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Interfaces with Other Disciplines

A dynamic by-production framework for analyzing inefficiency associated with corporate social responsibility

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ABSTRACT

This article integrates corporate social responsibility (CSR) into a dynamic by-production framework and examines the factors associated with CSR performance. The application focuses on panel data of European food and beverage firms over the period 2013-2017. The results show that material input, labour input and undesirable output can be contacted by 11.3%, 12.0% and 10.4% respectively while marketable output can be expanded by 66.35%, socially responsible output by 4.3% and the potential of doing investment by 25.46% of the value of the capital stock. Higher CSR performance was associated with a larger firm size, and a higher R&D intensity. Furthermore, firms in network-oriented systems (Germanic or Latin) tend to have a better corporate social responsibility performance than firms in market oriented systems (Anglo-Saxon).

1. Introduction

The past decades have seen a growing pressure from various stakeholder groups on corporate firms to consider social and environmental consequences of their operations within their decision making. As a response, the business world has quickly embraced the concept of corporate social responsibility (CSR) (Eccles & Krzus, 2010), which encompasses not only aspects such as philanthropy and pollution but also a broad range of social, environmental, and governance metrics (Peloza et al, 2012).

Existing research on the relation between CSR and performance has focused mainly on the strategic and financial implications of engaging in corporate social responsibility. Rodger and George (2017) demonstrate that firms adopting CSR preserve the positive dynamics of "competing" stakeholders, i.e. by improving collaboration between stakeholders such as industry, landowners, and environmentalists, it is feasible to optimize return on profits for companies, to provide royalties to landowners, and to satisfy environmentalists. Baron (2001) and McWilliams and Siegel (2001) hypothesized that firms undertaking CSR activities expect a strategic benefit through a better competitive position. However, CSR is also often criticized for being inconsistent with the corporate goal of value maximization for shareholders. Karnani (2010) found that CSR activities increase costs - for example charitable donations, activities to reduce pollution or initiatives for community improvement - which are not fully matched by the financial benefits for the firm. Other authors such as Moore (2001) and Aupperle et al. (1985) found a negative relationship between CSR and financial performance; Nelling and Webb (2009) on the other hand found no evidence that CSR is related to a firm's financial performance.

Another line of Literature on empirical finance and corporate strategy reports the financial implications of firms for engaging in corporate responsibility. Eccles et al. (2014) claim '…sustainability companies significantly outperform their counterparts in the long term, both in terms of stock market and accounting performance'. Flammer (2015) also argues that 'the adoption of close call CSR proposals leads to positive announcement returns and superior accounting performance, implying that these proposals are value enhancing'. Lin et al (2015) is also another contribution that show a positive association between CSR and financial performance.

Yet another stream of literature on the relation between CSR and performance integrates CSR in a production economics framework. Within this stream of literature, Guillamon-Saorin, et al. (2018) investigated the relation between CSR and technical efficiency for several sectors of the US economy; other studies focused on exploring this relation for specific sectors of the economy such as the semi-conductor industry (Lu, et al., 2013) the telecommunications industry (Wang et al. 2014), the chemical industry (Sun and Stuebs 2013), the creative industry (Hou et al., 2019), and the

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manufacturing industry (Jacobs et al., 2016). When doing so it is important to acknowledge two distinct aspects of employing CSR activities. First, firms employing CSR activities may see a decrease of the production of marketable output or an increase of the use of inputs to produce marketable outputs (Karnani, 2010; Puggioni & Stefanou, 2016; McWilliams and Siegel, 2000; 2001). Hence, CSR activities may imply a shift of productive resources from the production of marketable outputs to socially responsible outputs and to a reduction of undesirable outputs. Second, when modelling CSR activities it is important to define a technology that allows for different relations between inputs and outputs (desirable and undesirable). In particular, Murty et al. (2012) demonstrated that a by-production model can capture substitution and complementarity between desirable inputs and undesirable outputs, whereas a regular distance function can only capture substitution between inputs and undesirable outputs. Puggioni and Stefanou (2016) were the first to integrate CSR in a by-production framework. However, their by-production model was developed within a static context[1] which ignores adjustment costs associated with investments in quasi fixed inputs. These adjustment costs may come in the form of search costs for new capital, costs of installing new equipment, costs of learning to use new equipment, and are generally assumed to increase with the level of investments. (Oude Lansink, Verstegen, & Van den Hengel, 2001; Silva & Stefanou, 2003, 2007). Worse, static models of production may confound inefficiency with adjustment costs (Silva & Stefanou, 2003, 2007) and, as a result, they will generate misleading estimates of performance (Nick & Wetzel, 2016).

In the light of the aforementioned, the objective of this study was to assess input- and output-specific technical inefficiency of firms undertaking CSR activities within a dynamic by-production framework. The contribution of this study to the existing literature is twofold. First, we develop a dynamic by-production framework for assessing input- and output-specific inefficiency in the presence of CSR. Second, we empirically demonstrate the applicability of the indicator using panel data of the European food and beverage firms. We start from a by-production model that builds on earlier work of Puggioni and Stefanou (2016) and Dakpo and Oude Lansink (2019). Our work differs from Puggioni and Stefanou (2016) by integrating CSR in a dynamic by-production framework, whereas we build on Dakpo and Oude Lansink (2019) by extending the dynamic by-production model to integrate CSR. By doing so, we account for different trade-offs between inputs and outputs (that include CSR variables).

The next section describes the dynamic by-production model of corporate social responsibility and the bootstrap- truncated regression approach. This is followed by the description of the data of European Food and Beverage manufacturing firms. The sections to follow present the results of the dynamic by production model of corporate social responsibility and the bootstrap- truncated regression approach and concluding comments.

2. Methods

In this section, we develop a dynamic by-production model to characterise a production technology that integrates CSR activities. Next, we specify a bootstrap-truncated regression model to examine the factors that explain the variations in input and output-specific inefficiencies.

2.1. Dynamic by-production model of corporate social responsibility

Consider a by-production technology that consists of two sub-technologies: one describing the sub-production of desirable outputs and the other the sub-production of undesirable outputs. The desirable output technology consists of marketable outputs and socially responsible outputs. Specifically, this by-production technology uses inputs $v(t)$ and invests $i(t)$ to produce three types of outputs given $k(t)$: marketable outputs $yd(t)$, socially responsible outputs $yr(t)$, and undesirable outputs$b(t)$. $yd(t)$ are the primary, marketable outputs by which the production process is motivated; $b(t)$ are the undesirable outputs that are unwanted but inevitably generated as by-products of the desirable outputs, and can be potentially detrimental to the firm or society; and $yr(t)$ consists of socially responsible activities implemented by firm managers to reduce the undesirable outputs $b(t)$.

Let $v(t)$, $v \in \mathcal{R}_+^J$, denote a vector of variable inputs at time t; $k(t)$, $k \in \mathcal{R}_+^L$, a vector of quasi-fixed inputs; $i(t)$, $i \in \mathcal{R}_+^L$, a vector of gross investments; $yd(t)$, $yd \in \mathcal{R}_+^Q$, a vector of marketable outputs; $yr(t)$, $yr \in \mathcal{R}_+^E$, a vector of socially responsible outputs; $b(t)$, $b \in \mathcal{R}_+^R$, a vector of undesirable outputs; N, the number of decision-making units; and t, time.

This dynamic by-production technology $\Psi(t)$ can be mathematically represented by the intersection of the desirable-outputs sub-technology $\Psi_g(t)$ and the undesirable-output sub-technology $\Psi_b(t)$:

$$\Psi(t) = \Psi_g(t) \cap \Psi_b(t)$$

where

$$\Psi_g(t) = [(v(t),\ i(t), yd(t), yr(t), b(t)) :\ (v(t),\ i(t)) \text{ can produce } yd(t) \text{ and } yr(t),\ \text{given } k(t)\ ]$$

and

$$\Psi_b(t) = [(v(t),\ i(t), yd(t), yr(t), b(t)) :\ (v(t),\ i(t),\ yr(t)) \text{ can produce } b(t),\ \text{given } k(t)]$$

The set $\Psi_g(t)$ is a convex technology set, representing the desirable-output sub-technology that transforms inputs into marketable outputs and socially responsible output. Properties of $\Psi_g(t)$ is based on (Dakpo and Oude Lansink, 2019; Silva et al., 2015; Silva & Stefanou, 2003)

- g.1 No free lunch and inactivity
- g.2 Input essentiality and attainability
- g.3 Non-emptiness and closedness
- g.4 Boundedness
- g.5 Positive monotonicity in $v(t)$: if $v(t) \in \Psi_g(t)$ and $v'(t) \geq v(t)$ then $v'(t) \in \Psi_g(t)$
- g.6 Negative monotonicity in $i(t)$: if $i(t) \in \Psi_g(t)$ and $i'(t) \leq i(t)$ then $i'(t) \in \Psi_g(t)$
- g.7 Free disposability of marketable output: if $yd(t) \in \Psi_g(t)$ and $yd'(t) \leq yd(t)$ then $yd'(t) \in \Psi_g(t)$
- g.8 Free disposability of socially responsible output: if $yr(t) \in \Psi_g(t)$ and $yr'(t) \leq yr(t)$ then $yr'(t) \in \Psi_g(t)$

[1] Going back to production theory fundamentals, several representations of the production technology are defined and characterized in the static theory of production (Shephard, 1970; Färe and Primont, 1995; Chambers and Färe, 2008; Ball et al., 2002; Färe et al., 2005). The static theory of production is criticized as it does not account for adjustment costs associated with changes in the level of the quasi-fixed factors. In contrast, dynamic theory of production accounts for adjustment cost associated with changes in levels of quasi-fixed factors, which are the source of the time interdependence of the firm's production decisions. Including investment (change in the level of the quasi-fixed factors) in the production technology implies maximum output levels depend not only on variable and quasi-fixed factors but also depends on the magnitude of the change in the dynamic factors (investment). Recently, several representations of the adjustment-cost production technology have emerged in the literature. Silva et al (2015) built on earlier work of Silva and Stefanou (2003) to define a directional input distance function to represent an adjustment-cost production technology. Kapelko et al (2017) addresses adjustment costs and developed a measurement of input-specific dynamic productivity change. Dakpo and Oude Lansink (2019) show that an adjustment-cost production technology can be represented when modelling pollution-adjusted inefficiency under the by-production of bad outputs.

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g.9 Reverse nestedness in $k(t)$: if $k(t) \in \Psi_g(t)$ and $k'(t) \geq k(t)$ then $k'(t) \in \Psi_g(t)$

g.10 Convexity in $(v(t),\ i(t), yd(t), yr(t))$

In particular, Property g.6 indicates the presence of adjustment costs. It states that $\Psi_g(t)$ is negatively monotonic in i, implying positive costs associated with investment in quasi-fixed inputs. Property g.8 indicates the opportunity cost of producing socially responsible output in terms of marketable outputs. Property g.9 establishes that outputs are increasing in quasi-fixed inputs, indicating that the marginal products of quasi-fixed inputs are positive. Properties g.6 and g.9 together show the trade-off between current and future production. Current additions to quasi-fixed inputs reduce the current output level but improve the prospective level by improving future capital.

Given these properties and assuming a piecewise linear technology under variable returns to scale (VRS),[2] the desirable-outputs sub-technology is defined as:

$$\Psi_g(t) = [(v(t),\ i(t), k(t), yd(t), yr(t), b(t)) :$$

$$yd_o(t) \leq \sum_{n=1}^{N} \mu_n^g yd_n(t), \tag{1.1}$$

$$yr_o(t) \leq \sum_{n=1}^{N} \mu_n^g yr_n(t), \tag{1.2}$$

$$v_o(t) \geq \sum_{n=1}^{N} \mu_n^g v_n(t), \tag{1.3}$$

$$i_o(t) - \delta k_o(t) \leq \sum_{n=1}^{N} \mu_n^g (i_n(t) - \delta k_n(t)), \tag{1.4}$$

$$\sum_{n=1}^{N} \mu_n^g = 1, \forall n \tag{1.5}$$

$$(v(t),\ i(t), k(t), yd(t), yr(t), b(t)) \in \mathcal{R}_+^{J+L+L+Q+E+R}]$$

where δ is the depreciation rate vector associated with the quasi-fixed inputs k; in this way, $i_o(t) - \delta k_o(t)$ represents the net investments.

The undesirable-output sub-technology $\Psi_b(t)$ is convex and satisfies the following properties (Dakpo and Oude Lansink, 2019). The properties are opposite to those of the desirable-output sub-technology

b.1 Positive monotonicity in $b(t)$: if $b(t) \in \Psi_b(t)$ and $b'(t) \geq b(t)$ then $b'(t) \in \Psi_b(t)$

b.2 Positive monotonicity in $yr(t)$: if $yr(t) \in \Psi_b(t)$ and $yr'(t) \geq yr(t)$ then $yr'(t) \in \Psi_b(t)$

b.3 Negative monotonicity in $v(t)$: if $v(t) \in \Psi_b(t)$ and $v'(t) \leq v(t)$ then $v'(t) \in \Psi_b(t)$

b.4 Positive monotonicity in $i(t)$: if $i(t) \in \Psi_b(t)$ and $i'(t) \geq i(t)$ then $i'(t) \in \Psi_b(t)$

b.5 Negative monotonicity in $k(t)$: if $k(t) \in \Psi_b(t)$ and $k'(t) \leq k(t)$ then $k'(t) \in \Psi_b(t)$

b.6 Convexity in $(v(t),\ i(t), b(t), yr(t))$

The properties specific to the undesirable-output sub-technology are the costly disposability of undesirable and socially responsible outputs. Properties b.1 and b.2 suggest that undesirable outputs $b(t)$ are by-products of the production process and the disposability is costly. The property of positive monotonicity in socially responsible outputs (property b.2) implies that socially responsible activities can mitigate undesirable output (Puggioni & Stefanou, 2016). This property indicates negative trade-offs between the undesirable outputs $b(t)$ and the socially responsible outputs $yr(t)$ since socially responsible activities can reduce undesirable outputs. Putting it differently, the socially responsible output is linked to undesirable output in the undesirable sub technology and it has a property of positive monotonicity with socially responsible outputs. This implies that socially responsible activities (i.e. socially responsible outputs) can mitigate undesirable output and socially responsible output is treated as 'purification possibility' (pollution control). This property in the technology can capture the trade-offs between these outputs and in turn helps to provide a more accurate representation of the production process. The property of negative monotonicity in variable inputs for the undesirable sub technology (property b.3) implies that the use of more inputs is associated with more undesirable outputs(social and environmental risks). The property of positive monotonicity in investments (property b.4) suggests that investments in quasi-fixed inputs can mitigate undesirable outputs. This assumption is reasonable when new investments lead to more cleaner technologies that produce less undesirable outputs.

Given these properties and assuming a piecewise linear technology with variable returns to scale (VRS), the undesirable-output sub-technology is defined as:

$$\Psi_b(t) = [(v(t),\ i(t), k(t), f(t),\ yd(t), yr(t),\ b(t)) :$$

$$b_o(t) \geq \sum_{n=1}^{N} \mu_n^b b_n(t), \tag{2.1}$$

$$yr_o(t) \geq \sum_{n=1}^{N} \mu_n^b yr_n(t), \tag{2.2}$$

$$v_o(t) \leq \sum_{n=1}^{N} \mu_n^b v_n(t), \tag{2.3}$$

$$i_o(t) - \delta k_o(t) \geq \sum_{n=1}^{N} \mu_n^b (i_n(t) - \delta k_n(t)),\ . \tag{2.4}$$

$$\sum_{n=1}^{N} \mu_n^b = 1,\ \ \forall n, \tag{2.5}$$

$$(v(t),\ i(t), k(t), yd(t), yr(t), b(t)) \in \mathcal{R}_+^{J+L+L+Q+E+R}]$$

The estimation of the two independent sub-technologies assumed that 'the production of the undesirable output does not have any direct effect on the production of the desirable output'(Puggioni and Stefanou (2016) and Murty et al (2012)). However, Dakpo *et al.* (2016) criticized the independence between the two sub-technologies and introduced dependence constraints for modelling interconnected sub-processes. Dakpo et al (2016) have further extended the initial by-production model of Murty et al (2012) by introducing interdependance between the desirable-output sub-technology and the undesirable-output sub-technology. Interdependence between the two sub-technologies is introduced through constraints 3.1 and 3.2 by setting equal values of the common variables (i.e. variable inputs, investments and socially responsible outputs) involved in the sub-technologies (Dakpo and

[2] We adopt the variable-returns-to-scale (VRS) assumption because it is more realistic and conceptually more flexible than the constant-returns-to-scale (CRS) assumption. The CRS technology is appropriate when firms operate in a perfectly competitive market, while the VRS technology is appropriate when firms face government regulations and imperfect competition (Huguenin, 2012). In addition, the VRS technology allows a firm to be compared to peers firms on the frontier having a similar size. This comparison can evaluate feasible efficiency improvements in the short-term and generate implications that are more practical. Therefore, we decide to adopt the VRS assumption for our analysis.

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Oude Lansink, 2019).

$$\sum_{n=1}^{N}\mu_n^g v_n(t)=\sum_{n=1}^{N}\mu_n^b v_n(t), \tag{3.1}$$

$$\sum_{n=1}^{N}\mu_n^g (i_n(t)-\delta k_n(t))=\sum_{n=1}^{N}\mu_n^b (i_n(t)-\delta k_n(t)), \tag{3.2}$$

$$\sum_{n=1}^{N}\mu_n^g yr_n(t)=\sum_{n=1}^{N}\mu_n^b yr_n(t), \tag{3.3}$$

The dynamic by-production approach in this article uses the directional distance function proposed in Chambers et al. (1998). The directional distance function has previously been used to characterize production process and measure technical inefficiency (Berre et al., 2013; Chung et al., 1997; Hampf & Krüger, 2014; Njuki & Bravo-Ureta, 2015; Puggioni & Stefanou, 2016). It is a generalization of Farrell's and Shephard's proportional approaches with the flexibility of several direction possibilities. However, the results are sensitive to the choice of the directional vector (Vardanyan & Noh, 2006). In this article, we use a general formulation of the non-radial form of directional distance function (Zhang & Choi, 2014), for which the dynamic version and the overall technology $\Psi(t)$ that combines $\Psi_g(t)$ and $\Psi_b(t)$ is represented by:

$$\vec{D}_t^{dyn}\left(v(t),i(t),k(t),yd(t),yr(t),b(t);\vec{g}_{yd},\vec{g}_{yr},\vec{g}_b,\vec{g}_v,\vec{g}_i\right)$$
$$=\max_{\beta,\mu^g,\mu^b}\frac{1}{N_{\vec{g}}}[\beta_{yd}+\beta_{yr}+\beta_b+\beta_v+\beta_i]$$

$$s.t.\ yd_o(t)+\beta_{yd}\vec{g}_{yd}\le\sum_{n=1}^{N}\mu_n^g yd_n(t), \tag{4.1}$$

$$yr_o(t)+\beta_{yr}\vec{g}_{yr}\le\sum_{n=1}^{N}\mu_n^g yr_n(t), \tag{4.2}$$

$$v_o(t)-\beta_v\vec{g}_v\ge\sum_{n=1}^{N}\mu_n^g v_n(t), \tag{4.3}$$

$$i_o(t)-\delta k_o(t)+\beta_i\vec{g}_i\le\sum_{n=1}^{N}\mu_n^g (i_n(t)-\delta k_n(t)), \tag{4.4}$$

$$b_o(t)-\beta_b\vec{g}_b\ge\sum_{n=1}^{N}\mu_n^b b_n(t), \tag{4.5}$$

$$yr_o(t)+\beta_{yr}\vec{g}_{yr}\ge\sum_{n=1}^{N}\mu_n^b yr_n(t), \tag{4.6}$$

$$v_o(t)-\beta_v\vec{g}_v\le\sum_{n=1}^{N}\mu_n^b v_n(t), \tag{4.7}$$

$$i_o(t)-\delta k_o(t)+\beta_i\vec{g}_i\ge\sum_{n=1}^{N}\mu_n^b (i_n(t)-\delta k_n(t)), \tag{4.8}$$

$$\sum_{n=1}^{N}\mu_n^g v_n(t)=\sum_{n=1}^{N}\mu_n^b v_n(t), \tag{4.9}$$

$$\sum_{n=1}^{N}\mu_n^g (i_n(t)-\delta k_n(t))=\sum_{n=1}^{N}\mu_n^b (i_n(t)-\delta k_n(t)), \tag{4.10}$$

$$\sum_{n=1}^{N}\mu_n^g yr_n(t)=\sum_{n=1}^{N}\mu_n^b yr_n(t),. \tag{4.11}$$

$$\sum_{n=1}^{N}\mu_n^g=1, \tag{4.12}$$

$$\sum_{n=1}^{N}\mu_n^b=1, \tag{4.13}$$

where $N_{\vec{g}}$ is the number of variables in the objective function. We assign the same weight to each inefficiency score to show an equal emphasis on both the contraction of inputs and expansion of outputs and investments. For the generalization of the non-radial approach, each of the β technical inefficiency can be individualized with different corresponding variables of $(\beta_{ydq},\beta_{yre},\ \beta_{br},\ \beta_{vj},\ \beta_{il})$.

Solution to the problem in (4) yields estimates of dynamic technical inefficiency that quantify how much marketable outputs, socially responsible outputs, and investments can be expanded and how much undesirable outputs and inputs can be contracted within the feasibility constraint imposed by the technology $\Psi(t)$.

The dynamic inefficiency estimates can be compared to those of a static inefficiency model. In the static model ($\vec{D}_t^{static}$), quasi-fixed inputs are assumed to adjust instantaneously like variable inputs. Hence, the objective function of the directional distance function also includes β_k, the inefficiency associated with the quasi-fixed inputs k. Furthermore, the static directional distance function has no constraints on investments. In other words, the static model has similar formulations as the dynamic version but excludes the constraints in (4.4), (4.8) and (4.10). The objective function and constraints associated with quasi-fixed inputs k for the static version are represented as:

$$\vec{D}_t^{static}\left(v(t),i(t),k(t),yd(t),yr(t),b(t);\vec{g}_{yd},\vec{g}_{yr},\vec{g}_b,\vec{g}_v,\vec{g}_k\right)$$
$$=\max_{\beta,\mu^g,\mu^b}\frac{1}{N_{\vec{g}}}[\beta_{yd}+\beta_{yr}+\beta_b+\beta_v+\beta_k]$$

$$k_o(t)-\beta_k\vec{g}_k\ge\sum_{n=1}^{N}\mu_n^g k_n(t) \tag{5.1}$$

$$k_o(t)-\beta_k\vec{g}_k\le\sum_{n=1}^{N}\mu_n^b k_n(t) \tag{5.2}$$

$$\sum_{n=1}^{N}\mu_n^g k_n(t)=\sum_{n=1}^{N}\mu_n^b k_n(t) \tag{5.3}$$

2.2. Bootstrap-truncated regression

The dynamic by-production described in the previous section characterizes the production process and can generate estimates of dynamic technical inefficiency specific to each type of inputs and output including social responsible outputs (i.e. CSR). For a companion question, researchers have searched for the sources of heterogeneity in firm performance, especially performance related to CSR, using observed traits of firms. Margolis et al. (2009) performed a meta-analysis and found that industry category, firm size, and risk have most frequently been associated to differences in performance, although other variables such as research and development (R&D) intensity, leverage, liquidity, and profitability have also been reported to affect performance (Nelling and Webb (2009). Below we provide a brief review and discussion of how various factors may affect firms' performance.

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2.2.1. Firm Size

The firm size, which is often measured by the value of firms' assets, can improve firms' competitive advantage through economies of scale, economies of scope, or learning effects (Penrose, 1995). On the other hand, Robinson (1962) identified three scenarios for an inverse relation between efficiency and firm size to occur: (1) costs caused by boredom and diminished creativity outweighing the gains from labour division; (2) reduced speed and flexibility; and (3) increased costs of coordination. As a result, the empirical evidence has been mixed. For example, Khataza et al. (2019) and Majumdar (1997) found a negative relation between size and productivity, while Kapelko and Oude Lansink (2014) and Zelenyuk and Zheka (2006) found a positive relation. Regarding CSR performance, larger firms are more likely to show sustainable behavior since they are politically more accountable for the pressure from different stakeholders (Artiach et al., 2010; Surroca & Tribó, 2008; Surroca, Tribó, & Waddock, 2010).

2.2.2. Leverage

The ratio of total debt to total assets, i.e. leverage, measures the relative importance of financial stakeholders such as shareholders and debtholders. Debtholders, as suppliers of capital to firms, can exert substantial influences, and hence company managers are more likely respond to debtholders' interest than those of other stakeholders (Hossain et al., 2005; Ullmann, 1985). In contrast, firms with a higher level of engagement in CSR may have more incentive to mitigate the agency conflicts between shareholders and bondholders and lower agency costs of debt financing due to the improved shareholder-stakeholder relationships (Webb, 2005). The lower costs of debt financing may thus increase the leverage in the optimal capital structure.

2.2.3. Free cash flow

This variable reflects liquidity and firms' financial slack to continue their operations in the short term. When firms face low liquidity and profitability, financial stakeholders will have a higher priority compared to other stakeholders such as employees or the community (Artiach et al., 2010; Ullmann, 1985). On the other hand, a large free cash flow may allow firms to engage in social programs without compromising the demands of financial stakeholders.

2.2.4. Profitability

The level of profitability, measured by return on asset (ROA) in this study, influences investment decisions on CSR like free cash flows (Artiach et al., 2010). In periods of better economic performance, firms face low pressure from financial stakeholders. High levels of profitability may help meet shareholders' expectations and maintain the ability to attain social stakeholders' demands through investments in programs with social merits.

2.2.5. Innovation and product differentiation

R&D investments can possibly lead to process and product innovations that may help address societal concerns (Alene, 2010). For instance, an organic, pesticide-free label clearly implies the use of organic methods, which constitutes a process innovation by farmers, and the creation of a new product category, which is a product innovation by natural foods retailers. We measure research and innovation by the ratio of R&D expenditure to total revenue.

2.2.6. Corporate governance system

Corporate governance influences corporate decisions and behavior (Aguilera et al., 2008; Sánchez-Ballesta & García-Meca, 2007). Empirical results show that different corporate governance systems lead to different sustainable practices. According to Weimer and Pape (1999), the prevailing corporate governance systems in industrialized countries include the "market-oriented" system in Anglo-Saxon countries (e.g. USA and UK) and the "network-oriented" system (e.g. Germany and the Netherlands). The network-oriented system can be further divided into the Germanic model (e.g. Germany and the Netherlands), the Latin model (e.g. France and Italy), and the Japanese model. The chief feature of the market-oriented system is that the active external market may command and control managerial decision-making in an indirect mode (Fisher & Lovell, 2009). In comparison, oligarchic groups in the network-oriented system significantly affect managerial decision-making in a more direct manner and can orient companies towards a more sustainable and socially responsible pathway (Fisher & Lovell, 2009). A market-oriented system depends on the market while the network-oriented system relies on relationships among stakeholders.

For the first stage, we estimate inefficiencies using a dynamic by-production model. At the second stage, we use regression analysis to investigate the marginal effects of the above independent variables. The dependent variables, i.e. estimates of technical efficiencies, are serially correlated (Leopold Simar & Wilson, 2007). Furthermore, the underlying data generating process of inefficiency are truncated. Leopold Simar and Wilson (2007) thus proposed a bootstrap-truncated regression approach to solve both issues simultaneously. It is important to note that the bootstrap model at the second stage does not necessarily indicate causality but only association between variables. In addition, the two-stage analysis assumes the separability between efficiency estimates and the second stage variables. In other words, the separability assumption requires the second stage variables to be separable from the variables in the production technology (Daraio et al., 2018; Leopold Simar & Wilson, 2007).

3. Data description

The empirical analysis focused on panel data of European food and beverage firms over the period 2013-2016. A focus on the food and beverage industry is warranted since it is linked to several societal concerns, such as food safety, labour rights, and animal welfare (Hartmann, 2011; Heyder & Theuvsen, 2012). Given these concerns, there is high pressure and rising public scrutiny on the leading food companies regarding their CSR initiatives in environmental issues (e.g. Program on Green Procurement) as well as social issues (e.g. Policy on the Elimination of Discrimination). The EU food manufacturing sector has also been characterized by the implementation of the General Food Law (Regulation (EC) No 178/2002), the EU regulation regarding food safety (Commission, 2002). The dataset consists of 195 firm-year observations with an average of 49 observations per year. The sample period is limited to four years as we were only able to obtain complete data for that period. Access to more complete data on a large number of firms is one of the challenge for more applied research on CSR. In the current study, the pooled sample of the 192 observations is used assuming there is no technological changes within such a short time span and all changes in technology are attributed to changes in technical efficiency.

Data on CSR were obtained from Sustainalytics, a company assesses management systems, practices, policies and other indicators reflecting the environmental, social and governance (ESG) performance of firms. The data set provided by Sustainalytics consists of detailed indicators on favorable/positive and controversial/negative aspects of ESG. Data from Sustainalytics are suitable for the analysis in this paper because it consists of detailed scores for different CSR indicators (60–80 Metrics compared to 37 Metrics of MSCI, for example). This helps to obtain data on socially responsible output and socially undesirable output for the empirical

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Table 1
Input and output variables.

Variable	Description	Indicator	Source
yd	Marketable output	Sales	Orbis
yr	Socially responsible output	Policy on Bribery and Corruption	Sustainalytics
		Signatory to UN Global Compact	
		Board independence	
		Policy on Freedom of Association	
		Formal Policy on the Elimination of Discrimination	
		Programs to Increase Workforce Diversity	
		Formal environmental policy	
		Environmental management system	
		Formal Policy or Program on Green Procurement	
		Programs and Targets to Stimulate Sustainable Agriculture	
		Programs & Targets to Reduce Water Use	
		Scope of Social Supply Chain Standards	
b	Undesirable output	Business-Ethics-Related Controversies or Incidents	Sustainalytics
		Governance-Related Controversies or Incidents	
		Public-Policy-Related Controversies or Incidents	
		Employee-Related Controversies or Incidents	
		Social supply chain incidents	
		Customer-Related Controversies or Incidents	
		Society-&-Community-Related Controversies or Incidents	
		Operations-Related Controversies or Incidents	
		Environmental supply chain incidents	
		Products-&-Services-Related Controversies or Incidents	
v_1	Material	Material cost	Orbis
v_2	Labour	Employee cost	Orbis
k	Quasi fixed input	Fixed asset	Orbis
i	Investment	Cash flow from investing activities	Orbis

illustration of the framework developed in this paper. The detailed nature of the database is particularly useful when identifying measures of mitigating CSR outputs (scores for the positive indicators) and measures of undesirable outputs (scores for the negative indicators). Composite measures for socially responsible outputs yr and undesirable outputs b are constructed based on the favorable (positive) indicators and the controversial (negative) indicators using a method that combines principal component analysis (PCA) and data envelopment analysis (DEA), illustrated in Engida et al. (2018). The method first applies PCA to reduce the number of indicators and to construct a few uncorrelated synthesized components for each respective output. Next, DEA is used to construct composite measures for socially responsible and undesirable output using the synthesized components. Table 1 provides further details on the ESG indicators.

Data on conventional desirable, marketable output and conventional inputs were taken from the ORBIS dataset maintained by Bureau van Dijk using the information included in companies' annual financial reports. Following the existing literature on modelling the European food industry (e.g. Kapelko et al, 2015(a,b); Kapelko and Oude Lansink et al, 2017), we distinguished one marketable output, two variable inputs and one quasi-fixed input. Sales (in US dollars) were used as a measure of the marketable output(yd) and were deflated using the industrial price index for outputs. The two variable inputs were material input, which was measured as the costs of materials consumed, and labour input, which was measured as the costs of employees. Material input and labour inputs were deflated using the industrial price index for consumer non-durables and labour cost index in manufacturing, respectively. The quasi-fixed input includes fixed assets and is deflated by the industrial price index for capital goods. To allow for adjustment costs, we obtain gross investments in fixed assets. We use the cash flow from investing activities as a measure of gross investment. Table 1 provides further details on the outputs and inputs that were used in the dynamic DEA models.

Before implementing the dynamic by-production model, we applied the super efficiency technique (Banker and Gifford, 1988; Simar, 2003; Banker and Chang, 2006) in order to detect outliers in our dataset. The basic idea of this technique is that in the linear mathematical program used by DEA, each DMU is excluded from its optimization, thus allowing some efficiency scores reach values greater than one. We use a cut of 1.3 to identify the outliers. This cut of level is motivated after looking at the results of Banker and Chang(2006) that 'the procedure improves with an increase in the screen level to 1.2 and deteriorates when the screen level is increased further to 1.6. That is, the use of a more stringent screening level such as 1 is likely to misclassify many uncontaminated efficient observations as outliers, while the use of a less stringent screening level such as 1.6 or greater may fail to remove many contaminated observations.' The results of super efficiency detected eight observations that show super efficiency ratings and these eight observations were excluded from further analysis.

Table 2 reports descriptive statistics of the variables used in the dynamic DEA models. The variation in marketable outputs (sales) and inputs (capital, labour, and material inputs) is high, while undesirable and socially responsible outputs have a less disperse distribution. The investment variable is characterized by a large variance, which reflects the different behaviors of companies in capital acquisition.

The directional vectors in the DEA models were set as the observed values for variable inputs, and as unity for socially responsible output and undesirable output, i.e. $\vec{g}_{yd} = yd_o$, $\vec{g}_{yr} = 1$, $\vec{g}_b = 1$, $\vec{g}_v = v_o$. The directional vectors of socially responsible and undesirable output were set at unity because the observed values for socially responsible output and undesirable output are scores between 0 and 1 and there is low variation in the data set (Table 2). Following Kapelko et al. (2015b) the directional vector for investments was set to 20% of the capital stock, i.e. $\vec{g}_i = 0.2 \times k_o$, because the actual investments can be zero and using the actual value could then preclude a solution of the DEA models.

Data on the explanatory variables in the truncated bootstrap regression model were taken from the Orbis database. In case of missing values, the data were supplemented with information from companies' annual reports that were retrieved from the company's website by the authors. Table 3 presents the descriptive statistics of explanatory variables.

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Table 2
Summary statistics of the pooled sample for the period 2013 to 2016.

Symbol	Description of variable	Unit	Mean	Median	Std. Dev.
yd	Desirable output sales	Mln USD	8.983	2.661	15.908
yr	Socially responsible output (Score)	Score	0.819	0.838	0.120
v1	Material cost	Mln USD	0.698	0.126	1.797
v2	Cost of employee	Mln USD	1.165	0.324	2.335
k	Fixed assets	Mln USD	11.280	1.671	25.817
i	Investments	Mln USD	0.900	0.126	4.621
D2	Depreciation	Mln USD	1.128	0.167	2.582
b	Undesirable output (Score)	Score	0.014	0.001	0.028

Table 3
Descriptive statistics of determinants of technical inefficiency.

Variable	Description	Units	Mean	Median	SD
Size	Natural log of total assets	2013 USD	14.762	14.329	1.658
Leverage	Ratio of total debt divided to total shareholder value	Ratio	0.899	0.694	0.816
FCF	Free cash flow divided by total sales	Ratio	0.116	0.110	0.106
ROA	Earnings Before Interest and Tax (EBIT) divided by total assets	Ratio	0.092	0.083	0.060
R&D Intensity	Ratio of total R&D expenditure to total sales	Ratio	0.010	0.002	0.028
Market-oriented model		Dummy	0.315	0.000	0.466

Table 4
Sample distribution across countries.

	Frequency	Percent
Belgium	4	2.1
Channel Islands	2	1.1
Denmark	10	5.3
France	16	8.6
Germany	8	4.3
Greece	3	1.6
Ireland	13	7.0
Italy	7	3.7
Luxembourg	3	1.6
Netherlands	15	8.0
Norway	14	7.5
Spain	11	5.9
Sweden	12	6.4
Switzerland	19	10.2
Ukraine	4	2.1
United Kingdom	46	24.6

Table 5
Inefficiency estimates: dynamic vs. static production technology.

	Dynamic Technologies	Static Technologies	Li-Test
Marketable output	0.663	0.207	7.06***
Socially responsible output	0.043	0.041	0.015
Material	0.113	0.267	22.626***
Labour	0.120	0.389	18.67***
Capital	-	0.200	
Investment	1.273	-	
Undesirable output	0.104	0.118	1.469

Note: Asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

In order to capture the effect of the country of origin of the company and the country-related factors, we introduced a variable 'corporate governance system'. Corporate governance systems were represented by a dummy variable indicating market-oriented model of Anglo-Saxon countries, whereas the network-oriented (Germanic and Latin) serve as the reference group. Table 3 also summarizes the corporate governance system and shows that 31.5% of the analyzed companies belong to the market-oriented system and 68.5% belongs to the network-oriented system. Table 4 presents the summary of sample distribution across countries and shows the sample comes from a reasonably large number of countries.

4. Results and discussion

In this section, we first present and compare the technical inefficiency estimates of dynamic and static by-production models that integrate CSR, and then discuss the results of bootstrap-truncated regression analysis of the inefficiency associated factors.

4.1. Dynamic inefficiency estimates

Table 5 presents the average technical inefficiencies associated with each input and output assuming either a dynamic or a static technology. It shows that the average inefficiencies are lower under the dynamic framework than under the static framework. For example, material and labour inputs can be decreased by 11.3% and 12.0%, respectively, under the dynamic technologies, while they can be reduced by 26.7% and 38.9% in the static context. Nick and Wetzel (2016) found a similar comparison between static and dynamic input technical inefficiencies. It is intuitive that the dynamic technical inefficiency is lower than the static estimates because the dynamic model accounts for adjustment costs of quasi-fixed inputs; these costs are mistakenly interpreted as inefficiency in the static context. The result also shows that the potential for increasing marketable output is lower with the dynamic approach than with the static approach. Regarding socially responsible and undesirable outputs, the improvement potential is also lower under dynamic technologies. There is high inefficiency associated with investments since companies vary greatly in terms of their investments. If we ignore adjustment costs and estimate inefficiencies using a static instead of dynamic technology, the average inefficiencies specific to material input, labour input, and undesirable output would be overstated by 15.4, 26.9, 0.004 and 0.014 percentage points, respectively. This finding is also consistent with Dakpo, & Oude Lansink (2019) who estimated input and output-specific technical inefficiency scores in the dynamic context and compares them with efficiency measures from the conventional static context.

We further estimated and compared the density distributions of technical efficiency estimates under the two technologies. The non-parametric Simar-Zeleyuk-adapted Li test, or Adapted Li test, (Li, 1996; Léopold Simar & Zelenyuk, 2006) is used to draw statistical inferences. This test uses kernel densities to compare two

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Table 6
Inefficient and efficient firms across input output dimensions.

	Inefficient firms		Efficient firms	
	Count	%	Count	%
Marketable output only	88	47	99	53
Socially responsible output only	64	34	123	66
Material input only	43	23	144	77
Labour input only	80	43	107	57
Investment	131	70	56	30
Undesirable output only	73	39	114	61
All inputs and outputs	149	80	38	20
At least in one input or output	0	0	187	100

unknown distributions (Epure et al., 2011; Li, 1996). The adapted Li test rejects the null hypothesis of equal distributions of inefficiency estimates specific to marketable output, material input and labour input (Table 5). We did not find statistically significant difference between the dynamic and static approaches for the inefficiency specific to socially responsible output and undesirable output. Comparing the density plots of the dynamic and static inefficiency (Appendix A.1) also reveals notable differences between static and dynamic technologies. The results confirm the necessity of accounting for adjustment costs. Therefore, the analysis and discussion in the subsequent sections are based on the inefficiency results from the dynamic production approach. Under the dynamic by-production approach, material input, labour input and undesirable output can be contacted by 11.3%, 12.0% and 10.4% respectively while marketable output can be expanded by 66.3%, socially responsible output by 4.3% and the potential of doing investment by 25.46% (1.273*0.2*100) of the capital stock. Under the static by-production approach, on the other hand, material input, labour input, capital input and undesirable output can be contacted by 26.7%, 38.9%, 20.0% and 11.8% respectively while marketable output and socially responsible output can be expanded by 20.7% and 4.1% respectively.

The dynamic by-production model developed in this article evaluates input-output specific dynamic inefficiency in the presence of CSR. Our results support the view in Oude Lansink et al (2001), Silva & Stefanou (2003), Silva et al (2015) and Oude Lansink et al (2015) that failing to account adjustment costs associated with investments in quasi fixed assets confounds inefficiency with adjustment costs. Our findings confirm the importance of accounting for adjustment costs in quasi-fixed inputs.

Table 6 shows the counts and percentages of inefficient and efficient firms in each input and output dimension under dynamic production technologies. It indicates that the largest source of technical inefficiency is marketable output because 47% of the firms are inefficient in this dimension. The second and third largest sources of inefficiency are labour input and undesirable outputs with 43% and 39% of the firms being inefficient, respectively. With regard to socially responsible outputs, 34% of the firms are inefficient. This result is consistent with the average inefficiency result in Table 5.

The percentage of efficient firms is quite high in the sample of European food and beverages manufacturing firms analyzed here. The result shows that firms are technically efficient in at least one input or output dimension. This finding is consistent with results of Puggioni and Stefanou (2016) who reported a high level of efficiency for their sample of firms. Commenting on the observation of a large number of efficient firms, Puggioni and Stefanou (2016) noted that: "More freedom and more choices available to firms generate a very peculiar technology set that can accommodate for different production 'recipes' and make it easier for firms to be efficient".

Yet another explanation follows from the small variation of undesirable output and socially responsible output while the variation in conventional inputs and marketable output was quite large. This was attributable to the fact that the CSR performance of firms is much more homogeneous- looked as a minimum standards that every firm strives to achieve. The low variability could also stem from the measurement of dimensions of CSR that are assigned with a raw score from 0 to 100. The low variability in the data negatively affects the ability of the by-production model to distinguish efficient from inefficient firms. This can also be observed from the results in Table 6 which indicate that the fraction of efficient firms is quite high for socially desirable output and undesirable output.

4.2. Results of bootstrapped truncated regression

The results of the regression of firm specific factors on dynamic technical inefficiency specific to CSR variables and other inputs & outputs are presented in Table 7. The results on the relationship between factors associated with dynamic specific to CSR variables are summarized as follows. First, lower levels of technical inefficiency specific to socially responsible output are associated with a larger firm size. The coefficient for size is -0.0395 and it indicates that a one-percent increase in size is associated with a 0.0395 decrease in inefficiency specific to socially responsible output. This finding strongly supports the view that a large firm size is associated with high levels of performance in corporate social responsibility. This finding is consistent with that of Artiach et al. (2010) who reported firm size is a crucial factor as society's pressure for CSR initiatives is disproportionately higher for large companies. Second, ROA was negatively related with technical inefficiency specific to undesirable output, in line with prior expectations that at times of high levels of profitability (ROA), firms will have the financial means to devise strategies that mitigate undesirable output. Third, high levels of R&D intensity are associated with better CSR performance (i.e. lower levels of technical inefficiency specific to socially responsible output and undesirable output). R&D helps reduce inefficiency specific to socially responsible and undesirable outputs. This is partly because CSR initiatives motivate R&Ds. R&D is an investment aiming at enhancing knowledge that leads to product and process innovations which can also be

Table 7
Bootstrap-truncated regression estimates on factors associated with inefficiencies specific to outputs and inputs.

	CSR Variables		Conventional output	Inputs	
	Socially responsible output	Undesirable output	Marketable output	Material	Labour
Constant	0.598***	-12.647***	11.588***	0.925*	1.597***
Size	-0.0395***	-0.749***	-0.888***	-0.034	-0.091***
Leverage	0.001	-0.039	1.023**	0.231***	0.05*
FCF	0.008	2.883	-6.149**	.-0.859*	-0.031
ROA	0.207	-14.64***	6.637	-1.115	-0.561
R&D Intensity	-2.215*	17.436**	-39.860***	18.572***	0.336
Market-oriented model	0.124***	1.386**	-3.595***	-0.167	-0.256*

Note: Asterisks ***,**, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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CSR related (McWilliams & Siegel, 2001). For example, R&D activities might improve processes that reduce the amount of energy a firm consumes, with cost reductions and less pollution. The estimated parameter of the dummy variable for a market-oriented (Anglo-Saxon) corporate governance system is positively associated with the inefficiency specific to socially responsible and undesirable outputs at the critical 1% significance levels. This supports the hypothesis that firms in network-oriented systems (Germanic and Latin) tend to be more socially responsible. In the network-oriented systems, networks of relationships between stakeholders influence managerial decision-making such that the firm incorporates sustainability and social responsibility principles into its strategy to satisfy the needs of multiple stakeholders.

The coefficient for size is negative and statistically significant at the 5% level for inefficiencies specific to material and labour inputs. This shows that a larger firm size is related to a lower level of inefficiency specific to marketable output and inputs. Leverage was positively associated with inefficiency specific to material and labour inputs. This result is in line with the argument, as discussed in Mok et al (2007) and Hossain et al (2005), that firms with higher levels of debts are monitored by creditors to service the debts on time and focus more on debtholders' interest than shareholders' interest to invest in improving the production potential. The coefficient of free cashflows (FCF) is negative and statistically significant for the dynamic inefficiency specific to material input. This outcome indicates that an increase in FCF is associated with a decrease in inefficiency specific to material input. R&D and technical inefficiency specific to material input were positively associated. A possible explanation for this finding could be that R&D initiatives divert resources away from investment in direct material inputs. The dummy variable for a market oriented system has a statistically significant and negative association with inefficiency specific to labour input. This result suggests that firms in market oriented governance systems devise better strategies on the use of labour compared to their network oriented counterparts.

5. Conclusion

This article extends the by-production approach to integrate CSR in the production process and account for adjustment costs in quasi fixed assets. The by-production model distinguishes two sub-technologies to allow for more flexibility in the relations between outputs, inputs and CSR activities. The empirical analysis focused on a sample of European food and beverage manufacturing firms over the period 2013-2017. The results show that material input, labour input and undesirable output can be contacted by 12.4%, 12.0% and 10.4% respectively while marketable output can be expanded by 65.5%, socially responsible output by 4.2% and the potential of doing investment by 25.18% of the value of the capital stock. The comparison of the static and the dynamic approach showed that ignoring adjustment costs when benchmarking performance leads to an overestimation of technical inefficiency. The results of the bootstrap-truncated regression model showed that higher CSR performance was associated with a larger firm size, and a higher R&D intensity. Furthermore, firms in network-oriented systems (Germanic or Latin) tend to have a better corporate social responsibility performance than firms in market oriented systems.

This study generated insights that can help to accurately evaluate firm's performance adopting CSR activities. The outcomes of this research could be utilized by advisory firms and regulatory bodies that promote CSR activities among corporate firms. Also stakeholders could utilize these results in their decision making, i.e. investors with a CSR mission could use the outcomes to decide on their investments portfolio's; NGO's could use the results in their communication to society about the firm's performance. The tools developed in this article could be exploited in future research by applying them to other sectors of the economy. Yet another avenue for future research is to extend our work by estimating shadow prices of the inputs and outputs to understand the value of CSR in the dynamic by-production framework. This helps to quantify the value of engaging in CSR activities and prioritize the most valuable CSR activities for the firm. The proposed input-output production framework uses directional distance functions (DDFs) representing a flexible way to evaluate performance(efficiency) of DMUs. Permitting the selection of a direction towards the efficient frontier is often useful in empirical applications. Future research that integrates CSR in the multiple input-output settings could also endogenize the directional vector where data-driven and objective directional vector is used in the estimation as introduced by Färe et al, (2013) and Zofio et al (2013). This permits the heterogeneity of DMUs and their diverse contexts that may influence their input and/or output mixes (Daraio and Simar, 2017.)

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2020.05.022.

References

Aguilera, R. V., Filatotchev, I., Gospel, H., & Jackson, G. (2008). An organizational approach to comparative corporate governance: Costs, contingencies, and complementarities. *Organization science, 19*(3), 475–492.
Alene, A. D. (2010). Productivity growth and the effects of R&D in African agriculture. *Agricultural economics, 41*(3-4), 223–238.
Artiach, T., Lee, D., Nelson, D., & Walker, J. (2010). The determinants of corporate sustainability performance. *Accounting & Finance, 50*(1), 31–51.
Aupperle, K., Carroll, A., & Hartfield, J. (1985). An empirical examination of the relationship between corporate social responsibility and profitability. *Academy of Management Journal, 28*(2), 446–463.
Ball, V. E., Färe, R., Grosskopf, S., Hernandez-Sancho, F., & Nehring, R. (2002). The environmental performance of the U. S. agriculture sector. In V. E Ball, & G. Norton (Eds.), *Agricultural Productivity, Measurement and Sources of Growth*. Kluwer Academic Publishers.
Banker, R. D., & Chang, H. (2006). The super-efficiency procedure for outlier identification, not for ranking efficient units. *European Journal of Operational Research, 175*(2), 1311–1320.
Banker, R. D., & Gifford, J. L. (1988). A relative efficiency model for the evaluation of public health nurse productivity. *Pittsburgh: Carnegie Mellon University*.
Baron, D. P. (2001). Private politics, corporate social responsibility and integrated strategy. *Journal of Economics and Management Strategy, 10*, 7–45.
Berre, D., Boussemart, J.-P., Leleu, H., & Tillard, E. (2013). Economic value of greenhouse gases and nitrogen surpluses: Society vs farmers' valuation. *European Journal of Operational Research, 226*(2), 325–331.
Chambers, R. G., Chung, Y., & Färe, R. (1998). Profit, directional distance functions, and Nerlovian efficiency. *Journal of optimization theory and applications, 98*(2), 351–364.
Chambers, R. G., & Färe, R. (2008). A 'calculus' for data envelopment analysis. *J. Prod. Anal., 30*, 169–175.
Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *Journal of environmental management, 51*(3), 229–240.
Commission, E. (2002). Regulation (EC) No 178/2002 of the European Parliament and of the Council of 28 January 2002 laying down the general principles and requirements of food law, establishing the European Food Safety Authority and laying down procedures in matters of food safety. *Official Journal of the European Communities, 31*(01/02/2002), 1–24.
Dakpo, K. H., Jeanneaux, P., & Latruffe, L. (2016). Modelling pollution-generating technologies in performance benchmarking: Recent developments, limits and future prospects in the nonparametric framework. *European Journal of Operational Research, 2502*, 347–359.
Dakpo, KH, & Lansink, Oude (2019). Dynamic pollution-adjusted inefficiency under the by-production or bad outputs. *European Journal of Operational Research, 276*(1), 202–211.
Daraio, C., & Simar, L. (2017). Efficiency and benchmarking with directional distances. A data driven approach. *Journal of the Operational Research Society, 67*, 928–944.
Daraio, C., Simar, L., & Wilson, P. W. (2018). Central limit theorems for conditional efficiency measures and tests of the 'separability'condition in non-parametric, two-stage models of production. *The Econometrics Journal, 21*(2), 170–191.
Eccles, R. G., & Krzus, M. P. (2010). *One report: Integrated reporting for a sustainable strategy*. John Wiley & Sons.
Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance, *Management Science* (60, pp. 2835–2857).

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Engida, T. G., Rao, X., Berentsen, P. B. M., & Oude Lansink, A. G. J. M. (2018). Measuring corporate sustainability performance– the case of European food and beverage companies. *Journal of Cleaner Production, 195*, 734–743.
Epure, M., Kerstens, K., & Prior, D. (2011). Bank productivity and performance groups: a decomposition approach based upon the Luenberger productivity indicator. *European Journal of Operational Research, 211*(3), 630–641.
Färe, R., & Primont, D. (1995). *Multi-Output Production and Duality: Theory and Applications*. Kluwer Academic Publishers.
Färe, R., Grosskopf, S., & Whittaker, G. (2013). Directional output distance functions: endogenous directions based on exogenous normalization constraints. *Journal of Productivity Analysis, 40*(3), 267–269.
Färe, R., Grosskopf, S., Noh, D.-W., & Weber, W. (2005). Characteristics of a polluting technology: theory and practice. *J. Econom., 126*, 469–492.
Fisher, C., & Lovell, A. (2009). *Business ethics and values: Individual, corporate and international perspectives*. Pearson education.
Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science, 61*, 2549–2568.
Guillamon Saorin, E., Kapelko, M., & Stefanou, S. E. (2018). Corporate social responsibility and operational inefficiency: A dynamic approach. *Sustainability, 10*(7), 2277.
Hampf, B., & Krüger, J. J. (2014). Optimal directions for directional distance functions: An exploration of potential reductions of greenhouse gases. *American Journal of Agricultural Economics, 97*(3), 920–938.
Hartmann, M. (2011). Corporate social responsibility in the food sector. *European Review of Agricultural Economics, 38*(3), 297–324.
Heyder, M., & Theuvsen, L. (2012). Determinants and effects of corporate social responsibility in German agribusiness: A PLS model. *Agribusiness, 28*(4), 400–420.
Hossain, F., Jain, R., & Govindasamy, R. (2005). Financial structure, production, and productivity: evidence from the US food manufacturing industry. *Agricultural economics, 33*, 399–410.
Hou, Ch.-E., Lu, W.-M., & Hung, S.-W. (2019). Does CSR matter? Influence of corporate social responsibility on corporate performance in the creative industry. *Annals of Operations Research, 278*, 255–279.
Huguenin, J.-M. (2012). Data Envelopment Analysis (DEA): a pedagogical guide for decision makers in the public sector.
Kapelko, M., & Oude Lansink, A. O. (2017). Dynamic multi-directional inefficiency analysis of European dairy manufacturing firms. *European Journal of Operational Research, 257*(1), 338–344.
Jacobs, B. W., Kraude, R., & Narayanan, S. (2016). Operational productivity, corporate social performance, financial performance, and risk in manufacturing firms. *Production and Operations Management, 25*(12), 2065–2085.
Kapelko, M., & Oude Lansink, A. (2014). Examining the relation between intangible assets and technical efficiency in the international textile and clothing industry. *The Journal of the Textile Institute, 105*(5), 491–501.
Kapelko, M., Oude Lansink, A., & Stefanou, SE (2017). Input - Specific Dynamic Productivity Change: Measurement and Application to European Dairy Manufacturing Firms. *Journal of agricultural economics, 68*(2), 579–599.
Kapelko, M., Oude Lansink, A., & Stefanou, S. E. (2015a). Analyzing the impact of investment spikes on dynamic productivity growth. *Omega, 54*, 116–124.
Kapelko, M., Oude Lansink, A., & Stefanou, SE (2015b). Effect of food regulation on the Spanish food processing industry: a dynamic productivity analysis. *PloS one, 10*(6), 0128217.
Karnani, A. (2010). The case against corporate social responsibility. *The Wall Street Journal*. August 23 https://www.wsj.com/articles/SB10001424052748703338004575230112664504890 .
Khataza, R. R., Hailu, A., Doole, G. J., Kragt, M. E., & Alene, A. D. (2019). Examining the relationship between farm size and productive efficiency: a Bayesian directional distance function approach. *Agricultural Economics, 50*(2), 237–246.
Li, Q. (1996). Nonparametric testing of closeness between two unknown distribution functions. *Econometric Reviews, 15*(3), 261–274.
Lin, C.-S., Chang, R.-Y., & Dang, V. T. (2015). An Integrated Model to Explain How Corporate Social Responsibility Affects Corporate Financial Performance. *Sustainability, 7*, 8292–8311.
Lu, W.-M., Wang, W.-K., & Lee, H.-L. (2013). The relationship between corporate social responsibility and corporate performance: evidence from the US semiconductor industry. *International Journal of Production Research, 51*(19), 5683–5695.
Majumdar, S. K. (1997). The impact of size and age on firm-level performance: some evidence from India. *Review of industrial organization, 12*(2), 231–241.
Margolis, J. D., Elfenbein, H., & Walsh, J. (2009). Does it pay to be good... and does it matter? A meta-analysis and redirection of research on corporate social and financial performance. In *Harvard University Working paper*.
McWilliams, A., & Siegel, D. (2000). Corporate social responsibility and financial performance: Correlation or misspecification. *Strat. Manag. J., 21*, 603–609.
McWilliams, A., & Siegel, D. (2001). Corporate social responsibility: A theory of the firm perspective. *Academy of management review, 26*(1), 117–127.
Mok, V., Yeung, G., Han, Z., & Li, Z. (2007). Leverage, Technical Efficiency and Profitability: an application of DEA to foreign-invested toy manufacturing firms in China. *Journal of Contemporary China, 16*(51), 259–274.
Moore, G. (2001). Corporate social and financial performance: An investigation in the U.K. supermarket industry. *Journal of Business Ethics, 34*(3/4), 299–315.
Murty, S., Russell, R. R., & Levkoff, S. B. (2012). On modeling pollution-generating technologies. *Journal of environmental economics and management, 64*(1), 117–135.
Nelling, E., & Webb, E. (2009). Corporate social responsibility and financial performance: the "virtuous circle" revisited. *Review of Quantitative Finance and Accounting, 32*(2), 197–209.
Nick, S., & Wetzel, H. (2016). The hidden cost of investment: the impact of adjustment costs on firm performance measurement and regulation. *Journal of Regulatory Economics, 49*(1), 33–55.
Njuki, E., & Bravo-Ureta, B. E. (2015). The economic costs of environmental regulation in US dairy farming: A directional distance function approach. *American Journal of Agricultural Economics, 97*(4), 1087–1106.
Oude Lansink, A. O., Verstegen, J., & Van den Hengel, J. (2001). Investment decision making in Dutch greenhouse horticulture. *NJAS-Wageningen Journal of Life Sciences, 49*(4), 357–368.
Lansink, Oude, O. , A., Stefanou, S., & Serra, T. (2015). Primal and dual dynamic Luenberger productivity indicators. *European Journal of Operational Research, 241*(2), 555–563.
Peloza, J., Loock, M., Cerruti, J., & Muyot, M. (2012). Sustainability: How stakeholder perceptions differ from corporate reality. *California Management Review, 55*(1), 74–97. doi:10.1525/cmr.2012.55.1.74.
Penrose, E. T. (1995). *The theory of the growth of the firm*. In. Retrieved from ebrary http://site.ebrary.com/id/10283659
Puggioni, D., & Stefanou, S. (2016). The Value of Being Socially Responsible. A DEA Approach for Analyzing Efficiency and Recovering Shadow Prices of CSR Activities. In *Paper presented at the 2016 Annual Meeting, July 31-August 2, 2016*.
Robinson, E. A. G. (1962). *The structure of competitive insustry*. Chicago: The University of Chicago Press.
Rodger, J. A., & George, J. A. (2017). Triple bottom line accounting for optimizing natural gas sustainability: A statistical linear programming fuzzy ILOWA optimized sustainment model approach to reducing supply chain global cybersecurity vulnerability through information and communications technology. *Journal of cleaner production, 142*, 1931–1949.
Sánchez-Ballesta, J. P., & García-Meca, E. (2007). Ownership structure, discretionary accruals and the informativeness of earnings. *Corporate Governance: An International Review, 15*(4), 677–691.
Shephard, R. W. (1970). *Theory of Cost and Production Functions*. Princeton University Press.
Silva, E., Oude Lansink, A. O., & Stefanou, S. E. (2015). The adjustment-cost model of the firm: Duality and productive efficiency. *International Journal of Production Economics, 168*, 245–256.
Silva, E., & Stefanou, S. E. (2003). Nonparametric dynamic production analysis and the theory of cost. *Journal of Productivity Analysis, 19*(1), 5–32.
Silva, E., & Stefanou, S. E. (2007). Dynamic efficiency measurement: theory and application. *American Journal of Agricultural Economics, 89*(2), 398–419.
Simar, L. (2003). Detecting outliers in frontier models: A simple approach. *Journal of Productivity Analysis, 20*(3), 391–424.
Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of econometrics, 136*(1), 31–64.
Simar, L., & Zelenyuk, V. (2006). On testing equality of distributions of technical efficiency scores. *Econometric Reviews, 25*(4), 497–522.
Surroca, J., & Tribó, J. A. (2008). Managerial entrenchment and corporate social performance. *Journal of Business Finance & Accounting, 35*(5-6), 748–789.
Surroca, J., Tribó, J. A., & Waddock, S. (2010). Corporate responsibility and financial performance: The role of intangible resources. *Strategic management journal, 31*(5), 463–490.
Sun, L., & Stuebs, M. (2013). Corporate social responsibility and firm productivity: Evidence from the chemical industry in the United States. *Journal of Business Ethics, 118*(2), 251–263.
Ullmann, A. A. (1985). Data in search of a theory: A critical examination of the relationships among social performance, social disclosure, and economic performance of US firms. *Academy of management review, 10*(3), 540–557.
Vardanyan, M., & Noh, D.-W. (2006). Approximating pollution abatement costs via alternative specifications of a multi-output production technology: a case of the US electric utility industry. *Journal of environmental management, 80*(2), 177–190.
Wang, W.-K., Lu, W.-M., Kweh, Q. L., & Lai, H.-W. (2014). Does corporate social responsibility influence the corporate performance of the U.S. telecommunications industry. *Telecommunications Policy, 38*(7), 580–591.
Webb, E. (2005). Agency costs, leverage, and corporate social responsibility: A test of causality. *Financial Decisions, 3*(1), 1–19.
Weimer, J., & Pape, J. (1999). A taxonomy of systems of corporate governance. *Corporate Governance: An International Review, 7*(2), 152–166.
Zelenyuk, V., & Zheka, V. (2006). Corporate governance and firm's efficiency: the case of a transitional country, Ukraine. *Journal of Productivity Analysis, 25*(1-2), 143–157.
Zhang, N., & Choi, Y. (2014). A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. *Renewable and Sustainable Energy Reviews, 33*, 50–59.
Zofio, J. L., Pastor, J. T., & Aparicio, J. (2013). The directional profit efficiency measure: on why profit inefficiency is either technical or allocative. *Journal of Productivity Analysis, 40*(3), 257–266.

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