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Abstract

This paper proposes a novel Corporate Social Responsibility (CSR) index based on a Data Envelopment Analysis (DEA) model. Acknowledging the argument that companies might favor those CSR dimensions that provide strategic competitive advantages, we argue that the index can capture companies' strategic approach to CSR. Furthermore, our findings reveal a neutral relationship between this strategic CSR index and economic performance as measured by ROA and Tobin's Q, when controlling for firm unobserved heterogeneity and past economic performance. By contrast, an equally-weighted index of the same CSR indicators is found to be negatively related with ROA, which reinforces our claim that this specific DEA-based index is a measure of strategic CSR.

Keywords: Corporate Social Responsibility, Data Envelopment Analysis, Strategic CSR, Difference-GMM

JEL: C23, C67, M14

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1. Introduction

There has been a continuing interest in what has become known as Corporate Social Responsibility (CSR) for at least 50 years. Despite disagreements over an appropriate definition, CSR is generally viewed as corporations' responsibility to integrate environmental, social, and governance (ESG) practices into their business model, *beyond mandatory legal requirements*. Moreover, CSR is often associated with the notion of sustainable development.

The increased interest in ESG issues has stimulated a rapid development of empirical literature (Crane et al., 2008) focusing on the relationship between corporate social performance and financial performance (measured by either accounting or market-based variables). While the results are generally mixed, marginally more studies seem to identify a positive, though generally weak, association between the two (Margolis et al., 2007).

One major difficulty in conducting such empirical research, i.e., when analyzing the link between CSR and economic performance, as well as one of the reasons for obtaining conflicting results, lies in defining adequate and representative *quantitative* measures for the complex CSR concept.³ This paper will address this problem through the construction of a more comprehensive aggregate measure of CSR. Waddock and Graves (1997) expressed the need for a multidimensional measure of CSR applied across a wide range of industries and larger samples of companies and actually designed a set of weights for the various dimensions, based on the views of a panel of experts. We argue that our constructed CSR index meets these requirements and at the same time accounts for the strategic decisions made by managers who bear in mind the ultimate goal of profit maximization.

Strategic CSR is a concept whose origins can be traced back to Baron (2001), who coined the term to refer to a profit-maximizing corporate strategy that can be regarded as socially responsible by some. Burke and Logsdon (1996) also adopted a view similar to strategic CSR, but focused on the corporate strategy attributes that could be linked to CSR. More recently, Siegel and Vitaliano (2007) performed an empirical investigation concerning the determinants of strategic CSR and also reported evidence of economic benefits derived from strategic CSR. While not in a strategic CSR framework, Elsayed and Patton (2005) presented dynamic panel

³ There are a number of additional reasons why it is challenging to find empirical support for the link between economic performance and CSR. For a more detailed exposure, see Waddock and Graves (1997), UNEP Finance Initiative-Mercer Report (2007), and Belu (2009).

data estimates for the link between environmental performance and companies' financial performance, arguing that very few studies have controlled for firm heterogeneity or considered dynamic effects in the financial/environmental performance relationship. The present paper addresses this problem by employing a Difference GMM estimation framework, as in Blundell and Bond (1998).

Porter and Kramer (2006) make a strong case for strategic CSR, arguing that companies should favor a strategic approach to CSR, i.e., they should identify the corporate agenda that can bring the greatest competitive benefit. They claim that "...the more closely tied a social issue is to a company's business, the greater the opportunity to leverage the firm's resources, and benefit society." Moreover, they argue that companies should carefully select the social issues that intersect with their particular business, because "No business can solve all of society's problems or bear the costs of doing so (...). Other social agendas are best left to those companies (...) that are better positioned to address them."

Recognizing the pertinence of their arguments, we proceed to construct CSR indices that account for the differences between the business models of companies, even within the same industry. In order to achieve this, we resort to Data Envelopment Analysis (DEA), a versatile non-parametric management tool widely used for assessing the relative performance and efficiency of individual decision-making units (DMU) (e.g., firms, schools, hospitals). The DEA feature that we are exploiting most in our study is the assignment of firm-specific sets of weights. These weights are the outcome of an optimization process that seeks to award the most favorable set of weights to each company, with higher weights for outputs where one particular company tends to perform better and lower weights for outputs where the company underperforms, relative to the performance of the other firms in the sample. In contrast to this approach, the current practice when constructing CSR indices is to award a subjectively chosen *a priori* set of weights to various CSR dimensions, the same for all companies in a sample or portfolio.

Please note that the strength of the CSR index we propose does not depend on the number of or the specific underlying CSR dimensions on which it is based. It resides rather in its ability to identify firms that achieve a lot with respect to CSR *relative to their peers* and *given a certain set of CSR dimensions*.

The contributions in this paper are the following: First, we develop an endogenous CSR index that accounts for *strategic* corporate social behavior. Second, we explore the impact of our newly defined measure of CSR on firm performance, measured by return on assets and Tobin's Q which are modeled as autoregressive processes. We therefore control for past economic performance that might influence both current values of economic performance as well as current CSR. We also control for firm-specific effects that have been shown to affect the relationship between CSR and economic performance (Becchetti et al., 2008; Baron et al., 2009). Moreover, our empirical model to some extent deals with concerns of causality in the relationship between CSR and firm performance, since it includes both unobserved firm-specific effects and past economic performance.

Descriptive statistics of our constructed strategic CSR index indicate that, as expected, in consumer durable and non-durable experience goods sectors more firms embrace strategic CSR than in any other consumer oriented sector. This confirms the hypothesis that CSR can be used to reduce information asymmetry between consumers and producers, especially for goods whose properties cannot be assessed before purchase (Siegel and Vitaliano, 2007). However, contrary to this hypothesis, we also find that the sector showing largest proportion of firms that behave CSR strategically is basic resources, which could be due to the higher environmental pressure that firms in this sector face, as a result of their environmental impact.

Using the outlined dynamic panel modeling framework, we find evidence that strategic CSR has a neutral impact on firm performance, when controlling for a number of other relevant factors. By contrast, an equally-weighted measure of CSR, based on the same underlying CSR scores, is found to have a persistently negative impact on return on assets. These contrasting findings emphasize the role played in empirical research by the specific aggregation technique of CSR indicators, as well as indicate that our DEA-based method can capture the strategic component of CSR. That the relationship was not found to be positive, as suggested in theory, might be due to the fact that strategic CSR is undertaken only to the extent that marginal cost equals marginal benefit.

The remainder of the paper is organized as follows: Section 2 discusses the heterogeneous nature of the CSR concept and how DEA can be used to construct strategic CSR indices. Section 3 describes our empirical strategy while Section 4 describes the data set. Section

5 presents and discusses our empirical findings as well as several robustness checks. Section 6 concludes the paper.

2. The CSR paradigm. Constructing an aggregate CSR measure

2.1 Difficulties with current CSR measures

There is an ongoing discussion about the appropriate definition of CSR. However, most of the proposed definitions⁴ agree that CSR is a multidimensional concept, which is an aspect of particular concern in this paper. Multi-dimensionality implies that various distinct aspects of the nature of a business need to be considered simultaneously when assessing a firm's CSR performance. These distinct criteria are very often clustered into three main subgroups: environmental, social, and governance related.

The methodologies developed by various CSR-rating agencies or data providers⁵ involve a subjective weighting of the CSR dimensions' importance. For instance, KLD Research & Analytics, a leading CSR-rating agency, bases its rating criteria on seven qualitative areas: community, diversity, employee relations, human rights (ascribed to the social dimension), environment, governance, and product safety. Furthermore, they detail the above criteria into *strengths* and *concerns*. Their ratings do not involve numbers, but rather qualitative descriptions noted with pluses and minuses.⁶

Sustainable Asset Management (SAM)⁷ uses a broader list of criteria for assessing CSR performance and updates it every year. For example, in 2007 the following criteria were rated: corporate governance, risk & crisis management, codes of conduct/corruption & bribery, environmental performance, environmental reporting, labor practice indicators, human capital development, talent attraction & retention, corporate citizenship/philanthropy, and social reporting.

⁴ One definition proposed by the European Commission (2001) is as follows: "CSR is a concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with stakeholders on a voluntary basis."

⁵ Innovest, IRRIC (Investor Responsibility Research Center), Asset4, Sarasin&Cie, KLD Research & Analytics, and Sustainable Asset Management are a few examples.

⁶ For details, see the KLD methodology at http://www.kld.com/research/ratings_indicators.html

⁷ Sustainable Asset Management is a Swiss-based asset management company that computes and updates the Dow Jones Sustainability Index. In addition to general CSR criteria, SAM also computes sector-specific criteria. See <http://www.sam-group.com/> for details.

SAM computes a score from 0 to 100 for each dimension, where 100 means maximum performance. The assessment of the score is done by in-house specialists based either on questionnaires completed by companies or on publicly available sources of information. In the present study, we will use the individual scores provided by SAM to construct our proposed CSR index.

One can notice from the criteria listed above that a wide range of issues are addressed simultaneously in an assessment of a firm's social responsibility. However, there might be differences in the way these issues affect different businesses. Some dimensions are certainly important for some businesses, while others are less relevant. For instance, oil and mining companies are very exposed to environmental risks and therefore deploy strategies with respect to environmental performance accordingly; banks and financial institution put a higher emphasis on risk and crisis management, while IT companies have extensive human capital development strategies and consequently are expected to score high in terms of labor practices. We assume that most managers carefully select the CSR issues that are deemed relevant for their company and then concentrate their efforts in those particular areas.

Different CSR dimensions imply different costs and might provide different benefits and opportunities for profit depending on the nature of the firm's core business. Thus, it is difficult to construct an aggregate measure of CSR in a fair manner, even if accurate information about the achievements in terms of each particular dimension is available. One has to decide on a set of weights to be used for computing an aggregate index. Depending on the structure of the weighting system, more emphasis might be placed on some dimensions and less on others. This subjective way of computing CSR indices is prone to criticism, as it might favor some dimensions over others and therefore some companies over others.

Another research strategy is to conduct separate analyses for each CSR component, i.e., to analyze the association between a measure of economic performance and one particular CSR component (e.g., corporate governance, environmental performance, or labor practices). While many authors have chosen this route (Hart and Ahuja, 1996; King and Lenox, 2001), the potential findings are not really relevant in the CSR context since even if a negative relationship is found between an individual CSR component and economic performance, this should not imply that that particular component/measure should be overlooked when pursuing a CSR agenda. On the other hand, if positive relationships are found, it is difficult to argue that the

result can be generalized for companies with significantly different businesses, and it is also unclear how much of its available resources a company should commit to that particular CSR dimension, perhaps to the detriment of other relevant CSR dimensions.

In addition to the above arguments, Baron (2001) argues that in the presence of opportunities for strategic CSR, a positive correlation between economic performance and CSR should be expected. However, when altruism rather than profit maximization drives CSR, a negative relationship might also be possible. Consequently, the empirical analyst should know beforehand whether displayed CSR is a result of altruism, profit maximization, or a threat by an activist. Assuming a generally accepted framework to measure CSR, it would be difficult to distinguish between these types of CSR. For example, Baron (2009) disentangles the strategic component of CSR based entirely on judgment, by selecting those strengths in the KLD database "...that correspond to activities that appear to favor the public directly and seem to be cast that way by the media." The remaining strength indicators are considered to measure a different type of CSR, i.e., responses to social pressure CSR. Our approach avoids such burdensome information requirements and subjective bias since this information is implicitly embedded in our constructed CSR indices based on DEA.

The present paper makes an empirical contribution to the recent strand of literature that distinguishes between various types of CSR: strategic, in response to a threat, and altruistic CSR. Much of this literature is normative and qualitative, mainly consisting of specific predictions based on increasingly complex theoretical models (Besley and Ghatak, 2006; Bagnoli and Watts, 2003; Baron, 2009). Empirical evidence is still scarce.

2.2 How can DEA be used to construct endogenous CSR indices?

The following brief presentation of the DEA method is based mainly on Cooper et al. (2000). The standard DEA models account for production-like processes, where multiple inputs are combined and transformed into several outputs. The main purpose of DEA is to construct an index (score) of relative (to the other units) performance. To obtain this, the first step is to

construct a virtual input and a virtual output for each DMU by using a set of (unknown *ex ante*) weights:

$$\text{Virtual input} = v_1x_{1o} + \dots + v_mx_{mo}$$

$$\text{Virtual output} = u_1y_{1o} + \dots + u_sy_{so},$$

where v and u are weights and x and y are inputs and outputs, respectively.

Please note that in our study we only have one input, which is unity, following the arguments presented in Lovell and Pastor (1997). DEA models are *input-oriented* or *output-oriented*. The distinction comes from the way adjustments are made to inefficient units in order to obtain their efficient projections. If adjustments are made in the input space, we have the *input-oriented* approach. If adjustments are made in the output space, we have *output-oriented* models. There is also a third choice, namely models that simultaneously adjust both outputs and inputs, the so-called *additive* models with their *slack-based* variants. However, in our case, the distinction is less relevant. For convenience, we will choose the output-oriented model, like in Banker et al. (1984). Given that there is only one input, the nature of returns to scale is not important either. Lovell and Pastor (1999) showed that an output-oriented model (which assumes constant returns to scale, like in Charnes et al., 1978) with a single constant input, coincides with the Banker et al. (1984) model (which allows for variable returns to scale) with a single input.

The next step is to determine the weights, using mathematical programming techniques, so as to maximize the ratio (θ) between the aggregated virtual output and the virtual input. Consequently, the optimal weights may vary from one DMU to another. Hence, deriving the optimal weights from data is an objective process, compared to fixing them in advance. It is important to realize that there is a ratio for each DMU, so we will get N maximal values (θ^*) and an optimal set of weights for each unit in the sample. The ratio θ^* is restricted to be less than or equal to 1 (or larger than or equal to one in the output-oriented models), and the units that have a $\theta^* = 1$ after optimization are considered to be efficient, i.e., performing best. The lower the calculated θ^* (or the greater than one, in output-oriented models), the more inefficient the unit. This ratio will constitute the base for the CSR index that will be used as an explanatory variable in the empirical model.

DEA constructs the weights endogenously by allowing them to be determined as part of an optimal solution to a formal aggregation problem. More precisely, DEA assigns higher

weights to dimensions where a company performs well and lower weights to dimensions where it performs less well. The weights will be chosen such that each company will be placed in the most favorable position in relation to all other companies in the sample. In this manner, we can obtain a score for the relative performance in terms of CSR, for each particular company. The optimal set of weights is determined as part of an optimization process and is company specific. In other words, the DEA weighting system favors dimensions where the company performs better, corresponding to the business strategy implemented by its manager. This means that CSR dimensions that provide competitive advantages and implicitly receive increased ex ante efforts from the manager, as reflected in correspondingly higher SAM marks, will weigh heavier in the aggregate CSR index.

Moreover, DEA provides the means to identify in which dimension a particular firm is lagging behind best practice in CSR terms. It can also provide precise quantitative qualifications to the sub-optimal level for a firm; hence it gives the percentage by which a particular sub-optimal firm should improve in a certain dimension in order to achieve best practice.

Finally a word on the originality of using DEA to construct a strategic CSR index: being a tool extensively used to measure efficiency, DEA is one of the favorite methodologies for measuring environmental performance embedded in firm economic efficiency (see, e.g., Färe et al., 1989). However, to the best of our knowledge, no study has used DEA in the wider context of CSR where it fits particularly well given the necessity to somehow assign weights to the CSR dimensions.

2.3 DEA-constructed strategic CSR index

For our empirical analysis, we construct a DEA index that considers all CSR dimensions as outputs. No particular quantity is considered as an input. We will base our approach on the model developed by Lovell and Pastor (1997), where only one constant input is considered. The reason for this is that we consider each firm as a stand-alone unit, without explicitly accounting for various inputs involved in obtaining the current environmental, social, or governance-related accomplishments. While it is obvious that achieving a satisfactory CSR level might require material inputs, it is usually not clear how these are converted into CSR scores. What we aim to measure is the commitment of a particular firm to the CSR requirements.

If we let $y_j = (y^{1j}, y^{2j} \dots y^{8j})$ represent the vector of CSR scores (provided by Sustainable Asset Management) for the firm $j, j=1 \dots N$ where N is the number of firms in the sample, then we can write the following optimization problem:

$$\begin{aligned} & \max_{\theta, \lambda} \theta \\ & \text{subject to} \\ & \theta y^{ij} \leq \sum_k \lambda_k y^{ik}, i = 1, \dots, 8 \\ & \lambda_k \geq 0, k = 1, \dots, j, \dots, N \quad , \\ & \sum_k \lambda_k = 1 \end{aligned}$$

where i indexes the CSR dimension, k indexes the firms under scrutiny, and λ_k are the assigned weights for each dimension. This model was proposed and used in Lovell and Pastor (1997) to analyze the operating performance of branch offices of a large financial institution in the context of target setting. In our case, we do not have any target requirements, although this procedure can be implemented by the screening agent in a fairly easy manner, as shown in the paper just mentioned.

Moreover, the separation into CSR-efficient and CSR-inefficient firms is performed at the industry level in order to reduce inter-industry heterogeneity, although a CSR index could be meaningfully computed industry-wide. By comparing the CSR standing of firms that are very similar in terms of business models, customer targets, and product classes, one can obtain an as close to strategic CSR measure as possible. Therefore, our DEA-based CSR index is best able to capture firm-specific CSR strategic behavior when looking at very homogeneous industrial sectors.

The DEA-based CSR index returns various degrees of inefficiency, ranging from very close to very far from the frontier. Please note that in an output-oriented model, the computed DEA scores are bound to be larger than one. Moreover, the degree of inefficiency does not vary linearly with the DEA score, and hence a meaningful transformation is required. In order to exploit in the best possible way the limited variation in the data, we construct, based on the industry and year-specific DEA scores, a CSR index with three values: a value of two for efficient firms (DEA score equal to 1), a value of one for slightly inefficient firms (DEA score between 1 and 1.1), and a value of zero for substantially inefficient firms (DEA score larger than

1.1 – and lower than 2, i.e., the maximum by definition). Thus, *the higher our constructed CSR variable, the more CSR-efficient* the firm. The cutoff point of 1.1 was a subjective and debatable decision but was made to ensure enough observations in each group.

One condition has to be met in order for DEA to work reasonably well. The number of firms has to be sufficiently larger than the number of outputs (i.e., the number of CSR dimensions) on which the frontier is built, or else there is a risk that all firms will appear on the frontier. Moreover, please note that the DEA scores are relative to the sample on which they were built, e.g., to a particular industry, each year. Hence, cross-industry inefficiency comparisons of DEA scores cannot be performed, i.e., it cannot be concluded that firms in two different industries with identical inefficient DEA scores are equally inefficient.

In order to provide a minimum evaluation of our constructed CSR index, we will also use an alternative measure of corporate social behavior based on the same underlying CSR scores, yet aggregated differently. It consists of an index that places equal weights on all CSR dimensions, i.e., their equally-weighted mean.⁸ Our DEA-based index provides a transparent way of judging one firm's CSR achievements against another's in a similar line of business by placing more weight on the dimensions in which each firm does (relatively) better. This measurement would capture the *strategic* nature of CSR, by emphasizing those dimensions that attract more efforts from a company's management. On the other hand, a simple average of the various CSR scores, which implies that each dimension is equally relevant, should be less likely to measure the strategic component of CSR and more strongly reflect *any non-strategic components* of CSR, i.e., CSR motivated by altruism or by threats by an activist. We will then proceed to investigate the empirical properties of these two CSR measures by analyzing their relationship to firm performance.

Firm performance is expected to be positively related to strategic CSR, since the motivation of embracing strategic CSR is to increase profits, and negatively related to other forms of CSR, since they would increase the costs of the firm (Baron, 2001). The effects of strategic CSR on a firm's economic performance can materialize through several channels: consumer reward, employee and supplier reward, and investor reward Baron et al. (2009), all due

⁸ Of course, one can think of many ways of evaluating our constructed CSR index. Its direct competitors would be the indexes built with weights subjectively chosen by analysts at the ranking agencies (which most often are confidential). However, before proceeding to the more complex indexes, we would like to confirm that there are benefits that our DEA CSR index brings relative to a simple average score, not least as it also incorporates a strategic dimension to CSR.

to the fact that various stakeholders value the CSR that the firm provides. *Consumers* might be willing to pay a premium for the goods and services of a firm that provides CSR, while *employees* might be more productive or even accept lower wages. Also, a firm providing CSR might attract better-skilled employees, or better services and products through the *supply chain* from firms that also value CSR. Finally, *investors* may be willing to pay a premium for shares in a firm engaged with CSR. Since the data does not allow separate identification of the individual effects of rewards by consumers, investors, and employees and other suppliers of factor inputs, a combined rewards effect is estimated through the marginal effect of CSR on *EcPerformance* in equation (1).

On the other hand, it is less obvious how CSR affects profitability if it is undertaken in the absence of a clear profit maximization motive. This relates to the two initial contrasting theories in management science which laid the foundation for the CSR discussion, i.e., *the shareholder view* of the firm and *the stakeholder theory*. The shareholder theory considers that “the sole social responsibility of business is to increase profits” and that doing otherwise will necessarily reduce shareholders value (Friedman, 1962). The opposing view, the stakeholder theory, emphasizes that managers should meet not only the requirements of stockholders, i.e., owners of the firm, but also those of a variety of stakeholders (e.g., consumers, employees, suppliers, local communities), whose support is crucial for the existence of the firm Freeman (1984). In so doing, the corporation will reduce asymmetric information and agency costs between the corporation and all its various stakeholders, which has a clear positive bearing on firm profitability. The empirical literature has so far provided evidence for both views.⁹

3. Empirical strategy

Our empirical exercise is mainly concerned with investigating the impact that different measures of CSR have on firm performance. As a proxy for economic performance, we will use both return on assets (ROA_{it}), a profitability measure that expresses the amount of net income plus (after tax) interest payments but before preferred dividends per unit of average current and last year's assets, as well as Tobin's Q, a forward-looking (expected profits) performance

⁹ See Becchetti et al. (2008) for an extensive discussion on the theoretical implications of the two views as well as related empirical evidence.

measure that is less prone to managerial manipulation. Tobin's Q is defined as the ratio of firm market value to the replacement cost of its assets, and we follow Baron et al. (2009) and measure it as the sum of market value of common stock, book value of preferred stocks, book value of long-term debt, and book value of common liabilities, divided by book value of total assets.

Our measures of socially responsible behavior are primarily the DEA-based CSR index described in Section 2.3 as well as an equally-weighted index. By design, the DEA-based CSR index is expected to capture more of the strategic aspect of CSR, while the latter is a better measure of altruistic CSR.

Along the lines of Fama and French (2000), who model ROA as a mean-reverting process, we use a dynamic model for both ROA and Tobin's Q where their current values are also linked to their first-lag values. Earlier studies (e.g., Elsayed and Patton, 2005; Baron et al., 2009) have also modeled the data-generating process for Tobin's Q as an autoregressive of order 1 process. Accounting for past values of economic performance also brings the advantage of partially correcting for the potential endogenous nature of CSR performance. If financially successful firms are more likely to undertake CSR activities, by controlling for past performance we implicitly correct for this effect as well (Elsayed and Patton, 2005). Formally, the model is:

$$\begin{aligned}
 EcPerformance_{it} = & \alpha + \beta_1 EcPerformance_{it-1} + \beta_2 CSR_{it} + \beta_3 X_{it} \\
 & + \sum_{j=1}^4 \gamma_j DY_j + \sum_{k=1}^8 \delta_k DInd_k + \sum_{l=1}^3 \theta_l DRe g_l + (u_i + \varepsilon_{it})
 \end{aligned} \tag{1}$$

where *EcPerformance* is either ROA or Tobin's Q, *CSR* is either the DEA-based CSR index or a simple average CSR index, *X* is a list of control variables specific to each economic performance measure, ε_{it} is the disturbance, distributed as $N(0, \sigma^2)$, and the Greek letters are parameters.

Following previous studies (e.g., Manescu and Starica, 2007), we consider a number of additional control variables to explain the cross-sectional variation in ROA, such as: firm size, measured as the natural logarithm of assets expressed in US dollars; firm risk, expressed as long-term debt/total assets; capital intensity, calculated as the ratio of capital expenditures to property, plant, and equipment; and sales growth, expressed as a 3-year change in sales (King and Lenox,

2001). In addition to these variables, the set of controls for Tobin's Q also includes dividend to book ratio (Baron et al. 2009) and firm age (Guenster et al., 2005).

Furthermore, economic performance is subject to three types of variation that may be independent of the operations and CSR activities of firms. The first includes factors such as macroeconomic conditions, general market sentiment, and political risks that can affect overall profitability ratios and market values. The second consists of industry-specific factors such as increased or decreased profitability due to shifts in demand or restrictions on supply (Baron, 2009). The third includes factors related to regional variation in accounting reporting standards or consumer preferences for CSR, which may differ, e.g., between Continental European and Anglo-Saxon countries. These types of variation are taken into account by, respectively, year fixed effects (DY_j), industry fixed effects ($DInd_k$), and regional fixed effects ($DReg_l$) (through dummy variables).

Moreover, as our sample covers firms that differ in terms of, e.g., productivity and management competence in the form of unobserved firm heterogeneity that is constant through time, we need to include time-invariant firm-specific effects, i.e., u_i , in the empirical model. This has become a standard procedure in the specialized literature, since it has been shown repeatedly that firm *ex-ante* characteristics matter a great deal when trying to estimate the effects of CSR on profitability (e.g. Becchetti et al., 2008, Baron et al. 2009).

When estimating a dynamic panel data model, the lagged dependent variable (as an explanatory variable) is *positively* correlated with the fixed-effects term entering the compound disturbance (u_i), which makes the OLS estimator inconsistent with an upward-bias. The Within Groups estimator eliminates this source of inconsistency by removing from each individual the mean values within its group, which eliminates the fixed effect. But for panels with a short time dimension, this transformation introduces a non-negligible *negative* correlation between the transformed lagged dependent and the transformed error term, which will lead to a downward-biased inconsistent Within Groups (i.e., Fixed Effects) estimator. The fact that these two estimators are likely to be biased in opposite directions is useful for evaluating a third consistent candidate estimator, which should lie between these two (Bond, 2002). The general approach relies on instrumental variable (IV) estimators in the General Method of Moments framework. It consists of first differencing the data to eliminate the fixed effects and then using second or earlier – as suitable – lagged values of the endogenous variable for subsequent first-differences

as instruments, provided that the ε_{it} components of the errors are uncorrelated. Arellano and Bond (1991) have developed the framework for this “Difference GMM” estimator, which makes use of the maximum number of lags of the endogenous variable as instruments at each point in time. This is the estimator that we will use to model economic performance in (1).

Furthermore, Blundell and Bond (1998) show that under certain circumstances, a new estimator constructed by adding equations in levels to the equations in differences, for which suitable first-differences of the endogenous lagged variable are used as instruments, could bring significant improvements at the cost of only an additional assumption. This estimator, the System GMM estimator, works much better especially if the series are close to being a random walk, so that their first-differences are close to being innovations, or if the variance of the permanent effects (u_i) is large relative to the variance of the transitory shocks (ε_{it}).

4. Data

Our data set consists of an average annual sample of 405 non-financial large publicly traded companies listed on the main international stock exchanges, leading to 2,027 firm-year observations from 2002 to 2006.¹⁰ The sample covers nine industries defined according to the MSCI global industry classification standards (GICS): oil and gas (10.2%), basic resources, industrials (23.8%), consumer goods (16.9%), healthcare (6.5%), consumer services (13.6%), telecommunications (4.4%), utilities (9.9%), technology (8%), and basic materials (6.7%). We exclude financials since they have a role of intermediaries in the economy and their balance sheet structure is different from that of other sectors (which may adversely distort the distribution of the financial variables). Also, their CSR characteristics are structurally different than those of other sectors.¹¹ The regional distribution of the sample looks as follows: 45% European, 30% North-American, 15% Japanese, and 10% other.

Moreover, we also use an alternative rearrangement of the GICS sectoral classification in order to isolate several consumer-oriented sectors, as done by Siegel and Vitaliano (2007). Thus,

¹⁰ The sample was reduced from an initial 2,092 non-financial sample for which CSR data was available as follows: 17 observations lost to missing values, 27 lost to negative book value of equity, 1 lost to Tobin’s Q larger than 10, 9 lost to ROA or lagged ROA smaller than -25%, 4 lost to ROA or lagged ROA larger than 40%, 2 lost to capital intensity larger than 1.5, and 5 lost to change in sales larger than 1.05.

¹¹ Some authors (e.g., Siegel and Vitaliano, 2007; Baron et al., 2009), however, do not exclude Financials.

in addition to basic resources (including the oil & gas producers and basic materials sectors), industrial goods, and industrial services (including oil & gas distributors), we consider consumer search goods, durable experience goods, non-durable experience goods, and experience services. For an exact classification, see Appendix B. This sectoral classification was only used to construct an alternative DEA-based CSR index to that based on a 10 industry classification.

The explanatory variables of interest are the two CSR aggregated indices, a DEA-based one and an equally-weighted average one, defined in Section 2.3. Both indices are constructed based on eight selected CSR dimensions that were rated every year of the analyzed period by Sustainable Asset Management, an asset management company specialized in sustainable investments. These CSR dimensions are: codes of conduct/bribery & corruption, corporate citizenship, corporate governance, eco-efficiency, human capital, risk management, talent attraction, and social reporting. Two other available CSR dimensions were excluded from the analysis due to their high correlation with the remaining ones. These are: environmental reporting (showing a 0.61 correlation with eco-efficiency and a 0.55 correlation with social reporting) and labor practices (>0.5 correlation with both labor practices and codes of conduct).

As mentioned, the dependent variable is Return on Assets (ROA) and Tobin's Q.¹² These two, together with the other control variables described in Section 3, were obtained based on data from Worldscope Datastream. Eight industry dummies, four year dummies, and four regional dummies were also included among the explanatory variables.

No wave of data is lost when using lagged ROA among the explanatory variables, as lagged ROA is saved as a separate variable and recorded even for the first year of data. One wave of data is however lost for Tobin's Q, and therefore the sample size reduces in this case to 1,372 observations. By estimating Model (1) in first-differences, an additional wave of data is lost in both cases.

¹² See the Appendix for additional data details.

5. Empirical results

5.1 Descriptive statistics and properties of our DEA-based CSR index

We begin our analysis by taking a look at how our DEA-based index behaves when calculated within industry, using the industry classification defined in accordance with Siegel and Vitaliano (2007). Summary statistics of the original DEA efficiency ratios are provided in Table 1. Recall that these DEA ratios are sample-specific and therefore comparisons of the ratios *per se* are not meaningful between samples. Also, a DEA ratio equal to one indicates an efficient firm, and the higher the ratio, the higher the degree of inefficiency. A typical DEA ratio sample distribution would be skewed to the right, indicating that most firms are on the frontier or close to it with fewer firms the further away from the frontier one goes.

The industry-wise DEA ratio statistics (Table 1) indicate that most firms in the consumer search goods and basic resources sectors are *relatively* efficient, as their average DEA ratios are closest to 1. Firms in these two sectors seem to behave more homogeneously with respect to CSR than those in the other sectors, as they achieve comparable values in all eight CSR dimensions. At the other end, firms in the experience services sector behave heterogeneously with respect to CSR, with only a small proportion (37%) being CSR efficient relative to the others.

Table 1. Summary Statistics of DEA ratio by industry

	Obs.	Mean	St. Dev.	Min.	Max.	% efficient
Basic resources	316	1.04	0.09	1	1.80	63%
Industrial goods	352	1.07	0.11	1	1.50	46%
Industrial services	154	1.05	0.08	1	1.37	54%
Cons. search goods	69	1.02	0.06	1	1.29	75%
Durable exp. goods	450	1.05	0.08	1	1.41	56%
Non-Durable exp. goods	281	1.06	0.10	1	1.66	50%
Experience services	405	1.08	0.11	1	1.67	37%

Operating the transformation of the industry-wise DEA efficiency score into a three-value discrete variable (2 for CSR efficiency, 1 for slight inefficiency, and 0 for high inefficiency) enables comparison of this CSR index between firms in different industries. A first

look at the values in Table 2, Column 1, suggests that within each industry, a majority of firms are either efficient or slightly inefficient, as their mean values range from 1.05 in experience services (the industry with the most inefficient firms) to 1.67 in consumer search goods (the industry with the least inefficient firms). Unfortunately, this industry-wise index cannot offer information about which industries do more than others in terms of strategic CSR. Siegel and Vitaliano (2007) claim that in sectors that provide products with characteristics that can only be assessed after purchase (such as the experience goods sector), CSR could be a useful tool in reducing asymmetric information between producers and consumers. These sectors are therefore more likely to embrace CSR. In order to find out which industries are more CSR strategic than others, we calculated a CSR index at the regional level (Table 2, Column 2). By calculating its mean by sectors, we can determine which sector contains the highest concentration of CSR-strategic firms (the highest mean value). The results are intriguing.

The most CSR-efficient firms, by a large margin, are found in the basic resources sector with a mean CSR index of 1.50, followed by the non-durable experience goods sector with a mean CSR index of 1.13¹³ (Table 2, Column 2). This might sound surprising, but it could be explained by the fact that such firms face increased pressure and scrutiny with respect to CSR (or may even face tougher regulation, which cannot be disentangled based on our raw CSR data) and therefore achieve more in this respect; or they simply operate in a business area that gives them a lot more scope for improving their CSR standing than firms in other industries.

¹³ The difference is statistically significant

Table 2. Summary statistics by industry for the CSR index-dummy built by industry (Column 1) and region (Column 2) and for the average CSR index (Column 3).

	(1)			(2)		(3)	
	CSR industry-wise			CSR region-wise		Average CSR	
	Obs.	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Cons. search goods	69	1.67	0.63	1.04	0.86	60	10
Basic resources	316	1.51	0.71	1.50	0.70	69	11
Industrial services	154	1.39	0.73	1.01	0.82	56	11
Durable exp. goods	450	1.37	0.79	1.26	0.78	65	10
Non-Durable exp. goods	281	1.27	0.81	1.13	0.81	61	13
Industrial goods	352	1.19	0.84	1.01	0.85	57	11
Experience services	405	1.05	0.83	0.98	0.83	58	13

The CSR index is a dummy variable taking the value 2 for efficient firms (DEA ratio=1), 1 for slightly inefficient firms ($1 < \text{DEA ratio} \leq 1.1$), and 0 for substantially inefficient firms ($\text{DEA ratio} > 1.1$). Average CSR is the average CSR score across the eight CSR dimensions.

In line with findings in Siegel and Vitaliano (2007), the durable and non-durable experience goods sectors have a higher proportion of firms that behave CRS strategically than any other consumer-oriented sector. A contrasting finding is that the experience services sector, also consumer-oriented, shows the lowest proportion of strategic CSR firms. The mean CSR index is actually slightly biased toward highly CSR-inefficient firms (with a mean value below 1 in Table 2, Column 2, which is statistically different from 1.26 – the mean value in durable experience goods). One explanation could be that their result, which was especially strong for the financial services subsectors and much weaker for the other services subsectors, cannot be replicated here as the financial sector was excluded. This raises a caution flag when dealing with CSR and financials in general.

In Table 2, we have also presented summary statistics for a simple average CSR index (in Column 3), which puts equal weights on the CSR dimensions instead of the endogenously determined weights in the DEA-based index. When comparing it with the between-industries regional DEA-CSR index (Column 2), one can observe that they generally deliver an identical ranking of industries in terms of CSR standing. The mean value differences of either index between any two of the sectors, i.e, industrial goods, industrial services and experience services,

are not statistically significant at any conventional level. This correspondence between the two very different indices indicates that, generally, firms that are best-in-sample along one particular CSR dimension tend to do well along other dimensions as well. Thus, extreme cases (and by some undesirable) such as firms that are terrible on many dimensions (e.g., spilling large amounts of oil into the sea, workers dying as a result of work accidents, etc.) but really good at one (which could be “human capital” here) are rare or non-existent.

At the same time, the two indices do not convey an identical message everywhere. For example, while the average CSR index indicates that firms in the non-durable experience sector do statistically more with respect to CSR than firms in the industrial services sectors, the DEA-CSR index indicates that they are in fact comparable (the difference in DEA-CSR index mean values is not statistically significant at conventional levels).

Looking at these findings differently, we could infer that our constructed CSR index indicates, once again, that CSR can also serve other purposes than reducing information asymmetry between producers and consumers, as it does not materialize strongly in all consumer experience goods or services sectors and it is even strongly present in industries not dealing directly with consumers (like basic resources).

5.2. Econometric analysis

A unilateral comparison of our DEA-CSR index does not reveal all its features. In order to evaluate it in greater detail, we also investigated how it relates to economic performance and, more importantly, whether its relationship to economic performance differs from that of an average CSR index. To this end, we estimated Model 1 for ROA and Tobin’s Q, using alternatively our DEA-based index and an average index as the explanatory variable of interest. For the econometric analysis, the DEA index is calculated industry-wise, based on a 10 industry classification. It is expected that by measuring a firm’s CSR relative to its industry peers, defined in a strict and not broad sense, one can better capture any strategic elements of CSR, and thus it increases the chances of capturing any existing link with economic performance through the econometric analysis.

The summary statistics for the 2,027 firm-year observations in Table 3 indicate that the average firm has a 6.63% ROA and a 1.63 Tobin’s Q and that it is close to being CSR efficient

(CSR index 1.32). Also, most firms are large – with an average size of \$11.8 million and the others tightly distributed around this average. Moreover, the average firm has a 20% level of long-term debt to assets and an average life of more than 23 years.

Regarding the strategic and average CSR indices, it is noteworthy that our strategic CSR index has a five times higher variation than the average CSR index. Multi-collinearity (untabulated results) among the explanatory variables in Model 1 is not a concern. Most coefficients lie between the reasonable values of -.28 (between firm size and lagged Tobin’s q) and .26 (between dividend-to-book and lagged Tobin’s q). One can also note that while our strategic CSR index has a .25 correlation coefficient with firm size, an average CSR index has a correlation coefficient of .42 – i.e., almost twice as high. Thus, our CSR measure reduces the typically found bias of higher CSR performance among larger companies. Also, the correlation between our CSR measure and the average CSR index is .64.

Table 3. Summary statistics for all explanatory variables in Model (1)

Variable	Obs.	Mean	St. Dev.	Min	Max
ROA (%)	2027	6.63	5.76	-22.31	37.18
Tobin’s Q	2027	1.34	0.92	0.12	8.99
Strategic CSR	2027	1.32	0.80	0	2
Average CSR	2027	61.45	12.31	19.49	94.22
Roa_t-1 (%)	2027	6.06	5.68	-22.72	36.66
Tobin’s Q_t-1	1376	1.31	0.91	0.12	6.52
ln(TobinsQ_t-1)	1376	0.10	-0.57	2.13	1.87
ln(tobinsQ)	2027	0.12	-0.56	2.13	2.20
Firm Size (ln)	2027	16.28	1.26	11.30	20.44
Firm Risk	2027	0.20	0.13	0.00	0.85
Sales growth	2027	0.07	0.12	-0.48	0.69
Cap. Intensity	2027	0.19	0.12	0.00	1.31
Div-to-Book	2021	0.07	0.15	0.00	3.31
Age (years)	2027	23.59	11.19	0.48	42.94

By modeling the cross-sectional and time variation in the financial and strategic CSR performance of firms through Model 1, one can note the positive relation between strategic CSR

and either return on assets or firm value (Tables 4 and 5, Column 1).¹⁴ After controlling for industry, region, and year-specific effects as well as lagged ROA and the other controls, we observe a 0.22% higher ROA for a firm that goes either from highly inefficient to slightly inefficient, or from slightly inefficient to efficient. A similar, though statistically weaker, positive relation can be observed between strategic CSR and firm value (Table 5, Column 1). However, as soon as firm-specific effects are taken into account (Tables 4 and 5, Columns 3), any such effect vanishes and we find evidence of no impact of strategic CSR on ROA or Tobin's Q. This holds even after fully correcting for the endogenous nature of lagged ROA – due to correlation with the fixed effects component of the error term – as the consistent estimates obtained using the Arellano-Bond Difference GMM technique still show no relationship between our strategic CSR measure and ROA and Tobin's Q respectively (Tables 4 and 5, Column 5).¹⁵ Finally, it is noteworthy that all models behave well in the sense that the effects of the control variables have the sign predicted by the established theory.

A few words regarding the legitimacy of relying on the Difference GMM estimator for our sample are required. Fixed effects are important in our panel data, as they account for more than 70% of the variation of the compound error terms (.73 for ROA and .99 for Tobin's Q). At the same time, there is no evidence either from the Hansen test or from the serial correlation tests (m2 and m3) that either of these AR(1) models are misspecified and thus we can trust the instruments we have used. Moreover, both ROA and Tobin's Q autoregressive coefficient estimates (0.14 and 0.80 respectively) lie within the ranges given by the OLS and Fixed Effects estimates (0.09-0.63 for ROA and 0.32-0.88 for Tobin's Q), which is reassuring. However, we were still led to believe that, in the model for Tobin's Q, both consistency and efficiency could be improved by using a System GMM estimator, i.e., by exploiting the correlations between first-differences lagged dependent and its level. The indications came from the high autoregressive coefficient for Tobin's Q, .80, corroborated with a very large variance of permanent shocks (a 99% of total error term variance due to fixed effects). In spite of this, such an estimator was not validated, as the extra-overidentifying restrictions – of zero correlation between the first-differences lagged dependent variable (instrument) and the compound error term in levels – did not hold (Difference-in-Hansen test of 0.02). This could be due to the

¹⁴ All estimations were done using Stata10.1.

¹⁵ The Difference GMM was implemented as a one-step estimator with Windmeijer-corrected cluster-robust errors.

additional assumption about initial conditions of System GMM, i.e., that the fastest growing individuals (i.e., firms) in terms of Tobin's Q are not systematically closer or farther from their steady-states than slower-growing ones (Roadman, 2006), not holding in our sample. Thus, the difference GMM estimator performs best on our sample(s).

Table 4. Pooled OLS (Col. 1, 2); Fixed-Effects (Col. 3, 4); Difference GMM (Col. 5, 6).
Estimation of Model (1) for ROA, with either a strategic CSR measure (Columns I) or an average CSR measure (Columns II) as explanatory variable.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	OLS (I)	OLS (II)	FE (I)	FE (II)	Diff- GMM (I)	Diff- GMM (II)
Strategic CSR	0.22** (0.05)		-0.07 (0.64)		0.00 (0.99)	
Average CSR		0.02** (0.05)		-0.01 (0.45)		-0.04** (0.03)
Lag(ROA)	0.63*** (0.00)	0.63*** (0.00)	0.09* (0.07)	0.09* (0.06)	0.14** (0.04)	0.14** (0.04)
Firm Size	-0.27*** (0.00)	-0.29*** (0.00)	-2.74*** (0.01)	-2.75*** (0.01)	-2.10** (0.02)	-2.21** (0.01)
Firm Risk	-3.26*** (0.00)	-3.24*** (0.00)	-10.53*** (0.00)	-10.58*** (0.00)	-11.41*** (0.00)	-11.61*** (0.00)
Sales Growth	0.78 (0.41)	0.83 (0.38)	2.96* (0.06)	2.99* (0.06)	3.01* (0.06)	3.08* (0.06)
Capital Intensity	1.72 (0.12)	1.72 (0.12)	5.86*** (0.01)	5.86*** (0.01)	3.40** (0.04)	3.33** (0.04)
Constant	6.76*** (0.00)	6.48*** (0.00)	49.39*** (0.00)	50.32*** (0.00)		
Year Dummies	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	N	N	N	N
Region Dummies	Y	Y	N	N	N	N
m2	-	-	-	-	0.67	0.67

m3	-	-	-	-	0.47	0.47
Rho(FE)			0.73	0.73		
Hansen	-	-	-	-	0.49	0.50
# Overid. restr.	-	-	-	-	10	10
Observations	2027	2027	2027	2027	1376	1376
Groups	-	-	615	615	464	464
R-sq.	0.55	0.55	0.18	0.18	-	-
F-statistic	74.10	76.34	16.22	16.31	14.74	14.86
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

P-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Rho indicates the fraction of total variance due to that of fixed effects u_i . m2, and m3 are second-order and third-order serial correlation in the first-differenced residuals, asymptotically $N(0,1)$. Hansen is a test of the validity of overidentifying restrictions for the GMM estimators. # Overid. restr. indicates number of overidentifying restrictions tested by Hansen test. P-values are reported for all tests.

Table 5. Pooled OLS (Col. 1, 2); Fixed-Effects (Col. 3, 4); Difference GMM (Col. 5, 6). Estimation of Model (1) for log (Tobin's Q), with either a strategic CSR measure (Columns I) or an average CSR measure (Columns II) as explanatory variable.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	FE	FE	Diff- GMM	Diff- GMM
Variables	(I)	(II)	(I)	(II)	(I)	(II)
Strategic CSR	0.01*		-0.00		0.00	
	(0.09)		(0.73)		(0.84)	
Average CSR		0.00*		-0.00		-0.00
		(0.07)		(0.35)		(0.51)
Lag Tobin'sQ	0.88***	0.88***	0.32***	0.32***	0.80***	0.82***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm Size	-0.03***	-0.03***	-0.28***	-0.28***	-0.33***	-0.33***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm Risk	-0.14***	-0.14***	-0.02	-0.02	-0.09	-0.09
	(0.00)	(0.00)	(0.85)	(0.84)	(0.48)	(0.47)
Sales Growth	-0.06	-0.06	-0.06	-0.06	-0.07	-0.07
	(0.11)	(0.12)	(0.41)	(0.42)	(0.45)	(0.43)

Capital Intensity	-0.03 (0.49)	-0.03 (0.49)	-0.03 (0.70)	-0.03 (0.71)	-0.20*** (0.01)	-0.21*** (0.01)
DivToBook	0.13*** (0.01)	0.13*** (0.01)	0.11** (0.04)	0.11** (0.03)	0.08*** (0.01)	0.08*** (0.01)
age (Years)	0.00 (0.50)	0.00 (0.51)	0.08 (0.50)	0.08 (0.49)	0.34** (0.02)	0.34** (0.02)
Constant	0.64*** (0.00)	0.62*** (0.00)	3.03 (0.32)	3.05 (0.31)	-	-
Year Dummies	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	N	N	N	N
Region Dummies	Y	Y	N	N	N	N
m2	-	-	-	-	0.43	0.43
Rho(FE)	-	-	0.98	0.98	-	-
Hansen	-	-	-	-	0.82	0.82
# Overid. restr.	-	-	-	-	5	5
Observations	1372	1372	1372	1372	906	906
Groups	-	-	464	464	377	377
R-sq.	0.91	0.91	0.34	0.34	-	-
F-statistic	541.92 (0.00)	537.19 (0.00)	28.22 (0.00)	28.29 (0.00)	29.36 (0.00)	28.80 (0.00)

P-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Rho indicates the fraction of total variance due to that of fixed effects u_i ; m2 is the second-order serial correlation in the first-differenced residuals, asymptotically $N(0,1)$. Hansen is a test of the validity of overidentifying restrictions for the GMM estimators. # Overid. restr. indicates number of overidentifying restrictions tested by Hansen test. P-values are reported for all tests.

As noted by Baron et al. (2009), the difference between the estimates with and without firm fixed effects (i.e., Difference GMM vs. OLS) could be due to the situations of the firms prior to inclusion in the data sample. For some reason, some firms could have had both high strategic CSR and high economic performance, whereas others could have had low strategic CSR and low economic performance. These relations could then have persisted over the period of the analysis, which would explain the positive and significant coefficient of strategic CSR in the OLS estimation. These findings emphasize once again the necessity to control for unobserved firm heterogeneity when modeling CSR and firm performance since when this is not controlled for, inexistent positive or negative relationships between the two might emerge.

The behavior of the estimated impact of the average CSR index across the various estimations closely mimics that of strategic CSR, with one substantial distinction (Columns II versus Columns I, Tables 4 and 5). Its estimated impact on return on assets, though *initially positive, turns negative* when controlling for firm-specific effects (Column 6, Table 4). This finding actually emphasizes some of the benefits of our DEA-based index, as outlined in Section 2.1. Based on the same underlying CSR data, it becomes clear now that one aggregation technique might provide a CSR index with a persistent negative impact on firm performance, while another technique might reveal a neutral impact, leaving the analyst with the difficult task of confronting the conflicting results, when, in fact, the relationship between CSR and firm performance ultimately is dictated by the type of CSR one is measuring. Thus, the preference for one technique or another will depend on the kind of CSR one would like to measure. As claimed in Section 2.3, our DEA-based index can capture more of a *strategic* feature of CSR while a simple average of the same underlying CSR scores could measure *other non-strategic* component of CSR, e.g., altruistic or social pressure CSR. This alleged dichotomy, in aggregation terms, is further emphasized by the distinct impacts they have on firm performance, the latter negative and the former neutral. As indicated by Baron (2001), undertaking CSR for altruistic reasons or in response to a threat by an activity might lead to lower profitability as it only implies additional costs. Moreover, our results also provide evidence in favor of the shareholder view, as outlined in Section 2.3, which is broadly in line with other previous findings (e.g. Becchetti et al. 2008).

Unlike the predictions of Baron (2001), however, our data analysis did not find evidence for a positive association between our strategic CSR measure and profitability; rather, a neutral association. Yet, the relationship is not negative, indicating that strategic CSR might in fact be undertaken only up to the extent that marginal costs equal marginal benefits. In a further analysis on regions, we found some evidence that the lack of an overall effect might be due to contrasting effects on different regions, with a positive effect in Continental Europe and a negative in Anglo-Saxon countries, yet these results were not statistically significant. It could be that a richer dataset in each region, with a larger sample in each industry and a more detailed industry classification, would be helpful in revealing stronger effects. However, this is left for future research.

Our results are related to several lines of empirical findings on the link between CSR performance and economic performance. First, not only do we investigate the impact of environmental performance on profitability measures as most studies in this area (Russo and Fouts, 1997; Waddock and Graves, 1997; Hart and Ahuja, 1996), we also account for other CSR dimensions, as only a few other studies do (e.g., Manescu and Starica, 2007). Second, we show that firm-specific effects and past economic performance – which is likely to drive CSR performance to some extent in the next period – play an important role in explaining the relationship between economic performance and CSR. Finally, we have shown that *strategic* CSR has a neutral impact on both return on assets and firm value, while *an equally-weighted index* of the same CSR dimensions has a negative impact on return on assets.

5.3 Robustness checks

Our results are robust to a variety of alternatives used either for building the DEA-based index or measuring Tobin's Q. First, we tried different alternatives for the transformation of the DEA ratios into the discrete-variable CSR index (e.g., a two-value dummy variable, bundling together the slightly and highly inefficient firms; extending the efficient CSR firm to include firms that are very close to the efficient frontier – with DEA ratios lower or equal to 1.05; or a three-value dummy variable, similar to the one currently used, but with more or less restrictive cutoff points than 1.1) with overall qualitatively similar results, statistically stronger in some cases and weaker in others.

Then, a CSR index built on a 7 sectors versus a 10 industry classification was also used in the econometric analysis, yielding a stronger impact on $\ln(\text{Tobin's } Q)$, but a lower impact on return on assets (in the pooled OLS estimation). Third, different alternatives of calculating Tobin's Q as in Guenster et al. (2005) or Elsayed and Paton (2009) do not qualitatively alter the results. Finally, using Tobin's Q directly, instead of its natural logarithm transform, produces statistically weaker results.

6. Conclusions

In empirical investigations where a quantitative measure of corporate social responsibility is required, one of the main difficulties is to account for the multidimensional and heterogeneous nature of the concept. It is difficult to aggregate company achievements with respect to various CSR dimensions in a way that leads to a fair and meaningful index.

This paper proposes a novel method based on Data Envelopment Analysis (DEA), a mathematical model traditionally used for efficiency analyses, to aggregate various CSR dimensions while considering the notion of strategic CSR, as proposed by Baron (2001) and argued for in Porter and Kramer (2006). We assume that most managers correctly identify and favor dimensions of CSR that might provide their companies with competitive advantages, and our constructed CSR index accounts for this strategic CSR behavior.

Statistical properties of this DEA-based CSR index, calculated at the regional level and based on a set of eight dimension-specific CSR scores provided by SAM, a specialized rating agency, indicate that most CSR-strategic firms, by a large margin, are in the basic resources sector. This might be explained either by the fact that firms in this sector are faced with high environmental pressures and therefore have to deliver more in this respect, or by the fact that this sector offers a larger scope for engagement in CSR. Additionally, our strategic-CSR measure provides support for the claim that strategic CSR may be used to reduce asymmetric information between producers and buyers (Siegel and Vitaliano, 2007), as firms in the durable and non-durable experience goods sectors are found to behave CSR strategically to a larger extent than in any other consumer-oriented sector.

Furthermore, we also tested whether strategic CSR is profit-enhancing, as expected in theory, since it is motivated by profit-maximization. Employing a Difference-GMM estimation technique, in a dynamic framework, we analyzed the relationship between our strategic CSR index and economic performance, measured by ROA and Tobin's Q, using a 5-year panel of 405 non-financial publicly traded large corporations. Our findings indicate that firm-specific effects are found responsible for a positive estimated relationship between economic performance (measured by Return on Assets, ROA, and Tobin's Q) and both our measure of strategic CSR, built at the industry level (on a ten industry classification), and an equally-weighted CSR index. Once these effects are controlled for, we find a neutral relationship between strategic CSR and

economic performance, and a negative relationship between ROA and the equally-weighted CSR index. It could be that, for some reason, before entering the panel, firms have both high (low) economic performance and high (low) levels of CSR, and that this persists throughout the analysis period, which emphasizes the need to control for firm-specific effects. The contrasting estimated impacts on profitability of the two CSR indices, which were based on the same underlying CSR indicators but aggregated differently, is evidence that aggregation matters greatly when investigating CSR and firm performance. It also suggests, once again, that our DEA-based CSR index might succeed in capturing strategic CSR.

While additional research is needed to explain the diverse reasons (e.g., social pressure, profit-maximization, altruism) as to why firms adopt a CSR stance (Siegel and Vitaliano, 2007), the evidence presented here supports the view that strategic CSR can be compatible with a profit-maximizing strategy as it does not hurt economic performance.

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APPENDIX A. **Data description**

Compilation of CSR data is usually a tedious process. For example, CSR performance in year t is reflected in the CSR scores published in September of year $t+1$. We therefore need to ensure that both the dependent variable (i.e., return on assets) and the explanatory variables (i.e., CSR variable and controls) are *contemporaneous*. As the ends of the fiscal years of the firms in our samples range from January to December, we have designed a representative matching rule according to which there is at least a six month overlap between the period reflected by the CSR measure and the financial data. Thus, CSR data for year t (which in fact reflects CSR performance in year $t-1$) is linked to financial data for either January-May in year t or for June-December in year $t-1$, depending on the firms' fiscal year ends.

APPENDIX B. **Industrial classification**

The regrouping of the Datastream sectoral classification, in order to obtain the sector classification used in Siegel and Vitaliano (2007), is as follows:

- I. Basic resources sector includes oil & gas producers (Datastream Industry code 530) and basic materials (1000).
- II. Industrial goods sector includes construction materials (2300), aerospace & defense (2710), general industrials (2720), electronic and electric equipment (2730), and industrial engineering (2750).
- III. Industrial services sector includes oil equipment, services and distribution (570), industrial transportation (2770), and support services (2790).
- IV. Consumer search goods sector includes personal goods (3760) and furnishings (3726)
- V. Durable experience goods sector includes automobiles & parts (3300), durable household products (3722), home constructions (3728), leisure goods (3740), pharmaceutical & biotech (4570), medical equipment (4535), and utilities (7000).
- VI. Non-durable experience goods sector includes technology (9000), food & beverages (3500), non-durable household products (3724), and tobacco (3780).
- VII. Experience services sector includes consumer services (5000), telecommunications (7000), healthcare providers (4533), and healthcare suppliers (4537).