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Portfolio Selection for Socially Responsible Investment via Nonparametric Frontier Models

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Abstract

This paper provides an effective stock portfolio screening tool for socially responsible investment (SRI) based upon corporate social responsibility (CSR) and financial performance. The proposed approach utilizes nonparametric frontier models. Data envelopment analysis (DEA) has been used to build SRI portfolios in a few previous works; however, we show that free disposal hull (FDH), a similar model that does not assume the convexity of the technology, yields superior results when applied to a stock universe of 253 Korean companies. Over a four-year time span (from 2006 to 2009) the portfolios selected by the proposed method consistently outperform those selected by DEA as well as the benchmark.

Keywords: Corporate social responsibility, data envelopment analysis, efficiency, ESGF-efficiency, free disposal hull.

1. Introduction

Socially responsible investment (SRI) has been emerging as an effective alternative to traditional investment strategies for those who want to vote with their dollars against business practices they find objectionable (Wagner, 2001) as well as for the mainstream investment institutions. Making a stand against bad business or supporting socially sustainable and environmentally responsible industry and services through investment cannot continue as a legitimate financial tool if the investments are not profitable. In order for SRI to work, a socially responsible portfolio needs to compete favorably with investment portfolios with none of the constraints associated with a SRI portfolio.

Since the recent explosive growth of the SRI, many empirical studies have been conducted with the goal to support or debunk the value of SRI as an investment strategy(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 have been explored in the past using regression studies (Spicer, 1978; Chen and Metcalf, 1980; Mahapatra, 1984), event studies (Yamashita *et al.*, 1999; Hamilton, 1995), and portfolio studies (Galema *et al.*, 2008; Cortez *et al.*, 2009; Edmans, 2010). We take the portfolio approach and apply nonparametric frontier models to investigate the efficacy of SRI.

The criteria to select socially responsible stocks are classified into environmental, social, and governance(ESG). There are several dimensions under each category by which companies are judged;

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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. Companies are graded based on their performance in these dimensions and given an ESG score which provides a guideline for investors when compiling an SRI portfolio.

The objective of this article is to present effective socially responsible portfolios by taking both corporate social responsibility (CSR) and financial performance into account. For this, we consider three nonparametric frontier analysis models: 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. The portfolios selected by these three methods are compared against each other using a dataset of monthly returns for 253 stocks publicly listed on the Korean stock market, and FDH was singled out as the most preferable means to select SRI portfolios.

The remainder of the paper is organized as follows. Section 2 discusses the methods to integrate CSR achievement and financial performance of firms via nonparametric frontier models. Section 3 analyzes 253 Korean companies based on the approach proposed in Section 2. Finally, the concluding section follows and outlines the results of the empirical study with a discussion on future work.

2. The Method

For both investors and enterprise managers, CSR or ESG itself cannot be an utmost goal. In this section we present a model to evaluate the ESG level of a firm with its financial achievement in mind at the same time. The key instrument in this paper to achieve this goal is the nonparametric frontier model from a productivity analysis that was originally used to analyze the efficiency of a firm's production activities through a comparison of observed input and output levels.

2.1. Nonparametric frontier models

Let $\mathbf{x} = (x_1, x_2, \dots, x_p)$ denote the vector of p positive values of inputs (or costs) used while producing q output levels $\mathbf{y} = (y_1, y_2, \dots, y_q)$ in a production system. Consider a set Ψ, called the production set (or the production technology), which is a collection of all technically feasible pairs of $\mathbf{x}$ and $\mathbf{y}$:

$$\Psi = \{(\mathbf{x}, \mathbf{y}) \,|\, \mathbf{x} \text{ can produce } \mathbf{y}\}.$$

In economics, the production technology Ψ is usually assumed to be free disposable (F) and convex (C):

$$(F) \quad (\mathbf{x}, \mathbf{y}) \in \Psi \;\text{ implies that } (\tilde{\mathbf{x}}, \tilde{\mathbf{y}}) \in \Psi \text{ if } \tilde{\mathbf{x}} \geq \mathbf{x} \text{ and } \tilde{\mathbf{y}} \leq \mathbf{y}.$$

$$(C) \quad (\mathbf{x}, \mathbf{y}), (\tilde{\mathbf{x}}, \tilde{\mathbf{y}}) \in \Psi \;\text{ implies that } \alpha(\mathbf{x}, \mathbf{y}) + (1-\alpha)(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}) \in \Psi \text{ for any } 0 \leq \alpha \leq 1,$$

where the inequality between vectors are defined to be componentwise. Given a specific firm with a pair of input-output levels $(\mathbf{x}, \mathbf{y})$, its efficiency is defined in a radial way as follows:

$$\theta(\mathbf{x}, \mathbf{y}) = \inf\{\theta > 0 \,|\, (\theta\mathbf{x}, \mathbf{y}) \in \Psi\}.$$

By construction, the efficiency score $\theta(\mathbf{x}, \mathbf{y})$ has the value between 0 and 1. The closer to 1 the efficiency score $\theta(\mathbf{x}, \mathbf{y})$ is, the better the production activity is proved to perform. Furthermore, $\theta(\mathbf{x}, \mathbf{y}) = 1$ means that the production activity is efficient since it is technically impossible to reduce the input level less than $\mathbf{x}$ in order to produce the output level $\mathbf{y}$. Refer to Coelli *et al.* (2005) for a general introduction to the analysis of production efficiency.

In practice, Ψ is not observed; therefore, how can we observe all technically possible production activities? Instead we observe the production activities carried out by n firms

$$\mathcal{X}_n = \{(\mathbf{x}_1, \mathbf{y}_1), (\mathbf{x}_2, \mathbf{y}_2), \ldots, (\mathbf{x}_n, \mathbf{y}_n)\}$$

laid on Ψ. Therefore, we estimate the production technology Ψ based on $\mathcal{X}_n$. Among the existing nonparametric approaches, the most popular one is the *data envelopment analysis* (DEA) developed by Charnes *et al.* (1978) and Banker *et al.* (1984). Given the set of observations $\mathcal{X}_n$, the DEA estimator of Ψ is defined by the smallest free disposable and convex set that contains all observations in $\mathcal{X}_n$:

$$\widehat{\Psi}_{\text{DEA}} = \left\{ (\mathbf{x}, \mathbf{y}) \,|\, \mathbf{x} \geq \sum_{i=1}^{n} \gamma_i \mathbf{x}_i,\ \mathbf{y} \leq \sum_{i=1}^{n} \gamma_i \mathbf{y}_i \text{ for some } \gamma_i \geq 0 \text{ such that } \sum_{i=1}^{n} \gamma_i = 1 \right\}.$$

Then, given a firm's production activity $(\mathbf{x}, \mathbf{y})$, the corresponding (relative) efficiency score compared with $\mathcal{X}_n$ is computed by

$$\begin{aligned}
\widehat{\theta}_{\text{DEA}}(\mathbf{x}, \mathbf{y}) &= \min \left\{ \theta > 0 \,|\, (\theta \mathbf{x}, \mathbf{y}) \in \widehat{\Psi}_{\text{DEA}} \right\} \\
&\equiv \min \left\{ \theta > 0 \,|\, \theta \mathbf{x} \geq \sum_{i=1}^{n} \gamma_i \mathbf{x}_i,\ \mathbf{y} \leq \sum_{i=1}^{n} \gamma_i \mathbf{y}_i \text{ for some } \gamma_i \geq 0 \text{ such that } \sum_{i=1}^{n} \gamma_i = 1 \right\}.
\end{aligned}$$

The process above describes a production process where 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 despite an increase in hirings and capital. DEA under VRS (DEA VRS) is generally appropriate when it is unreasonable or impractical to assume such proportionality in the data. However, constant returns to scale (CRS) makes such an assumption, and can certainly be substituted for DEA VRS where appropriate. Note that DEA CRS can be implemented concurrently to DEA VRS with the important omission of the following constraint: $\sum_{i=1}^{n} \gamma_i = 1$.

DEA assumes for the production technology both free disposability (F) and convexity (C). For the case that we should drop the convexity assumption (C), Deprins *et al.* (1984) proposed to use the smallest free disposable set containing $\mathcal{X}_n$ called the *free disposal hull* (FDH):

$$\widehat{\Psi}_{\text{FDH}} = \{(\mathbf{x}, \mathbf{y}) \,|\, \mathbf{x} \geq \mathbf{x}_i,\ \mathbf{y} \leq \mathbf{y}_i,\ i = 1, 2, \ldots, n\}.$$

Then, the FDH efficiency score of $(\mathbf{x}, \mathbf{y})$ is simply given by

$$\widehat{\theta}_{\text{FDH}}(\mathbf{x}, \mathbf{y}) = \min \{\theta > 0 \,|\, \theta \mathbf{x} \geq \mathbf{x}_i,\ \mathbf{y} \leq \mathbf{y}_i,\ i = 1, 2, \ldots, n\},$$

or equivalently

$$\widehat{\theta}_{\text{FDH}}(\mathbf{x}, \mathbf{y}) = \min_{i:\, \mathbf{y} \leq \mathbf{y}_i} \max_{1 \leq j \leq p} \frac{\mathbf{x}_i^{(j)}}{\mathbf{x}^{(j)}},$$

where $\mathbf{v}^{(j)}$ denotes the j^{th} element of a vector $\mathbf{v}$.

The problem in estimating the efficiency is equivalent to estimating the directional edges of support, with shape restrictions, where the observed data points are generated. The statistical properties of DEA and FDH are now well-known. Park *et al.* (2010) derived the asymptotic distribution of FDH estimator. Kneip *et al.* (1998) showed the consistency of DEA VRS estimator. For the limit distribution of DEA VRS estimator, see Gijbels *et al.* (1999), Jeong (2004), Jeong and Park (2006) and Kneip *et al.* (2008). For the asymptotic study of DEA CRS estimator, refer to Park *et al.* (2010).

2.2. Integration of CSR achievement and financial performance

A popular nonparametric tool for productivity analysis is data envelopment analysis (DEA); subsequently, several works integrate CSR achievement and financial performance via DEA. Einolf (2007) computed *responsible efficiency scores* (RES) for 978 companies by DEA, where input variables were IW Financial ESG scores and output variables were the Value Line projected the alpha and the Morning Star Rating. Belu (2009) adopted a DEA model with financial performance indicators as input variables and ESG scores as output variables. In that work, return on assets (ROA), return on equity (ROE) and average (yearly) stock returns (ASR) were selected as financial performance indicators; in addition, corporate governance, environmental performance, human capital development, labor practice indicators and social reporting were also included for the ESG dimensions.

This paper presents an input-oriented approach by putting financial performance indicators as outputs and inverted ESG scores as input factors. Einolf (2007) and Belu (2009) assumed CSR performance as output factors and financial performances as input factors and they applied DEA to obtain the efficiency scores in an output-oriented approach. They supposed that the firms use their financial gain to improve their CSR. However, the purpose of economic activity by firms is not behave ‘good’; their ultimate goal is to earn money in a socially responsible manner if possible. We wanted to be in accordance with the concept of *eco-efficiency* (WBCSD, 2000) which is defined as the economic value that a corporation creates relative to the waste it generates. In our approach, ESG scores are inverted to ESG costs. Our interpretation on the framework is that these variables correspond to the costs shifted to our society while a company yields the financial gains as outputs. The resulting efficiency scores become consistent in concept with the sense of responsible investment and are called *ESGF-efficiency* or *ESGF-efficiency scores* throughout this paper.

DEA assumes the convexity of the technology; however, to the best of our knowledge, no answer has been given about the issue on the convexity assumption for the technology with ESG variables. Averaging is a key element to define the convexity and the controversy is related with the physical meaning of averaging intangibles such as ESG scores that measure CSR achievement. Like most practices presented in the literature on the evaluation of intangibles, the CSR achievement scoring scheme in this study is based on composite indicators composed of many sub-indicators that are very often qualitative (but ordinal) in nature. The scale of the ESG scores should be handled quite differently from other scores by quantitative measurements; therefore, there is convexity of the technology with ESG variables that is hard to justify. Even if the technology with original measurements was convex, convexity can be readily collapsed in practice by varying the ESG scoring scheme or by transforming the variables in a nonlinear way. However, free disposability still holds as long as the scoring scheme and the transform of variables are order-preserving. The free disposal hull (FDH) model emerges as a promising alternative, and the empirical results in subsequent sections support this view.

3. Empirical Study

In this section, the results from the ESGF-efficiency analyzes applied to the Korean stock market are presented. Section 3.1 details the dataset, the ESG variables and the financial performance measures are considered. Section 3.2 defines the ESGF-efficiency scores for our analysis. The comparisons of DEA and FDH models by portfolio returns and capital asset pricing model measures are shown in Section 3.3 and Section 3.4, respectively.

3.1. Data description

We consider 253 Korean companies publicly listed on the Korean stock market that includes all companies in the KOSPI (The Korea Composite Stock Price Index) 200. The dataset is composed of their financial performance measures and ESG scores assessed in 2009 provided by Sustinvest Co. Ltd., a leading company on the SRI industry in Korea. Note that the social score was broken into a qualitative and a quantitative component. For the financial performance measures, we chose return on assets (ROA), return on equity (ROE) and operating profit percentage (OPP) that have been shown to be closely related to stock price.

The environmental score (denoted by E.score) was determined by key performance indicators (KPIs) falling into 4 distinct categories (communication, management system, production and produc). The communication category concerns how well the company reports the effect of their operations on the environment and if they have compiled with regulations in this area. For the management system category, stated company policies regarding environmental impact are investigated, and whether the company has a dedicated infrastructure in place to mitigate damage to the environment is taken into account. The production process category evaluates 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 takes care of waste materials such as the disposal of materials and the efficiency of the infrastructure built to manage the waste.

The social component score is denoted by the S.score. The KPIs for the quantitative social components of the ESG ratings consist of elements that indicate how well attuned companies are to the needs of 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, retirement allowances, and the welfare benefit. The KPIs for the qualitative component include the level of diversity among the employee base, the quality of career development programs for the staff and the management for employment rights.

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

As a preliminary step to investigate any association between ESG scores and financial achievement scores, we computed the Pearson's correlation, Kendall's tau and Spearman's rho among the variables (see Table 1). We observe significant within concordant associations among ESG scores and among financial performance measures. However, the association between ESG variables and financial performances is vague. Although only the S.score (quantitative) statistically reveals some association with financial variables, its practical significance is doubtful since the magnitudes of the coefficients are relatively small compared to those within ESG variables and within financial variables. These financial variables have been proved to be highly associated with stock prices and we cannot expect any satisfactory performance from a portfolio built to consider only ESG variables.

3.2. ESGF-Efficiency scores

We transformed the ESG scores for each company into ESG cost variables as follows: for a company indexed by i

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

Table 1: Pearson's correlation coefficients, Kendall's tau and Spearman's rho among the variables. $*$ and $**$ indicate their p-values to test the associations < 0.05 and < 0.01, respectively.

Pearson's correlation	E.score	S.score (quan.)	S.score (qual.)	G.score	ROE	ROA	OPP
E.score	1.000	-	-	-	-	-	-
S.score (quan.)	0.354**	1.000	-	-	-	-	-
S.score (qual.)	0.255**	0.288**	1.000	-	-	-	-
G.score	0.143**	0.257**	0.166**	1.000	-	-	-
ROE	0.025	0.090	0.011	0.067	1.000	-	-
ROA	−0.038	0.201**	0.028	−0.020	0.345**	1.000	-
OPP	−0.071	0.011	0.067	−0.003	0.034	0.431**	1.000
Kendall's tau	**E.score**	**S.score (quan.)**	**S.score (qual.)**	**G.score**	**ROE**	**ROA**	**OPP**
E.score	1.000	-	-	-	-	-	-
S.score (quan.)	0.250**	1.000	-	-	-	-	-
S.score (qual.)	0.179**	0.180**	1.000	-	-	-	-
G.score	0.080	0.192**	0.092*	1.000	-	-	-
ROE	−0.017	0.171**	−0.019	0.039	1.000	-	-
ROA	−0.061	0.170**	−0.012	0.023	0.789**	1.000	-
OPP	−0.084	0.114**	−0.017	0.024	0.439**	0.477**	1.000
Spearman's rho	**E.score**	**S.score (quan.)**	**S.score (qual.)**	**G.score**	**ROE**	**ROA**	**OPP**
E.score	1.000	-	-	-	-	-	-
S.score (quan.)	0.330**	1.000	-	-	-	-	-
S.score (qual.)	0.238**	0.267**	1.000	-	-	-	-
G.score	0.109	0.280**	0.138*	1.000	-	-	-
ROE	−0.025	0.256**	−0.028	0.053	1.000	-	-
ROA	−0.085	0.255**	−0.014	0.035	0.919**	1.000	-
OPP	−0.113	0.166**	−0.023	0.037	0.605**	0.651**	1.000

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

where $\epsilon > 0$ is a small constant that makes all the values of cost variables strictly positive. Note that, when the input variable allows a value of 0, DEA and FDH efficiency score in an input-oriented approach cannot be computed since a divide by 0 problem may occur.

ROE, ROA and OPP were chosen for the financial performance indicators; subsequently, these variables are considered as output variables in our analysis. Then, we put the 4 input variables and the 3 output variables into the three nonparametric frontier models - FDH, DEA VRS and DEA CRS. The resulting efficiency scores are obtained by benchmarking the best practices that burden our society with technically minimal ESG costs to yield their financial performance levels. We call the efficiency score the *ESGF-efficiency score*.

3.3. Comparison of portfolio returns

We constructed three mutually exclusive portfolios for each DEA CRS, DEA VRS and FDH model as follows: the upper-25% portfolio is composed of the stocks for which the ESGF-efficiency scores are in the top 25% of the scores for the 253 companies under investigation, the lower-25% portfolio is composed of the bottom 25% companies, and the remaining 50% companies forms the mid-50% portfolio. In addition, we consider the overall portfolio with all 253 companies. The weights for

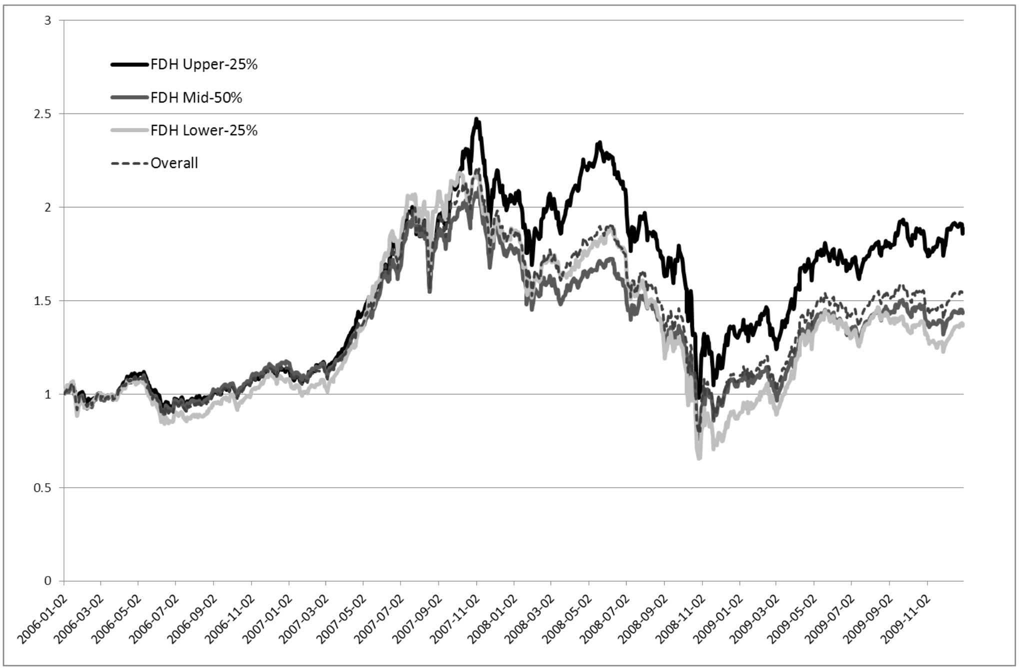

Figure 1: *Cumulative daily returns of portfolios (January 2, 2006 – December 30, 2009) built by FDH.*

each stock are equally assigned. The primary focus of our investigation is to verify the superior performance of the upper-25% portfolios for each DEA CRS, DEA VRS and FDH model.

Figures 1–3 graph the cumulative daily returns of the portfolios from January 2, 2006 to December 30, 2009, where we observe a distinct outperforming feature of the upper-25%-portfolios for each model. The FDH method to define the grades of portfolios illustrated in Figure 1 shows positive results, as the separation between the upper-25% portfolio and the lower-25% portfolio becomes more pronounced over time. The FDH upper-25% portfolio also substantially outperforms the overall portfolio comprised of all 253 stocks in the study. It is also interesting to note that the performance of the other two FDH portfolios do not seem to differ much from each other. Figures 2 and 3 show the results of selecting the portfolios according to DEA criteria. Figure 3 displays little to no difference between the portfolios selected by DEA CRS and suggests the poor utility of this method. However, Figure 2 looks very much like the Figure 1 of the FDH results, though the separation between the upper-25% portfolio and the lower-25% portfolio is less pronounced.

Table 2 summarizes the final portfolio values at the end of the time period compared to their initial values, where the outperforming feature of the proposed approach is reconfirmed. During the 4-year time period, the upper-25% portfolios are more profitable than the overall portfolio up to 35%p. Figure 4 compares the performances of the upper-25% portfolios for each model. This shows that the FDH upper-25% portfolio is the most financially rewarding endeavor over the time span of the study. Our conjecture on the discrepancies between FDH, DEA CRS and DEA VRS, are due to the validity of the assumptions made for each model. For instance, DEA CRS failed to show significant distinctions between the portfolios in Figure 3 because the constant returns to scale assumption is perhaps a deeply flawed one apart from the convexity assumption. However, FDH is a most flexible approach that does not assume constant returns to scale or convexity as well as one that yields the best performance.

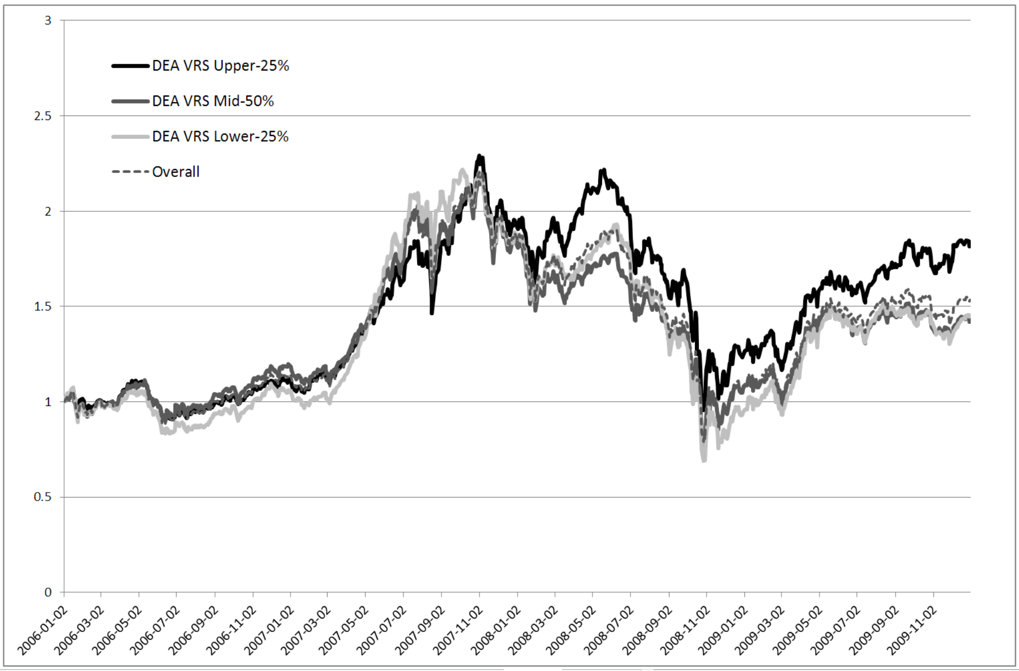

Figure 2: *Cumulative daily returns of portfolios (January 2, 2006 – December 30, 2009) built by DEA VRS.*

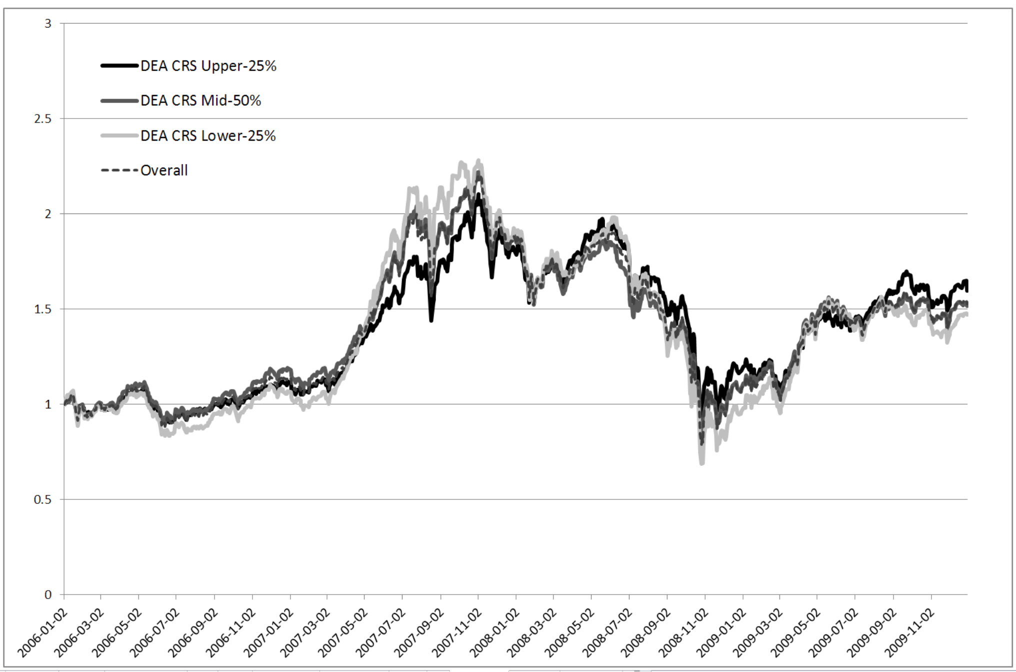

Figure 3: *Cumulative daily returns of portfolios (January 2, 2006 – December 30, 2009) built by DEA CRS.*

Table 2: Portfolio values at the end of the time period compared to initial values.

Model	Portfolio			
	Upper-25%	Mid-50%	Lower-25%	Overall
FDH	188.3%	143.9%	137.2%	153.5%
DEA VRS	183.6%	142.3%	145.0%	
DEA CRS	160.9%	152.7%	147.6%	

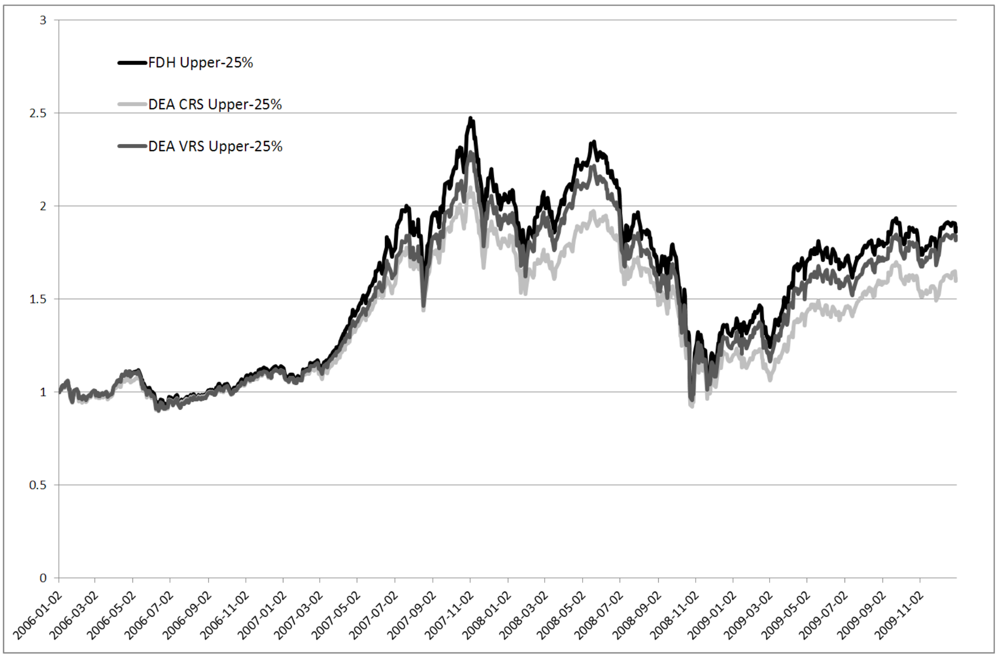

Figure 4: *Cumulative daily returns of upper-25% portfolios (January 2, 2006 – December 30, 2009).*

3.4. Comparison of CAPM measures

In this subsection, we additionally compare some capital asset pricing model (CAPM) measures for the portfolios to ensure that the performance of the portfolios (evidenced by the charts) align with traditional indicators of financial performance. Using the monthly returns (48 returns over 4 years) for all portfolios of the same period (as in the previous subsection), we fit the CAPM linear model of the form: for $t = 1, 2, \ldots, T(= 48)$,

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

where R_t denotes the monthly return of the portfolio in month t, $R_{f,t}$ is the one-month return of the Certificate of Deposit (CD) interest rate at month t as a risk-free return, $R_{BM,t}$ is the return on KOSPI 200 index in month t as a benchmark return, and ϵ_t is an error term of mean zero. The fitted values $\hat{\alpha}$ and $\hat{\beta}$ for α and β are called Jensen's alpha and beta, respectively. Other measures calculated include the simple average returns

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

the volatility (standard deviation)

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

Sharpe ratio

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

and Treynor ratio

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

Table 3 summarizes these statistics. The figures in parentheses are the relative ratios compared to their values of the overall portfolio. For the upper-25% portfolios of both FDH and DEA VRS, the average return, Jensen's alpha, Sharpe ratio, and Treynor ratio are all considerably higher than the lower-25% portfolios relative to the same measures for the overall portfolio containing all 253 companies. The measures for DEA CRS also display similar but less pronounced discrepancies between portfolios. Smaller values of volatility and beta for the upper-25% portfolios than those for the overall portfolio also support another favorable feature of the upper-25% portfolios; however, even they are composed of only 25% of the 253 stocks they still are less risky than the overall portfolio.

4. Concluding Remarks

The results of the study are promising and 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. This strongly suggests the inappropriateness of DEA to measure 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, while appropriate in some cases in which efficiency frontier estimation can be effectively applied, does not work well in consideration of ESG scores and financial performance indicators used for this study. Second, the portfolios selected with the FDH method outperformed those selected by the DEA methods and also clearly outperformed the overall market portfolio for the 253 Korean companies under consideration in the entire length of the study. The results provide strong support for the assertion that the SRI strategy can function as a reliable means of accomplishing fiduciary duty as well as a tool for social betterment. For an investor contemplating the use of SRI to compile a portfolio comprised of Korean companies, this study strongly suggests that investments in socially responsible companies selected using the FDH method would be a financially prudent decision, regardless of any desire to make a sustainability statement.

In SRI evaluation, determination of the weights for ESG scores and financial performance has been an important issue as different weights yield different ranks among the companies under consideration. The nonparametric frontier models circumvent this issue by adaptively choosing these weights from the data and is a significant advantage over existing methods that rely on subjective choices.

One of the limitations of this study is that the outstanding performance of the FDH method was demonstrated only empirically. We suggest further theoretical research in economics, particularly on

Table 3: Empirical comparison of the portfolios via CAPM measures (monthly, January 2006 – December 2009). The figures in parentheses are the relative ratios compared to their values of the overall portfolio composed of all 253 stocks under consideration.

		Portfolio			
		Upper-25%	Mid-50%	Lower-25%	Overall
FDH	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
DEA VRS	Average return	1.65% (126.16%)	1.15% (87.04%)	1.35% (102.30%)	1.32%
	Volatility	8.56% (94.60%)	8.91% (98.54%)	10.56% (116.78%)	9.04%
	Beta	1.1291 (94.46%)	1.1686 (97.76%)	1.3253 (110.87%)	1.1953
	Jensen's alpha	0.87% (129.71%)	0.35% (52.06%)	0.47% (69.36%)	0.67%
	Sharpe ratio	0.1731 (136.15%)	0.1099 (86.43%)	0.1117 (87.88%)	0.1271
	Treynor ratio	0.0131 (136.36%)	0.0084 (87.11%)	0.0089 (92.57%)	0.0096
DEA CRS	Average return	1.31% (99.88%)	1.30% (98.84%)	1.42% (107.86%)	1.32%
	Volatility	7.88% (87.11%)	8.99% (99.46%)	10.90% (120.52%)	9.04%
	Beta	1.0574 (88.47%)	1.1805 (98.76%)	1.3740 (114.95%)	1.1953
	Jensen's alpha	0.58% (86.02%)	0.50% (74.16%)	0.51% (76.36%)	0.67%
	Sharpe ratio	0.1457 (114.64%)	0.1261 (99.21%)	0.1150 (90.45%)	0.1271
	Treynor ratio	0.0109 (112.88%)	0.0096 (99.90%)	0.0091 (94.83%)	0.0096

the convexity of the technology with ESG variables. Another limitation is that the empirical results in this work are all from in-sample analysis. Therefore, it is difficult to assure that the proposed approach would be an effective future portfolio selection tool. An out-of-sample style study with a more pragmatic portfolio selection strategy that allows for rebalancing is highly suggested in future work. Research within different sectors of the world market would be helpful to consolidate a strong argument for the use of SRI regardless of context.

Investment strategies like SRI will become more important to global corporate and private investors as the world becomes more attuned to sustainability issues that affect all of us. This study illustrates the usefulness of SRI strategy when appropriately applied; however, significant work remains to be done to solidify SRI as a fully integrated, mainstream investment approach. Whether or not it will get there within the near future, FDH shows significant promise as a proper implementation of SRI and should be a topic of academia and business for years to come.

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