

## Analysis

## An Efficiency Perspective on Carbon Emissions and Financial Performance

Arjan Trinks<sup>a,\*</sup>, Machiel Mulder<sup>a</sup>, Bert Scholtens<sup>a,b</sup><sup>a</sup> Department of Economics, Econometrics & Finance, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands<sup>b</sup> School of Management, University of St. Andrews, The Gateway, North Haugh, St. Andrews KY16 9RJ, UK

## ARTICLE INFO

## JEL classification:

D24  
D62  
G32  
M14  
Q41

## Keywords:

Carbon efficiency  
Financial performance  
Directional distance function  
Total factor productivity  
Data envelopment analysis

## ABSTRACT

International policy actions to constrain carbon emissions create substantial risks and opportunities for firms. In particular, production processes that are relatively high emitting will be more sensitive to the uncertain costs of emitting carbon dioxide and might further reflect productive inefficiencies. We employ a productive efficiency model to evaluate firms' carbon emission levels relative to those of best-practice (efficient) peers with comparable production structures. By accounting for total factor productivity and sector-relative performance aspects, this measure of carbon efficiency helps to quantify and rank firms' relative dependence on carbon in the production process. We investigate the impact of carbon efficiency on various financial performance outcomes and evaluate the role of general resource efficiency in explaining these impacts. Using an international sample of 1572 firms over the years 2009–2017, we find superior financial performance in carbon-efficient (best-practice) firms. On average, a 0.1 higher carbon efficiency is associated with a 1.0% higher profitability and 0.6% lower systematic risk. While carbon efficiency closely relates to resource efficiency, it also has distinct financial performance impacts, particularly lowering systematic risk. Overall, our findings suggest that carbon-efficient production can be valuable from both operational and risk management perspectives.

## 1. Introduction

International policy actions to constrain carbon emissions<sup>1</sup> pose substantial risks and opportunities for firms. A major risk, commonly referred to as carbon risk, concerns the uncertain future cost of emitting carbon. International climate commitments require additional regulatory measures, such as carbon pricing, subsidies, fines, and product requirements (Busch and Hoffmann, 2007; IPCC, 2018). These measures imply that carbon emissions become an important part of firms' cost function. At the same time, the transition towards a lower-carbon economy may create competitive opportunities from comparative advantages to innovations and improvements in eco-efficiency (Ambec and Lanoie, 2008; Porter and van der Linde, 1995). Eco-efficiency broadly reflects an objective to reduce ecological damage in economic activities (WBCSD and WRI, 2004). Yet, the operationalization of this concept and its relationship with the economic notion of efficiency generally remain ambiguous.<sup>2</sup> In this respect, a specific, increasingly salient issue for corporate managers and stakeholders is the extent to

which carbon emissions are reduced in production processes: firms producing relatively abundant carbon emissions will face greater sensitivity to uncertain costs from carbon regulation (Eccles et al., 2011) and—at a more general level—might exhibit inefficiencies in resource usage (Ambec and Lanoie, 2008; Porter and van der Linde, 1995).

To date, however, much is still unclear about firms' emission-reduction performance and how such performance relates to financial outcomes (Chen, 2014; Eccles et al., 2011; KPMG, 2017). A growing body of literature has begun to explore the relationship between carbon emissions and financial performance (Busch and Lewandowski, 2018). However, this literature tends to rely on either generic ratings of eco-efficiency (Derwall et al., 2005; Guenster et al., 2011) or indicators of carbon emission levels and carbon intensities (carbon emissions scaled by a business metric) (Busch and Lewandowski, 2018; Trinks et al., 2020). Investment practitioners also strongly rely on ratings or policies to altogether exclude high-emitting sectors or firms (Krüger et al., 2020; Trinks et al., 2018). A shortcoming of these measures and practices is that they do not account for the inextricable link between carbon

\* Corresponding author.

E-mail address: [arjantrinks@gmail.com](mailto:arjantrinks@gmail.com) (A. Trinks).

<sup>1</sup> In this paper, we use the term 'carbon emissions' as a shorthand for emissions of seven greenhouse gases (GHGs) covered by the Kyoto Protocol: carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF<sub>6</sub>), and nitrogen trifluoride (NF<sub>3</sub>). It is common practice to express GHGs as a single unit called CO<sub>2</sub>-equivalents (CO<sub>2</sub>e), which signifies the amount of CO<sub>2</sub> that would have the equivalent impact on global warming.

<sup>2</sup> A widespread measure of eco-efficiency is a productivity ratio of economic value per unit of an environmental pressure (WBCSD and WRI, 2004).

emissions and the production function. Economic theory represents production as an activity to transform a set of factor inputs into a set of outputs (Farrell, 1957), typically a mix of economic goods and bads (Chung et al., 1997). Firms trade-off and substitute between alternative input-output combinations based on opportunity costs. In addition, the objective of firms is to reduce inefficiencies, to become the best-practice among competitors with similar production processes. Hence, to improve our understanding of emission-reduction performance among firms, it is fruitful to model such performance in a production framework and to closely relate it to the economic notion of efficiency.

This paper studies firm-level carbon emissions from a productive efficiency perspective. Following the state-of-the-art environmental efficiency measurement literature (Chung et al., 1997; Picazo-Tadeo et al., 2005; Picazo-Tadeo and Prior, 2009), we employ a directional distance function (DDF) model to measure *carbon efficiency*. Carbon efficiency is defined as the extent to which a given level of output is produced with minimum feasible carbon emissions relative to direct sector peers. Specifically, carbon efficiency provides firms with a score between 0 (inefficient) and 1 (efficient) that reflects the fraction by which carbon emissions can be reduced while maintaining similar levels of inputs and output.<sup>3</sup>

Being firmly grounded in production theory, our measure of carbon efficiency offers two main contributions to the commonly used indicators of carbon emission levels or carbon intensities. Firstly, our carbon efficiency measure helps to understand better how firms perform in reducing carbon emissions in a given production process. This is because the DDF approach we adopt explicitly models carbon emissions in a joint production framework that accounts for the costly disposal of carbon emissions and substitution effects among production factors. As the total factor productivity and sector-relative aspects of firms' carbon emission levels are accounted for, a more accurate assessment can be made of firms' relative dependence on carbon in a given input-output process (see Section 3.1 for details). Secondly, within our efficiency framework, a direct link can be made between carbon emissions and productive or resource efficiency.

We conjecture that carbon-inefficient producers are more sensitive to uncertain carbon regulation (e.g., higher carbon prices) than their more efficient peers. Carbon regulation typically incentivizes emission reduction of production within sectors and identifies technical possibilities for efficiency improvements by benchmarking firms against sector peers (Mullins, 2018).<sup>4</sup> In addition, emission reduction might create comparative advantages from efficient resource usage, which are—by definition—defined relative to sector peers. Lastly, financial investors typically apply best-in-class selection methods for asset allocation. Thereby they show an interest in identifying dependence on carbon emissions within production processes (Eccles et al., 2011).

Given the potentially strong but hitherto unknown association of carbon efficiency and financial performance outcomes, we employ a second-stage analysis to study this association. We investigate two valuation-related outcome variables, namely return on assets (ROA) and Tobin's Q. ROA identifies the effects of carbon efficiency on short-term accounting profits, whereas Tobin's Q captures long-term performance effects as reflected by forward-looking stock market valuations. Next, given that carbon efficiency may mitigate firms' sensitivity to uncertain

costs of emitting carbon dioxide, we investigate two risk-related outcome variables, namely systematic risk and total risk. Systematic risk reflects the sensitivity of stock returns to macroeconomic fluctuations; it provides a measure of risk which investors require to be compensated for with higher returns, and therefore—from the perspective of the firm—drives financing costs (Albuquerque et al., 2019; Elton et al., 2014; Sharfman and Fernando, 2008). Total risk reflects the total degree of variation in a firm's stock returns (Elton et al., 2014).

Using an international sample of 1572 firms over the period 2009–2017, we identify substantial differences in carbon efficiency and find superior financial performance in carbon-efficient firms. On average, an improvement in carbon efficiency of 0.1 is associated with a 1.0% higher profitability and 0.6% lower systematic risk. This suggests that carbon efficiency might coincide with operational efficiency and (relatedly) serves to reduce the risk of uncertain carbon pricing regulation (Lins et al., 2017; Porter and van der Linde, 1995; Sharfman and Fernando, 2008). In further analysis, we indeed find a close link between carbon efficiency and resource efficiency. Yet, despite this interrelationship, carbon efficiency remains to have financial performance impacts unexplained by resource efficiency, particularly on systematic risk: for every 0.1 rise in carbon efficiency, systematic risk drops by on average 0.4%. Taken together, our results showcase the combined environmental and financial relevance of carbon efficiency.

This paper makes three contributions. First, we contribute to the ongoing debate on the relationship between corporate environmental and financial performance (Horváthová, 2010). Our analysis concentrates on corporate actions (impact) rather than words (disclosed policies) and investigates a range of financial performance outcomes. We thereby provide a solid microeconomic understanding of how environmental sustainability affects market behavior (Dam and Scholtens, 2015; Kitzmueller and Shimshack, 2012).

Secondly, we answer the call, from both research and practice, for relevant indicators of firm-level emission-reduction performance (Chen, 2014; Eccles et al., 2011). We explicitly model carbon emissions in a productive efficiency framework, adding to the literature focusing on carbon emission levels or carbon intensity indicators (Busch and Lewandowski, 2018). Our model of carbon efficiency provides a straightforward tool to identify assets that optimize economic value relative to carbon emissions (representing social costs) and traditional factor inputs (representing private costs). This is highly relevant to investors with preferences for eco-efficiency or portfolio decarbonization (Boermans and Galema, 2019) and to policymakers which aim to identify efficient levers of sustainable development.<sup>5</sup> To date, research on the impacts of carbon emission reduction on valuation and risk premia primarily has a macroeconomic focus (Dietz et al., 2018), while empirical evidence of firm-level impacts seems underdeveloped.

Thirdly, our finding that carbon efficiency positively affects financial performance, be it only weakly, helps inform policymakers that markets at least partly allow for aligning environmental and financial objectives (PDC, 2017; TCFD, 2017).

This paper is structured as follows. In the next section, we develop the main hypotheses regarding the association between carbon efficiency and financial performance. Section 3 describes the construction of our carbon efficiency measure and discusses in greater detail the

<sup>3</sup> For instance, when a firm has a carbon efficiency of 0.7, this implies that there is an efficient peer with similar input and good output levels which produces only 70% the amount of carbon emissions. That is, compared to an efficient peer, the firm can emit 30% less carbon with a similar set of inputs and good output.

<sup>4</sup> For example, in the EU ETS, there have been clear sector differences regarding inclusion in the scheme, allowances allocation amounts and methods. Since 2013, an important allocation method has become allocation based on a benchmark of the 10% least carbon-intensive installations, which will be tightened annually.

<sup>5</sup> Note that eco-efficiency is a measure of relative environmental pressure and as such does not guarantee macro-level sustainability, which depends on absolute levels of the pressure (Kuosmanen and Kortelainen, 2005). The importance of efficiency measurement, however, lies in its ability to facilitate reduction of pressures by identifying the most efficient and effective ways of doing so. For instance, policies targeting improvement in relative performance may be easier to implement and less costly to achieve than policies restricting the level of economic activity (Kuosmanen and Kortelainen, 2005; Mullins, 2018). Moreover, eco-efficiency can operationalize key sustainability aspects, which is much more informative and useful for practice than generic concepts of (and proxies for) sustainability.

distinct contribution of efficiency-based measures to dominant environmental performance and carbon intensity measures. In Sections 4 and 5, we describe the methodology and data. Results are presented and discussed in Section 6. Section 7 concludes.

## 2. Carbon efficiency and financial performance: hypotheses

There are several mechanisms through which corporate carbon emission reduction might affect financial performance (Dam and Scholtens, 2015). To provide a rich understanding of the relationship between carbon efficiency and financial performance, we discuss short- and long-term performance aspects as well as effects on firm risk. In this, we closely follow the literature studying the financial performance impacts of environmental performance (Horváthová, 2012) and carbon performance (Busch and Lewandowski, 2018).

Firstly, firms that emit relatively fewer amounts of carbon might intuitively divert from pure profit-maximizing behavior, given that emitting carbon typically reflects an externalized cost. As such, achieving carbon-efficient production might impose high net private costs that reduce operating profits and put the firm at a competitive disadvantage. Low-carbon production technologies can thus be expected to remain underutilized by profit-maximizing firms. However, the presence of carbon pricing regulation turns carbon emissions into private internalized costs, implying profitability per unit of output will increase given decreasing marginal returns (Dam and Scholtens, 2015). That is, when emitting carbon becomes more costly, firms with low-carbon production technologies benefit relative to those with higher-carbon technologies. Besides, high carbon efficiency may also affect profitability insofar as it reflects an underlying efficient resource usage. Firms may thus achieve comparative improvements in productivity through reduced resource usage, pollution, and waste levels (Ambec and Lanoie, 2008; Porter and van der Linde, 1995). Consistent with this argument, the empirical literature tends to find higher short-term profitability in low-carbon firms (see Busch and Lewandowski, 2018 for an overview). Therefore, we test whether carbon efficiency positively relates to short-term accounting-based operating performance, measured as *return on assets (ROA)*:

**H<sub>1</sub>.** *Carbon efficiency is positively related to return on assets.*

Apart from its association with short-term profits, firms' carbon efficiency may affect long-term performance expectations as reflected in market valuations. In this respect, a deep-rooted belief in the corporate finance literature and practice is that activities directed at reducing environmental impact impair firms' market value if management departs from the objective to maximize shareholder value (Jensen and Meckling, 1976). However, theoretically, two economic mechanisms could drive a positive relationship between carbon efficiency and market value, as corroborated by the closely related empirical literature (Busch and Lewandowski, 2018). First, investors may attach higher valuations to carbon-efficient firms insofar as these firms exhibit superior resource efficiency, as discussed above (expected future cash flows will be higher), and/or lower risk (future cash flows will be valued more as investors apply a lower discount rate), as we hypothesize shortly hereafter. Second, carbon-efficient assets may be traded at a premium when investors value good environmental performance in and of itself (Dam and Scholtens, 2015; Kitzmueller and Shimshack, 2012). Consistent with these mechanisms, Dyck et al. (2019) provide causal evidence that institutional shareholders promote environmental and social goals, indicating they see additional value in such issues. We, therefore, hypothesize that carbon efficiency is positively related to firm value measured by Tobin's Q:

**H<sub>2</sub>.** *Carbon efficiency is positively related to Tobin's Q.*

A growing stream of literature theorizes that good environmental performance has cash-flow preserving effects (Albuquerque et al., 2019; Chava, 2014; Lins et al., 2017; Sharfman and Fernando, 2008). The risk

mitigation hypothesis predicts that high Corporate Social Responsibility (CSR), and specifically high environmental performance, makes costly regulations, reputational damages, and litigation events less likely and less costly. Lins et al. (2017) argue that high-CSR firms have stronger stakeholder relations, a form of social capital that provides insurance against event risk. They find high-CSR firms fare better in recessionary periods. Albuquerque et al. (2019) theoretically show that CSR reduces systematic risk through a lower incidence and intensity of CSR-related shocks. A complementary theoretical model is provided in Grey (2018), which explains the firm's environmental protection activities as a competitive strategy that enhances market share and safeguards returns when the firm has strategically lobbied for environmental regulations.

Regarding carbon efficiency, we argue that firms which are less reliant on carbon emissions in a given production process will be less sensitive to uncertainty about the future cost of emitting carbon dioxide (Andersson et al., 2016; Busch and Hoffmann, 2007; Sharfman and Fernando, 2008). Next to mitigating regulatory risk, high carbon efficiency might further reduce litigation risk (e.g., penalties and fines from traceable damages (Sharfman and Fernando, 2008)), reputational risk (reflected by stakeholder pressures for emission reduction) (Eccles et al., 2011), and competitive risk (due to superior production technology and alignment with stakeholder pressures (Grey, 2018; Porter and van der Linde, 1995)). In sum, we may interpret carbon-efficient production as a form of 'environmental capital' that provides insurance against external shocks to the costs of emitting carbon.

To investigate this notion empirically, we test whether carbon efficiency impacts long-term risk-related metrics, namely systematic risk exposure and total risk. First of all, systematic risk measures the sensitivity of the firm's stock returns to market-wide fluctuations. We expect carbon efficiency to affect systematic risk as shocks to the cost of carbon likely will be economy-wide and thereby difficult to diversify (Battiston et al., 2017; Dietz et al., 2018; TCFD, 2017). From the perspective of the firm, systematic risk is the conventional channel through which the cost of equity capital is determined (Albuquerque et al., 2019; Fisher-Vanden and Thorburn, 2011; Sharfman and Fernando, 2008). These closely related studies, therefore, adopt a similar framework. Our third hypothesis reads:

**H<sub>3</sub>.** *Carbon efficiency is negatively related to systematic risk.*

The sources of risk that carbon efficiency might be associated with (as just mentioned) could be partly diversifiable and/or not fully captured by standard systematic risk factors (Becchetti et al., 2015). As such, carbon efficiency could affect idiosyncratic or firm-specific risk as well. Therefore, we further investigate the relationship of carbon efficiency with total risk, which is measured as the standard deviation of stock returns and thereby encompasses systematic and idiosyncratic risk. We hypothesize:

**H<sub>4</sub>.** *Carbon efficiency is negatively related to total risk.*

## 3. Measuring carbon efficiency using a directional distance function

This section introduces our measure of carbon efficiency and discusses its relevance as an indicator of environmental performance. We also provide a brief background to data envelopment analysis (DEA) and the directional distance function (DDF) approach on which our measure is based.

### 3.1. Carbon efficiency vs. single-factor productivity indicators

The finance literature and practice heavily rely on generic indices (ratings) for measuring corporate environmental protection practices (e.g., see Albuquerque et al., 2019; Chava, 2014; El Ghoul et al., 2011; Liang and Renneboog, 2017). Unfortunately, there are several shortcomings to these indices that significantly limit their usefulness for

evaluating environmental performance and potential relationships between environmental and economic performance. For instance, there are concerns about validity, measurement, and nontransparent and arbitrary aggregation of individual environmental performance elements (Gonenc and Scholtens, 2017; Trinks et al., 2020). A growing literature, therefore, focuses on individual performance attributes, such as eco-efficiency ratings (Derwall et al., 2005; Guenster et al., 2011)<sup>6</sup> or carbon emission intensity (Busch and Lewandowski, 2018; Trinks et al., 2020).

A downside of single-factor productivity measures, however, is that they abstract from the interrelationships and trade-offs between output and input factors, potential technical inefficiencies in the production of outputs (e.g., overuse of costly capital, labor, or energy), substitution effects between factor inputs, effects of changing economy-wide conditions, and performance comparisons against best-practice competitors (see, e.g., Cooper et al., 2007; Kumar Mandal and Madheswaran, 2010; Mahlberg et al., 2011). These issues are incorporated into the economic notion of efficiency (Debreu, 1951; Farrell, 1957; Koopmans, 1951). In production theory, a decision-making unit (DMU), such as a firm, is deemed efficient if no equiproportional reduction in inputs is possible for a given level of output, i.e., if its input-output vector lies on the frontier which defines the best observed practice in the reference set (Farrell, 1957). As such, the economic notion of efficiency provides two essential ingredients: (1) a representation of the firm's production function, or more generally the firm's objective to maximize good output with minimum feasible amounts of resources, and (2) an evaluation of performance relative to a set of efficient peers (ibid.).

To illustrate the difference with single-factor productivity indicators, consider the production of a given level of output and carbon emission resulting from a technically inefficient process: this implies a carbon inefficiency since the same vector of inputs and carbon emissions could produce higher levels of output, or, conversely, per unit of output less carbon could be emitted. An inefficient process thus generates excessive amounts of carbon emissions, as direct peers emit less given the same input-output structure. Hence, an efficiency perspective evaluates carbon emissions relative to a best-practice given the same production structures. It further allows us to explore the relationship between carbon efficiency and general productive or resource inefficiencies.

In sum, since carbon emissions are directly linked to the production decision, an appropriate method to evaluate the efficiency of carbon management will be a joint production framework, accounting for total factor productivity aspects (see, e.g., Cooper et al., 2007; Kumar Mandal and Madheswaran, 2010; Mahlberg et al., 2011). This integrated perspective of economic goods and bads also closely aligns with the way sustainable market behavior and outcomes are modeled (Kitzmueller and Shimshack, 2012). In the following, we discuss how the joint production framework can be applied to measure carbon efficiency.

### 3.2. Carbon emissions in a directional distance function model

The traditional measurement of technical efficiency typically ignores negative external effects from production (economic bads), such as carbon emissions, given the absence of price signals driving allocation (Koopmans, 1951, p. 38). However, the modeling of such *bad outputs* (as they are typically referred to in the environmental efficiency literature) now represents a growing field of interest in efficiency analysis (Zhang and Choi, 2014; Zhou et al., 2018). Two relevant contributions of this field are (1) providing measures of 'true' or

'overall' efficiency, crediting firms for producing high levels of economic goods and discrediting high levels of bads (e.g., Mahlberg et al., 2011; Zhang et al., 2008), and (2) providing subvector measures of environmental efficiency or eco-efficiency (Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al., 2005).

The purpose of our analysis is to provide a subvector measure of *carbon efficiency*, which evaluates firms' carbon emissions in excess of their efficient peers, for given levels of inputs and good output. This is in line with Korhonen and Luptacik (2004), Kumar Mandal and Madheswaran (2010), Picazo-Tadeo et al. (2014), Reinhard et al. (1999), among others. The directional distance function (DDF) is a suitable approach to modeling such a process (Picazo-Tadeo et al., 2012; Picazo-Tadeo et al., 2005; Picazo-Tadeo and Prior, 2009). The DDF, introduced by Chambers et al. (1996) and first used in environmental efficiency modeling by Chung et al. (1997), generalizes the radial Shephard's input and output distance functions,<sup>7</sup> by allowing the analyst to select the direction in which an inefficient DMU is projected onto the efficient frontier. As such, it provides a very flexible tool to evaluate efficiency, accommodating alternative evaluation objectives of researchers, policymakers, or firm managers (Picazo-Tadeo et al., 2012).

We adapt the DDF model by specifying a direction vector  $d = (-d^x, d^g, -d^b) = (0, 0, 1) = (0, 0, -y^b)$ . As such, we adopt a bad output-minimizing approach, in which DMUs are evaluated in the direction of the bad output ( $y^b$ ), carbon emissions.<sup>8</sup> Carbon-efficient DMUs have no peers with lower carbon emission levels for given factor inputs ( $x$ ) and good outputs ( $y^g$ ), while carbon-inefficient DMUs can reduce emissions by a proportion such that they reach the levels of carbon-efficient peers (targets). Hence, in line with the environmental efficiency literature (Kuosmanen and Kortelainen, 2005; Picazo-Tadeo et al., 2005), we define carbon efficiency as the ratio of target-to-actual carbon emissions.

Fig. 1 explains how carbon efficiency is measured using a stylized graphical illustration. We refer to Appendix A.1 for a formal definition of the associated linear program. To allow for a convenient interpretation, all DMUs are scaled to have similar input levels. The solid line (OABC) represents the efficient frontier formed by the DMUs for which maximum feasible output is produced for a given level of input. Carbon efficiency of the inefficient DMUs D and E is measured by projecting their respective observation points  $(x, y) = (4, 2)$  and  $(2.5, 1)$  in a horizontal direction onto the efficient points  $(2, 2)$  and  $(1, 1)$  respectively. That is, DMUs D and E are each evaluated against an efficient, best-practice counterpart or virtual DMU that produces the same good output levels with identical input amounts but with 2 Mt  $(4 - 2)$  and 1.5 Mt  $(2.5 - 1)$  lower CO<sub>2</sub>e emissions respectively. The carbon efficiencies of DMUs D and E are thus calculated as:  $1 - ((4 - 2)/4) = 0.5$  (DMU D); and  $1 - ((2.5 - 1)/2.5) = 0.4$  (DMU E).

A well-established technique to empirically estimate efficiency is data envelopment analysis (DEA) (Banker et al., 1984; Charnes et al., 1978). Being a nonparametric approach, DEA does not require explicit assumptions about the functional relationship between inputs and outputs, weights or factor input prices.<sup>9</sup> Instead, efficiency is examined relative to a frontier constructed from a piecewise linear combination of

<sup>7</sup> Note that the Shephard input distance function measures inefficiency as the radial or proportional reduction which is feasible for a given level of output.

<sup>8</sup> We carry out the estimation in MATLAB using the DEA toolbox package by Álvarez et al. (2020), available from <http://www.deatoolbox.com>.

<sup>9</sup> This feature of DEA can, for instance, be employed to assess sustainability performance based on many underlying indicators without the need to specify subjective weights for each indicator (Allevi et al., 2019; Chen and Delmas, 2011; Dyckhoff, 2018). However, DEA techniques still require specifying a list of indicators to evaluate firms on. Moreover, including many individual indicators reduces the discriminatory power of the DEA model; intuitively, specialization in individual dimensions creates many "best-practice" DMUs (Chen et al., 2015).

<sup>6</sup> But eco-efficiency ratings are susceptible to the same concerns, and most of them tend to put the cart before the horse by constructing the rating based on environmental issues that are financially material (e.g., see Derwall et al., 2005).



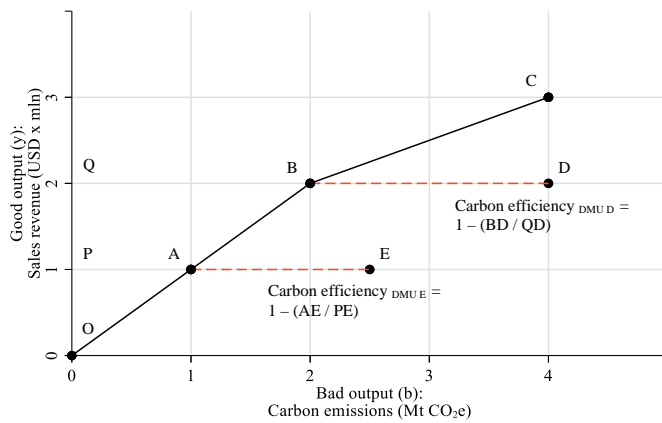


Fig. 1. Isoquant with one good output and one bad output.

observed inputs and outputs in a sample of DMUs that form the reference set. Given that the purpose of our analysis is to evaluate firms relative to an observed best-practice, and to be in line with the environmental efficiency literature, DEA is chosen to estimate efficiency.<sup>10</sup>

We compare DMUs with their direct Industry Classification Benchmark (ICB) sector-level competitors in the same year. Being a widely recognized classification, which is applied in major global markets, the ICB sectors closely reflect the nature of the business (primary source of revenue) and have a minimal inter-sector correlation.<sup>11</sup> The 33 sectors strike a balance between comparability of activities and precision and discriminatory power of the efficiency estimates. The number of firms being compared to their sector-year peers is on average 35, ranging from 3 to 70, and in the analysis 19% of all firms are ranked as fully efficient. As different decision-makers might apply different classification schemes and given that this choice might affect the efficiency estimates, we perform additional robustness analyses in which carbon efficiency scores are re-estimated based on alternative sector classifications with differing levels of aggregation.<sup>12</sup>

### 3.3. Resource efficiency effects

Our measure of carbon efficiency compares the carbon emissions of a focal firm with those of its efficient peer and, as such, attributes all inefficiency to excessive carbon emission levels. However, carbon-inefficient firms might have relatively abundant emissions because of their technical inefficiency, i.e., they might produce comparatively low levels of output given the set of factor inputs employed. Therefore, we additionally investigate whether and to what extent carbon efficiency reflects an efficient utilization of resources (Chen et al., 2015). To this

<sup>10</sup> Charnes et al. (2013) and Cooper et al. (2007) provide excellent introductions to DEA. Recent applications to environmental efficiency measurement are surveyed in Zhang and Choi (2014) and Zhou et al. (2018). In a parametric alternative to DEA, Stochastic Frontier Analysis (SFA), an explicit production function is assumed and econometric techniques are used to estimate the functional parameters. A benefit of DEA is that it makes only a minimal set of general axiomatic assumptions (Färe et al., 1989; Färe and Primont, 1995). Yet, in standard DEA models all deviations from the frontier are interpreted as inefficiencies, whereas SFA (or stochastic DEA) models can account for randomness in these deviations.

<sup>11</sup> <https://www.ftserussell.com/financial-data/industry-classification-benchmark-icb> (accessed: May 10, 2019).

<sup>12</sup> A drawback of more granular classifications such as the 114 ICB subsectors is that a very low number of firms are being included in each subsector-year benchmarking group: With an average of 17 firms and much more prevalent extremely small samples (e.g., < 3 firms), 34% of all firms would be classified as fully efficient. This issue becomes more severe in subsample analyses, e.g. when benchmarking firms from the same country or geographical region.

end, we include an additional (control) variable, *resource efficiency*, which is defined as the technical efficiency determined by the DDF model using a direction vector  $d = (-x, 0, 0)$  (Picazo-Tadeo and Prior, 2009; Wang et al., 2012 also apply such a direction vector). Appendix A.1 provides a mathematical formulation of the associated linear program.

## 4. Carbon efficiency and financial performance

We estimate the effect of carbon efficiency on financial performance using the following panel regression model:

$$\begin{aligned} \text{Financial performance}_{it} &= \alpha + \beta \text{Carbon efficiency}_{it-1} + \gamma \text{Resource efficiency}_{it+1} \\ &+ \delta'X_{it-1} + \Lambda + \varepsilon_{it} \end{aligned} \quad (1)$$

where *Financial performance<sub>it</sub>* is the measure of firm *i*'s financial performance at time *t*. Note that we lag the independent variables to ensure they are available when financial performance is measured and to be in line with the related literature (Albuquerque et al., 2019 Chava, 2014). We measure short-term operating performance using *Return on Assets (ROA)*, which is defined as (net income/total assets) \* 100%. Long-term firm value is measured by *Tobin's Q*, which is calculated as: (common equity market value – common equity book value + total assets)/total assets. Next, we consider firms' *systematic risk*, which is defined as the sensitivity of stock returns to the market rate of return; it is estimated using a Capital Asset Pricing Model (CAPM) regression of individual stock's daily excess returns on the Fama-French global market factor return from end-of-June of year *t-1* until end-of-June of year *t*.<sup>13</sup> We use short-window CAPM regressions to capture the time-varying nature of market beta and its potential causes (Fama and French, 2006 Levi and Welch, 2017). Finally, we obtain a measure of *total risk*, which is the annualized standard deviation of total returns from end-of-June of year *t-1* until end-of-June of year *t*, expressed in %. Note that the one-year lag specification in Eq. (1) implies that we estimate the effects of carbon efficiency on the risk measures in the period end-of-June of year *t* until end-of-June of year *t+1*.

The main independent variable of interest is *Carbon efficiency<sub>it-1</sub>*, which is a firm's projected to actual level of carbon emissions. It is based on the DDF model with direction vector  $d = (0, 0, -y^b)$  estimated using DEA. *Resource efficiency<sub>it-1</sub>* represents a firm's overall technical efficiency, which we use to isolate the effects of carbon efficiency and resource efficiency. Resource efficiency is estimated using the DDF model with a direction vector  $d = (-x, 0, 0)$ . Both efficiency measures are described in Section 3.2 and formulated in Appendix A.1. *X<sub>it-1</sub>* is a set of factors that are regarded as important determinant factors of financial performance (Margolis et al., 2009). We control for *size*, measured as the natural logarithm of total assets, and *leverage*, measured as total debt over total assets, as larger and less levered firms might exhibit superior financial performance and lower (default) risk (Fama and French, 1993). In the regressions with systematic and total risk as the dependent variables, we further control for *book-to-market ratio (B/M)*, which is common equity book value divided by its market value, due to its relevance as a risk factor (Fama and French, 1993).

Additionally, we include a set of fixed effects, denoted by  $\Lambda$ , which includes year-, industry-, and country-fixed effects, to rule out potential confounding from unobserved factors that might drive both carbon efficiency and financial performance over time and across sectors and countries (Fama and French, 1997; Gormley and Matsa, 2014; Horváthová, 2010).<sup>14</sup> In additional robustness analyses, we aim to

<sup>13</sup> We address outliers by winsorizing excess returns at the 0.5th and 99.5th percentiles before estimating betas, and CAPM regressions are required to include at least 75% of non-missing return observations.

<sup>14</sup> Our estimates are unaffected by the inclusion of high-dimensional (interacted) fixed effects (results are available upon request). For instance, industry-

eliminate further potential confounding events using additional control variables and a firm-fixed effects panel estimator. We cluster standard errors at the firm level to control for the correlation between multiple carbon efficiency observations of the same firm over time. Appendix A.3 includes a description of all variables.

## 5. Data

We obtain data on inputs, outputs, and other variables from Thomson Reuters' Asset4 and Bloomberg<sup>15</sup> for all firms with available data. Table 1 summarizes the main variables as well as the inputs and outputs used to construct the carbon efficiency and resource efficiency measures. Note that the summary statistics of both efficiency measures will be discussed in the results section (Section 6.1). We use the book value of property, plant, and equipment (PPE) in millions of USD as a measure for capital usage, as it represents the physical capital attracted by the firm to operate its business. Labor and energy input are the number of employees and terajoules (TJ) of total energy use, respectively. Given corporate aims to maximize the direct value of produced goods or services, we use net sales in millions of USD as a measure for good output (to be maximized). The bad output (to be minimized) is Scope 1 carbon emissions in megatonnes (Mt) of CO<sub>2</sub>e.<sup>16</sup> We focus on

direct Scope 1 emissions, given our purpose to identify heterogeneity in production processes. In this respect, Scope 1 emissions are the closest to the production process and under the direct control of firm management; by contrast, Scopes 2 and 3 emissions can much more readily be adjusted without substantial long-term changes to production activities (Busch and Lewandowski, 2018).

Fig. 2 shows the number of firms reporting Scope 1 emission data. We follow the sampling procedure of Trinks et al. (2020), which focuses on the period 2008–2016, due to quantity and quality of carbon emission reporting, and addresses extreme observations of carbon emissions in a systematic and conservative manner. In short, this procedure amounts to excluding zero reported emissions, firms with extreme emission figures resulting from unconsolidated reporting, and firms with extreme year-on-year changes in emission intensity. A detailed description is included in Trinks et al. (2020). In additional robustness analyses, we re-estimate carbon efficiency and resource efficiency for different specifications of the bad output (Scopes 1 + 2 emissions), labor input (wages), and capital input (total assets).

After removing firms belonging to the financial sector and those reporting on an unconsolidated basis, the sample consists of approximately 7800 firm-year observations (N), covering 1572 firms, spanning 47 countries. Our study period is 2009–2017, given that we study fi-

**Table 1**  
Summary statistics of efficiency and financial variables. Variable definitions are included in Appendix A.3.

	(1) N	(2) Mean	(3) Median	(4) StDev	(5) Min	(6) Max	(7) Skewness	(8) Kurtosis
<i>Efficiency estimates (2008–2016)</i>								
Carbon efficiency (0 to 1)	7800	0.31	0.12	0.38	0.00	1.00	1.02	2.35
Resource efficiency (0 to 1)	7796	0.56	0.50	0.30	0.02	1.00	0.21	1.70
Capital (mln USD)	7800	8417.54	2576.53	18869.89	1.69	263593.69	6.06	54.15
Labor (employees)	7800	42841.31	17931.00	72135.78	28.00	2200000.00	6.46	118.50
Energy (TJ)	7800	54469.67	5750.92	217159.41	1.48	6073969.00	13.14	253.74
Good output (mln USD)	7800	17128.57	6908.00	31624.26	10.62	476294.00	5.45	48.12
Bad output (Mt CO <sub>2</sub> e)	7800	3.88	0.20	12.73	0.00	176.00	6.82	64.03
<i>Financial performance outcomes (2009–2017)</i>								
ROA (%)	7689	5.79	5.46	7.71	−73.23	37.00	−1.61	19.39
Tobin's Q	7489	1.87	1.66	0.81	−0.35	7.00	2.21	10.87
Systematic risk	7657	0.87	0.83	0.46	−0.14	2.34	0.49	3.19
Total risk (%)	7657	32.14	29.04	13.35	14.11	89.34	1.41	5.30
<i>Baseline control variables (2008–2016)</i>								
Size	7800	16.07	16.04	1.33	11.75	18.58	−0.08	2.58
Leverage (%)	7800	26.61	25.17	16.05	0.00	96.13	0.68	3.87
B/M	7511	0.70	0.56	0.61	−0.26	6.85	3.38	23.66

(footnote continued)

by-year fixed effects would rule out potential confounding effects from unobserved factors that might drive performance across industries over time, such as demand or productivity shocks (Gormley and Matsa, 2014). A drawback of high-dimensional fixed effects is attenuation bias from potential measurement error (ibid.).

<sup>15</sup> The dataset is constrained primarily by the available data on carbon emissions. From Asset4, we obtain carbon emission data as reported by firms in public sources, mostly annual and CSR reports. From Bloomberg, we use the data as reported in the Carbon Disclosure Project (CDP) survey. According to a recent survey among large institutional investors in 2017/2018, both sources are currently being used with no clear preference for one source over the other (Krüger et al., 2020). Given the public nature of the data from Asset4, we use these data in our main analysis; Bloomberg data are employed for robustness analysis (results are available upon request). Note that both the Asset4 and Bloomberg ESG databases contain additional data on 'estimated carbon emissions' for firms which have not (yet) publicly reported emission data. However, due to the lack of comparability between carbon emission estimation models and the extrapolation used to estimate emissions, using these data would likely increase measurement error in the DEA efficiency estimates.

<sup>16</sup> It is common practice to classify carbon emissions using the three

financial performance outcomes one year ahead of the independent variables (Eq. (1)).

We address the effect of potential outliers on our financial performance regressions by winsorizing financial variables at the 1<sup>st</sup> and 99<sup>th</sup> percentiles; our results do not change when leaving out this procedure. Note that we do not winsorize the variables used in the estimation of efficiency, as this could induce severe bias in the efficiency estimates. Instead, in robustness analyses, we systematically examine data issues by alternating the specification of the reference group, inputs, and DEA model.

Table 2 shows how carbon efficiency is correlated with factor inputs

(footnote continued)

categories or Scopes from the GHG protocol (WBCSD and WRI, 2004). Scope 1 emissions refer to direct emissions, from sources directly owned or controlled by the firm, such as emissions from the combustion of fossil fuels in power plants, factories, or vehicles. Scope 2 covers the indirect emissions associated with purchased electricity. Scope 3 includes any other indirect emissions associated with production activities within a firm's value chain.

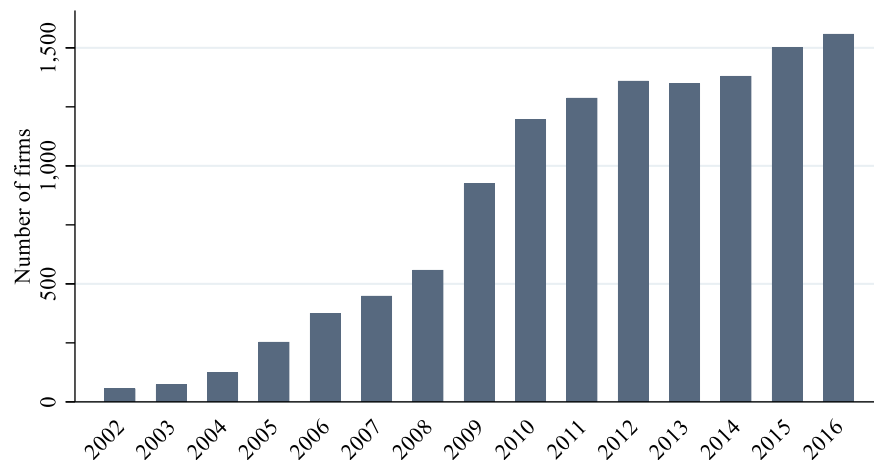


Fig. 2. Number of non-financial firms reporting Scope 1 CO<sub>2</sub>e emissions.

Table 2

Pairwise correlations between carbon efficiency, resource efficiency, factor inputs and outputs, and single-factor carbon intensity (2008–2016). Variable definitions are included in Appendix A.3. All correlation coefficients except (2):(3) and (3):(9) are significant at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Carbon efficiency (1)	1.00								
Resource efficiency (2)	0.64	1.00							
Capital (3)	−0.06	−0.01	1.00						
Labor (4)	−0.06	−0.04	0.32	1.00					
Energy (5)	−0.09	−0.06	0.41	0.10	1.00				
Good output (6)	0.03	0.09	0.73	0.60	0.33	1.00			
Bad output (7)	−0.12	−0.09	0.58	0.11	0.54	0.39	1.00		
Carbon intensity (8)	−0.16	−0.15	0.06	−0.08	0.17	−0.06	0.40	1.00	
Sector-adj. carbon intensity (9)	−0.30	−0.25	−0.00	−0.03	0.14	−0.07	0.22	0.48	1.00

and outputs. Consistent with findings by Cole et al. (2013), the level of carbon emissions is not only correlated with good outputs but also, and more strongly, with the use of capital and energy inputs. This finding underscores the importance of evaluating emissions in a total factor productivity framework, as we do in this paper (see also Cooper et al., 2007; Kumar Mandal and Madheswaran, 2010; Mahlberg et al., 2011).

## 6. Results

This section first summarizes the carbon efficiency estimates. Then, we report the results regarding the impact of carbon efficiency on financial performance.

### 6.1. Carbon efficiency

Table 1 summarizes the carbon efficiency scores and the financial performance variables used in the main analysis. The average carbon efficiency score is 0.31, which implies that the level of carbon emissions per unit of output of the average firm is 69% higher than the sector-year efficient peer. Hence, when we focus on carbon emissions only, firms seem to exhibit substantial differences in emissions generated from similar production (input-good output) structures. Related studies applying comparable directional vectors also tend to find relatively low average carbon efficiency levels (Oggioni et al., 2011; Picazo-Tadeo et al., 2014; Wang et al., 2012; Zhang et al., 2008). The resource efficiency measure exhibits considerable within-sector heterogeneity as well, given that the average firm uses 44% more inputs compared to the sector best-practice for observed output levels.

In Table 2, we explore the relationship between our carbon efficiency measure and simple indicators of carbon intensity, i.e., carbon emissions divided by sales. Carbon efficiency appears to only weakly correlate with (sector-adjusted) carbon intensity. Our efficiency-based

measure thus clearly differs from simple single-factor intensity-based measures of carbon emissions, not only conceptually (as described in Section 3.1) but also empirically.

We further document in Table 2 that carbon efficiency is strongly positively correlated with resource efficiency. Nearly two-thirds of the variation in firms' carbon efficiency can be explained by their resource (factor input) efficiency. Given this finding, it seems important to investigate to what extent the association between carbon efficiency and financial performance might be driven by heterogeneity in resource efficiency. In Section 6.3, we, therefore, aim to isolate the financial performance impacts of carbon efficiency from those of general resource efficiency.

Table 3 provides more detailed by-sector statistics. We find that carbon efficiency tends to be lower in high-emitting sectors, such as oil and gas production, chemicals, industrials, construction and materials, and electricity, as compared to most other sectors. This does *not* imply that high-emitting sectors as a whole are less efficient. Instead, because efficiency is a relative concept, it indicates that particularly in high-emitting sectors, more pronounced differences are observed between firms regarding the amounts of carbon emitted for a given input-output vector.

### 6.2. Carbon efficiency and financial performance

We evaluate the effect of carbon efficiency on financial performance ( $H_1$ – $H_4$ ) using the model outlined in Section 4 (Eq. (1)). Carbon efficiency is positively related to short-term profitability (ROA) and negatively to systematic risk (Table 4). On average, a 0.1 higher carbon efficiency, i.e., realizing 10% lower carbon emissions while keeping constant the input-good output production structure, is associated with a 0.06 percentage points (1.0%) higher profitability and 0.005 (0.6%) lower market beta (systematic risk). No significant associations with

**Table 3**  
Carbon efficiency by sector (2008–2016).

	ICB Sector name	(1) N	(2) Mean	(3) StDev
1	Oil & Gas Producers	426	0.28	0.32
2	Oil Equipment & Services	123	0.54	0.43
3	Alternative Energy	52	0.68	0.42
4	Chemicals	477	0.19	0.28
5	Forestry & Paper	88	0.74	0.35
6	Industrial Metals & Mining	272	0.24	0.34
7	Mining	361	0.38	0.34
8	Construction & Materials	449	0.16	0.31
9	Aerospace & Defense	132	0.63	0.33
10	General Industrials	220	0.40	0.44
11	Electronic & Electrical Equipment	248	0.40	0.36
12	Industrial Engineering	404	0.27	0.34
13	Industrial Transportation	302	0.26	0.38
14	Support Services	204	0.33	0.42
15	Automobiles & Parts	278	0.34	0.34
16	Beverages	156	0.31	0.37
17	Food Producers	259	0.33	0.34
18	Household Goods & Home Construction	165	0.30	0.33
19	Leisure Goods	83	0.51	0.38
20	Personal Goods	185	0.35	0.40
21	Tobacco	71	0.67	0.34
22	Health Care Equipment & Services	179	0.15	0.27
23	Pharmaceuticals & Biotechnology	329	0.26	0.34
24	Food & Drug Retailers	127	0.33	0.37
25	General Retailers	215	0.37	0.43
26	Media	225	0.33	0.38
27	Travel & Leisure	387	0.20	0.35
28	Fixed Line Telecommunications	180	0.48	0.40
29	Mobile Telecommunications	165	0.37	0.44
30	Electricity	266	0.31	0.40
31	Gas, Water & Multiutilities	141	0.40	0.41
32	Software & Computer Services	212	0.47	0.43
33	Technology Hardware & Equipment	419	0.15	0.31

Tobin's Q or total risk are found. This result suggests that carbon-efficient firms excel in their short-term operating performance and are rewarded in equity markets in the form of lower systematic risk. The latter implies lower expected stock returns, potentially owing to the lower sensitivity to uncertain carbon regulation (Lins et al., 2017; Sharfman and Fernando, 2008).

The estimated coefficients for our control variables are generally in line with the theoretical predictions (Fama and French, 1993). Larger

firms do not exhibit superior financial performance in our sample but do have higher systematic risk levels; more levered firms are riskier and less profitable; book-to-market is a strong predictor of risk. Financial performance also significantly varies over time and between industries and countries.

Next, we test whether the effect of carbon efficiency captures a more general effect of efficient resource usage, which does not explicitly relate to firms' success in minimizing carbon emissions in their production structure. To this end, we include resource efficiency as an additional control in Eq. (1) to help isolate the influence of carbon efficiency and general resource efficiency. Although carbon efficiency and resource efficiency happen to be strongly correlated, they are two distinct measures by construction, as described in Section 3.3. A potential downside of this analysis is the presence of multicollinearity: as the two measures are strongly correlated, our estimates—while still unbiased—might fail to precisely infer the distinct influence of each measure on our outcome variables. Tests, however, do not indicate strongly inflated standard errors in our analysis: correlations between the explanatory variables are moderate ( $< 0.8$ ) (Table 3) and variance inflation factors (VIFs) of our variables of interest range up to 1.9, which is well below even the most conservative thresholds. In Table 4 columns (2), (4), (6), and (8), we find that the positive association between carbon efficiency and financial performance is partly attributable to its implicit relation with resource efficiency. This result might be an attractive feature for corporate stakeholders pursuing both financial and carbon efficiency objectives. Yet, carbon efficiency also remains to have impacts of similar magnitude, which cannot be attributed to variation in resource efficiency, particularly reducing systematic risk.

Overall, these findings are consistent with our hypothesis that carbon-efficient economic activity is less sensitive to macroeconomic shocks, in particular those stemming from intensified carbon regulations, which raise the cost of emitting carbon.

Economically, the effects of carbon efficiency we estimate seem modest. In some sectors, such as electricity generation, firms with the highest carbon efficiency have tens of megatonnes lower direct carbon emissions than their least carbon-efficient peers. Reducing emissions to their 'efficient' levels will thus require substantial operational changes and upfront investments. As a result, the financial benefits from carbon efficiency improvements might not be reaped so easily.

By comparison, environmental performance ratings, while being

**Table 4**  
Carbon efficiency and financial performance (2009–2017).

The estimated equation is:  $Financial\ performance_{it} = \alpha + \beta Carbon\ efficiency_{it-1} + \gamma Resource\ efficiency_{it-1} + \delta X_{it-1} + \Lambda + \epsilon_{it}$  (Eq. (1)). *Financial performance* represents return on assets (ROA) (columns (1) and (2)), Tobin's Q (columns (3) and (4)), systematic risk (columns (5) and (6)), and total risk (columns (7) and (8)). *Carbon efficiency* is a firm's efficiency with respect to Scope 1 CO<sub>2</sub>e emissions, i.e., the ratio of projected to actual carbon emission levels. It is determined by the DDF model described in Appendix A.1 using a direction vector  $d = (0, 0, -y^b)$ . *Resource efficiency* represents a firm's efficiency with respect to input usage, i.e. the ratio of projected to actual input levels. It is determined by the DDF model described in Appendix A.1 using a direction vector  $d = (-x, 0, 0)$ .  $X$  is a set of controls, which includes firm size, leverage, and in columns (5)–(8) book-to-market ratio (B/M);  $\Lambda$  is a set of year-, industry-, and country-fixed effects. All variables are defined in Appendix A.3. Robust standard errors clustered at the firm level are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

	ROA (1)	(2)	Tobin's Q (3)	(4)	Systematic risk (5)	(6)	Total risk (7)	(8)
Carbon efficiency	0.597* (0.333)	0.554 (0.340)	0.036 (0.037)	0.054 (0.037)	−0.048*** (0.017)	−0.032* (0.017)	−0.464 (0.503)	−0.535 (0.508)
Resource efficiency		0.092 (0.436)		−0.037 (0.051)		−0.031 (0.023)		0.176 (0.683)
Size	−0.060 (0.142)	−0.062 (0.142)	−0.133*** (0.016)	−0.133*** (0.016)	0.013** (0.007)	0.014** (0.007)	−2.241*** (0.200)	−2.243*** (0.201)
Leverage	−0.048*** (0.012)	−0.048*** (0.012)	−0.006*** (0.001)	−0.006*** (0.001)	0.001** (0.001)	0.001** (0.001)	0.116*** (0.018)	0.117*** (0.018)
B/M					0.048*** (0.012)	0.048*** (0.012)	1.806*** (0.327)	1.810*** (0.327)
N	7689	7685	7489	7485	7430	7427	7430	7427
Adj. R <sup>2</sup>	0.122	0.122	0.291	0.291	0.433	0.433	0.483	0.483



predominantly related to the firm's disclosed policies rather than actual emission-reduction performance, seem to have more pronounced and significant effects on financial performance (Chava, 2014; Margolis et al., 2009). For instance, Chava (2014) finds that for each 'environmental concern' that firms score in four environmental performance categories, the cost of equity capital increases by 4.4% relative to the median firm. Additionally, compared to studies using carbon intensity measures, our estimates are particularly weak for Tobin's Q and ROA (Busch and Lewandowski, 2018) but qualitatively similar for risk; for instance, in a highly comparable sample, Trinks et al. (2020) find a 0.013 rise in systematic risk for each standard deviation increase in sector-adjusted Scope 1 carbon intensity.<sup>17</sup> Altogether, it seems that the adoption of our productive efficiency perspective provides a more nuanced picture of firm-level emission-reduction performance, with potentially material implications for the literature on the carbon-financial performance nexus.

### 6.3. Robustness analyses

Our analysis thus far suggests that firms' excessive dependence on carbon emissions relative to firms with similar production activities affects operating performance and firm risk. As we argue, these effects relate to investors' perception of the impact of carbon constraints on those firms' future performance and the close connection to resource efficiency. However, there might be alternative explanations for our results, namely specification issues of our efficiency estimates and confounding events (Horváthová, 2010). We perform several robustness analyses to test these explanations. Taken together, the results indicate that our main conclusions are not driven by the specification of the DDF-DEA model, its inputs, the reference set, or by potential sources of confounding. Our results further suggest that the effect of carbon efficiency is particularly strong in high-emitting industries. The robustness results are included in Appendix B.

#### 6.3.1. Alternative sector classifications

Given the sensitivity of DEA estimates to data specification, we re-estimate carbon efficiency and resource efficiency using alternative sector classifications that are widely applied and are relatively close to the ICB sectors in terms of granularity, namely the Fama-French 49 industries (FF49), the two-digit Standard Industry Classification codes (SIC2), and the Thomson Reuters Business Classification industry groups (TR4). In addition, we alternate the level of granularity by using the ICB sub-sector level (ICB4) and industry level (ICB1). In Table B.1, we find results are qualitatively similar to our main results. An exception is the insignificant results when estimating efficiency among firms within the aggregate industry group (ICB1) (Panel E), which could be explained by the widely heterogeneous business activities being benchmarked. Furthermore, in some cases in columns (5)–(8), negative effects are estimated for either carbon efficiency or resource efficiency. Contrary to our main analysis, we find a problematic correlation between both measures, and a regression using either of the measures separately results in very similar estimates. This indicates a great difficulty disentangling individual effects. Still, as we continue to find consistent estimates for carbon efficiency, we are confident that our main results are indeed driven by heterogeneous efficiency levels across firms rather than by the specification of the reference set.

#### 6.3.2. Alternative inputs and window analysis

To further alleviate potential concerns about data specification, we employ two additional analyses. First, we apply a window analysis, in which we smoothen the input-output vectors by taking two-year rolling

window average values before calculating efficiency scores. Second, we re-estimate efficiency using total assets as an alternative specification of capital input, wages for the labor input, and Scopes 1 and 2 carbon emissions for the bad output. As we find, the carbon efficiency scores indeed tend to differ along with the different specifications of the input-output vector. For instance, the carbon efficiency measure based on Scopes 1 and 2 emissions has only a 0.65 correlation with our main carbon efficiency measure. This divergence can be explained by the higher amount of variation in the bad output, the reduced number of observations (for about 400 firm-year cases, Scopes 1 and 2 are not both observed), and relatedly, the different composition of the benchmarking group (cf. Table B.1). Ultimately, the definition of the benchmarking groups and variables will depend on the objectives of the benchmarking exercise. Nonetheless, we find in Table B.2 (Panels A–D) that alternative input-output specifications do not materially alter our main estimates. As such, it seems unlikely that measurement issues substantially affect our conclusions.

#### 6.3.3. Constant reference set

Our main estimate of efficiency is based on an unbalanced sample, which closely follows how firms and investors would use all the information available to them to benchmark firms. However, to rule out the possibility that the documented effects come from a changing reference set rather than actual improvements in firms' underlying production activity, we rerun the analysis using a fully balanced sample. That is, we track the performance of the same set of firms through time. To ensure a minimum number of firms are eliminated from our main sample, we focus on input-output data in the 2014–2016 period. In Table B.3, we find results to be qualitatively similar to our baseline results, despite the considerable reduction in statistical power. Hence, carbon efficiency values and their effects on financial performance do not appear to be driven by year-on-year changes in the reference set.

#### 6.3.4. Alternative DEA models

Even though we specified our main DEA model as a suitable tool to measure carbon efficiency (Cook et al., 2014; Dyckhoff, 2018), we want to rule out the possibility that model specification drives our results. In the environmental efficiency literature, there are two main alternative approaches to treating bad outputs: (1) transforming the DEA model, or (2) applying the traditional DEA model using transformed values of the bad output or treating such outputs as inputs. Our baseline results are built upon the first, employing a specific direction vector which focuses on contracting only carbon emissions. An alternative corporate objective might be to strive for a contraction of bad output and a simultaneous expansion of good output, which follows the original DDF formulation by Chung et al. (1997). In Appendix A.1, we include a mathematical description of this model. Secondly, following a large stream of the environmental efficiency literature, we apply a traditional, well-established input-oriented DEA model (Banker et al., 1984; Zhou et al., 2018) and include carbon emissions as an additional input to be minimized (a similar approach is taken by Chen and Delmas (2011), Cropper and Oates (1992), Hailu and Veeman (2001), Korhonen and Luptacik (2004), Kumar Mandal and Madheswaran (2010), and Zhang et al. (2008)). By doing so, a measure of 'carbon efficiency' is obtained that reflects the extent to which the firm minimizes carbon emissions alongside traditional factor inputs (capital, labor, and energy) as much as possible by the same proportion  $\theta$ , for given levels of good output. Appendix A.2 provides a mathematical formulation of the associated linear program. This second approach provides an intuitive manner to model firms' objective to minimize carbon emissions (Dyckhoff and Allen, 2001; Hailu and Veeman, 2001).<sup>18</sup> Also, from an ecological perspective, firms' emissions reflect

<sup>17</sup> We confirm these findings for our analysis when we re-estimate Eq. (1), replacing carbon efficiency with carbon intensity or sector-adjusted carbon intensity (results are available upon request).

<sup>18</sup> Note that in this approach DEA is effectively used as a multiple-criteria

their required amount of carbon usage, which essentially signifies the input of the atmosphere's capacity to absorb emissions (Färe et al., 2007). In Table B.4, we find that our results are very similar across the main alternative DEA models.

### 6.3.5. High-emitting industries and regional results

Naturally, emission-reduction performance is a more salient issue in high-emitting industries. In these industries, substantial stakeholder pressures exist and low-carbon production will have more immediate competitive benefits. For instance, in the power sector, a focal firm's sales are directly determined by the generation portfolio of competitors due to the merit order effect. We, therefore, expect carbon efficiency to have a more pronounced positive impact on financial performance in high-emitting industries.

Secondly, our main analysis evaluated an international reference set, whereas regional factors might affect both production activity and financial performance effects of carbon efficiency.

Therefore, we re-estimate Eq. (1) for the subsample of high-emitting industries and re-estimate efficiency scores for the subsamples of EU-firms and US-firms. We find more pronounced effects on systematic risk in high-emitting industries (Table B.5, Panel A). As hypothesized, high carbon efficiency thus seems particularly valuable in environmentally sensitive industries for mitigating financial risk, such as the risk of intensified carbon regulation. In Table B.5, Panel B, we do not find evidence to suggest that effects are particularly strong in the EU subsample. In fact, we find somewhat stronger effects in the US compared to the EU. A possible explanation for this finding is the low discriminatory power of the DEA model, resulting from small subsamples: the US subsample includes 316 firms, implying an average group size of 9, and resulting in 45% of firms being classified as fully efficient; for the EU, this is 498, 15, and 33% respectively. Another explanation is the reduced statistical power of the regression model.

### 6.3.6. Confounding factors

We employ two strategies to address potential confounding in our main regression specification (Eq. (1)). First, we saturate Eq. (1) with additional control variables to ensure carbon efficiency effects do not merely reflect effects from generic environmental performance, sensitivity to energy prices, capital intensity, R&D intensity, and other potential confounding factors shown in Tables B.6 and B.7; these are in line with the related literature (Chava, 2014; El Ghouli et al., 2011; Lioui and Sharma, 2012).<sup>19</sup> Second, on top of the extensive set of additional control variables, we control for time-invariant unobserved heterogeneity that might drive our main results using a firm fixed effects estimator, which focuses on within-firm changes over time (Gormley and Matsa, 2014).<sup>20</sup> In Tables B.6 and B.7, we find coefficients to be consistent with our main results, although not all results remain statistically significant due to reduced statistical power.

### 6.3.7. Selection bias

Firms' decisions to disclose carbon emission data, and therefore to have a carbon efficiency score, is unlikely to be random. For instance, disclosure might correlate with sustainability policies and might be

driven by strategic financial motives. To control for the sample selection bias potentially resulting from this, we use the two-step Heckman (1979) selection procedure. In the first step, we estimate the selection hazard (disclosure of carbon emission data) using a probit model; the variables determining selection are those included Eq. (1) but augmented with two variables that help identify disclosure of carbon emission data, namely the Thomson Reuters' Asset4 overall environmental sustainability rating (*ENVSCORE*) and the number of ICB Sector peer firms that disclose Scope 1 carbon emission data in year  $t$  (*peer disclosure*). Disclosure by peer firms relates to a focal firm's disclosure decision through peer effects (Cao et al., 2019; Cheng et al., 2014) but is theoretically unlikely to influence financial performance outcomes. Our results are similar when omitting both exclusion restrictions from the first-stage probit estimation. In the second step, we estimate Eq. (2) including the selection hazard (Inverse Mills ratio), which controls for selection bias.

We use the Asset4 ESG database of over 7900 firms to construct a comprehensive group of non-disclosers, leading to a sample of disclosers (26.3%) and non-disclosers (73.7%). In Table B.8, the significant Inverse Mills ratio indicates that (unobserved) factors that make carbon emission disclosure more likely tend to be associated with significantly lower ROA and Tobin's Q, and higher total risk. Selection bias-corrected estimates (Table B.8) suggest that selection is of minor concern as it even slightly weakened our baseline results.

## 7. Conclusion and discussion

We employ a productive efficiency perspective to evaluate firms' carbon emission levels relative to those of best-practice (efficient) peers with comparable production activities. Specifically, based on a directional distance function (DDF) model, we construct a measure of *carbon efficiency* that reflects the percentage by which carbon emissions can be reduced in a given input-good output structure. By accounting for total factor productivity and sector-relative performance aspects, the measure helps to quantify and rank firms' relative dependence on carbon in the production process. In addition, within our efficiency framework, a direct link can be made between carbon emissions and productive or resource efficiency.

We examine how carbon efficiency relates to various financial performance outcomes, namely short-term operating performance, long-term market valuation, systematic risk, and total risk. Using an international sample of 1572 firms over the years 2009–2017, we find superior financial performance in carbon-efficient (best-practice) firms. On average, a 0.1 higher carbon efficiency is associated with a 1.0% higher profitability and 0.6% lower systematic risk.

These findings suggest that carbon-efficient production may have operational efficiency benefits and (relatedly) serve to reduce the risk of uncertain carbon pricing regulation (Lins et al., 2017; Porter and van der Linde, 1995; Sharfman and Fernando, 2008). Further analysis indeed reveals that carbon efficiency, for a large part, coincides with resource efficiency, consistent with the idea that abundant levels of carbon emissions reflect operational inefficiencies. Yet, despite this interrelationship, we find that carbon efficiency has financial performance impacts that cannot be attributed to general resource efficiency, particularly on systematic risk: for every 0.1 rise in carbon efficiency, systematic risk drops by on average 0.4%. These results, which survive an extensive series of robustness analyses, suggest a combined environmental and financial relevance of carbon efficiency.

Our analysis contributes to the literature relating environmental and financial performance, which has thus far yielded mixed evidence and is based on generic ratings of corporate environmental sustainability (Busch and Lewandowski, 2018; Chava, 2014; Horváthová, 2010; Margolis et al., 2009; Sharfman and Fernando, 2008). By concentrating on corporate actions (impact) rather than words (disclosed policies), our analysis contributes to a solid microeconomic understanding of how corporate emission-reduction performance affects

(footnote continued)

decision-making problem in which DMUs are alternatives and performance is evaluated based on a set of criteria to be maximized or minimized, representing preferences for economic goods and economic bads (Cook et al., 2014; Dyckhoff, 2018).

<sup>19</sup> We do not include R&D intensity in our main regression (Eq. (1)), as it reduces our sample by approximately 50%.

<sup>20</sup> Given the persistence of the dependent variable in Eq. (1) and the small time dimension of the dataset ( $T = 6$  years, on average), it is less useful to employ a firm fixed-effects estimator that discards valuable between-firm variation and potentially amplifies noise from measurement error (Gormley and Matsa, 2014).

market behavior. Bénabou and Tirole (2010) theorize that the social objectives firms pursue might reflect altruistic, strategic, or green-washing behavior. By investigating the firm's production- and sector-relative carbon emissions, and relating carbon efficiency to resource efficiency, our analysis underscores the strategic value of low-emitting production.

Our results have several practical implications for strategic management, investment, and policy. Both from an academic and practitioner perspective, there is strong demand for indicators of the dependence on carbon emissions in production at the firm level (Chen, 2014; Eccles et al., 2011). We feel our carbon efficiency measure is highly suitable for firms and investors to assess emission-reduction performance and to identify assets that optimize economic value relative to carbon emissions (representing social costs) and traditional factor inputs (representing private costs). Our finding that carbon efficiency significantly impacts financial performance helps better understand the growing interest in corporate emission disclosure and reduction, particularly in environmentally sensitive industries (cf. Bénabou and Tirole, 2010). Specifically, our results align with and contribute to a growing literature that documents risk-mitigation effects of low-carbon investment assets (Andersson et al., 2016; Trinks et al., 2020). Furthermore, our analysis may provide policymakers with insights into how existing production depends on carbon sources and in which areas there is most potential for emission reduction. The relatively modest financial performance benefits of carbon efficiency explain the relatively limited uptake of substantial emission-reduction practices; policymakers are informed that markets currently seem to only partly allow for aligning environmental objectives with corporate interests (PDC, 2017; TCFD, 2017). Still, it can be expected that when climate policy intensifies, carbon efficiency will become a more salient indicator.

In all, we establish that carbon efficiency is an important aspect of corporate carbon emission-reduction performance with significant financial performance implications. Our measure of carbon efficiency serves as a straightforward and coherent measure that closely follows the environmental efficiency modeling literature. However, our analysis also has several limitations, which we leave for future research. First, given the substantial heterogeneity in carbon efficiency scores, there might be a need for using more fine-grained reference groups and input-output vectors, but this will crucially depend on the specific purpose of the benchmarking exercise (Cook et al., 2014; Dyckhoff, 2018). Secondly and relatedly, our DEA model could be refined, for instance, by addressing random variation in efficiency estimates using stochastic DEA models (Charnes et al., 2013; Cooper et al., 2007). Finally, while our analysis considers direct carbon emissions as a critical undesirable output factor, additional external effects of production warrant consideration, such as waste and local pollutant emissions. In this respect, a promising feature of the DDF model used in this paper is that it can be readily extended to accommodate multiple sustainability factors with different measurement units.

## Declaration of competing interest

None.

## Acknowledgements

We are thankful for the valuable discussions with Javier Barbero, Skarleth Carrales, Glen Gostlow, Mikael Homanen, Bart Los, Emilie Rosenlund Soysal, Barry Quinn, José Zofio, and participants at the 6th International Symposium on Environment and Energy Finance Issues (ISEFI) in Paris in May 2018, the 41st International Association for Energy Economics (IAEE) international conference in Groningen in June 2018, and the Global Research Alliance for Sustainable Finance and Investment (GRASFI) inaugural conference in Maastricht,

September 2018. We also thank the editor and four anonymous reviewers for their comments and suggestions on earlier versions of the paper. The usual disclaimer applies.

## Appendices. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolecon.2020.106632>.

## References

- Albuquerque, R., Koskinen, Y., Zhang, C., 2019. Corporate social responsibility and firm risk: theory and empirical evidence. *Manag. Sci.* 65 (10), 4451–4949.
- Allevi, E., Basso, A., Bonenti, F., Oggioni, G., Riccardi, R., 2019. Measuring the environmental performance of green SRI funds: a DEA approach. *Energy Econ.* 79, 32–44.
- Álvarez, I., Barbero, J., Zofio, J.L., 2020. A data envelopment analysis toolbox for MATLAB. *J. Stat. Softw.* forthcoming. <https://nl.mathworks.com/matlabcentral/fileexchange/56025-data-envelopment-analysis-toolbox-for-matlab>, Accessed date: 3 January 2020.
- Ambe, S., Lanoie, P., 2008. Does it pay to be green? A systematic overview. *Acad. Manag. Perspect.* 22 (4), 45–62.
- Andersson, M., Bolton, P., Samama, F., 2016. Hedging climate risk. *Financ. Anal. J.* 72 (3), 13–32.
- Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* 30 (9), 1078–1092.
- Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., Visentin, G., 2017. A climate stress-test of the financial system. *Nat. Clim. Chang.* 7 (4), 283–288.
- Becchetti, L., Ciciretti, R., Hasan, I., 2015. Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. *J. Corp. Finan.* 35, 297–309.
- Bénabou, R., Tirole, J., 2010. Individual and corporate social responsibility. *Economica* 72 (305), 1–19.
- Boermans, M.A., Galema, R., 2019. Are pension funds actively decarbonizing their portfolios? *Ecol. Econ.* 161, 50–60.
- Busch, T., Hoffmann, V.H., 2007. Emerging carbon constraints for corporate risk management. *Ecol. Econ.* 62 (3), 518–528.
- Busch, T., Lewandowski, S., 2018. Corporate carbon and financial performance a meta-analysis. *J. Ind. Ecol.* 22 (4), 745–759.
- Cao, J., Liang, H., Zhan, X., 2019. Peer effects of corporate social responsibility. *Manag. Sci.* 65 (12), 5449–5956.
- Chambers, R.G., Chung, Y., Färe, R., 1996. Benefit and distance functions. *J. Econ. Theory* 70 (2), 407–419.
- Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* 2 (6), 429–444.
- Charnes, A., Cooper, W.W., Lewin, A.Y., Seiford, L.M., 2013. *Data Envelopment Analysis: Theory, Methodology, and Applications*. Springer Science & Business Media, New York.
- Chava, S., 2014. Environmental externalities and cost of capital. *Manag. Sci.* 60 (9), 2223–2247.
- Chen, C.M., 2014. Evaluating eco-efficiency with data envelopment analysis: an analytical reexamination. *Ann. Oper. Res.* 214 (1), 49–71.
- Chen, C.M., Delmas, M., 2011. Measuring corporate social performance: an efficiency perspective. *Prod. Oper. Manag.* 20 (6), 789–804.
- Chen, C.M., Delmas, M.A., Lieberman, M.B., 2015. Production frontier methodologies and efficiency as a performance measure in strategic management research. *Strateg. Manag. J.* 36 (1), 19–36.
- Cheng, B., Ioannou, I., Serafeim, G., 2014. Corporate social responsibility and access to finance. *Strateg. Manag. J.* 35 (1), 1–23.
- Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. *J. Environ. Manag.* 51 (3), 229–240.
- Cole, M.A., Elliott, R.J.R., Okubo, T., Zhou, Y., 2013. The carbon dioxide emissions of firms: a spatial analysis. *J. Environ. Econ. Manag.* 65 (2), 290–309.
- Cook, W.D., Tone, K., Zhu, J., 2014. Data envelopment analysis: Prior to choosing a model. *Omega* 44, 1–4.
- Cooper, W.W., Seiford, L.M., Tone, K., 2007. *Data Envelopment Analysis: A Comprehensive Text With Models, Applications, References and DEA Solver Software*, 2nd edition. Springer, New York.
- Cropper, M.L., Oates, W.E., 1992. Environmental economics: a survey. *J. Econ. Lit.* 30 (2), 675–740.
- Dam, L., Scholtens, B., 2015. Toward a theory of responsible investing: on the economic foundations of corporate social responsibility. *Resour. Energy Econ.* 41, 103–121.
- Debreu, G., 1951. The coefficient of resource utilization. *Econometrica* 19, 273–292.
- Derwall, J., Guenster, N., Bauer, R., Koedijk, K., 2005. The eco-efficiency premium puzzle. *Financ. Anal. J.* 61 (2), 51–63.
- Dietz, S., Gollier, C., Kessler, L., 2018. The climate beta. *J. Environ. Econ. Manag.* 87, 258–274.
- Dyck, A., Lins, K.V., Roth, L., Wagner, H.F., 2019. Do institutional investors drive corporate social responsibility? International evidence. *J. Financ. Econ.* 131 (3), 693–714.
- Dyckhoff, H., 2018. Multi-criteria production theory: foundation of non-financial and sustainability performance evaluation. *J. Bus. Econ.* 88 (7–8), 851–882.
- Dyckhoff, H., Allen, K., 2001. Measuring ecological efficiency with data envelopment



- analysis (DEA). *Eur. J. Oper. Res.* 132 (2), 312–325.
- Eccles, R.G., Serafeim, G., Krzus, M.P., 2011. Market interest in nonfinancial information. *J. Appl. Corp. Financ.* 23 (4), 113–127.
- El Ghoul, S., Guedhami, O., Kwok, C.C.Y., Mishra, D.R., 2011. Does corporate social responsibility affect the cost of capital? *J. Bank. Financ.* 35 (9), 2388–2406.
- Elton, E.J., Gruber, M.J., Brown, S.J., Goetzmann, W.N., 2014. *Modern Portfolio Theory and Investment Analysis*. John Wiley & Sons, New York.
- Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *J. Financ. Econ.* 33 (1), 3–56.
- Fama, E.F., French, K.R., 1997. Industry costs of equity. *J. Financ. Econ.* 43 (2), 153–193.
- Fama, E.F., French, K.R., 2006. The value premium and the CAPM. *J. Financ.* 61 (5), 2163–2185.
- Färe, R., Primont, D., 1995. *Multi-output production and duality: Theory and applications*. In: *Multi-Output Production and Duality: Theory and Applications*. Kluwer Academic Publishers, Boston.
- Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *Rev. Econ. Stat.* 71 (1), 90–98.
- Färe, R., Grosskopf, S., Pasurka, C.A., 2007. Environmental production functions and environmental directional distance functions. *Energy* 32 (7), 1055–1066.
- Farrell, M.J., 1957. The measurement of productive efficiency. *J. R. Stat. Soc. Ser. A* 253–281.
- Fisher-Vanden, K., Thorburn, K.S., 2011. Voluntary corporate environmental initiatives and shareholder wealth. *J. Environ. Econ. Manag.* 62 (3), 430–445.
- Gonenc, H., Scholtens, B., 2017. Environmental and financial performance of fossil fuel firms: a closer inspection of their interaction. *Ecol. Econ.* 132, 307–328.
- Gormley, T.A., Matsa, D.A., 2014. Common errors: how to (and not to) control for unobserved heterogeneity. *Rev. Financ. Stud.* 27 (2), 617–661.
- Grey, F., 2018. Corporate lobbying for environmental protection. *J. Environ. Econ. Manag.* 90, 23–40.
- Guenster, N., Bauer, R., Derwall, J., Koedijk, K., 2011. The economic value of corporate eco-efficiency. *Eur. Financ. Manag.* 17 (4), 679–704.
- Hailu, A., Veeman, T.S., 2001. Non-parametric productivity analysis with undesirable outputs: an application to the Canadian pulp and paper industry. *Am. J. Agric. Econ.* 83 (3), 605–616.
- Heckman, J.J., 1979. Sample specification Bias as a selection error. *Econometrica* 47 (1), 153–161.
- Horváthová, E., 2010. Does environmental performance affect financial performance? A meta-analysis. *Ecol. Econ.* 70 (1), 52–59.
- Horváthová, E., 2012. The impact of environmental performance on firm performance: short-term costs and long-term benefits? *Ecol. Econ.* 84, 91–97.
- Intergovernmental Panel on Climate Change (IPCC), 2018. *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*. Geneva, Switzerland. [https://www.ipcc.ch/site/assets/uploads/sites/2/2019/06/SR15\\_Full\\_Report\\_High\\_Res.pdf](https://www.ipcc.ch/site/assets/uploads/sites/2/2019/06/SR15_Full_Report_High_Res.pdf), Accessed date: 20 September 2019.
- Jensen, M.C., Meckling, W.H., 1976. Theory of the firm: managerial behavior, agency costs, and ownership structure. *J. Financ. Econ.* 3 (4), 305–360.
- Kitzmueller, M., Shimshack, J., 2012. Economic perspectives on corporate social responsibility. *J. Econ. Lit.* 50 (1), 51–84.
- Koopmans, T.C., 1951. An analysis of production as an efficient combination of activities. In: Koopmans, T.C. (Ed.), *Activity Analysis of Production and Allocation*. Cowles Commission for Research in Economics, Monograph No. 13. Wiley, New York.
- Korhonen, P.J., Luptacik, M., 2004. Eco-efficiency analysis of power plants: an extension of data envelopment analysis. *Eur. J. Oper. Res.* 154 (2), 437–446.
- KPMG, 2017. *The KPMG Survey of Corporate Responsibility Reporting*. Amstelveen, The Netherlands. <https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2017/10/kpmg-survey-of-corporate-responsibility-reporting-2017.pdf>, Accessed date: 24 January 2018.
- Krüger, P., Sautner, Z., Starks, L.T., 2020. The importance of climate risks for institutional investors. *Rev. Financ. Stud.* 33 (3), 1067–1111.
- Kuosmanen, T., Kortelainen, M., 2005. Measuring eco-efficiency of production with data envelopment analysis. *J. Ind. Ecol.* 9 (4), 59–72.
- Levi, Y., Welch, I., 2017. Best practice for cost-of-capital estimates. *J. Financ. Quant. Anal.* 52 (2), 427–463.
- Liang, H., Renneboog, L., 2017. On the foundations of corporate social responsibility. *J. Financ.* 72 (2), 853–910.
- Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. *J. Financ.* 72 (4), 1785–1824.
- Lioui, A., Sharma, Z., 2012. Environmental corporate social responsibility and financial performance: disentangling direct and indirect effects. *Ecol. Econ.* 78, 100–111.
- Mahlberg, B., Luptacik, M., Sahoo, B.K., 2011. Examining the drivers of total factor productivity change with an illustrative example of 14 EU countries. *Ecol. Econ.* 72, 60–69.
- Mandal, S.K., Madheswaran, S., 2010. Environmental efficiency of the Indian cement industry: an interstate analysis. *Energy Policy* 38 (2), 1108–1118.
- Margolis, J.D., Elfenbein, H.A., Walsh, J.P., 2009. Does it Pay to be Good? A Meta-analysis and Redirection of Research on the Relationship Between Corporate and Social and Financial Performance. Working paper. <http://ssrn.com/abstract=1866371>, Accessed date: 27 September 2019.
- Mullins, J.T., 2018. Motivating emissions cleanup: absolute vs. relative performance standards. *J. Environ. Econ. Manag.* 91, 66–92.
- Oggioni, G., Riccardi, R., Toninelli, R., 2011. Eco-efficiency of the world cement industry: a data envelopment analysis. *Energy Policy* 39 (5), 2842–2854.
- Picazo-Tadeo, A.J., Prior, D., 2009. Environmental externalities and efficiency measurement. *J. Environ. Manag.* 90 (11), 3332–3339.
- Picazo-Tadeo, A.J., Reig-Martínez, E., Hernández-Sancho, F., 2005. Directional distance functions and environmental regulation. *Resour. Energy Econ.* 27 (2), 131–142.
- Picazo-Tadeo, A.J., Beltrán-Estevé, M., Gómez-Limón, J.A., 2012. Assessing eco-efficiency with directional distance functions. *Eur. J. Oper. Res.* 220 (3), 798–809.
- Picazo-Tadeo, A.J., Castillo-Giménez, J., Beltrán-Estevé, M., 2014. An intertemporal approach to measuring environmental performance with directional distance functions: greenhouse gas emissions in the European Union. *Ecol. Econ.* 100, 173–182.
- Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* 9 (4), 97–118.
- Portfolio Decarbonization Coalition (PDC), 2017. *Portfolio investment in a carbon constrained world: the third annual progress report of the portfolio decarbonization coalition*. Geneva, Switzerland. <https://unepfi.org/pdc/wp-content/uploads/PDC-Progress-Update-2017.pdf>, Accessed date: 1 November 2018.
- Reinhard, S., Lovell, C.A.K., Thijssen, G., 1999. Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms. *Am. J. Agric. Econ.* 81 (1), 44–60.
- Sharfman, M.P., Fernando, C.S., 2008. Environmental risk management and the cost of capital. *Strateg. Manag. J.* 29 (6), 569–592.
- Task Force on Climate-related Financial Disclosures (TCFD), 2017. *Recommendations of the Task Force on Climate-Related Financial Disclosures*. Basel, Switzerland. <https://www.fsb-tcfd.org/wp-content/uploads/2017/06/FINAL-2017-TCFD-Report-11052018.pdf>, Accessed date: 20 September 2019.
- Trinks, A., Scholtens, B., Mulder, M., Dam, L., 2018. Fossil fuel divestment and portfolio performance. *Ecol. Econ.* 146, 740–748.
- Trinks, A., Ibikunle, G., Mulder, M., Scholtens, B., 2020. Carbon intensity and the cost of equity capital. Working paper. <https://doi.org/10.2139/ssrn.3035864>, Accessed date: 4 January 2020.
- Wang, Q., Zhou, P., Zhou, D., 2012. Efficiency measurement with carbon dioxide emissions: the case of China. *Appl. Energy* 90 (1), 161–166.
- World Business Council for Sustainable Development (WBCSD), World Resources Institute (WRI), 2004. *Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard*. Geneva, Switzerland and Washington, DC.
- Zhang, B., Bi, J., Fan, Z., Yuan, Z., Ge, J., 2008. Eco-efficiency analysis of industrial system in China: a data envelopment analysis approach. *Ecol. Econ.* 68 (1–2), 306–316.
- Zhang, N., Choi, Y., 2014. A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. *Renew. Sust. Energy. Rev.* 33, 50–59.
- Zhou, H., Yang, Y., Chen, Y., Zhu, J., 2018. Data envelopment analysis application in sustainability: the origins, development and future directions. *Eur. J. Oper. Res.* 264 (1), 1–16.