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RESEARCH ARTICLE

Corporate social responsibility and dynamic productivity change in the US food and beverage manufacturing industry

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Abstract

This study examines the relationship between corporate social responsibility (CSR) and dynamic productivity change of each input employed and investment undertaken in the US food and beverage manufacturing industry. We compute input- and investment-specific dynamic Luenberger indicators and decompose them into the contributions of input- and investment-specific dynamic technical inefficiency changes and dynamic technological changes. We then relate these indicators to an overall CSR measure and aspect-specific CSR measures (governance, environment, and social). Our results confirm that the association between CSR and productivity change has different signs and effects on specific inputs or investments. We also find that only certain aspects of CSR participate in the association between CSR and dynamic productivity change and its components. [EconLit citations: C61, D24, L66, M14].

1 | INTRODUCTION

The concept of corporate social responsibility (CSR) relates to companies voluntarily integrating social and environmental concerns in their business activities and in their relations with stakeholders (European Commission, 2002). This definition of CSR signifies that corporate performance is judged not just by the profits a company makes, but also by the impacts that firms have on social well-being and on the environment. The further implication of CSR is that firms are accountable not just to their shareholders but also to other stakeholders, including suppliers, retailers, and consumers. Consumers appear to be particularly concerned with CSR (Bhattacharya & Sen, 2004).

Indeed, the quality and safety of the products that companies offer to their consumers is increasingly regarded as an integral part of a food and beverage company's CSR (e.g., Calveras & Ganuza, 2018). CSR engagement is highly relevant in the food and beverage industry, due to its strong impact on the economy, the environment, and society (Hartmann, 2011). Food and beverage companies attempt to differentiate from competitors by reporting voluntary projects to demonstrate CSR (Chaddad & Mondelli, 2013). The food and beverage industry has expanded economic opportunities in many ways. The US food production sector has experienced notable growth in the value of output (i.e., the value of shipments), rising by 2.5 times over the past 60 years. But even more interesting is the evidence that this growth in output has occurred with relatively low increase in the total joined use of inputs (e.g., capital, labor, purchased inputs; Wang & Ball, 2014). Indeed, the increase in output is attributed mostly to an increase in the quality of labor, capital, and technology inputs. This illustrates the importance of efficiency and productivity in the US food and beverage industry. Simultaneously, academic research has explored the link between CSR and the food sector (Hartmann, 2011) and the importance of CSR for the food and beverage industry (Kong, 2012; Larissa, Van Rijnsoever, & Hekkert, 2016; Zhang, Ma, & Morse, 2018), as well as the challenges of implementing this concept (Boland, Cooper, & White, 2016) and the impact of CSR activities (fair trade) on product prices (Marconi et al., 2017).

The present study investigates the performance implications of CSR engagement by studying its association with productivity change in the food and beverage industry. CSR is related to competitiveness through a learning and innovation cycle (Vilanova, Lozano, & Arenas, 2009). Learning takes place and generates innovative ideas and practices leading to competitiveness. Vilanova et al. (2009) found that competitiveness includes five dimensions: (a) financial performance, (b) productivity, (c) quality of products or services, (d) innovation in products or services, and (e) image/reputation. The majority of previous CSR studies have focused on examining the association between CSR and the first competitiveness dimension (financial performance), with mixed results.[1] Some researchers have argued that CSR activities increase costs (such as charitable donations, plans for community improvement, procedures to reduce pollution) without sufficiently increasing the benefits for the firm (e.g., Karnani, 2010). For example, Aupperle, Carroll, and Hartfield (1985) and Moore (2001) found a negative relationship between CSR and financial performance, while Nelling and Webb (2009) and Heyder and Theuvsen (2012) found no evidence that CSR is related to a firm's financial performance. Nevertheless, it is worth mentioning that the value that CSR creates for the firm is generally not reported. Hence, the negative impact of CSR might be overestimated in these studies. However, many other CSR-financial performance studies have documented a positive relationship between CSR and financial performance. In this line, early work by Cochran and Wood (1984), McGuire, Sundgren, and Schneeweis (1988), and Waddock and Graves (1997), and later work by Prior, Surroca, and Tribo (2008) and Surroca, Tribo, and Waddock (2010), found a significant and positive association between engaging in social responsible actions and firm financial performance. In the extreme, some research finds that even nonsocially responsible firms can achieve the benefits of investing in CSR if this is combined with investment in innovation (e.g., Blanco, Guillamón-Saorín, & Guiral, 2013).

Research exploring the relation of CSR with other dimensions of competitiveness such as efficiency and/or productivity developed along two lines. One stream of literature integrates CSR into a production framework and includes CSR as netput in the production process to measure efficiency (Chambers & Serra, 2018; Puggioni & Stefanou, 2019), while the other stream is interested in analyzing the relationship between CSR and efficiency and/or productivity change. Integrating CSR in the production framework builds on the assumption that CSR affects efficiency or productivity change (without showing this relation in the analysis), and in this study, we empirically analyze the relationship between CSR and productivity change rather than imposing that to the model. Hence, we follow the second stream of literature.

[1]The literature review on the studies relating CSR and financial performance is undertaken by Beurden and Gossling (2008) and Margolis, Elfenbein, and Walsh (2009).

Within the second stream of literature, a few studies have investigated the relationship between technical or cost efficiency and CSR in specific sectors, such as the semiconductor industry (Lu, Wang, & Lee, 2013), the telecommunications industry (Wang, Lu, Kweh, & Lai, 2014), the chemical industry (Sun & Stuebs, 2013), banking sector (Zhu, Stjepcevic, Baležentis, Yu, & Wang, 2017), thrift institutions (Vitaliano & Stella, 2006), the creative industry (Hou, Lu, & Hung, 2019), and the manufacturing industry (Jacobs, Kraude, & Narayanan, 2016). Only Guillamon-Saorin et al. (2018) took a broader perspective by investigating the association between CSR and technical inefficiency in different sectors.[2] Furthermore, several studies have investigated the implications of CSR for productivity change of all inputs simultaneously, that is, Färe, Grosskopf, and Pasurka (2006) and Granderson (2006)[3,4] CSR may, however, be related with the productivity change of only some inputs or it could be associated with some inputs more than with others. For example, some CSR measures may require the use of more labor, whereas others may require the use of more materials. In the context of food and beverage manufacturing industry in the USA, the importance of addressing the input-specific nature of firms' performance change has been highlighted in previous research (Morrison Paul, 1999). Yet another limitation of existing studies is that none of them was undertaken in the specific context of the food and beverage manufacturing industry. CSR is gaining importance in the US food and beverage firms, because food and beverage products are animal and plant-based and hence issues such as animal welfare or genetically modified organisms present a challenge. It is also due to the complex, labor-intensive nature of this industry's supply chains and the inherent pressure to ensure a fair income to farmers or to offer the fair-trade prices to suppliers (Maloni & Brown, 2006). Finally, previous studies on the relation between CSR and productivity change have been conducted in the static context. The implication of the static approach is that all inputs can be adjusted instantaneously. However, it is well known that quasi-fixed factors of production are not easily adjusted to their optimal levels and adjustments come with adjustment costs. Adjustment costs represent transaction or reorganization costs. For example, investment in new machinery or buildings comes with additional costs such as search costs, costs of installing a new machine, or costs associated with learning to use the new technology. Such adjustment costs may confound with inefficiency if not controlled for, and results from a static approach may provide incorrect estimates of productivity change. The dynamic production framework (Kapelko, Oude Lansink, & Stefanou, 2014; Silva & Stefanou, 2007; Silva, Oude Lansink, & Stefanou, 2015) accounts for adjustment costs related with firms' investments in quasi-fixed factors of production. A dynamic approach is suitable in the context of the food and beverage industry in the USA, which is capital-intensive and subject to adjustment costs (Morrison Paul, 1997).

The present paper fills in the gaps in the literature outlined above and contributes to the literature by focusing on the productivity dimension of competitiveness by investigating the relation between CSR and dynamic input- and investment-specific productivity change and its components. Our approach allows for a more detailed analysis of the relation between CSR and productivity change of each input and investment separately. Our approach is also more informative about the sources of dynamic productivity change as it decomposes productivity change into the contributions of dynamic technical inefficiency change and dynamic technological change. Input- and investment-specific dynamic productivity change is operationalized using the input- and investment-specific dynamic Luenberger indicator (Kapelko, Oude Lansink, & Stefanou, 2017), which is computed using Data Envelopment Analysis (DEA) (Banker, Charnes, & Cooper, 1984; Charnes, Cooper, & Rhodes, 1978).

The rest of this article is organized as follows. Section, 2 describes the methodology to measure input and investment-specific dynamic productivity change and its components. Section 3 provides information on the

[2]Additional CSR research within efficiency framework concerns the measurement of CSR using the methodologies taken from the efficiency research (Belu, 2009; Belu & Manescu, 2013; Chen & Delmas, 2011; Lee & Saen, 2012).

[3]Although Sun and Stuebs (2013) and Jacobs et al. (2016) refer to the relation between CSR and productivity, what they actually measure is firms' efficiency.

[4]Also, Kapelko (2020) analyzed the relation between CSR and productivity change, but for all inputs simultaneously.

dataset and variables used, followed by Section 4 that outlines the empirical strategy applied. We then describe and interpret the results, before the final section concludes.

2 | INPUT- AND INVESTMENT-SPECIFIC DYNAMIC PRODUCTIVITY CHANGE

In this section, we introduce the method used for estimating input- and investment-specific dynamic productivity change, which follows largely from Kapelko et al. (2017).[5]

Consider $j = 1, \ldots J$ firms at time t, each of which uses (vectors of) N variable inputs (x^t), F gross investments (I^t), and F quasi-fixed factors (k^t) to produce M outputs (y^t). The dynamic directional input distance function at time t is defined as follows (Silva et al., 2015):

$$\vec{D}^t\left(x^t, I^t, y^t, k^t; g_x^t, g_I^t\right) = \max\left\{\beta: \left(x^t - \beta g_x^t, I + \beta g_I^t, y^t, k^t\right) \in P^t\right\}, \tag{1}$$

if $(x^t - \beta g_x^t, I + \beta g_I^t) \in P^t$ for some values of β, $\vec{D}^t(x^t, I^t, y^t, k^t; g_x^t, g_I^t) \to -\infty$ when $(x^t - \beta g_x^t, I + \beta g_I^t) \notin P^t$,

where P^t is dynamic production technology, (g_x^t) and (g_I^t) represent the directional vectors for variable inputs and investments, respectively, while β is a measure of dynamic technical inefficiency. The dynamic directional input distance function is defined by simultaneously contracting variable inputs x^t in the direction of g_x^t, and expanding gross investments I^t in the direction of g_I^t. The expansion of investments is assumed since investments allow for cost saving over the long run. The dynamic production technology P^t transforms variable inputs and gross investments into outputs at a given level of quasi-fixed inputs and is defined as (Silva et al., 2015):

$$P^t = \{(x^t, I^t, y^t, k^t): x^t, I^t \text{can produce} y^t, \text{given} k^t\}. \tag{2}$$

The input- and investment-specific version of dynamic directional input distance function at time t has a following form (Kapelko et al., 2017):

$$\vec{D}^t\left(x^t, I^t, y^t, k^t; g_x^t, g_I^t\right) = \sup\left\{\sum_{n=1}^{N}\beta_n + \sum_{f=1}^{F}\gamma_f: \left(x_n^t - \beta_n g_{xn}^t, I_f^t + \gamma_f g_{If}^t, y_m^t, k_f^t\right) \in P_t\right\}, \tag{3}$$

where β_n and γ_f measure the degree of input n- and investment f-specific inefficiencies at time t. To compute input- and investment-specific dynamic productivity change via dynamic Luenberger indicator, one must also calculate input- and investment-specific dynamic directional input distance functions for time $t+1$ as well as two-cross period functions—that is, for observations at time $t+1$ in relation to the technology at time t and for observations at time t in relation to the technology at time $t+1$—which are defined similar to (3).

We use DEA to compute input- and investment-specific dynamic directional input distance functions (Banker et al., 1984; Charnes et al., 1978). In particular, following Kapelko et al. (2017), four DEA models need to be solved to measure input- and investment-specific dynamic directional input distance for time t, for observations at time t

[5]The method for estimating dynamic productivity change for all inputs simultaneously was developed in Oude Lansink, Stefanou, and Serra (2015) and Kapelko, Oude Lansink, and Stefanou (2015), and applied in Kapelko, Oude Lansink, and Stefanou (2016). Another line of research within dynamic production framework concerns dynamic network DEA models, with productivity change analysis undertaken by, for example, Skevas and Oude Lansink (2014) and Fukuyama and Weber (2017). These studies, however, do not take into account adjustment costs.

in relation to the technology at time $t+1$, for observations at time $t+1$ in relation to the technology at time t, and for time $t+1$, respectively:

$$\begin{aligned}
&\overrightarrow{D}^{t}(x^{t}, I^{t}, y^{t}, k^{t}; g_{x}^{t}, g_{I}^{t}) = \max_{\beta_{n}^{1},\gamma_{f}^{1},\lambda_{j}^{1}}\left(\sum_{n=1}^{N}\beta_{i}^{1} + \sum_{f=1}^{F}\gamma_{f}^{1}\right)\\
&s.\ t.\\
&\sum_{j=1}^{J}\lambda_{j}^{1}y_{mj}^{t} \geq y_{m0}^{t},\ m = 1, \ldots, M\\
&\sum_{j=1}^{J}\lambda_{j}^{1}x_{nj}^{t} \leq x_{n0}^{t} - \beta_{n}^{1}g_{xn}^{t},\ n = 1, \ldots, N\\
&\sum_{j=1}^{J}\lambda_{j}^{1}(I_{fj}^{t} - \delta k_{fj}^{t}) \geq I_{f0}^{t} + \gamma_{f}^{1}g_{If}^{t} - \delta k_{f0}^{t},\ f = 1, \ldots, F
\end{aligned} \tag{4}$$

$$\begin{aligned}
&\overrightarrow{D}^{t+1}(x^{t}, I^{t}, y^{t}, k^{t}; g_{x}^{t}, g_{I}^{t}) = \max_{\beta_{n}^{2},\gamma_{f}^{2},\lambda_{j}^{2}}\left(\sum_{n=1}^{N}\beta_{i}^{2} + \sum_{f=1}^{F}\gamma_{f}^{2}\right)\\
&s.\ t.\\
&\sum_{j=1}^{J}\lambda_{j}^{2}y_{mj}^{t+1} \geq y_{m0}^{t},\ m = 1, \ldots, M\\
&\sum_{j=1}^{J}\lambda_{j}^{2}x_{nj}^{t+1} \leq x_{n0}^{t} - \beta_{n}^{2}g_{xn}^{t},\ n = 1, \ldots, N\\
&\sum_{j=1}^{J}\lambda_{j}^{2}(I_{fj}^{t+1} - \delta k_{fj}^{t+1}) \geq I_{f0}^{t} + \gamma_{f}^{2}g_{If}^{t} - \delta k_{f0}^{t},\ f = 1, \ldots, F
\end{aligned} \tag{5}$$

$$\begin{aligned}
&\overrightarrow{D}^{t}(x^{t+1}, I^{t+1}, y^{t+1}, k^{t+1}; g_{x}^{t+1}, g_{I}^{t+1}) = \max_{\beta_{n}^{3},\gamma_{f}^{3},\lambda_{j}^{3}}\left(\sum_{n=1}^{N}\beta_{i}^{3} + \sum_{f=1}^{F}\gamma_{f}^{3}\right)\\
&s.\ t.\\
&\sum_{j=1}^{J}\lambda_{j}^{3}y_{mj}^{t} \geq y_{m0}^{t+1},\ m = 1, \ldots, M\\
&\sum_{j=1}^{J}\lambda_{j}^{3}x_{nj}^{t} \leq x_{n0}^{t+1} - \beta_{n}^{3}g_{xn}^{t+1},\ n = 1, \ldots, N\\
&\sum_{j=1}^{J}\lambda_{j}^{3}(I_{fj}^{t} - \delta k_{fj}^{t}) \geq I_{f0}^{t+1} + \gamma_{f}^{3}g_{If}^{t+1} - \delta k_{f0}^{t+1},\ f = 1, \ldots, F
\end{aligned} \tag{6}$$

$$\begin{aligned}
&\overrightarrow{D}^{t+1}(x^{t+1}, I^{t+1}, y^{t+1}, k^{t+1}; g_{x}^{t+1}, g_{I}^{t+1}) = \max_{\beta_{n}^{4},\gamma_{f}^{4},\lambda_{j}^{4}}\left(\sum_{n=1}^{N}\beta_{i}^{4} + \sum_{f=1}^{F}\gamma_{f}^{4}\right)\\
&s.\ t.\\
&\sum_{j=1}^{J}\lambda_{j}^{4}y_{mj}^{t+1} \geq y_{m0}^{t+1},\ m = 1, \ldots, M\\
&\sum_{j=1}^{J}\lambda_{j}^{4}x_{nj}^{t+1} \leq x_{n0}^{t+1} - \beta_{n}^{4}g_{xn}^{t+1},\ n = 1, \ldots, N\\
&\sum_{j=1}^{J}\lambda_{j}^{4}(I_{fj}^{t+1} - \delta k_{fj}^{t+1}) \geq I_{f0}^{t+1} + \gamma_{f}^{4}g_{If}^{t+1} - \delta k_{f0}^{t+1},\ f = 1, \ldots, F
\end{aligned} \tag{7}$$

In the above models, β_n and γ_f indicate the maximum feasible contraction of each input and expansion of each investment, respectively,λ_j represents the vector of firm weights, δ indicates the depreciation rate of capital, and δk reflects the value of depreciation.

Using the optimal values from the above programs, the Luenberger indicator of input-specific dynamic productivity change for input n (n = 1, … N) is computed as:

$$DPC\_input_n = \frac{1}{2}\cdot\left(\beta_n^2 - \beta_n^4 + \beta_n^1 - \beta_n^3\right), \tag{8}$$

while the Luenberger indicator of investment-specific dynamic productivity change for investment f (f = 1, … F) is calculated from the below formula:

$$DPC\_inv_f = \frac{1}{2}\cdot\left(\gamma_f^2 - \gamma_f^4 + \gamma_f^1 - \gamma_f^3\right). \tag{9}$$

The positive (negative) values of input- and investment-specific dynamic Luenberger indicate growth (decline) in productivity of each input and investment between t and $t + 1$.

The indicator of input-specific dynamic productivity change can be decomposed to identify the contributions of input-specific dynamic technical inefficiency change (DEC_input_n) and input-specific dynamic technological change (DTC_input_n) ($DPC\_input_n = DEC\_input_n + DTC\_input_n$), while the indicator of investment-specific dynamic productivity change can be broken down into the components of investment-specific dynamic technical inefficiency change (DEC_inv_f) and investment-specific dynamic technological change (DTC_inv_f) ($DPC\_inv_f = DEC\_inv_f + DTC\_inv_f$) (Kapelko et al., 2017). The components are given by the following formulas:

$$DEC\_input_n = \beta_n^1 - \beta_n^4, \tag{10}$$

$$DTC\_input_n = \frac{1}{2}\cdot\left(\beta_n^4 - \beta_n^3 + \beta_n^2 - \beta_n^1\right), \tag{11}$$

$$DEC\_inv_f = \gamma_f^1 - \gamma_f^4, \tag{12}$$

$$DTC\_inv_f = \frac{1}{2}\cdot\left(\gamma_f^4 - \gamma_f^3 + \gamma_f^2 - \gamma_f^1\right). \tag{13}$$

Input- and investment-specific dynamic inefficiency changes measure the change in the distance of firm relative to dynamic production technology in time t as compared to technology in time $t + 1$ as a result of the differences in the firms' managerial and organizational skills. Input- and investment-specific dynamic technological changes represent the shift in dynamic production technology between t and $t + 1$ due to the firm's exposure to innovation and adaptation of new technologies.

The positive (negative) values of components of input- and investment-specific dynamic Luenberger indicators show positive (negative) contributions of these components to input- and investment-specific dynamic productivity growth.

3 | DATASET AND OPERATIONALIZATION OF VARIABLES

The data for CSR activities of firms in the food and beverage industry in the US was obtained from the Kinder, Lydenberg, and Domini (KLD) database, which has been widely used in previous research studies (Blanco et al., 2013; McWilliams & Siegel, 2000; Servaes & Tamayo, 2013). Financial data came from COMPUSTAT Global Vantage. KLD contains detailed annual data on CSR of the largest (by market capitalization) publicly traded firms in the USA. Our analysis is restricted to the 2004–2015 period because CSR data in this period has the largest coverage of firms in the KLD dataset. The KLD data are prepared based on multiple sources such as annual questionnaires sent to firms, financial statements, annual and quarterly reports, or press releases. KLD contains detailed annual ratings on CSR activities in seven categories or dimensions: community, diversity, employee relations, human rights, product, natural environment, and corporate governance. Each CSR dimension contains strengths that indicate positive indicators of CSR, and concerns that refer to negative aspects of CSR. Strengths and concerns are measured in the KLD dataset as dummy variables: when a firm presents a certain strength or concern it is assigned a value of 1, and a value of 0 otherwise. The examples of strengths include charitable giving, employment of disabled workers, work-related health and safety, women and minority contracting, indigenous people relations, product safety, pollution prevention, and ownership strength. The examples of concerns are negative economic impact, workforce diversity controversies, workforce reductions, product quality and safety controversies, substantial emissions, and business ethics controversies. Initially, there were, depending on the year, between 146 and 184 food and beverage firms in the KLD dataset. We merged KLD data with accounting data in COMPUSTAT Global Vantage and also eliminated outliers following the method of Simar (2003). The resulting sample consists of 416 observations for 61 firms that operated in the US for at least two consecutive years during the 2004–2015 period (unbalanced panel).

To estimate the dynamic Luenberger indicator and its components we use one output (proxied by the firms' revenues), two variable inputs (consisting of costs of goods sold, i.e., materials and other direct inputs, and number of employees), one quasi-fixed input (measured as the firms' beginning value of fixed assets), and one investment input (i.e., gross investments in quasi-fixed inputs computed as the beginning value of fixed assets in year $t+1$ minus the beginning value of fixed assets in year t, plus the beginning value of depreciation in year $t+1$). We divide all these variables (except of the number of employees) by the appropriate price index, thereby creating the implicit quantity indices.[6] The application of such input-output variables follows from previous research (e.g., Kapelko et al., 2014; Puggioni & Stefanou, 2019; Guillamon-Saorin et al., 2018). Table 1 summarizes the descriptive statistics of input-output variables for DEA analysis.

To measure CSR, consistent with prior research (e.g., Chatterji, Levine, & Toffel, 2009; Dhaliwal, Li, Tsang, & Yang, 2011; Siegel & Vitaliano, 2007), we created an overall (net) *CSR_Score* by subtracting total concerns from total strengths along all seven categories: community, diversity, employee relations, human rights, product, environment, and corporate governance. However, given that the number of categories in KLD is not constant over the years, following Servaes and Tamayo (2013), we made an adjustments in scores by scaling the strength and concern scores for each firm in each year within each CSR category by the maximum number of items of the strength and concern scores of that category in each year. We further look into dimensions of CSR and split *CSR_Score* into *CSR_Soc*, which represents the social dimension of CSR (constructed by summing the net differences between adjusted strengths and concerns related with community, diversity, employee relations, human rights, and product; *CSR_Env*, which represents environmental dimension of CSR (measured as a difference between the adjusted strengths and adjusted concerns considering the single dimension of environment); and *CSR_Gov*, which represents corporate governance dimension of CSR (calculated by subtracting the adjusted strengths from the adjusted concerns for the single governance dimension). The details on the construction of the CSR variables are provided in Appendix A[7,8] CSR activities may have an effect on the use of inputs and the production of outputs. The implementation of CSR activities may require, for example, more labor during the implementation phase, and for reporting on CSR compliance. Also, more firms that undertake CSR activities could, for example, reduce the use of polluting inputs or could change their sourcing strategies to ensure, for example, fair prices to suppliers. Such sourcing strategies could increase the material costs.

[6]Output is deflated by the producer price index for food and beverage manufacturing industry. Costs of goods sold (i.e., materials and other direct inputs) are deflated by the indices reflecting the prices of supplies to manufacturing industries. Fixed assets and investments are deflated using the price indices for the private capital equipment for manufacturing. All price indices are supplied by the US Bureau of Labor Statistics.

[7]The correlations between CSR variables are as follows: *CSR_Score/CSR_Soc* = 0.942; *CSR_Score/CSR_Env* = 0.690; *CSR_Score/CSR_Gov* = 0.476; *CSR_Soc/CSR_Env* = 0.487; *CSR_Soc/CSR_Gov* = 0.202; and *CSR_Env/CSR_Gov* = 0.425.

[8]Our research question concerns the relation between dynamic productivity change and CSR in levels. Hence, we use CSR variables in level terms, which is also in line with previous research that applies the second stage analysis using Luenberger indicators or Malmquist indexes.

TABLE 1 Descriptive statistics of input-output variables, 2004–2015

Variable	Mean	Std. dev.	Coefficient of variation
Fixed assets	1692.640	2780.040	1.642
Materials and other direct inputs	5279.079	10335.602	1.958
Number of employees	0.023	0.044	1.896
Revenues	7234.684	11759.369	1.625
Investments	314.291	624.423	1.987

Note: Fixed assets, materials and other direct inputs, revenues and investments are in millions of US dollars, constant prices from 2003. Numbers of employees are in millions.

Our main independent variables are: dynamic productivity changes for materials and other direct inputs, employees, and investments (*DPC_mat*, *DPC_emp*, and *DPC_inv*), dynamic technical inefficiency changes for materials and other direct inputs, employees, and investments (*DEC_mat*, *DEC_emp*, and *DEC_inv*), and dynamic technological changes for materials and other direct inputs, employees, and investments (*DTC_mat*, *DTC_emp*, and *DTC_inv*).

Following prior research (e.g., Lys, Naughton, & Wang, 2015; Mahoney & Roberts, 2007; Prior et al., 2008; Servaes & Tamayo, 2012; Surroca et al., 2010), we also include a set of control variables that are most frequently used in CSR studies. In particular, we control for *Size*, measured as the natural logarithm of total assets, which is widely regarded as a determinant of firms CSR. The relation between CSR and size is unclear. On one hand, larger firms may have greater resources for CSR expenditures and hence greater pressure to engage in CSR (Lys et al., 2015), resulting in a positive association between CSR and size. On the other hand, as larger firms tend to be older, they might have lower investment opportunities than younger firms (Servaes & Tamayo, 2012), which implies a negative association between size and CSR. We also control for *MTB*, which is the market value of equity divided by the book value of shareholder's equity. It is expected that more stable firms with higher market-to-book ratios will have higher CSR engagement (Lys et al., 2015). Furthermore, we control for financial structure (Prior et al., 2008) by introducing two variables: (a) *Leverage*, which is defined as the ratio of total debt to total assets, and (b) *Cash_assets*, which is the ratio of cash to total assets. *Leverage* measures debt capacity, which is closely related to risk, and firms with lower risk are generally more likely to engage in CSR (Lys et al., 2015). *Cash_assets* approximates the firms' liquidity and it is expected that the higher the firm's liquidity, the greater the opportunity to invest in CSR (Surroca et al., 2010). To control for financial performance (profitability), following Lys et al. (2015), rather than including return on assets (ROA) itself, we split ROA into its two constituent components: *Asset_turnover* measured as the ratio of sales to total assets, and *Profit_margin* defined as net profit to sales. This allows us to explore which component of ROA is associated more strongly with CSR. In general, the evidence on the relation between CSR and profitability is mixed with studies reporting a positive association (e.g., Prior et al., 2008) or negative or no relationship at all (e.g., Moore, 2001; Nelling & Webb, 2009). The association is expected to be driven by asset turnover rather than profit margin due to its larger persistence (Lys et al., 2015). Finally, we also control for time effects through the introduction of dummies related with the financial crisis: precrisis period (2004–2006), crisis period (2007–2009), and postcrisis period (2010–2015) (National Bureau of Economic Research, 2012).[9] This enables us to compare the CSR engagement between different periods and to analyze whether the financial crisis was an obstacle for firms to invest in CSR or, on the contrary, was a motivating factor for firms to, for example, protect themselves against lower demand. Prior research has proven the importance of CSR engagement during period of financial distress. Specifically, Lins, Servaes, and Tamayo (2017) demonstrate that during the 2008–2009

[9]There are also two control variables—advertising expenses and R&D expenses—that are often used in CSR research as potential factors that may determine the capacity of the company to invest in CSR (e.g., McWilliams & Siegel, 2000; Servaes & Tamayo, 2012). However, due to the lack of data for these variables for the majority of firms, we are not able to apply them in our research.

financial crisis, firms with higher engagement in CSR experienced higher profitability, growth, and sales per employee relative to companies with low CSR engagement. This evidence is consistent with prior research suggesting that the trust between a firm and both its stakeholders and investors, built through engagement in CSR, pays off when corporations and markets suffers a negative shock (e.g., Godfrey, Merrill, & Hansen, 2009). Introduction of dummies reflecting different time periods allows also to control for the change of an attitude of firms towards CSR that is firms' increased interest in CSR investment from approximately 2010.

Table 2 summarizes the descriptive statistics for variables used in the regression analysis. The statistics for our main independent variables (i.e., dynamic productivity change and each of its components) are summarized in Section 5.1. Table 2 indicates that the mean of our main dependent variable (*CSR_Score*) is positive, with a value of 0.033. Hence, on average, firms in the sample are socially responsible, although there is also a large variation in the sample for this variable. The mean value of social activities (*CSR_Soc* = 0.017) is lower than environmental CSR aspects (*CSR_Env* = 0.042). However, governance (*CSR_Gov* = −0.025) is the lowest of the three aspects of CSR. In addition, control variables of *MTB* and *Profit_margin* present the highest coefficient of variation.

4 | EMPIRICAL STRATEGY

The first step in our empirical strategy involves estimating the input- and investment-specific dynamic productivity change, dynamic technical inefficiency change, and dynamic technological change, operationalized as a dynamic Luenberger indicator and its components. The Luenberger indicator and its components are determined for each firm for a pair of consecutive years using the actual quantities of variable inputs as directional vector for inputs (g_x^t), and actual quantities of investments as directional vector of investments (g_I^t). The use of the actual values of investments is possible here, since none of the observations had zero investments.

In the second step, we investigate the relation between input- and investment-specific dynamic productivity change and its components, and CSR measures. Our empirical analysis estimates the following general regression

TABLE 2 Descriptive statistics of regression variables (except of dynamic productivity change and its components), 2004–2015

Variable	Mean	Std. dev.	Coefficient of variation
Dependent variables			
CSR_Score	0.033	0.853	25.737
CSR_Soc	0.017	0.679	40.423
CSR_Env	0.042	0.175	4.199
CSR_Gov	−0.025	0.194	−7.637
Control variables			
Size	7.861	1.687	0.215
MTB	5.275	36.808	6.978
Leverage	0.224	0.168	0.752
Cash_assets	0.068	0.077	1.135
Asset_*turnover*	1.276	0.648	0.508
Profit_margin	0.061	0.138	2.266
Pre_crisis	0.260	0.439	1.691
Crisis	0.252	0.435	1.723

model to test the association between CSR and dynamic indicator (productivity change, technical inefficiency change, or technological change) and control variables, not requiring any causal relationship:

$$\mathrm{CSR}_{jt} = \beta_0 + \beta_1\ \mathrm{Dynamic\_indicator}_{jt} + \beta_2\ \mathrm{Controls}_{jt} + \mu_j + \vartheta_{jt}, \tag{14}$$

where μ is the intercept for each firm, and ϑ is an error term. Given the complexity of the association between CSR and productivity change, we do not intend to establish the causality of the relationship, but merely show the relevant links among the components of CSR and dynamic productivity changes. To analyze these links, we run regressions including these variables and propose CSR as the dependent variable suggesting that dynamic indicators and a set of control variables explain the CSR engagement (Equation (14)). Changes in productivity, technology, and inefficiency consume resources which could decrease the possibility of other investments such as CSR. Our model is estimated using panel data linear regression with fixed effects with heteroscedasticity and autocorrelation robust standard errors. Three regression models are estimated for each CSR measure: (a) a model with three dynamic productivity change measures—that is, for materials and other direct inputs, for employees and for investments; (b) a model involving three dynamic inefficiency change measures—that is, for materials and other direct inputs, for employees and for investments; and (c) a model including three dynamic technological change measures—that is, for materials and other direct inputs, for employees, and for investments.[10]

The analysis carried by model (14) may be subject to endogeneity problems that arise when a predictor variable correlates with the error term. There are a number of reasons why this may happen, for example, omitted variables, measurement error, and simultaneity (Wooldridge, 2002). In our context, a firm's dynamic productivity changes (and its components) could be endogenously determined. To account for this problem, we apply an endogeneity test of endogenous regressors within instrumental variables approach (IV).[11] The critical step in undertaking this analysis is the choice of instruments, that are uncorrelated with an error term, but correlated with the variable to be measured. Lagged variables are commonly used as instruments since they are expected to have little to no correlation with the error term in the present period (Wooldridge, 2002).[12] In our context, we use the following lags of variables as instruments: lagged leverage (ratio of total debt to total assets), lagged size (natural logarithm of total assets), lagged asset turnover (ratio of sales to total assets), lagged profit margin (ratio of net profit to sales), and lagged diversification (number of business segments).[13] These instruments satisfy the conditions of being valid instruments in that they affect productivity change and their relation with productivity change is analyzed elsewhere (e.g., Cummins & Xie, 2013; Wijesiri & Meoli, 2015; Worthington, 2000; Sun & Stuebs, 2013), but they are unlikely to influence the error term due to their lag's form. In addition, the validity of these instruments was tested using the Hansen (1982) J-test, which showed that all instruments are appropriate. The results of the endogeneity tests indicated that the null hypothesis that dynamic productivity change (and each of its components) are exogenous cannot be rejected. This suggests that the results of our regressions are robust to endogeneity. Hence, OLS regression

[10]It is not possible to include all dynamic measures in one model due to high correlations. In particular, dynamic productivity change is highly correlated with both dynamic technical inefficiency change and dynamic technological change, as well as dynamic technical inefficiency change and dynamic technological change are highly correlated between them.

[11]The endogeneity test applied is the regression-based form of the Hausman (1978) test (Baum, Schaffer, & Stillman, 2003). The intuition behind this test is the comparison of the models' results using OLS regression and IV approach, in which the null hypothesis is that OLS estimator is consistent and fully efficient. We use the most common IV estimator, that is the two-stage least squares estimation (2SLS). 2SLS is inefficient in the presence of heteroscedasticity, and when facing heteroskedasticity generalized method of moments (GMM) approach should be used (Baum et al., 2003). In our context, the application of GMM instead of 2SLS produces similar results.

[12]It is worth adding, however, that the use of lagged variables as instruments only solves a part of the endogeneity problem, that is: (a) in the case of no first-order autocorrelation in the residuals, and (b) if the lagged variables are themselves not relevant explanatory factors that have to be included in the main equation (e.g., Bellemare, Masaki, & Pepinsky, 2017; Betz, Cook, & Hollenbach, 2018; Hirsch, Mishra, Möhring, & Finger, 2019).

[13]We also tried the other combinations of lags of variables such as: (a) lagged leverage, lagged size, lagged asset turnover, lagged profit margin, lagged market to book value, and lagged cash to assets; (b) lagged leverage, lagged size, lagged asset turnover, lagged profit margin, lagged market to book value, lagged cash to assets, and lagged dynamic productivity change and each of its components; (c) lagged leverage, lagged size, lagged ROA, and lagged diversification, and the results on the endogeneity test remain largely the same.

results are consistent, and the empirical analysis can be based on this approach. In addition, it is important to highlight that the fixed effects model applied in the paper allows dealing with endogeneity related with omitted variable that is time-invariant (Antonakis, Bendahan, Jacquart, & Lalive, 2010).

5 | RESULTS

We start this section by presenting the results of input- and investment-specific dynamic Luenberger indicators and their components for each pair of consecutive years and for the whole period (2004–2015). We then analyze the results of regression models linking input- and investment-specific dynamic Luenberger indicator and each of its components with the measures of CSR.

5.1 | Input- and investment-specific dynamic productivity change and its components

Table 3 presents the estimated dynamic productivity change indicators for each input used and investment undertaken by US food and beverage manufacturing firms during the period 2004/2005–2014/2015. The results show that dynamic productivity change has, on average, been negative for materials and other direct inputs, and investments, but slightly positive for employees. The sample averages of −0.003 for materials and other direct inputs, 0.002 for employees, and −0.759 for investments imply that firms needed on average 0.3% more materials and other direct inputs, 0.2% less employees and could invest 75.9% less each year in the sample period to produce the same quantity of output. The increase in the dynamic productivity of employees was largely driven by dynamic technological change. Technological change was such that, on average 0.5% fewer employees were required annually over the sample period to produce the same quantity of outputs. The positive contribution on employee's productivity change of the increase of dynamic technological change was partly undone by a 0.2 percent annual decrease in the dynamic technical efficiency with which labor was used. The decrease of the productivity of materials and other direct inputs, and investments were mainly caused in both cases by a decrease in the efficiency

TABLE 3 Input- and investment-specific dynamic productivity change and its components, 2004/2005–2014/2015

Period	*DPC_Mat*	*DPC_Emp*	*DPC_Inv*	*DEC_Mat*	*DEC_Emp*	*DEC_Inv*	*DTC_Mat*	*DTC_Emp*	*DTC_Inv*
2004/2005	0.005	0.012	−0.453	−0.153	−0.187	0.580	0.158	0.199	−1.033
2005/2006	−0.009	0.029	0.580	0.008	0.271	0.227	−0.017	−0.242	0.353
2006/2007	−0.013	−0.023	−0.412	0.028	0.067	−2.321	−0.041	−0.090	1.909
2007/2008	−0.011	0.017	−0.985	−0.047	−0.080	−5.102	0.035	0.097	4.117
2008/2009	−0.001	0.011	1.687	0.056	−0.054	4.501	−0.058	0.065	−2.814
2009/2010	−0.002	0	0.905	−0.013	0.195	1.330	0.011	−0.195	−0.424
2010/2011	−0.008	0	−0.374	−0.031	−0.108	1.148	0.024	0.108	−1.522
2011/2012	−0.015	0.006	−6.366	−0.015	0.056	−6.608	0	−0.049	0.243
2012/2013	0.003	0.003	0.200	0.027	−0.218	−1.743	−0.024	0.221	1.943
2013/2014	0.003	−0.011	−1.872	−0.038	0.105	−1.008	0.041	−0.115	−0.864
2014/2015	0.016	−0.007	−0.004	0.052	−0.070	1.568	−0.036	0.062	−1.571
2004/2005–2014/2015	−0.003	0.002	−0.759	−0.011	−0.002	−0.775	0.008	0.005	0.016

with which these inputs were deployed. Dynamic technological change made positive contributions to dynamic productivity change of materials and other direct inputs, and investments, but these were insufficient to undo the negative effect of dynamic technical efficiency loss.

5.2 | Relation between input- and investment-specific dynamic productivity change and corporate social responsibility

The summary of the results on the relation between input- and investment-specific dynamic productivity change and its components, and CSR and its components, is presented in Appendix B.

5.2.1 | Main analysis—overall CSR score

Table 4 presents the results of the regression of the overall *CSR_Score* on input- and investment-specific dynamic productivity change (*DPC_Mat*, *DPC_Emp*, *DPC_Inv*) and its components (technical inefficiency change and technological change).

The results in Table 4 show that investment-specific dynamic productivity change associates negatively with the overall *CSR_Score*. The parameter value of −0.001 for *DPC_Inv* suggests that firms having a one unit higher productivity change of investments, *ceteris paribus*, have a 0.001 lower *CSR_Score*. Since the average *CSR_score* is 0.033, it can be concluded that the effect of a one unit change in the productivity change of investments is very small. The negative relation between *CSR_score* and productivity change of investments is mainly attributable to a lower efficiency of the use of the existing technology, as shown by the negative relation between *CSR_Score* and *DEC_Inv*. The parameter value of −0.001 for investment-specific inefficiency change is the same as the parameter value for investment-specific productivity change.

Results in Table 4 also show that a higher *CSR_Score* associates with a lower dynamic technological change and a higher dynamic inefficiency change of the use of materials and other direct inputs. The result suggests that a one unit increase in the dynamic technical inefficiency change of materials and other direct inputs is associated with an 0.307 higher *CSR_Score*, whereas a one unit increase in dynamic technical change of materials is associated with a 0.355 lower *CSR_Score*. In light of the average values of *CSR_Score* of 0.033, this suggests a strong effect. However, the firms succeed in undoing the negative effect of the new technology on the use of materials and other direct inputs by increasing the efficiency with which the new technology is used.

The negative association between CSR and productivity change for investments in our results are in line with those of Granderson (2006), who suggested CSR activities limit the productive effects of productivity change. Our finding of a positive association between CSR and inefficiency change for materials and other direct inputs is in line with previous studies (Guillamon-Saorin et al., 2018; Hou et al., 2019; Sun & Stuebs, 2013; Wang et al., 2014). It should be noted though that the aforementioned studies found a positive relation between CSR and the efficiency of all inputs simultaneously, whereas our study analyzes the relationship for each input separately. Materials and other direct inputs being the main variable input of firms, could drive the positive association between overall efficiency and CSR.

Overall, the results of the control variables are robust across specifications. Hence, the same variables are significant, and the signs of the parameters do not change across the three specifications. The results of the control variables show that *CSR_Score* negatively associates with *Size* and positively associates with the *MTB* ratio. Hence, larger firms have, *ceteris paribus*, lower *CSR_Scores* than smaller firms. This relation could confirm an earlier finding that larger firms are often older firms that have fewer investment opportunities (Servaes & Tamayo, 2013). The finding that firms with a relatively high market value have, *ceteris paribus*, higher *CSR_Score* is in line with the prior expectation that more stable firms with higher market-to-book ratios will have higher CSR engagement (Lys et al., 2015). All of the other financial and profitability measures included in the control variables have no

TABLE 4 Input- and investment-specific dynamic productivity change and its components and *CSR_Score*

Dependent variable	(1) *CSR_Score*	(2) *CSR_Score*	(3) *CSR_Score*
Variables of interest			
DPC_Mat	0.069		
DPC_Emp	0.222		
DPC_Inv	−0.001*		
DEC_Mat		0.307*	
DEC_Emp		−0.073	
DEC_Inv		−0.001**	
DTC_Mat			−0.355*
DTC_Emp			0.122
DTC_Inv			0.003
Control variables			
Size	−0.355*	−0.365**	−0.360**
MTB	0.001**	0.001**	0.001**
Leverage	−0.253	−0.284	−0.219
Cash_assets	0.510	0.487	0.539
Asset_turnover	−0.202	−0.228	−0.209
Profit_margin	0.029	0.086	0.105
Pre_crisis	−0.840***	−0.828***	−0.822***
Crisis	−0.751***	−0.743***	−0.745***
Constant	3.499*	3.614**	3.529*
Fixed effects	Yes	Yes	Yes
R^2	0.274	0.277	0.276

*Statistical significance at 10% level

**Statistical significance at 5% level.

***Statistical significance at 1% level.

statistically significant association with *CSR_Score*. These findings suggest that CSR policy is not likely affected by year-to-year changes in these variables. The time dummies reflecting the precrisis, crisis, and postcrisis periods suggest that the *CSR_Score* was ceteris paribus lower in the precrisis and crisis years than in the postcrisis period, and that firms speeded up their CSR efforts substantially after the crisis. The postcrisis reflects the period when CSR became a more prominent activity for firms. It should be noted though that the time dummies do not only pick up the effect of the crisis, but generally any factor that differs between precrisis and crisis years and that is not captured by any of the other regressors in the model.

5.2.2 | Additional analysis—CSR dimensions (social, environmental, and governance CSR)

Our study also investigates the relation between CSR dimensions of social, environmental, and governance CSR (*CSR_Soc*, *CSR_Env*, and *CSR_Gov*, respectively) and dynamic productivity change for each input and investment and each of its components (input- and investment dynamic technical inefficiency change technological change). Table 5 presents the findings.

The results for *CSR_Env* and *CSR_Gov* in Table 5 confirm the negative association between investment-specific dynamic productivity changes with overall *CSR_Score* that was found in Table 4. Hence, a one unit improvement in the investment-specific dynamic productivity comes with a 0.001 decrease of *CSR_Env* and *CSR_Gov*. These results could suggest that measures taken by firms for improving the environmental and governance CSR performance draw on resources and reduce the firm's investment capacity. The implementation of the CSR measures may require more resources such as materials and other direct inputs, and employees that could otherwise have been used to enable the implementation of new investments.

The negative relation between *DTC_Mat* and *CSR_Score* in Table 4 is confirmed in Table 5 by a negative association between *DTC_Mat* and the CSR governance score. Hence, an increase of dynamic technological change of materials and other direct costs, which reduces the quantity needed of materials and other direct inputs for producing the same quantity of output is associated with a lower *CSR_Gov* score. This suggests that the implementation of measures enhancing the CSR governance performance requires the use of more materials. Improvements in the dynamic efficiency with which materials and other direct inputs are used, on the other hand, comes with an increase of the *CSR_Soc* score; this suggests that firms that have implemented CSR social measures are also better at using the production potential of materials and other direct inputs. Hence, firms that simultaneously pursue a higher score for *CSR_Soc* and *CSR_Gov*, will have small increase due to technological change induced by *CSR_Gov* (−0.147), which is more than offset by a decrease in the use due to a more efficient use of inputs as induced by *CSR_Soc* (0.260).

The results in Table 5 also confirm the negative relation between dynamic inefficiency change of investments with CSR which was found in Table 4. It can be seen that dynamic inefficiency change of investments is negatively associated with *CSR_Env* and *CSR_Gov* Hence, these results suggest that firms that have implemented *CSR_Env* and *CSR_Gov* have a lower potential to conduct investments.

The results in Table 5 also find a relation that remained undetected in the regression of the overall *CSR_Score*, which is the positive relation between *CSR_Soc* and employee-specific dynamic technological change (*DTC_Emp*). This result implies that a higher CSR social performance is associated with a higher employee-specific dynamic technological change, suggesting that firms that enhance the competences and skills of their labor increase their CSR social performance simultaneously. This result might also suggest that employees of the frontier firms become more motivated and their firms score better in terms of CSR social performance. The higher contribution of employee-specific dynamic technological change is partly offset by a lower, albeit statistically insignificant, dynamic inefficiency change.

The results of the control variables largely remain unchanged compared to the *CSR_score* regression in Table 4. The main differences are that *Size* does not associate significantly with *CSR_Soc*, and *MTB* does not associate significantly with *CSR_Env* and *CSR_Gov*. Hence, large firms, *ceteris paribus*, only have a lower *CSR_Env* and *CSR_Gov* score, but do not have a lower *CSR_Soc* score than small firms. Also, firms with a relatively high market-to-book ratio, *ceteris paribus*, only have a larger *CSR_Soc* score and do not differ from firms with lower *MTB* ratios in terms of *CSR_Env* and *CSR_Gov*. This implies that *CSR_Soc* is important for the market value of the firm and that size is a more important determinant of the *CSR_Env* and *CSR_Gov* score. The results in Table 5 also suggest that firms with a higher efficiency of the use of their assets (*Asset_turnover*), *ceteris paribus*, have a lower *CSR_Env* and in one case a lower *CSR_Gov* score. Hence, higher asset efficiency comes at the cost of, in particular, the CSR environmental performance of the firm, but less for the other CSR components. The results of the precrisis and crisis dummies present the same message as those of the *CSR_Score* regression in Table 4. That is, firms have considerably speeded up their CSR efforts after the crisis and when firms increased their interests in promoting CSR, and the efforts affect all CSR dimensions. Nevertheless, the results suggest that CSR improvement is more pronounced for the CSR social performance than for the CSR environmental and CSR governance performance.

We also conducted a number of additional tests to determine the robustness of the findings. First, we analyzed an alternative construction of CSR variables. Following prior research (Flammer, 2015), we measured CSR through strengths only and our results of regressions remained unchanged. Second, we undertook several robustness tests related to control variables. In particular, we tried an alternative measure of firm size using the natural logarithm of the number of employees, and our main findings remained unchanged. Also, instead of using two components of ROA (*Asset_turnover* and *Profit_margin*) in the regression, we used ROA itself and our findings persisted. Finally, we also checked the change in the definition of the crisis dummy. Although the US economic recession ended in 2009,

TABLE 5 Input- and investment-specific dynamic productivity change and its components and *CSR_Soc*, *CSR_Env*, and *CSR_Gov*

Dependent variable	(1) *CSR_Soc*	(2) *CSR_Soc*	(3) *CSR_Soc*	(4) *CSR_Env*	(5) *CSR_Env*	(6) *CSR_Env*	(7) *CSR_Gov*	(8) *CSR_Gov*	(9) *CSR_Gov*
Variables of interest									
DPC_Mat	0.244			−0.098			−0.076		
DPC_Emp	0.102			0.028			0.092		
DPC_Inv	0.001			−0.001***			−0.001***		
DEC_Mat		0.260**			−0.036			0.084	
DEC_Emp		−0.092			0.018			0.000	
DEC_Inv		0.001			−0.001***			−0.001***	
DTC_Mat			−0.213			0.005			−0.147*
DTC_Emp			0.129**			−0.017			0.010
DTC_Inv			0.001			0.001			0.000
Control variables									
Size	−0.144	−0.149	−0.144	−0.124***	−0.124***	−0.125***	−0.086***	−0.091***	−0.091***
MTB	0.001***	0.001***	0.001***	−9.69E-05	−1.02E-04	−1.16E-04	4.43E-05	4.37E-05	3.82E-05
Leverage	−0.081	−0.085	−0.069	−0.082	−0.089	−0.066	−0.090	−0.110	−0.085
Cash_assets	0.234	0.227	0.261	0.163	0.162	0.166	0.112	0.098	0.113
Asset_turnover	−0.012	−0.024	−0.013	−0.100**	−0.103**	−0.099**	−0.090	−0.101*	−0.097
Profit_margin	0.006	0.063	0.067	0.021	0.012	0.013	0.002	0.011	0.024
Pre_crisis	−0.467***	−0.451***	−0.446***	−0.200***	−0.205***	−0.206***	−0.173***	−0.173***	−0.170***
Crisis	−0.493***	−0.484***	−0.480***	−0.147***	−0.148***	−0.152***	−0.112***	−0.111***	−0.113***
Constant	1.406	1.457	1.388	1.241***	1.250***	1.244***	0.852***	0.908***	0.898***
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.187	0.190	0.188	0.280	0.280	0.260	0.111	0.113	0.112

***Statistical significance at 1% level.
**Statistical significance at 5% level.
*Statistical significance at 10% level.

the recovery after this year was still weak. Therefore, we extended the crisis dummy to include 2010 and 2011, and we found that it did not change our results.[14,15]

6 | CONCLUSIONS

The method in this study has enabled us to progress prior work by carrying out a detailed analysis of the links between productivity change and CSR. With our approach, we can answer the question of whether CSR is related with dynamic productivity changes of each input employed and investment undertaken by the US food and beverage companies. The use of a dynamic production framework that allows us to capture the determinant role of adjustment costs related with firms' investments permits the development of unbiased measures of firm performance (Kapelko et al., 2014; Silva & Stefanou, 2003, 2007; Silva et al., 2015). Using this framework, we have found that the association between dynamic productivity change and CSR reflects only specific inputs or investments. Moreover, only certain dimensions of the CSR measure participate in this association.

Our study supports the overall evidence in prior research that CSR is associated with firm's competitiveness by productivity change. The article contributes to the literature by being the first empirical research to analyze the relation between input- and investment-specific dynamic productivity change and CSR of firms. Our results show that the firm's CSR performance is negatively associated with investment-specific dynamic productivity change and with dynamic technological change related with materials and other direct inputs, whereas it is positively associated with dynamic efficiency improvement associated with materials and other direct inputs. The analysis for individual CSR dimensions—social, environmental, and governance—provides further insights into the linkages between CSR and productivity change. Firms that have larger social and governance CSR scores are characterized by higher dynamic efficiency of materials and other direct inputs, but a lower dynamic technological change of materials and other direct inputs. Higher dynamic productivity of investments is particularly associated with a lower score of the social and governance CSR dimensions, and higher dynamic technological change of employees is positively associated with the CSR performance in the social dimension.

The findings of our study have managerial implications. Managers can better understand what aspects of CSR are relevant for companies in the food and beverage industry and also what input and investments have a greater role in the association between CSR and productivity change. It is important to understand these issues to maintain the competitiveness of companies in the current global economy.

Future research needs to assess the robustness of these findings. In particular, despite the efforts to address the endogeneity, future research could consider applying other methods. The other limitation of our study is the selection bias derived from the use of KLD database. The companies included and rated by KLD are possibly better performers than those that were not included. The use of KLD to capture CSR could be replaced by other types of proxies (such as other measures of customer support, positive supplier relations, and employee perceptions of organization concern). Also, our research did not consider the role of ownership structure such as ownership concentration and the shareholder's sophistication, which could affect the corporate investment decisions. An interesting line of future research would be to develop a model to measure dynamic efficiency and/or productivity change integrating CSR as netput. Finally, our study focuses on a specific sector in a specific country, that is, food and beverage in the USA, which means the results are not necessarily generalizable and are potentially different for other sectors and countries. Future research could extend our analysis method and framework to other sectors and/or countries.

[14]We also tried the interaction variables and nonlinearities in the models, but we did not find significant results.

[15]Detailed results for all additional robustness tests can be obtained from the authors upon request.

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APPENDIX A: CONSTRUCTION OF CSR VARIABLES A

Adjusted strength and concern scores for each CSR category *j*

$$\text{adjusted strength for firm } i \text{ and category } j = \frac{\text{sum of all strength scores of category } j \text{ for firm } i \text{ at year } t}{\text{maximum number of strengths of category } j \text{ at year } t}$$

$$\text{adjusted concern for firm } i \text{ and category } j = \frac{\text{sum of all concern scores of category } j \text{ for firm } i \text{ at year } t}{\text{maximum number of concerns of category } j \text{ at year } t}$$

Net scores for each CSR category *j*

COMMUNITY_i = (adjusted community strength for firm *i* − adjusted community concern for firm *i*)

DIVERSITY_i = (adjusted diversity strength for firm *i* − adjusted diversity concern for firm *i*)

EMPLOYEE_i = (adjusted employee relations strength for firm *i* − adjusted employee relations concern for firm *i*)

HUMAN_i = (adjusted human rights strength for firm *i* − adjusted human rights concern for firm *i*)

PRODUCT_i = (adjusted product strength for firm *i* − adjusted product concern for firm *i*)

ENVIRONMENT_i = (adjusted natural environment strength for firm *i* − adjusted natural environment concern for firm *i*)

GOVERNANCE_i = (adjusted corporate governance strength for firm *i* − adjusted corporate governance concern for firm *i*)

CSR variables

CSR_Score = COMMUNITY + DIVERSITY + EMPLOYEE + HUMAN + PRODUCT + ENVIRONMENT + GOVERNANCE

CSR_Soc = COMMUNITY + DIVERSITY + EMPLOYEE + HUMAN + PRODUCT

CSR_Env = ENVIRONMENT

CSR_Gov = GOVERNANCE

Note: *j* = community, diversity, employee relations, human rights, product, natural environment, corporate governance.

APPENDIX B: SUMMARY OF RESULTS ON THE RELATION BETWEEN CSR AND DYNAMIC INDICATORS B

		CSR_Score	*CSR_Soc*	*CSR_Env*	*CSR_Gov*
Dynamic productivity changes	Materials and other inputs	NS	NS	NS	NS
	Employee	NS	NS	NS	NS
	Investments	Neg.	NS	Neg.	Neg.
Dynamic technical inefficiency changes	Materials and other inputs	Pos.	Pos.	NS	NS
	Employee	NS	NS	NS	NS
	Investments	Neg.	NS	Neg.	Neg.
Dynamic technological changes	Materials and other inputs	Neg.	NS	NS	Neg.
	Employee	NS	Pos.	NS	NS
	Investments	NS	NS	NS	NS

Note: Pos. and Neg. indicate either positive or negative significant coefficients at the 1%, 5%, or 10% levels. NS indicates nonsignificant coefficients.