silvapulle, “Experimental evidence on robustness of data envelopment analysis,” *J. Oper. Res. Soc.*, vol. 54, no. 6, pp. 654–660, 2003.
[34] K. Gilley, D. Worrell, and A. El-Jelly, “Corporate environmental initiatives and anticipated firm performance: the differential effects of process-driven versus product-driven greening initiatives,” *J. Manage.*, vol. 26, no. 6, pp. 1199–1216, 2000.
[35] J. Gonzalez-Benito and O. Gonzalez-Benito, “Environmental proactivity and business performance: An empirical analysis,” *Omega*, vol. 33, no. 1, pp. 1–15, 2005.

[36] J. Gonzalez-Benito and O. Gonzalez-Benito, "Operational management practices linked to the adoption of ISO 14001: An empirical analysis of Spanish Manufacturers," *Int. J. Prod. Econ.*, vol. 113, no. 1, pp. 60–73, 2008.

[37] M. F. Grace and Y. Yuan, "The effect of premium taxation on U.S. life insurers," *J. Insurance Regul.*, vol. 30, no. 1, pp. 227–259, 2011.

[38] K. W. Green, P. J. Zelbst, J. Meacham, and V. S. Bhadauria, "Green supply chain management practices: Impact on performance," *Int. J. Supply Chain Manage.*, vol. 17, no. 3, pp. 290–305, 2012.

[39] M. Halme, T. Joro, and M. Koivu, "Dealing with interval scale data in data envelopment analysis," *Eur. J. Oper. Res.*, vol. 137, no. 1, pp. 22–27, 2002.

[40] G. S. Hansen and B. Wernerfelt, "Determinants of firm performance: The relative importance of economic and organizational factors," *Strategic Manage. J.*, vol. 10, no. 5, pp. 399–411, 1989.

[41] S. Hart, "A natural resource-based view of the firm," *Acad. Manage. Rev.*, vol. 20, no. 4, pp. 874–907, 1995.

[42] S. Hart and G. Ahuja, "Does it pay to be green? An empirical examination of the relationship between emission reduction and firm performance," *Bus. Strategy Environ.*, vol. 5, no. 1, pp. 30–37, 1996.

[43] K. B. Hendricks, V. R. Singhal, and J. K. Stratman, "The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations," *J. Oper. Manage.*, vol. 25, no. 1, pp. 65–82, 2007.

[44] HP Global Citizenship Report. (2012). [Online]. Available: http://www.corporateregister.com

[45] IBM and the Environment Report. (2012). [Online]. Available: http://www.corporateregister.com

[46] L. R. James, R. G. Demaree, and G. Wolf, "Estimating within-group interrater reliability with and without response bias," *J. Appl. Psychol.*, vol. 69, no. 1, pp. 85–98, 1984.

[47] T. Joro, P. Korhonen, and J. Wallenius, "Structural comparison of data envelopment analysis and multiple objective linear programming," *Manage. Sci.*, vol. 44, pp. 962–970, 1998.

[48] A. A. King and M. J. Lenox, "Does it really pay to be green? An empirical study of firm environmental and financial performance," *J. Ind. Ecol.*, vol. 5, no. 1, pp. 105–116, 2001.

[49] A. A. King and M. J. Lenox, "Lean and green? An empirical examination of the relationship between lean production and environmental performance," *Prod. Oper. Manage.*, vol. 10, no. 3, pp. 244–256, 2001.

[50] A. A. King and M. J. Lenox, "Exploring the locus of pollution reduction," *Manage. Sci.*, vol. 42, no. 2, pp. 289–299, 2002.

[51] R. D. Klassen and C. P. McLaughlin, "The impact of environmental management on firm performance," *Manage. Sci.*, vol. 42, no. 8, pp. 1199–1214, 1996.

[52] P. R. Kleindorfer, K. Singhal, and L. N. Van Wassenhove, "Sustainable operations management," *Prod. Oper. Manage.*, vol. 14, no. 4, pp. 482–492, 2005.

[53] P. J. Korhonen and M. Luptacik, "Eco-efficiency analysis of power plants: An extension of data envelopment analysis," *Eur. J. Oper. Res.*, vol. 154, no. 2, pp. 437–446, 2004.

[54] S. Link and E. Naveh, "Standardization and discretion: Does the environmental standard ISO 14001 lead to performance benefits?" *IEEE Trans. Eng. Manage.*, vol. 53, no. 4, pp. 508–519, Nov. 2006.

[55] J. D. Linton and V. Jayaraman, "A conceptual framework for product life extension," *Int. J. Prod. Res.*, vol. 43, no. 9, pp. 1807–1829, 2005.

[56] F. H. Lotfi, A. A. Noora, G. R. Jahanshahloo, J. Gerami, and M. R. Mozaffari, "A slacks-base measure of super-efficiency for DEA with negative data," *Australian J. Basic Appl. Sci.*, vol. 4, no. 12, pp. 6197–6210, 2010.

[57] E. Lowitt, "How to survive climate change and still run a thriving business," *Harvard Bus. Rev.*, vol. 92, no. 4, pp. 86–92, 2014.

[58] S. Mahapatra, S. A. Melnyk, and R. J. Calantone, "Understanding environment management systems performance: An expanded empirical study," *Int. J. Prod. Qual. Manage.*, vol. 2, no. 2, pp. 263–286, 2007.

[59] I. Maslennikova and D. Foley, "Xerox's approach to sustainability," *Interfaces*, vol. 30, no. 3, pp. 226–233, 2000.

[60] S. Melnyk, R. Sroufe, and R. Calantone, "Assessing the impact of environmental management systems on corporate and environmental performance," *J. Oper. Manage.*, vol. 21, no. 3, pp. 329–351, 2003.

[61] J. L. Miller, C. W. Craighead, and K. R. Karwan, "Service recovery: A framework and empirical investigation," *J. Oper. Manage.*, vol. 18, no. 4, pp. 387–400, 2000.

[62] F. Montabon, R. Sroufe, and R. Narasimhan, "An examination of corporate reporting, environmental management practices and firm performance," *J. Oper. Manage.*, vol. 25, no. 5, pp. 998–1014, 2007.

[63] J. K. H. Nga, "The influence of ISO 14000 on firm performance," *Social Respon. J.*, vol. 5, no. 3, pp. 408–422, 2009.

[64] R. Nidumolu, C. K. Prahalad, and M. R. Rangaswami, "Why sustainability is now the key driver of innovation," *Harvard Bus. Rev.*, vol. 87, no. 9, pp. 57–64, 2009.

[65] R. J. Orsato, "When does it pay to be green?" *California Manage. Rev.*, vol. 48, no. 2, pp. 127–143, 2006.

[66] A. C. Porter, "Measuring the content of instruction: Uses in research and practice," *Educ. Researcher*, vol. 31, no. 7, pp. 3–14, 2002.

[67] I. M. Premachandra, G. S. Bhabra, and T. Sueyoshi, "DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique," *Eur. J. Oper. Res.*, vol. 193, no. 2, pp. 412–424, 2009.

[68] P. Rao and D. Holt, "Do green supply chains lead to competitiveness and economic performance?" *Int. J. Oper. Prod. Manage.*, vol. 25, no. 9, pp. 898–916, 2005.

[69] J. P. Royston, "An extension of the Shapiro and Wilk's W test for normality to large samples," *Appl. Statist.*, vol. 31, pp. 115–124, 1982.

[70] J. Sarkis, "Manufacturing's role in corporate environmental sustainability—Concerns for the new millennium," *Int. J. Oper. Prod. Manage.*, vol. 21, nos. 5/6, pp. 666–686, 2001.

[71] R. Sroufe, "Effects of environment management systems on environment management practices and operations," *Prod. Oper. Manage.*, vol. 12, no. 3, pp. 416–432, 2003.

[72] T. Sueyoshi and M. Goto, "Environmental assessment by DEA radial measurement: U.S. coal-fired power plants in ISO (Independent System Operator) and RTO (Regional Transmission Organization)," *Energy Econ.*, vol. 34, no. 3, pp. 663–676, 2012.

[73] S. Sawilowsky and R. C. Blair, "A more realistic look at the robustness and type II error properties of the t test to departures from population normality," *Psychol. Bull.*, vol. 111, no. 2, pp. 353–360, 1992.

[74] Student, "The probable error of a mean," *Biometrika*, vol. 6, no. 1, pp. 1–25, 1908.

[75] R. Sousa and C. A Voss, "Contingency research in operations management practices," *J. Oper. Manage.*, vol. 26, no. 6, pp. 697–713, 2008.

[76] S. Talluri and J. Sarkis, "A model for performance monitoring of suppliers," *Int. J. Prod. Res.*, vol. 40, no. 16, pp. 4257–4269, 2002.

[77] C. Tangpong, "Content analytic approach to measuring constructs in operations and supply chain management," *J. Oper. Manage.*, vol. 29, pp. 627–638, 2011.

[78] E. Thanassoulis, M. Kortelainen, G. Johnes, and J. Johnes, "Costs and efficiency of higher education institutions in England: A DEA analysis," *J. Oper. Res.*, vol. 62, no. 7, pp. 1282–1297, 2011.

[79] M. Thierry, M. Salomon, J. Van Nunen, and L. N. Van Wassenhove, "Strategic issues in product recovery management." *California Manage. Rev.*, vol. 37, no. 2, pp. 114–136, 1995.

[80] G. Vastag, C. J. Corbett, and D. A. Kirsch, "Revisiting ISO 14000 diffusion: A new "look" at the drivers of certification/response," *Prod. Oper. Manage.*, vol. 13, no. 3, pp. 260–267, 2004.

[81] R. P. Weber, *Basic Content Analysis*, 2nd ed. Newbury Park, CA, USA: Sage, 1990.

[82] Weyerhaeuser Sustainability Report. (2012). [Online]. Available: http://www.corporateregister.com

[83] L. Woellert, "HP wants your old PCs back," *BusinessWeek*, pp. 82—83, Apr. 2006.

[84] R. A. Wolfe, R. P. Gephart, and T. E. Johnson, "Computer-facilitated qualitative data analysis: Potential contributions to management research," *J. Manage.*, vol. 19, no. 3, pp. 637–660, 1993.

[85] S. H. M. Zailani, T. K. Eltayeb, C. C. Hsu, and K. C. Tan, "The impact of external institutional drivers and internal strategy on environmental performance," *Int. J. Oper. Prod. Manage.*, vol. 32, no. 6, pp. 721–745, 2012.

[86] Q. Zhu and J. Sarkis, "Relationships between operational practices and performance, among early adopters of green supply chain management practices in Chinese manufacturing enterprises," *J. Oper. Manage.*, vol. 22, no. 3, pp. 265–289, 2004.

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