Assessment of Nonparametric Frontier Models Applied to Socially Responsible Investment

by

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(Under the direction of Dr. Cheolwoo Park)

Abstract

The goal of this thesis is to provide an effective tool for screening a stock portfolio, with socially responsible investment (SRI) in mind, using efficient frontier models. Data envelopment analysis (DEA) has been used previously to build SRI portfolios, but this thesis shows that free disposal hull (FDH), a similar model which does not assume the convexity of the decision-making units, yields superior results when applied to a stock universe of 253 Korean companies. Over a four-year time span from 2006 to 2009, portfolios selected using the FDH method consistently outperform those selected using DEA with both variable returns to scale and constant returns to scale assumptions.

Index words: Socially responsible investment, corporate social responsibility, frontier model, data envelopment analysis, free disposal hull, portfolio.

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Chapter 1

Introduction

Monetary gain, a goal for any capitalistic endeavor, whether on the scale of a local hardware establishment or a global multi-million dollar entertainment industry, can sometimes be the end-all, be-all for the managers and officials who run these enterprises, to the detriment of society as a whole. Perhaps the most noteworthy example of such a case would be the corporation that willfully and egregiously pollutes the environment rather than adhere to more eco-friendly alternatives in the interest meeting the bottom line, but this would be just one of the many ways that the pursuit of financial profit could result in socially undesirable acts. Such instances are exactly why socially responsible investment (SRI) exists as an alternative to traditional investment strategies, because people want a way to vote with their dollars against business practices they find objectionable (Wagner, 2001).

Of course, making a stand against bad business or, conversely, supporting socially sustainable and environmentally responsible industry and services with investments cannot possibly endure as a legitimate financial tool for investors in the private, government, or corporate sectors if it means that these investments are consistent money-losers. In order for SRI to work, a socially responsible portfolio needs to compete favorably with investment portfolios with none of the constraints associated with the SRI portfolio. Many have theorized that sustainable business is good business, and therefore investing in those corporations which observe certain environmental, social, and governance responsibilities should be a profitable endeavor (Porter and Van der Linde, 1995). Still others suggest that any limitations on one's investment horizon is necessarily detrimental to potential returns, according to traditional investment portfolio theory. Luckily, it is not necessary to rely on theory to test the validity of the SRI investment approach, as there are many empirical methods available that should provide evidence for the debate, and several of these methods will be explored in this thesis.

Since the recent explosive growth of the SRI movement, many empirical studies have been performed with the goal of supporting or debunking SRI's worth as an investment strategy, with mixed but encouraging results (Mercer 2009). As with almost any economic problem, the systemic complexity of the problem makes definitive statistical findings elusive and the selection of an appropriate statistical method all the more crucial. Several methods which have been explored in the past, and continue to be used in current studies, will be introduced over the course of the next several pages before settling on the nonparametric frontier analyses used to investigate the efficacy of SRI for this thesis.

Nonparametric frontier estimation is applicable to cases in which the boundary of a distribution support is unknown, except for certain known geometric properties of the boundary such as convexity or a monotone increasing or decreasing behavior, for example. There have been several methods of nonparametric frontier estimation developed for the purposes of productivity analysis, typically in the interest of testing the efficiency of production units within a company or even the performance of companies relative to each other. In such a case, the input and output pairing of each company can be considered as a multivariate observation, in which case the objective of nonparametric frontier analysis is to find the boundary of its support. For more detailed information on nonparametric frontier estimation, see Korostelev et al. (1995).

Three frontier analysis methods in particular, data envelopment analysis with constant returns to scale (DEA CRS), data envelopment analysis with variable returns to scale (DEA VRS), and free disposal hull (FDH) analysis will be elaborated upon further. Then all three methods will be used to build socially responsible portfolios, which will be compared against each other using a dataset of monthly returns for a number of stocks on the Korean marketplace, with one of the three methods being singled out as the most preferable means of selecting SRI portfolios. If the best of these methods is successful in selecting a proper SRI portfolio and SRI works as a tool for financial gain, as well as sustainability, then we should see the highest grade portfolio consistently outperforming the lower grades and the Korean marketplace as a whole.

Before the experiment which is the focus of this thesis is performed, however, and the nonparametric statistical methods detailed, a brief history of the SRI movement will be given in order to further motivate the problem. The history will be accompanied by a review of some influential academic papers which utilized methods not covered in full detail here, and also papers which developed and fleshed out the DEA and FDH methods, which will be fully explained and implemented in the following chapters of the thesis. Finally, a concluding chapter will follow, briefly outlining the results of the experiment and discussing some limitations associated with the study.

Chapter 2

Socially Responsible Investment

Socially responsible investment is an old concept that has gained quite a bit of momentum in recent years, as evidenced by the substantial increase in assets held by socially screened portfolios from $2.16 trillion in 2003 to $2.71 trillion in 2007 (Social Investment Forum 2007). What started as an investment strategy designed primarily to discourage practices deemed harmful to society has become, for some, a legitimate tool for financial gain as well. Today, methods by which SRI is conducted vary from investment in mutual funds, which have undergone some kind of screening process to insure that certain social responsibility criteria are met, to shareholder advocacy, which concerns activism within the company to promote a socially responsible business model. No matter how SRI is implemented, the end goal is always to encourage corporate social responsibility (CSR) and, simultaneously, to maximize financial gain.

The core tenets of modern SRI have their roots in religious practices as early as the eighteenth century, notably extant in the business ethos of Methodist minister John Wesley (1703-1791), which was exemplified in his sermon "The Use of Money." In the sermon, Wesley mentions that it is the Christian's imperative to "gain all you can," but not at the expense of "hurting our neighbor in his body" (Wesley, 1840). Wesley uses the alcohol industry as a prime example of a business to avoid when making financial gains, a strategy that is still employed to this day by many proponents of SRI, and an instance of negative screening, which will be discussed in detail further on below.

Although the main idea behind SRI has been around for hundreds of years, the modern expansion of the concept into a valid and popular investment strategy began in the 1960's amidst heavy social upheaval and political unrest. The civil rights movement led by Dr. Martin Luther King and the Vietnam War, in particular, sparked many changes in traditional attitudes toward prudent investment. A prominent catalyst of the SRI movement was the infamous photograph of nine-year-old Phan Thi Kim Phc naked, running down the road with her back lit aflame by Agent Orange, which instigated widespread outrage directed against Dow Chemicals, the manufacturer of Agent Orange, and prompted investment funds such as Pax World Fund and Dreyfus Third Fund to divest from companies holding military contracts (SRI Stocks).

One of the most notable victories for the SRI strategy came in the 1980's, as businesses and colleges led a disinvestment campaign against apartheid in South Africa. Among national colleges and universities alone, the number participating in divesting from South Africa and companies with major South African interests increased from 53 in 1984 to 155 in 1988, a movement prompted largely in part by organized student bodies appalled at the state of South African politics at the time. Due to South Africa's reliance on trade from the West, the campaign's effects were especially potent, as inflation began to rise at a rate of 12-15% a year, forcing South African officials to seriously reconsider their current plan of action (Knight, 1990).

Today, amid growing environmental concerns and social sensitivity, SRI has become a popular alternative to traditional investment approaches, and there continues to be a good deal of research investigating the potential financial gain associated with such a strategy. Mercer (2009) found that, among the 16 influential and/or prize-winning academic articles sampled within a 9-year span, 10 showed evidence of a positive association between SRI and financial performance, 2 found a negative association, and 4 were neutral. Much research remains both to identify more efficient means of implementing SRI and to bolster current evidence supporting SRI as a valid strategy performance-wise, but existing results are promising.

The criteria for selection of socially responsible stocks typically fall under the headings of environmental, social, and governance, or ESG for short. There are several dimensions under each category by which companies are judged; for instance, environmental performance, reporting and waste management typically constitute the environmental criteria, labor practice indicators and human rights issues the social criteria, and codes of conduct, corruption, and crisis management the governance criteria (Belu, 2009). Companies are graded based on their performance in these areas and given an ESG score which provides a guideline for investors when constructing an SRI portfolio.

Since the main goal of this thesis is to examine the relative effectiveness of a socially responsible portfolio of stocks, a review of the various means of constructing such a portfolio will follow. The first such method, negative screening, involves excluding stocks from companies that fail to meet certain ESG criteria. Stocks from tobacco, gambling, and adult entertainment companies are a few such examples of items excluded from consideration, and there have been many studies, such as Einolf (2007) which have compared negatively screened portfolios to some sort of market index or another portfolio which has not been screened. Critics of this method have suggested, however, that excluding whole industries from one's portfolio, while perhaps noble, often comes at the cost of loss of stock diversification and a decrease in potential profit (Walley and Whitehead, 1994).

One popular method of constructing an SRI portfolio which arguably avoids the pitfall of a loss of diversification is termed "positive investing." Instead of excluding certain industries wholesale, investors who implement this strategy analyze a company's performance in certain social or environmental sectors relative to other companies in the same industry. Companies with the highest ESG scores (calculated differently according to the organization which produces them) are selected to comprise the stock portfolio and adequate diversification is achieved. The analysis done in this thesis reflects a positive investment approach.

Chapter 3

SRI Literature Review

In the effort to fully explore the link between corporate social responsibility and stock returns as an indicator of financial performance, there are three main methods that researchers have used in the past, as identified by Wagner (2001): regression studies, event studies, and portfolio studies. Each of the three can be subdivided into further categories of methodology, but the broader headings will be reviewed below. Despite the fact that this thesis utilizes a portfolio study only to examine practicality of SRI strategies, it is useful to consider some pros and cons of each of the methods.

3.1 Regression Studies

Regression studies examine the impact of environmental, corporate, and/or governance factors on stock returns over the long-term, but suffer from the poor explanatory power of many of the best models fit, as evidenced in papers such as Spicer (1978) and Mahapatra (1984), which focused on the U.S. pulp and paper industry. The reason for this limited statistical support lies in the fact that there are many latent factors which drive price fluxes in stocks that are hard, or impossible, to control. Such factors include market size, industry type, and market sensitivity among others.

In Spicer (1978), associations between corporate performance of pollution control and financial indicators of investment value such as profitability, size, and price/earning ratio in a sample of companies belonging to the pulp and paper industry were tested using multiple regression analysis. Spicer (1978) found that the companies with the better pollution control records had higher profitability than the companies with poor records and lower stock betas as well (the beta measure is explored in the Capital Asset Pricing Model section). Of course, this study only took into account environmental factors, whereas many studies done today take all three of the ESG factors into consideration. Also, a later paper done by Chen and Metcalf (1980) which controlled for the size of the company when taking into account negative impact on the environment put the results of Spicer (1978) into question.

Mahpatra (1984) takes the same multiple regression approach that Spicer (1978) does, using the total expenditure a company makes on pollution control as the response and similar financial indicators of investment performance as explanatory factors, but controlling for market size. The results of Mahapatra (1984) are in contrast to the results of Spicer (1978), finding no significant association between the factors. The two papers' differing opinions are representative of the many conflicting results that the multiple regression analyses methods have yielded, again, most likely due to the presence of an abundance of lurking variables. Other methods have been developed to obviate these problems.

3.2 Event Studies

Event studies use critical time points in the history of a stock, such as the report of pollution figures by government agencies, to assess the impact of public knowledge of a company's environmental practices on the trading of that company's stock. These studies have typically shown the greatest evidence for the negative impact of poor ESG practices on stock returns.

In fact, only Yamashita et al. published in a 1993 issue of Fortune magazine did not find a significant impact of the reporting of these scores on stock performance (Derwall et al., 2005).

As an example of a paper that reported a heavy association between environmental reports and stock performance, Hamilton (1995) showed that pollution data published by the EPA accompanied an average (statistically significant) loss of $4.1 million in stock value on the first day the figures were reported. The study also reported that the higher the pollution figures, the more likely print journalists were to write about the toxic releases, which perhaps had something to do with the drastic drop in stock value accompanying the published figures.

Even Yamashita et al. (1999) acknowledges a weakly positive correlation between reported environmental performance and stock returns immediately following the publishing of said performance records, though it was not statistically significant. Despite the strong support for the impact of SRI given by these event studies, their limitations include the somewhat over-simplicity of the approach and the fact that most of the studies done have not dealt explicitly with the social and governance factors that typically accompany the SRI strategy. Portfolio studies, on the other hand, have ways to deal with all three of the ESG factors and can more meaningfully provide answers to the best way to implement SRI, given that it does work.

3.3 Portfolio Studies

Finally, portfolio studies compare the performance of multiple stock portfolios, screened based on some combination of ESG criteria, over a particular time horizon in order to determine whether or not socially responsible companies significantly outperform companies lagging behind in terms of adherence to CSR principles. Many papers have taken this approach to examining the link between CSR and financial performance, including Edmans (2010), Cortez et al. (2009), and Galema et al. (2008), with varying results. Some studies have found a negative association between CSR and stock returns, while others have found a significantly positive one and everything in between. Of course, the results are partially dependent on which screening method is used to separate the two portfolios, which is why careful attention is paid to describe the method used in this thesis and, perhaps more importantly, why it was chosen.

Edmans (2010) selects a portfolio of the 100 best companies to work for in America as published by *Fortune* magazine and compared the returns of this portfolio to the market and found significant statistical evidence for the superior earning power of the "Best Companies" portfolio after controlling for several factors such as returns on the market, value, size, and momentum. Of course, this study would fall only under the "social" heading of the three ESG factors, as the social factor taken into account is the happiness of the employees of these companies. Once again, the method employed in this thesis will be able to take into account all three ESG factors with equal weight given to each.

Galema et al. (2008) is one example of a study with neutral findings. After examining the stock performance of a group of SRI funds, they conclude that the SRI strategy affects performance only by lowering book-to-market ratios and not by generating positive alphas. However, it should be mentioned that papers such as Derwall et al. (2005) have controlled for book-to-market ratio when constructing their SRI portfolios and found a significant positive relationship between high CSR ratings and financial performance. Again, the results of these studies are highly dependent on the method of screening used to create the portfolios, which partially explains the somewhat large variation in results.

Chapter 4

Nonparametric Frontier Analysis

Before introducing the implementation of the main focus of this thesis, to compare stock portfolios in order to test the effectiveness of an SRI strategy, it is necessary to introduce the statistical methods that will be employed to achieve such a goal. The two primary methods used include data envelopment analysis (DEA), and free disposal hull (FDH), which both fall under the broader heading of nonparametric data analysis. In both cases, the data consist of inputs, typically a cost associated with a particular business or production system (labor, capital, etc.), and outputs, such as revenue. Both DEA and FDH are tools used to determine which units in the dataset are performing at an efficient level relative to the other units under examination, and, equally as important, which are not. These tools are examined individually below.

Building on the work by Charnes et al. (1978), there have been many books and articles written on the topic of data envelopment analysis, and what follows is a brief overview based mainly on the works of Cooper et al. (2000) and Jeong and Hardle (2005). As already stated, the primary purpose of DEA is to examine the efficiency of certain sets of inputs and outputs, termed decision making units (DMUs). To accomplish this task, an efficiency frontier is modeled based on the DMUs in the given dataset, along which lie the hypothetical (and real) DMUs which achieve the optimal output for given input, and vice versa. Once this efficiency frontier is obtained, a reasonable estimate for how much more output a DMU with a given level of input should produce, which becomes the basis for that DMU's efficiency score.

One concrete example of a set of DMUs is a trio of academic departments such as marketing, accounting, and computer science. Each of these departments contains a set of outputs, or things that the department produces. For this particular example, number of published papers from the department and number of graduates could be considered outputs, so each of these things would comprise an element of a 2×1 output vector, given those are the only outputs under consideration. Likewise, each academic department needs certain inputs in order to attain these outputs. Examples of inputs in this case would be number of faculty and the budget for the department. What the DEA and FDH methods attempt to accomplish is to estimate the maximum level of output for any given level of input, or the converse: minimum input for a given level of output. If DEA analysis was performed on the three academic departments mentioned, not only could the most inefficient department be determined, but the ideal allocation of resources could be estimated. This ideal is called the efficiency frontier.

DEA works under the assumption that the production set Ψ, which is composed of all possible DMUs, is both convex and free disposable (terms defined below):

$$\begin{aligned}\hat{\Psi}_{DEA} \; &= \{(x, y) \in R^p_+ \times R^q_+ |\; x \geq \textstyle\sum_{i=1}^n \gamma_i x_i,\; y \leq \sum_{i=1}^n \gamma_i y_i, \\ &\text{for some } (\gamma_1, ..., \gamma_n) \text{ such that} \\ &\textstyle\sum_{i=1}^n \gamma_i = 1, \gamma_i \geq 0,\; \forall\; i = 1, ..., n\}.\end{aligned}$$

In mathematical terms, the DEA production frontier is formed by the convex hull of the given DMUs, which encompasses all the convex combinations of the DMUs, convex combinations being linear combinations of the points (which can be vectors or scalars, depending on the dimensions of the inputs and outputs) where all coefficients are non-negative and add up to 1. The “free disposable” assumption means that for a given $(x, y) \in \Psi$ all (x', y') with $x' \geq x$ and $y' \leq y$ belong to Ψ, where the inequalities between vectors are understood componentwise.

The efficiency scores are obtained by minimizing (or maximizing) the objective function θ:

$$\begin{aligned} \hat{\theta}^{IN}(x_0, y_0) &= \min\{\theta \geq 0 | (\theta x_0, y_0) \in \hat{\Psi}_{DEA}\}, \\ \hat{\theta}^{OUT}(x_0, y_0) &= \max\{\theta \geq 0 | (x_0, \theta y_0) \in \hat{\Psi}_{DEA}\}, \end{aligned}$$

where $\hat{\theta}^{IN}$ represents the efficiency score for the input component and $\hat{\theta}^{OUT}$ the output. An important consideration to keep in mind when applying DEA to a dataset is that only non-negative values are accommodated, since the production process must include some positive input to obtain an output, so transformations may be necessary.

The process above describes a production process in which there are variable returns to scale (VRS), meaning an increase in input levels does not necessarily correspond to a proportional increase in output levels. Often, this is the case in real world examples, such as a business which reaches a production plateau in spite of increases in hirings and capital. DEA VRS is generally appropriate when it is unreasonable or impractical to assume such proportionality in the data. On the other hand, constant returns to scale (CRS), makes such an assumption, and can certainly be substituted for DEA VRS where appropriate. Both methods will be applied to the dataset of interest in this paper, with DEA CRS implemented the exact same way as VRS with the important omission of the following constraint: $\sum_{i=1}^{n} \gamma_i = 1$.

The other major nonparametric tool that will be applied, FDH, introduced by Deprins et al. (1984), is similar to DEA in the sense that both methods seek to estimate an efficiency frontier given the available data, but FDH drops the convexity assumption. Now, free disposability of inputs and outputs, the idea that it is always possible to obtain the same output with a greater than or equal to level of input and that a given level of input can always produce less output than the optimum, is the only assumption being made. This assumption can be expressed mathematically as follows:

$$\hat{\Psi}_{FDH} = \{(x, y) \in R_+^p \times R_+^q |\; x \geq x_i, y \leq y_i,\ i = 1, ..., n\}.$$

The efficiency scores for the DMUs using FDH can be obtained as follows:

$$\begin{aligned} \hat{\theta}^{IN}(x_0, y_0) &= \min_{i|y \leq y_i} \max_{1 \leq j \leq p} x_i^j / x_0^j, \\ \hat{\theta}^{OUT}(x_0, y_0) &= \max_{i|x \geq x_i} \min_{1 \leq k \leq q} y_i^k / y_0^k, \end{aligned}$$

where v^j is the jth component of vector v. In order to help visualize the differences between the two methods, simulations were run based on two hypothetical efficiency frontiers. Figure 4.1 displays the results of 50 simulated DMUs based on the following model and the frontier estimated by the DEA method. The model:

$$x_i \sim \text{Uniform}[0, 1],\ y_i = g(x_i)e^{-z_i},\ g(x) = 1 + \sqrt{x},\ z_i \sim \text{Exp}(3),$$

for $i = 1, ..., 50$. This scenario, with an exponential for the logarithm of the inefficiency term and 0.75 as an average of inefficiency are reasonable in the productivity analysis literature (Gjibels et al., 1999). It is apparent from a cursory examination of the figure that $\hat{\Psi}_{DEA} \subset \Psi$, and this is true for all DEA estimates of the efficiency frontier.

The same approach was taken for simulating an FDH frontier estimation, with the ex-

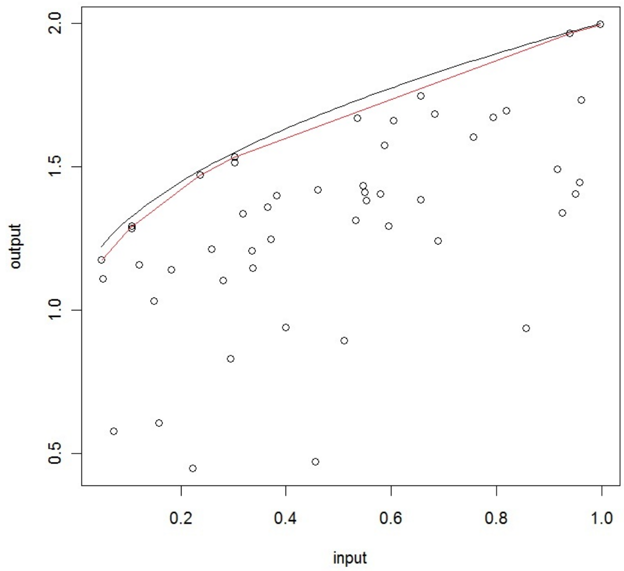

Figure 4.1: The true efficiency frontier, $g(x)$, is represented by the black line, while the DEA estimate is represented by the piecewise linear function formed by the red line. The 50 simulated DMUs lie below and are represented by the circles.

ception that the DMUs were simulated based on a different model:

$$x_i \sim \text{Uniform}[1,2],\ y_i = g(x_i)e^{-z_i},\ g(x) = 3(x-1.5)^3 + 0.25x + 1.125,\ z_i \sim \text{Exp}(3),$$

for $i = 1, ..., 50$. The true frontier function, given by $g(x)$, while different from the function used in the DEA example, is still quite appropriate for a productivity analysis setting. The results of the simulation are shown in Figure 4.2. Note that both of the plots shown illustrate efficiency frontier estimation in the $p = 1$, $q = 1$ case, which corresponds to DMUs with only one input and output level each. The same simulation could be run based on DMUs with input and output vectors instead of scalars, but the results would be harder, or impossible, to visualize.

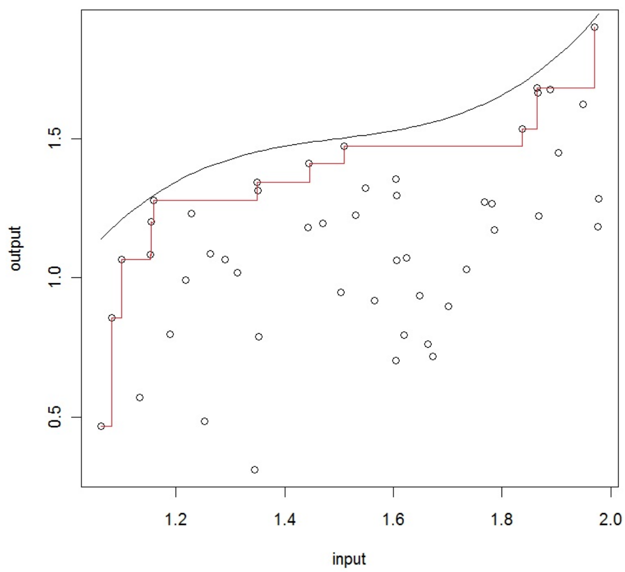

Figure 4.2: The true efficiency frontier, $g(x)$, is represented by the black line, while the FDH estimate is represented by the step function formed by the red line. The 50 simulated DMUs lie below and are represented by the circles.

Chapter 5

Data Analysis

5.1 Data Description

As was previously stated, the portfolios chosen to represent the different strata of social responsibility were separated via a positive screening method whereby companies' ESG scores and measures of financial performance were the deciding criteria. There are several works which investigated the same problem via positive screening using nonparametric analyses discussed in the literature. Einolf (2007) adopted such an approach, using a DEA framework with IW Financial ESG scores as the inputs and Morning Star Ratings and Value Line projected alpha as the outputs, and Belu (2009) took the same tack, except financial performance indicators were used as inputs and ESG scores as the outputs. For our purposes, ESG scores provided by Sustinvest Co. Ltd. (http://www.sustinvest.com) were used as inputs and return on assets (ROA), return on equity (ROE), and average yearly stock returns (ASR) were considered the outputs, in accordance with standard thinking that strong financial returns are the primary desired output of any company.

For this paper, 253 Korean company stocks publicly traded on the Korean market were considered. The names of these companies were coded to protect the privacy of their data.

What follows is a detailed summary of the items that Sustinvest Co. Ltd. used to manufacture the environmental, social (broken into a qualitative and a quantitative component) and governance scores for these companies, which serve as the inputs for the analysis, and the formulas for the financial performance indicators (the outputs). Not all of the items used by Sustinvest to create the scores are recounted, as this would be too long a list to recount here.

The Key Performance Indicators (KPIs) used to create the environmental ratings fall into four distinct categories: communication, management system, production, and product. The communication category deals with how well the company reports the effect of their operations on the environment and whether or not they have complied with regulations in this area. For the management system category, stated company policies regarding environmental impact are investigated, and whether or not the company has a dedicated infrastructure in place to mitigate damage to the environment is taken into account. The company's production process is also taken under consideration, including the environmental policies of its suppliers, the amount of energy consumed by the process, and the quantity and types of emissions the company produces. Finally, the product category refers to how well the company deals with waste materials, in particular the disposal of said materials and the efficiency of the infrastructure built to manage the waste.

The KPIs for the quantitative social component of the ESG ratings consist of elements indicating how well attuned companies are to the needs of their workers, and those seeking employment, which can be quantified. Examples include the number of labor union workers in the company, the sum of seniority, the number of female workers, the allowance made for retirement, the welfare benefits, etc. The KPIs for the qualitative component cannot be quantified directly, but are assigned a score as per the judgment of the Sustinvest raters. Examples of qualitative performance indicators include the level of diversity among the employee base, the quality of career development programs for the staff and the management for laborer's human rights, etc.

The KPIs for the governance component are used to determine how well companies hold their boards accountable for their actions, how well they report their finances to shareholders, and generally, how much they take into account the partial ownership of the shareholders. Examples of these measures include the existence of public announcements of the schedule of general meetings of shareholders, the presence of illegal insider trading within the company, and the dividend to net profit ratio.

Finally, the financial KPIs are simple formulas for operating profitability (net profit / gross sales), return on equity (net profit / equity capital), and return on assets (net profit / total assets). These three measures are commonly used to gauge the effectiveness of a company's operations from a financial perspective.

Table 5.1 gives an example of several companies and their corresponding ESG and financial performance data. After some necessary alterations which are discussed immediately below, this is the data that is used for the final analysis, where the companies are the DMUs, the ESG scores are the inputs, and the financial performance indicators are the outputs.

	ESG				Financial		
Company	SQL	SQN	GOV	ENV	Profit	ROE	ROA
18000	15.97	32	52.11	40	0.0703	0.0784	0.0232
96770	20.14	38	57.89	70	0.0414	0.1214	0.0395
10950	16.58	52	73.95	70	0.0607	0.1315	0.0583
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
6260	10.94	10.8	58.68	70	-0.4852	-0.0783	-0.0496
3600	13.96	25.2	57.11	10	0.9635	0.0387	0.0369

Table 5.1: SQL represents the qualitative component of the social rating and SQN represents the quantitative.

So that the ESG scores for these companies would agree with an efficient frontier data analysis method such as DEA and FDH, high scores (meaning good ESG performance) were converted to low costs as follows for a firm i:

$$\text{E.cost}_i = \frac{\max(\text{E.score}) - \text{E.score}_i}{\max(\text{E.score}) - \min(\text{E.score})} + \epsilon$$
$$\text{S.cost}_i = \frac{\max(\text{S.score}) - \text{S.score}_i}{\max(\text{S.score}) - \min(\text{S.score})} + \epsilon$$
$$\text{G.cost}_i = \frac{\max(\text{G.score}) - \text{G.score}_i}{\max(\text{G.score}) - \min(\text{G.score})} + \epsilon$$

where ϵ is a small constant to ensure that all the cost variables will be positive (the reason this is necessary will be explained below). The results will now be interpretable, as a higher cost corresponds to a larger strain on the environment for a given level of financial performance. Efficiency scores are generated based on FDH, DEA VRS (variable returns to scale), and DEA CRS (constant returns to scale) frameworks, each using the same inputs and outputs. A high efficiency score for a company means that the company attains its level of financial performance with a minimal burden to society as defined by the converted ESG factors.

The financial performance indicators underwent a similar transformation to be compatible with the DEA method, since the convexity assumption necessitates nonnegative inputs and outputs. This transformation preserves the meaning of the original output (higher values equals higher production), but removes any negative returns:

$$\text{Profit}_i = \frac{\text{Profit} - \min(\text{Profit})_i}{\max(\text{Profit}) - \min(\text{Profit})} + \epsilon$$
$$\text{ROE}_i = \frac{\text{ROE} - \min(\text{ROE})_i}{\max(\text{ROE}) - \min(\text{ROE})} + \epsilon$$
$$\text{ROA}_i = \frac{\text{ROA} - \min(\text{ROA})_i}{\max(\text{ROA}) - \min(\text{ROA})} + \epsilon$$

where ϵ is, again, a small constant.

Table 5.2 and Figure 5.1 were generated from the converted ESG scores and financial performance data. The histograms show the efficiency scores for both the inputs (ESG factors) and outputs (financial performance) for all 253 using FDH, DEA CRS, and DEA VRS. An efficiency score of 1 means that company is estimated to be using its resources efficiently, an input score of less than 1 means that the company could be using less input (by a factor of the score) to produce the same amount of output, and an output score of greater than 1 means that the company could be producing that much more output for the same amount of input. The relatively large amount of 1 scores is not an unnatural result, as these companies form the vertices for the estimated efficiency frontier. What could be a cause for concern, however, is the large number of poor output efficiency scores generated by the DEA CRS method.

	Mean	Median	Std. Deviation
SQL	0.4925	0.4916	0.1578
SQN	0.4925	0.4727	0.2358
GOV	0.6249	0.6370	0.1835
ENV	0.6146	0.7510	0.3380
Profit	0.8800	0.8795	0.0627
ROE	0.9709	0.9755	0.0618
ROA	0.5563	0.5513	0.1210

Table 5.2: Summary statistics for the converted ESG scores and financial performance data

5.2 Comparison

In order to test the performance of efficient companies based on the FDH, DEA CRS, and DEA VRS analysis against inefficient companies and the overall market, the 253 companies were given a grade. A grade of “A” means that the company’s efficiency score is in the upper 25% of all the companies for a given method (FDH, DEA CRS, and DEA VRS), a “B” means that the efficiency score falls in the middle 50%, and a grade of “C” means that the company’s score is in the bottom 25%. If socially responsible companies enjoy higher

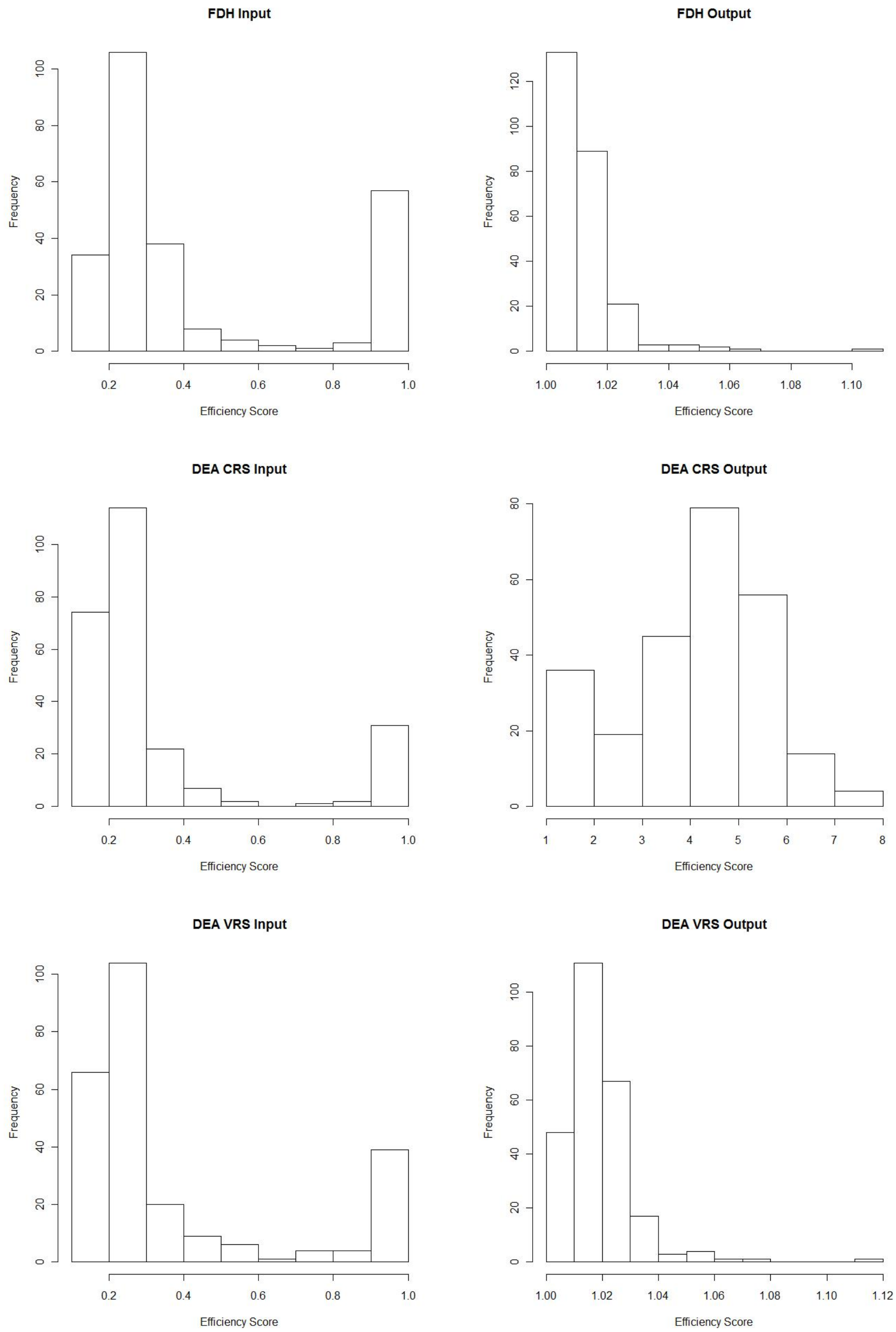

Figure 5.1: Efficiency scores generated from the three different methods

stock returns over the long-run, we should see the average cumulative returns for the A companies outperform the B and C companies in each case.

Figures 5.2-5.5 show the daily cumulative returns for the A, B, and C, portfolios from January 2, 2006, to December 30, 2009 separated by method. The FDH method of defining the grades of portfolios illustrated in Figure 5.2 shows encouraging results, as the separation between the highest graded portfolio and the lower grades becomes more and more pronounced over time. FDH grade “A” portfolio also substantially outperforms the overall portfolio comprised of all 253 stocks in the study. It is also interesting to note that the “B” and “C” grades using the FDH method do not seem to differ much from each other over the length of the study.

Figures 5.3 and 5.4 show the results of selecting the portfolios according to DEA criteria, with constant returns to scale and variable returns to scale respectively. Figure 5.3 displays little to no difference between the various grades of portfolios selected by DEA CRS, suggesting the poor utility of this method in distinguishing between socially responsible companies and irresponsible ones. Figure 5.4, on the other hand, looks very much like Figure 5.2 of the FDH results, though the separation between the grade “A” portfolio and the lower grade portfolios is less pronounced.

Figure 5.5 compares the performances of the top grades for each method and confirms the discrepancy between FDH and DEA VRS apparent in the two figures mentioned above.

The results of the analysis prove empirically that using the FDH method, in particular, to cull the top tier of companies in terms of social responsibility into an investment portfolio was a financially rewarding endeavor over the time span of the study. The reason for the discrepancies between FDH, DEA CRS, and DEA VRS, are likely due to the validity of the assumptions made under each method, and therefore, how closely each method matched the true efficiency frontier. The DEA CRS method failed to show significant distinctions between the three grades of companies most likely because the constant returns to scale assumption

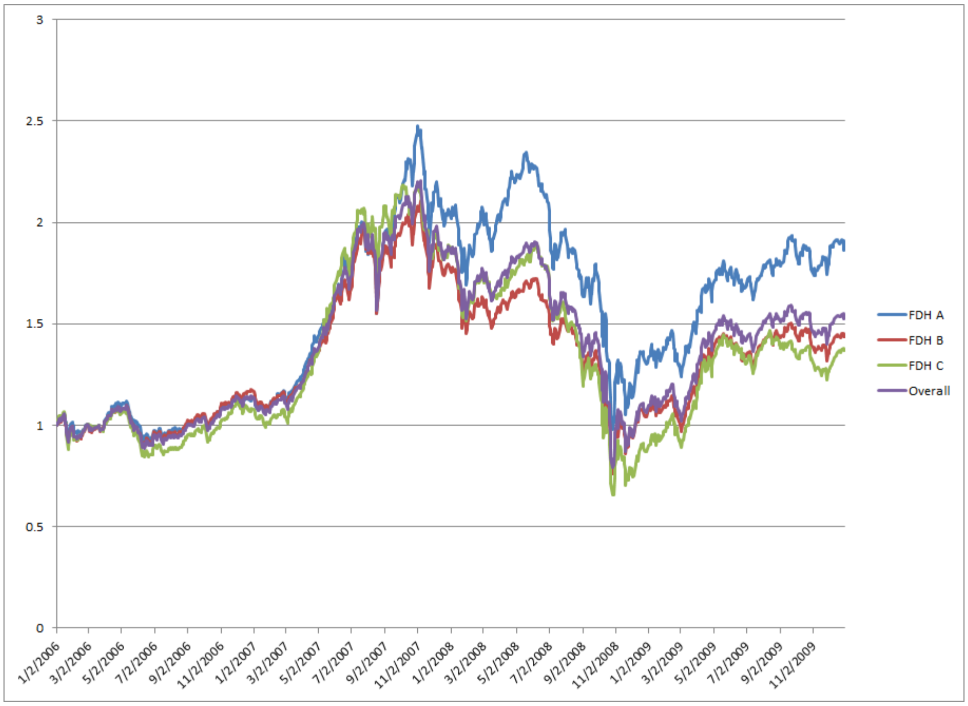

Figure 5.2: FDH grade A, B, and C portfolios, and the overall performance of all stocks

Figure 5.3: DEA CRS grade A, B, and C portfolios, and the overall performance of all stocks

Figure 5.4: DEA VRS grade A, B, and C portfolios, and the overall performance of all stocks

is a deeply flawed one, as a constant return to scale implies constant long-run average costs, which is just not seen in normal business conditions. FDH avoids these problems because it doesn't assume constant returns to scale or convexity of the DMU set like DEA VRS.

5.3 Capital Asset Pricing Model Analysis

Although the results of the study appear to indicate a strong association between social responsibility and financial earning power, some CAPM (Capital Asset Pricing Model) measures, introduced by Sharpe (1964), Lintner (1965), and Mossin (1966), were checked in order to ensure that the performance of the portfolios evidenced by the charts align with traditional indicators of financial performance. The 48 monthly return figures were used to

Figure 5.5: A direct comparison between the financial returns of the three methods employed. FDH is the winner, while DEA CRS is the clear loser.

fit the CAPM linear model of the form:

$$R_t - R_{f,t} = \alpha + \beta(R_{BM,t} - R_{f,t}) + \epsilon_t,$$

where $t = 1, \ldots, 48$, R_t denotes the monthly return in month t, $R_{f,t}$ is the risk-free return rate for month t, $R_{BM,t}$ is the return on the KOSPI200 index in month t as the benchmark, or market return rate, and ϵ_t is an error term of mean zero. The fitted values for α and β are called "Jensen's alpha" and "Beta," respectively. The fitted alpha value is meant to determine the abnormal excess (or deficient) return over the expected, and the fitted beta is a traditional measure of market risk that the portfolio represents. Other measures calculated include the simple average returns

$$\bar{R} = \frac{1}{T}\sum_{t=1}^{T} R_t,$$

the volatility

$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(R_t - \bar{R})^2},$$

Sharpe ratio

$$\frac{(1/T)\sum_{t=1}^{T}(R_t - R_{f,t})}{\hat{\sigma}},$$

and Treynor ratio

$$\frac{(1/T)\sum_{t=1}^{T}(R_t - R_{f,t})}{\hat{\beta}},$$

	Portfolios			
	A	B	C	Overall
Average return	1.74% (131.98%)	1.14% (86.89%)	1.25% (95.24%)	1.32%
Volatility	8.96% (99.05%)	8.65% (95.60%)	10.75% (118.88%)	9.04%
Beta	1.1680 (97.71%)	1.1360 (95.04%)	1.3554 (113.40%)	1.1953
Jensen's alpha	0.94% (139.94%)	0.37% (54.37%)	0.36% (53.16%)	0.67%
Sharpe ratio	0.1753 (137.93%)	0.1130 (88.91%)	0.1011 (79.53%)	0.1271
Treynor ratio	0.0134 (139.82%)	0.0086 (89.43%)	0.0080 (83.38%)	0.0096

Table 5.3: CAPM measures of financial performance for FDH. The figures in parentheses are the relative ratios compared to the values of the overall portfolio composed of all stocks under consideration.

where the Sharpe and Treynor ratio are both means of determining the excess return per unit of risk that investment in an asset or portfolio affords, with Sharpe using simple volatility as a measure of risk and Treynor using the estimated Beta. The methods which garnered the starkest contrast between portfolio grades, FDH and DEA VRS, are the methods for which the CAPM measures were applied in Tables 5.3 and 5.4. Table 5.5 shows the results applied to the DEA CRS method.

For the highest grades of both FDH and DEA VRS, the average return, Jensen's alpha, Sharpe ratio, and Treynor ratio are all considerably higher than the lower grades relative to the same measures for the portfolio containing all 253 companies. The CAPM measures for DEA CRS display similar, though less pronounced discrepancies between grades. These results seem to agree with the prior conclusion that the companies with the highest social responsibility grade of A are the most appealing investments. Also, all of these measures

	Portfolios			
	A	B	C	Overall
Average return	1.65%	1.15%	1.35%	1.32%
	(125.16%)	(87.04%)	(102.30%)	
Volatility	8.56%	8.91%	10.56%	9.04%
	(94.60%)	(98.54%)	(116.78%)	
Beta	1.1291	1.1686	1.3253	1.1953
	(94.46%)	(97.76%)	(110.87%)	
Jensen's alpha	0.87%	0.35%	0.47%	0.67%
	(129.71%)	(52.06%)	(69.36%)	
Sharpe ratio	0.1731	0.1099	0.1117	0.1271
	(136.15%)	(86.43%)	(87.88%)	
Treynor ratio	0.0131	0.0084	0.0089	0.0096
	(136.36%)	(87.11%)	(92.57%)	

Table 5.4: CAPM measures of financial performance for DEA VRS. The figures in parentheses are the relative ratios compared to the values of the overall portfolio composed of all stocks under consideration.

	Portfolios			
	A	B	C	Overall
Average return	1.31%	1.30%	1.42%	1.32%
	(99.88%)	(98.84%)	(107.86%)	
Volatility	7.88%	8.99%	10.90%	9.04%
	(87.11%)	(99.46%)	(120.52%)	
Beta	1.0574	1.1805	1.3740	1.1953
	(88.47%)	(98.76%)	(114.95%)	
Jensen's alpha	0.58%	0.50%	0.51%	0.67%
	(86.02%)	(74.16%)	(76.36%)	
Sharpe ratio	0.1457	0.1261	0.1150	0.1271
	(114.64%)	(99.21%)	(90.45%)	
Treynor ratio	0.0109	0.0096	0.0091	0.0096
	(112.88%)	(99.90%)	(94.83%)	

Table 5.5: CAPM measures of financial performance for DEA CRS. The figures in parentheses are the relative ratios compared to the values of the overall portfolio composed of all stocks under consideration.

were higher for the FDH "A" portfolio than the DEA VRS and CRS "A" portfolios, which is, again, in keeping with the conclusions drawn from Figures 5.2-5.5.

There is a decrease in the volatility and Beta measures both from FDH grade A to the less socially responsibly grade of B and from FDH to DEA VRS, which complicates matters a bit. If the higher earning portfolios were also less volatile than the lower earning portfolios, then FDH "A" would be the obvious winner of all the portfolios available, but since all the other measures, including the Sharpe and Treynor ratio, which account for volatility, agree in the superiority of FDH "A," this is not a large concern.

Chapter 6

Conclusion

The results of the study are promising, and they shed light on two important findings. First, portfolios selected using the DEA method, both with constant returns to scale and variable returns to scale, consistently underperform portfolios selected using FDH analysis over the time span of the experiment, which strongly suggests the inappropriateness of DEA for measuring the sustainability of these companies' actions. The inadequacy of the DEA methods can be attributed to the erroneous assumptions made by DEA CRS and VRS, which, while appropriate in some cases in which efficiency frontier estimation can be effectively applied, does not work well when considering the financial performance indicators used for this study.

Secondly, not only did the portfolios selected using the FDH method outperform those selected by the DEA methods, they also clearly outperformed the overall market portfolio of the 253 Korean companies under consideration over the entire length of the study. These results provide strong support for the assertion that the SRI strategy can function as a reliable means of financial gain as well as a tool for social betterment. For an investor contemplating the use of SRI for building a portfolio comprised of Korean companies, this study strongly suggests that investing in socially responsible companies selected using the

FDH method would be a financially prudent decision, regardless of any interest in making any kind of statement for sustainability.

One of the limitations of this study includes the relatively small time frame within which data was available for these companies, as it would have been preferable to follow the cumulative daily returns for more than three years. Also, further research within different sectors of the world market would be helpful in consolidating a strong argument for the use of SRI regardless of context. Both of these possible extensions were beyond the scope of this study.

As the world becomes more and more attuned to sustainability issues affecting every one of us, investment strategies like SRI will become all the more important to corporate and private investors around the globe. This study is but one of many illustrating the usefulness of the strategy when appropriately applied, but much work remains to be done in order to solidify SRI as a fully integrated, mainstream investment approach. Whether or not it will get there within the near future, FDH shows much promise as a proper implementation of SRI and should remain in the discussion, academically and in business, for years to come.

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