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RESEARCH ARTICLE

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A dynamic by-production framework for measuring productivity change in the presence of socially responsible and undesirable outputs: Evidence from European food processors

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Abstract

In the past decade, corporate firms have globally increasingly adopted corporate social responsibility (CSR) practices; however, so far less is known about how productivity change in the presence of socially responsible and undesirable output can be evaluated. This paper develops a framework that integrates CSR in a dynamic by-production technology which captures the transformation of multiple inputs into marketed outputs, socially responsible and undesirable outputs, while accounting for adjustment costs in quasi-fixed inputs. The paper illustrates the method using a sample of European food and beverage manufacturing firms. The results of the empirical application show that there is a decline in dynamic Luenberger productivity indicators mainly due to technical inefficiency change. Hence, firms should devise strategies to enhance utilization of resources and reduce technical inefficiency. The regression of productivity change indicators on firm-specific factors showed that more indebted firms experienced a

Abbreviations: CSR, corporate social responsibility; DEA, data envelopment analysis; ESG, environmental, social, and governance; LP, linear programming; OLS, ordinary least square; PCA, principal component; analysis; R&D, research and development; ROA, return on assets.

lower growth of the productivity of undesirable output, whereas more profitable firms have a lower productivity growth of variable inputs and a higher growth of the productivity of investments. [EconLit Citations: C02, C14, C6, D24]

KEYWORDS

corporate social responsibility, data envelopment analysis, dynamic Luenberger indicator, dynamic productivity change, food and beverage manufacturing industry

1 | INTRODUCTION

Corporate social responsibility (CSR) defines a set of corporate practices that improve the social and environmental standards of firms operating in markets. CSR shifts corporate goals from value maximization for shareholders towards a broader, multi-stakeholder satisfaction (Paul & Siegel, 2006). Whereas there is an increasing societal demand for firms to adopt CSR practices in all sectors of the economy, there is particularly high pressure on the food and beverage industry to take up CSR since it is subject to more scrutiny from both financial regulators and societal stakeholders. Recent decades have also seen a shift in customer preferences towards socially responsible consumption globally and in Europe in particular (European Commission, 2002).

CSR activities of food companies have evolved around environmental issues (e.g., Program on Green Procurement) as well as social issues (e.g., Policy on the Elimination of Discrimination). A focus on the food industry is warranted since it is linked to societal concerns, such as food safety, labor rights, and animal welfare (Hartmann, 2011; Heyder & Theuvsen, 2012). In addition, the EU food-manufacturing sector has implemented the General Food Law (Regulation (EC) No 178/2002), which requires companies to guarantee fair practices in food trade and to take responsibility for their environmental impact. Firm's CSR engagement in the past decade has been further driven by an increasing demand of institutional investors to invest in companies that pay due attention to CSR (Shiu & Yang, 2017). Several studies focused on the relationship between CSR and firm financial performance in terms of profitability measures (Baird et al, 2012; Barnett & Salomon, 2012). However, so far less is known about how the adoption of CSR-affected productivity growth and whether firms are becoming more productive in pursuing CSR activities over time.

When modeling productivity change, it is important to realize that socially responsible activities such as environmental programs and community programs which help to mitigate negative externalities of the firm's activities, also require resources that could have been employed in the production of marketable output. Hence, a production framework that forms the basis for modeling productivity change needs to capture trade-offs among inputs, marketable output, and CSR activities. More specifically, the underlying technology of a firm that adopts CSR practices may exhibit both substitution and complementarity relationships among inputs and CSR activities. As Murty et al. (2012) showed, a by-production approach can capture such relationships well.

Recently, Puggioni and Stefanou (2019) integrated CSR activities in a static by-production framework and estimated the economic and technical efficiency with which firms operate. Engida et al. (2020) extended the approach of Puggioni and Stefanou (2019) to the dynamic context by estimating technical inefficiency in a dynamic by-production framework that accounts for the role of adjustment costs associated with investments in capital assets. Research exploring the relation of CSR with productivity change is still limited (Guillamon-Saorin et al., 2018; Kapelko et al, 2020; Sun & Stuebs, 2013; Wang et al., 2014). The existing literature analyzes productivity change for all inputs simultaneously, thereby ignoring differences in productivity change between inputs and CSR activities. In addition, existing studies on the relation between CSR and productivity change are generally performed in a static context which fails to account for the adjustment costs associated with investments in capital assets. Static models may confound productivity change measures with adjustment costs and may therefore produce misleading results (Namiotko & Baležentis, 2017; Oude Lansink et al., 2001; Silva & Stefanou, 2003, 2007). Hence, the existing literature on evaluating productivity change of firms adopting CSR practices does not yet account for the role of adjustment costs and does not yet account for productivity change differences between variable inputs and CSR activities.

In light of the foregoing discussion, the objective of this study was to estimate productivity change for variable inputs, undesirable output, and investments and explain productivity change differences between firms. The paper uses a dynamic by-production model to characterize the transformation of multiple inputs into marketable, socially responsible, and undesirable outputs, thereby enabling for substitution and complementarity relationships among inputs and CSR activities. To measure the input-and output-specific productivity change, the paper employs a dynamic Luenberger indicator (Oude Lansink et al., 2015) and decomposes it into dynamic technical inefficiency change, dynamic scale inefficiency change, dynamic technical change, and scale change of dynamic technology. The contribution of this study to the existing literature is twofold. First, we develop dynamic productivity change in the presence of socially responsible and undesirable output. Second, we empirically demonstrate the applicability of the indicator using a dataset of the European food and beverage industry. Ordinary least square (OLS) bootstrap regression is employed to assess the association between firm-specific factors and the dynamic input-, output-, and investment-specific productivity change.

The next section develops the methodology of dynamic productivity change and shows its empirical implementation using Data Envelopment Analysis (DEA). The subsequent section presents the description of the sample of European food and beverage manufacturing firms. This is followed by the results of the estimation of the dynamic productivity change and the OLS bootstrap regression. The final section offers concluding comments.

2 | METHODS

2.1 | The Luenberger indicator of dynamic productivity change

The by production model was initially developed (Førsund, 2009) to model production technologies in the presence of undesirable outputs. This paper continues from the dynamic by-production model developed by Engida et al. (2020) in the CSR context, and extends this approach toward measuring productivity change and its components (technical change, technical inefficiency change, and scale inefficiency change).

A by-production technology consists of two sub-technologies: one describing the production of desirable outputs (marketable outputs and socially responsible outputs) and the other describing the production of undesirable outputs. Specifically, this by-production technology uses variable inputs ($v(t)$) and invests $i(t)$ to produce three types of outputs given the stock of quasi-fixed inputs ($k(t)$): marketable outputs ($ym(t)$), socially responsible outputs ($yr(t)$), and undesirable outputs ($b(t)$). Marketable outputs are those outputs by which the production process is motivated. Undesirable outputs are unwanted but inevitably generated as by-products of the production of marketable and socially desirable outputs, and can be potentially unfavorable to the firm or society. Socially responsible outputs are activities implemented by firm managers to reduce the negative consequences of undesirable outputs or increase the long-term performance of the firm. CSR is captured using these two outputs: Undesirable outputs and socially responsible activities. Undesirable outputs can, for example, be captured in terms of operations-related controversies, or environmental supply chain incidents. Some examples of socially responsible output include: programs to stimulate sustainable agriculture, and programs to reduce water use.

The representation of the by production technology is adapted from the by-production models first attempted by Førsund, (2009) and its modified versions by Murty et al. (2012), Dapko (2016), and Førsund (2018). The dynamic by-production technology $\Psi(t)$ is mathematically represented as the intersection of two technologies:

$$\Psi(t) = \Psi_g(t) \cap \Psi_b(t), \tag{1}$$

where $\Psi_g(t)$: good output sub technology $= [(v(t), i(t), ym(t), yr(t))$
$: (v(t), i(t))$ can produce $ym(t)$ and $yr(t)$, given $k(t)]$,
$\Psi_b(t)$: the undesirable output sub technology $= [(v(t), i(t), yr(t), b(t))$
$: (v(t), i(t), yr(t))$ can produce $b(t)$, given $k(t)$.

The dynamic by-production technology in this article uses the directional distance function (DDF) proposed by Chambers et al. (1998). A general representation of the non-radial form of the DDF with directional vectors undesirable output ($\vec{g}_b$), variable inputs ($\vec{g}_v$), and investments ($\vec{g}_i$), $\vec{D}_t^{\,i}(yr_t, b_t, k_t, v_t, i_t: \vec{g}_b, \vec{g}_v, \vec{g}_i)$, measuring dynamic technical inefficiency for each firm at time t, is defined as follows:

$$\begin{aligned}\vec{D}_t^{\,i}(ym_t, yr_t, b_t, k_t, v_t, i_t : \vec{g}_b, \vec{g}_v, \vec{g}_i) = \max_{\beta_b,\beta_v,\beta_i} [\beta_b + \beta_v + \beta_i \in \mathbb{R} : (b_t - \beta_b\vec{g}_b, v_t - \beta_v\vec{g}_v, i_t + \beta_i\vec{g}_i) \in \Psi(t), \vec{g}_b \in \mathbb{R}^R_+, \vec{g}_v \\ \in \mathbb{R}^J_+, \vec{g}_i \in \mathbb{R}^L_+, (\vec{g}_{yr}, \vec{g}_b, \vec{g}_v, \vec{g}_i) \neq (0^E, 0^R, 0^J, 0^L),\end{aligned} \tag{2}$$

where $\beta_b, \beta_v, \beta_i$ are measures of dynamic technical inefficiency specific to the socially undesirable output, variable inputs, and investments.

This study employed a dynamic Luenberger productivity (Kapelko et al., 2017) to estimate productivity change for variable inputs, undesirable output, and investments. The use of the Luenberger indicator over the Malmquist–Luenberger indicator is justified for the drawback of the Malmquist–Luenberger index as a tool for productivity measurement associated with the production of bad outputs (undesirable outputs) (Aparicio et al., 2013). The well-known weaknesses of the standard Malmquist productivity index are the computational infeasibilities and the failure to account for slacks. In addition, Aparicio et al. (2013) identified a drawback of the Malmquist–Luenberger index decomposition: "the usual interpretation of the technical change component in terms of production frontier shifts can be inconsistent with its numerical value, thereby resulting in an erroneous interpretation of this component that passes on to the index itself."

The computation of the dynamic Luenberger indicator for variable inputs, undesirable output, and investment requires the solution of four linear programming (LP) models, that is, two single period models (for time t and $t+1$) and two mixed period models (for a firm in t in relation to the technology in time $t+1$, and the other for a firm in $t+1$ in relation to the technology in time t).

The single period LP model for evaluating a firm in period t relative to the production technology in period t is given by

$$\vec{D}_t^{\,i}(v(t), i(t), k(t), ym(t), yr(t), b(t); \vec{g}_b, \vec{g}_v, \vec{g}_i) = \max_{\beta_b,\beta_v,\beta_i,\mu^g,\mu^b} [\beta_b^1 + \beta_v^1 + \beta_i^1],$$

$$\text{s. t. } ym_o(t) \leq \sum_{n=1}^{N} \mu_n^g ym_n(t),$$

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

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

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

$$b_o(t) - \beta_b \vec{g}_b \ge \sum_{n=1}^{N} \mu_n^b b_n(t), \tag{3}$$

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

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

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

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

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

The objective function of the LP model in Equation (3) assigns the same weight to each inefficiency score indicating the potential for contraction of variable inputs and undesirable outputs and the expansion of investments. 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 directional vector enters the constraints additively, and the inefficiency scores ($\beta_b, \beta_v, \beta_i$) have a lower bound at 0 and have no upper bound. A firm is fully efficient in undesirable outputs, variable inputs or investments if $\beta_b = 0, \beta_v = 0$, or$\beta_i = 0$, respectively. μ_n^g, μ_n^b are the two intensity variables associated with the production technology for good outputs (marketable outputs and socially responsible outputs) and the production technology for undesirable outputs.

The constraints: $\sum_{n=1}^{N} \mu_n^g v_n(t) = \sum_{n=1}^{N} \mu_n^b v_n(t)$ and $\sum_{n=1}^{N} \mu_n^g (i_n(t) - \delta k_n(t)) = \sum_{n=1}^{N} \mu_n^b (i_n(t) - \delta k_n(t))$ are interdependence constraints that ensure equality of the optimal values of variable inputs and investments in both technologies.

The mixed period LP model for evaluating a firm in time t relative to the production technology in time $t+1$ is given by

$$\vec{D}_{t+1}^{i}(v(t), i(t), k(t), ym(t), yr(t), b(t); \vec{g}_b, \vec{g}_v, \vec{g}_i) = \max_{\beta_b, \beta_v, \beta_i, \mu^g, \mu^b} [\beta_b^2 + \beta_v^2 + \beta_i^2],$$

$$\text{s. t. } ym_o(t) \le \sum_{n=1}^{N} \mu_n^g ym(t+1),$$

$$yr_o(t) \le \sum_{n=1}^{N} \mu_n^g yr_n(t+1), \tag{4}$$

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

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

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

$$yr_o(t) \ge \sum_{n=1}^{N} \mu_n^b yr_n(t+1),$$

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

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

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

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

The mixed period model for evaluating a firm in t+1 in relation to the technology in time t is estimated analogously to Equation (4):

$$\vec{D}_{t+1}^{i}(ym_{t+1}, yr_{t+1}, b_{t+1}, k_{t+1}, v_{t+1}, i_{t+1} : \vec{g}_b, \vec{g}_v, \vec{g}_i) = \max_{\beta_b, \beta_v, \beta_i, \mu^g, \mu^b} [\beta_b^3 + \beta_v^3 + \beta_i^3]).$$

The single period model for evaluating a firm in t+1 in relation to the technology in time $t+1$ is estimated analogously to Equation (4):

$$\vec{D}_{t+1}^{i}(ym_{t+1}, yr_{t+1}, b_{t+1}, k_{t+1}, v_{t+1}, i_{t+1} : \vec{g}_b, \vec{g}_v, \vec{g}_i) = \max_{\beta_b, \beta_v, \beta_i, \mu^g, \mu^b} [\beta_b^4 + \beta_v^4 + \beta_i^4]).$$

In what follows, the measures of dynamic technical inefficiency specific to the undesirable outputs, inputs, and investments are denoted by β_c, where the subscript $c = b, v, i$. The Luenberger indicators of input, investment, and undesirable output specific dynamic inefficiency changes (L_c) are computed as

$$L_c = \frac{1}{2}\left(\beta_c^2 - \beta_c^4 + \beta_c^1 - \beta_c^3\right). \tag{5}$$

The measure L_c can be decomposed into dynamic technical inefficiency change ($\mathrm{TEI}_c^{\mathrm{CRS}}$) and dynamic technical change (TC_c) for input, investment, and undesirable output

$$\mathrm{TEI}_c^{\mathrm{CRS}} = \beta_c^1 - \beta_c^4, \tag{6}$$

$$TC_c = \frac{1}{2}\left(\beta_c^4 - \beta_c^3 + \beta_c^2 - \beta_c^1\right). \tag{7}$$

$\mathrm{TEI}_c^{\mathrm{CRS}}$ evaluates the position of a firm relative to the dynamic production frontier between two time periods, while TC_c measures the shift of the frontier between two time periods. $\mathrm{TEI}_c^{\mathrm{CRS}}$ is dynamic technical inefficiency under the assumption of constant return to scale from models (1) and (4). It can be further decomposed into dynamic technical inefficiency change under variable returns to scale ($\mathrm{TEI}_c^{\mathrm{VRS}}$), and dynamic scale inefficiency change (SEI_c). The measures are computed by estimating the two single-period LP models for time t and $t + 1$, and adding the convexity restrictions to the model in (2): $\sum_{n=1}^{N} \mu_n^g = 1$ and $\sum_{n=1}^{N} \mu_n^b = 1$. This produces two estimates that are denoted as $\beta_i^{1\mathrm{VRS}}$ and $\beta_i^{4\mathrm{VRS}}$. The dynamic technical inefficiency changes under VRS ($\mathrm{TEI}_i^{\mathrm{VRS}}$) are then computed as

$$\mathrm{TEI}_c^{\mathrm{VRS}} = \beta_c^{1\mathrm{VRS}} - \beta_c^{4\mathrm{VRS}}. \tag{8}$$

Dynamic scale inefficiency change (SEI_c) is given by

$$\mathrm{SEI}_c = \left(\beta_c^1 - \beta_c^4\right) - (\beta_c^{1\,\mathrm{VRS}} - \beta_c^{4\,\mathrm{VRS}}). \tag{9}$$

Dynamic scale inefficiency change (SEI_c) evaluates the movement of firms towards or away from the optimal scale defined by constant returns to scale, where a larger value indicates a less optimal size. The variable input-, undesirable output-, and investment-specific dynamic productivity changes are decomposed into dynamic technical change TC_c, dynamic technical inefficiency change under variable returns to scale TEI_c^{VRS}, and dynamic scale inefficiency change SEI_c (see, e.g., Oude Lansink et al., 2015)

$$L_c = TC_c + TEI_c^{VRS} + SEI_c. \tag{10}$$

2.2 | OLS bootstrap regression

The association between firm-specific characteristics and dynamic Luenberger indicators of input-, undesirable output- and investment-specific productivity change are further explored using an OLS bootstrap regression separately for the dynamic Luenberger indicators of input-, undesirable output-, and investment-specific productivity change (L_c). The regression equation is written as

$$L_c = f' \cdot \gamma_c + \varepsilon, \tag{11}$$

where L_c is the Luenberger indicator of productivity change which has been computed using Equation (5) for variable input, investment, and undesirable output separately; γ_c is the corresponding vector of regression coefficients for variable input, investment, and undesirable output, f is the vector of explanatory variables, and ε is the error term that is independently and identically distributed: $\varepsilon \sim N(0, \delta^2)$.

The purpose of the OLS bootstrap regression is to examine the association between firm-specific characteristics and dynamic Luenberger indicators of input-, undesirable output-, and investment-specific productivity change. It is important to note that the OLS bootstrap regression utilized here does not allow for detecting causality in the relationship, rather it only shows an association between variables. The computation of productivity change is based on frontiers from two single period models (for time t and $t+1$) and two mixed period models (for a firm in t in relation to the technology in time $t+1$, and the other for a firm in $t+1$ in relation to the technology in time t). A previous period performance is correlated with current period since a frontier in period t is used to compute productivity change in period t and in period t+1 (see Equation 5). The bootstrap approach addresses this autocorrelation (Simar & Wilson, 2007).

The existing literature suggests several explanatory variables which are associated with changes in CSR performance. Margolis et al. (2009) performed a meta-analysis and found that firm size has been used frequently to explain differences in CSR performance. Other variables such as research and development (R&D) intensity, leverage, free cash flows, and return on asset(profitability) have also been reported to affect (changes in) CSR performance (e.g., Nelling & Webb, 2009).

The availability of free cash flows might influence decisions on CSR activities in the sense that firms with higher free cash flows have more financial means to invest in new CSR activities. The level of profitability, which can be measured by return on asset (ROA), 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 and environmental merits. Moreover, corporate governance systems and CSR performance can be related as corporate governance mechanisms influence corporate decisions including those related to sustainability and social responsibility (Aguilera & Cuervo-Cazurra, 2004; Aguilera et al., 2008; Sánchez-Ballesta & García-Meca, 2007). The prevailing corporate governance systems in industrialized countries include the "market-oriented" system in Anglo-Saxon countries (e.g., the USA and the UK) and the "network-oriented" system (e.g., Germany and the Netherlands) (Weimer & Pape, 1999). A market-oriented system depends on the market, while a network-oriented system relies on networks of relationships among stakeholders. The network-oriented systems tend to be more socially responsible since networks of relationships between stakeholders increase the likelihood of firm's incorporating sustainability and social responsibility considerations in their decision making (Engida et al., 2018; Weimer & Pape, 1999).

3 | DATA

This study focuses on data of European food processors. The data for this study were gathered from two databases: Sustainalytics to capture firms' CSR activities and ORBIS to obtain financial data.

Data on CSR were obtained from Sustainalytics.[1] Sustainalytics has been providing research, analysis, and consulting services related to environmental, social, and governance (ESG) practices.

The dataset from Sustainalytics comprised of indicators on favorable/positive and controversial/negative dimensions of ESG. This is particularly useful to identify 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 derived using a method that combines principal component analysis (PCA) and DEA (see Engida et al., 2018). The method uses PCA to reduce the number of indicators and to derive uncorrelated components for each respective CSR-related outputs. DEA is then used to derive composite measures for socially responsible and undesirable output using these uncorrelated components. Following Puggioni and Stefanou (2019), we distinguish ESG performance indicators that capture the socially responsible output and undesirable output. Table 1 provides further details on the ESG indicators used in this study.

Data on marketable output, and inputs were obtained from ORBIS. Marketable outputs (ym) weremeasured in sales (in US dollars) and were deflated using the industrial price index for outputs. Two variable inputs (materials and labor) and one quasi-fixed input were distinguished. Materials were measured as the costs of materials consumed, and labor was measured as employment cost. Materials and labor were deflated using the industrial price index for consumer non-durables and the labor cost index in manufacturing, respectively. The quasi-fixed input comprises fixed assets and it was deflated by the industrial price index for capital goods. Cash flow from investing activities was used to capture of gross investment in quasi-fixed inputs. All prices used for deflation were taken from Eurostat. Table 1 summarizes the descriptions of variables used in the LP models. The final dataset consisted of 185 observations for the period 2013–2016, with an average of 46 observations per year. The sample includes food processors from several European countries. Table A1 presents the summary of sample distribution across countries and shows the sample includes firms from seventeen European countries.

Table 2 reports descriptive statistics of the variables used in the LP to estimate dynamic input-, output- and investment-specific productivity change. Marketable output and inputs (materials, labor, and quasi-fixed inputs) have very high variability, while undesirable and socially responsible outputs demonstrate a lower variability. The investment variable is characterized by a large variance relative to the average, which reflects a high variation across years and between companies in investment activities.

The dynamic by-production technology in this article uses directional distance functions with directional vectors, which were set as the observed values for variable inputs, and as unity for undesirable output, that is, $\vec{g}_b = 1, \vec{g}_v = v_o$. We set the directional vector as unity because the observed values for socially responsible output and undesirable output are scored 0–1 and have low variation (Table 2). The directional vector for the investment

[1]http://www.sustainalytics.com/ "Sustainalytics is an award-winning global responsible investment research firm specialized in environmental, social, and governance (ESG) research and analysis. The firm offers global perspectives and solutions that are underpinned by local expertise, serving both values-based and mainstream investors that integrate ESG information and assessments into their investment decisions."

TABLE 1 Input and output variables: Description, measure, and data source

Variable	Description	Indicator	Source
ym	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	Materials	Material cost	ORBIS
v_2	Labor	Employee cost	ORBIS
k	Quasi-fixed input	Quasi-fixed input	ORBIS
i	Investment	Cash flow from investing activities	ORBIS

variable was set to 20% of the capital stock, that is, $\vec{g}_i = 0.2 \times k_o$, because the actual investments can be zero and using the actual value could then preclude a solution of the DEA models.

Data on variables that are used in the OLS regression were taken from the ORBIS database. In case companies had missing values in the ORBIS dataset, the data were supplemented with information from the annual reports that were recovered from the company's website. The descriptive statistics are presented in Table 3. Corporate governance systems are represented by a set of dummy variables indicating market-oriented (Anglo-Saxon) and network-oriented (Germanic and Latin) categories. In the regression, the network-oriented category is used as the reference group. Table 3 shows that 32.9% of the analyzed companies belonged to a market-oriented system while 67.1% belonged to a network-oriented system.

TABLE 2 Descriptive statistics of pooled sample for the period 2013–2016

	Units	Mean	*SD*	Min.	Max.
Marketable output	m. euro	10.300	18.100	0.1078	104.000
Socially responsible output	Score	0.790	0.111	0.461	0.950
Materials	m. euro	0.791	1.912	0.054	14.200
Labor	m. euro	1.337	2.729	0.001	17.400
Quasi-fixed inputs	m. euro	13.000	28.100	0.080	0.211
Investment	m. euro	1.039	4.894	0.000	60.100
Depreciation	m. euro	0.297	0.580	0.008	3.477
Undesirable output	Score	0.013	0.044	0.000	0.393

TABLE 3 Descriptive statistics of factors associated with productivity change

Variable	Description	Units	Mean	*SD*	Min.	Max.
Size	Natural log of total assets	USD	15.585	1.588	12.831	18.775
Leverage	Ratio of total debt and equity	Ratio	0.942	0.725	0.109	3.909
FCF	Free cash flow divided by net sales	Ratio	0.119	0.131	−0.747	0.392
ROA	Earnings Before Interest and Taxes divided by total assets	Ratio	0.090	0.053	−0.051	0.249
R&D Intensity	Ratio of total R&D expenditure to total sales	Ratio	0.062	0.198	0.000	1.466
Market-oriented	=1 for a market-oriented system and zero otherwise	Dummy	0.329	0.473	0.000	1.000

4 | RESULTS AND DISCUSSION

4.1 | Estimates of dynamic productivity change

Dynamic productivity change indicators associated with input, undesirable output, and investment, and their respective decompositions into technical change, technical inefficiency change, and scale inefficiency change were generated for each firm separately using data from two consecutive years (from 2013/2014 to 2015/2016). Table 4 reports arithmetic averages for year and the overall values.

The average annual dynamic productivity growth associated with variable input during the sample period was −0.003. This value implies that the use of variable input has increased by 0.03% per year during the sample period while still producing the same level of desirable output (i.e., in terms of marketable output and socially desirable output) and undesirable output. The key component driving the process of productivity decline of variable inputs is dynamic scale inefficiency change. The negative average scale inefficiency change associated with variable input (2.2%) implies productivity has decreased because the firms on average have moved further away from the optimal scale of operation. The value for technical change in variable input of 0.023 suggests that firms on average needed 2.3% less inputs each year to produce the same quantities of marketable outputs and socially desirable outputs. Table 4 also shows that firms changed from technical regress in 2013/2014 to technical progress in the subsequent years. The negative contribution of technical inefficiency change of

TABLE 4 Decomposition of Luenberger indicators of variable input, investment, and undesirable output for European Food and Beverage Companies

	2013/14	2014/15	2015/16	Overall
Variable input				
L	−0.035	0.065	−0.029	−0.003
TC	−0.009	0.036	0.033	0.023
TEI^{VRS}	0.007	0.015	−0.022	−0.003
SEI	−0.033	0.014	−0.040	−0.022
Investment				
L	0.424	−0.192	0.182	0.135
TC	−0.550	−0.070	2.112	0.772
TEI^{VRS}	−0.001	−0.072	−1.385	−0.636
SEI	0.975	−0.050	−0.545	−0.001
Undesirable output				
L	−0.055	−0.011	−0.020	−0.027
TC	−0.004	−0.004	−0.013	−0.008
TEI^{VRS}	−0.075	0.033	−0.041	−0.028
SEI	0.024	−0.041	0.034	0.009

variable input indicates that productivity on average decreased by 0.03% per year due to increasing technical inefficiency. The positive contribution of technical change is not sufficiently large to offset the negative contributions of scale inefficiency and technical inefficiency change on productivity growth of variable inputs. A similar pattern of dynamic productivity change and its components for variable input was observed by Kapelko et al. (2017), who investigated input-specific dynamic productivity change in European dairy manufacturing. Our empirical results also show that one of the main drivers of negative dynamic productivity growth for labor is the negative dynamic technical inefficiency change. This shows firms are using the existing production potential of labor less efficiently over time.

The average annual dynamic productivity growth associated with investment in capital during the sample period was positive with a value of 0.135. When giving an interpretation to this value, it is important to note that the directional vector for investments was set at 20% of the value of the capital stock. Hence, the value of 0.135 implies that the potential for doing investment in capital has, on average, increased by 2.7% (=0.135 × 0.2 × 100) of the capital stock per year during the sample period while producing the same level of marketable outputs and socially desirable outputs. This productivity improvement was mainly due to technical change, that is, the potential for investing in capital has increased by 15.44% (=0.772 × 0.2 × 100) as a result of technical progress. Over the sample period, the potential for doing investment in capital has decreased by 12.72% (=0. 636 × 0.2 × 100) as a result of a decline in the efficiency with which the investment potential is used. Finally, over the sample period, the potential for doing investment has decreased by 0.002% (=0.001 × 0.2 × 100) of the capital stock per year due to a deterioration of the optimal scale of operation.

The average annual dynamic productivity growth associated with undesirable output during the sample period was −0.027. Keeping in mind that the directional vector for undesirable outputs was set at 1, this value of −0.027 implies that production of undesirable outputs has increased by 0.027 units per year during the sample period while producing the same level of desirable output (i.e., in terms of marketable and socially desirable outputs). It is important to note that the productivity change associated with variable input and investment were interpreted as percentage changes since their directional vectors were set as the observed values for variable inputs and 20% of the capital stock for investments respectively. The main drivers of the productivity decline were technical change and technical inefficiency change. The negative average technical change implies that productivity decreased by 0.008 as a result of technological regress in undesirable output. The negative technical inefficiency change implies that productivity decreased by 0.028 because the gap between efficient and inefficient firms with regard to undesirable output increased on average. The positive average scale inefficiency change implies that productivity increased by 0.009 as a result of improvement in the optimal scale of operation associated with undesirable output.

This paper contributed to the wider application of the recently proposed by-production approach of Dakpo and Oude Lansink (2018) and measured productivity change in the context of firms employing CSR practices. More specifically, this paper extended the by-production model by integrating socially responsible outputs and undesirable outputs in a dynamic context. This framework accounts for resources diverted from the production of desirable outputs to CSR activities. A constraint on socially responsible outputs in the undesirable output technology was introduced to capture the mitigation effect of socially responsible output on undesirable output as socially responsible activities help to reduce the undesirable output. These additional constraints offer the opportunities to understand the way CSR is integrated in the production process.

4.2 | OLS bootstrap regression

The results of the regression of the dynamic Luenberger indicators for variable input, investment, and undesirable output on several firm characteristics are reported in Table 5.

The debt-equity ratio (leverage) is negatively associated with the productivity growth of undesirable output. This result suggests that more indebted firms have a lower growth of the productivity of activities that can mitigate undesirable outputs such as emissions of greenhouse gases, than less indebted firms. The underlying reason could

TABLE 5 Results of the OLS Bootstrap Regression on factors associated to dynamic Luenberger indicators specific to variable input, investment, and undesirable output

	Variable input	Investment	Undesirable output
Constant	0.026 (0.113)	−0.131(1.225)	0.341(0.169)
Size	−0.004 (0.009)	0.064(0.081)	−0.012(0.013)
Leverage	−0.002 (0.044)	−0.146(0.189)	−0.001736
FCF	0.526 (0.402)	−4.504(3.280)	−0.14(0.218)
ROA	−0.738**(0.360)	7.952**(3.333)	−0.091(0.203)
R&D Intensity	0.142*(0.078)	−0.485(0.603)	0.015(0.053)
Market-oriented model	0.028 (0.030)	−0.117968	−0.016(0.030)
Replications	1000	1000	1000
R^2	0.121	0.143	0.119
Adjusted R^2	0.052	0.075	0.051

Note: In the parenthesis are the standard errors (bootstrapped standard errors) of the coefficients and asterisks denote significance at the 10% (*), 5% (**), and l% (***) level.

be that more indebted firms give a lower priority to reducing undesirable outputs than less indebted firms (Sheikh 2019; Ullmann, 1985; Umutlu, 2010).

The coefficient of return on assets (ROA) is negative and statistically significant for the dynamic Luenberger indicator of variable input. This outcome indicates that an increase in ROA is associated with a decrease in productivity growth of variable input. On the other hand, ROA has a positive and statistically significant association with the dynamic Luenberger indicator of investment. These results for ROA indicate that the productivity of variable input grows less rapidly and that the potential for doing investment in quasi-fixed inputs grows more rapidly for more profitable firms.

The coefficient of R&D intensity is positive and statistically significant for the dynamic Luenberger indicator of variable input, indicating that an increase in R&D intensity is associated with higher productivity growth of variable input. This result suggests that R&D expenses are focused on developing capabilities that lead to more productive use of variable inputs. In other words, R&D initiatives contribute to business value through cost control (Roberts & Dowling, 2002).

The estimated parameter of the dummy variable for the market-oriented (Anglo-Saxon) corporate governance system is negative and statistically significant for the dynamic Luenberger indicator of investment. This result shows that firms in market-oriented systems have lower growth in the potential for making investments than firms in network-oriented systems; this could imply that firms in market-oriented systems are more focused on creating short-term shareholder value rather than the long-term viability of the firm. Studies have reported that firms in network governance have achieved unparalleled performance and resilience in both good and bad times (Aguilera et al., 2008; Pirson & Turnbull, 2015; Sánchez-Ballesta & García-Meca, 2007).

5 | CONCLUSION

The objective of this paper was to estimate productivity change for variable inputs, undesirable output, and investment and explain productivity change differences between firms. The model underlying the estimation of productivity change integrates CSR activities in a dynamic by-production model which accounts for adjustment costs in quasi-fixed inputs. Each Luenberger indicator was decomposed to identify the contributions of technical change, technical inefficiency change, and scale inefficiency change. The empirical application focused on a sample of European food and beverage manufacturing firms over the period 2013–2016.

The results of the empirical application show that the firms in the sample, on average, had a small decline in the productivity of variable input and undesirable output, whereas they had a large increase in the potential for doing investments. Technical change made the largest contribution to improving productivity growth of variable inputs and investments; this contribution was offset by a decrease in the optimal scale for using variable inputs and lower use of the technical potential to make investments. The decrease in productivity of undesirable output was mainly due to lower use of the technical potential to mitigate undesirable output.

The regression of productivity growth indicators on firm-specific factors showed that more indebted firms experienced a lower growth of the productivity of undesirable output, whereas more profitable firms have a lower productivity growth of variable inputs and a higher growth of the productivity of making investments. R&D intensity mainly contributes to higher productivity of variable inputs and firms in market-oriented models have a lower growth of the productivity of the potential for making investments.

The implications of the results of this paper are developed along the following four lines. First, the food and beverage firms can enhance the productivity growth of variable inputs by improving their scale of operation, whereas productivity growth of investments and undesirable output can be enhanced by more efficient use of the full potential of making investments and mitigating undesirable output, respectively. Second, technical change is the main contributor to productivity improvements of variable inputs and investments, suggesting that the adoption of new technologies is successfully enhancing the firms' performance in the economic dimension (variable inputs and investments), but not in the dimension of undesirable output. Third, more indebted firms appear to be less focused on enhancing their undesirable output performance. None of the other factors investigated had a significant relationship with the undesirable output performance; notable, also the type of corporate governance system (network vs. market oriented) had no significant relation with the undesirable output performance.

The main limitations of this article are that the sample of firms (i) is small; (ii) only covers four years of observations; and (iii) is restricted to those firms that are covered by the Sustainalytics database. Moreover, the sample might be influenced by selection bias since we only have the firms that report CSR measures in the sample. With more firms adopting CSR practices future research will be able to use a larger sample and longer time series to explore the long-term developments in variable input, investment, and undesirable output-specific productivity change of food and beverage firms. Also, future research might extend the analysis to other firm types and compare outcomes across sectors of the economy. Such research could shed light on the consistency of results across sectors and would add to the knowledge about the sources of productivity growth of firms employing CSR activities and factors explaining productivity growth.

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APPENDIX A:

Table A1

TABLE A1 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
Italy	7	3.7
Luxemburg	3	1.6
Netherlands	15	8
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