Sustentabilidade

Corporate Social Responsibility and Technical Efficiency: A Stochastic Frontier Approach

Carlos Manuel Pinheiro
jfalmeida@ua.pt
Universidade Europeia, BRU/ISCTE- Instituto Universitário de Lisboa, ISCAL – Instituto de Contabilidade e Administração de Lisboa, Instituto Politécnico de Lisboa

Paulo Pereira da Silva
fernandoazenha@ua.pt
Comissão do Mercado de Valores Mobiliários (CMVM), CEFAGE – University of Évora, ISCAL – Instituto de Contabilidade e Administração de Lisboa, Instituto Politécnico de Lisboa

Abstract
Sustainability has become the new normal for value creation in the long haul, and is on the top of board agendas. We assess the relationship between the social pillar of ESG and a firm's output gap justified by systematic inefficiency. To do so we apply a stochastic frontier model to a large sample of U.S. listed firms, spanning 2005 to 2019. Focusing on measures of companies' management commitment and effectiveness towards catering closely to their workforce job conditions and well-being, we document an economically sizable and statistically significant positive association between technical efficiency and social responsibility performance. Employee-oriented CSR practices appear to be relevant aspects in explaining the association of socially responsible practices with technical efficiency. Firm inefficiency is explained by firm specific factors and is a decreasing (increasing) function of size and external monitoring (leverage, blockholdings and foreign sales). It is mitigated by CSR practices and external governance mechanisms, as well as market surveillance. The association between CSR and technical efficiency is non-linear and varies across industry sectors. Our results should interest managers and stakeholders in general.

Palavras-chave: Stochastic Frontier, Technical Efficiency, Corporate Social Responsibility

1. Introduction

The top 500 Fortune global companies invest around 20 billion USD a year on corporate social responsibility (CSR) activities. Can environmental and social efforts save money and make organizations more efficient and productive (Carroll and Shabana, 2010; Meier and Cassar, 2018; Serafeim, 2022)?

Some argue that managers use CSR investments to build their reputations, going beyond the interest of the firm (Wright and Ferris, 1997; Ferrel et al., 2017), a view supported by agency theory (Jensen and Meckling, 1976). Others find that CSR practices favor firm performance (Harjoto and Jo, 2011; Madorran and Garcia, 2016; Lins et al., 2017), or increase firm value (Khuong and Anh, 2022), arguing that CSR might provide internal or external benefits enhancing stakeholder engagement (Cheng et al., 2014). This view agrees with stakeholder theory (Freeman, 1984) and resource-based underpinnings (Wernerfelt, 1984; Barney, 1991). Still others claim that managers can determine the level of CSR via cost-benefit analysis and profit maximization in the same way they analyze other investments (McWilliams and Siegel, 2001; Lopez et al., 2007).

These divergences have motivated a large number of empirical studies analyzing the link between CSR practices and almost exclusively firm financial performance[1]. The association between firm financial performance and CSR has been found predominantly positive.

Our study makes a number of contributions. First, despite the copious literature on how well can assets be used to produce revenue (proxied by firm financial performance) making the most of resources (proxied by firm efficiency), to the best of our knowledge our study is the first to analyze the link between CSR practices and firm's maximization of output given a set of inputs relative to the best possible reference set, which is denoted technical efficiency. Technical efficiency is proxied by value added along the lines of Lieberman and Dhawan (2005). Focusing on technical efficiency enables us to explore hypotheses concerning CSR and the firm's ability to produce a given set of output using as few inputs as possible[2].

Second, we run a stochastic frontier analysis (SFA) model, a succinct way to explore hypotheses concerning efficiency differentials among firms. Efficiency can be viewed as the distance to the optimum level of output at a given input. Simple financial ratios have been found unable to uncover the gap between actual and optimal performance (Richard et al., 2009; Arbelo et al., 2021). Frontier analysis is a concise way to explain variations in efficiency across firms (Reifschneider and Stevenson, 1991; Schmidt, 2011). SFA builds on the microeconomic

[1] Orlitzky (2001), Margolis and Walsh (2003), Orlitzky, Schmidt, and Rynes (2003), Beurden and Gössling (2008), Harjoto and Jo (2011), and Agudelo et al. (2019) are among those who reviewed extant studies on CSR. More recent studies on CSR and firm performance include Adegebite et al. (2019), Albuquerque et al. (2019), Ahmad et al. (2021).

[2] Unlike ours, most studies use economic efficiency as a measure of economic performance. Economic efficiency refers to the firm's ability to generate maximum possible profit at the lowest cost (cost efficiency) for a given level of output (profit efficiency) – see, for example, Fried et al. (2008) for an analysis of the various types of efficiency and methods to measure it. Cost efficiency can be represented as the sum of technical efficiency and allocative efficiency. The latter measures the inability of a firm to choose the correct input combination (Coelli et al., 1998).

concept of production function and is superior as compared to the traditional ordinary least squares' estimation method. SFA measures inefficiency as the failure to reach the frontier (Ang et al., 2021; Minh and Quang, 2022).

Third, we apply Battese and Coelli (1995)'s improved model of stochastic frontier analysis to estimate simultaneously firm efficiency scores and the determinants of firm efficiency. Finally, we delve into the social pillar of ESG and more specifically on companies' effectiveness to increase their workforce loyalty and productivity. The well-being of engaged workers more aligned with the company's values should drive firm technical efficiency.

Our results document a positive and significant association between corporate social responsibility and technical efficiency. Among social- and governance-oriented commitments by companies, workforce welfare yields the strongest relationship to technical efficiency. This relationship is economically more significant in labour-intensive industries, namely those requiring more skilled workers (e.g. agriculture, hospitality, mining, transportation).

We start by reviewing extant studies. In Section 3 we describe our data, method and variables. We present our findings in Section 4 and our conclusions in Section 5.

2. Literature Review and Related Hypotheses

CSR encapsulates economic, environmental and social imperatives, which are balanced by the firm to address the expectations of shareholders and stakeholders beyond what is required by regulations (Binh et al., 2022)[3]. Extant studies on CSR rarely analyzed outcomes other than firm performance (Pfajfar et al., 2022).

Through the lens of stakeholder theory, CSR might contribute to better firm reputation and legitimacy (Minh and Quang, 2022), appealing to socially minded consumers, investors and workers (Binh et al., 2022). Consumers favour buying products from socially responsible brands and motivated workers in employee-friendly firms become more aligned with the firm's goals becoming more productive. Building on stakeholder theory, we expect CSR engagement to pay off in terms of profit enhancement, thus reducing firm's technical inefficiency. Whether CSR practices relate to firm technical efficiency is ultimately an empirical question that we intend to test.

[3] The history of corporate social responsibility is long and vast (Agudelo et al., 2019). CSR evolved as socially responsible concerns were attended and legislation was enacted, calling for a holistic approach of the broad set of interested parties to optimize firm value in the long haul (Chandler, 2022).

Hypothesis 1: There is a negative relationship between CSR practices and firm technical inefficiency.

Extant studies use aggregate scores to analyze the relationship between CSR and corporate performance. An increasing number of recent studies builds on stakeholders' engagement and environmental economics (Ismail et al., 2019; Qureshi et al., 2020; Matakanye et al., 2021). The burgeoning literature on environmental, social and governance (ESG) corporate practices, while focusing on financial performance also calls for corporate environmental and social performance (Ellili, 2022). In fact, companies' efforts to reduce carbon emissions and climate change are a group of studies gaining traction (Ng and Leung, 2020; Garzón-Jiménez and Zorio-Grima, 2021). The main differentiation among firms in ESG stands out mostly in their environmental practices (Clare et al., 2022). Nonetheless, the vast majority of empirical studies regress CSR aggregated subscores (environmental, social responsibility, governance) on an outcome (e.g., performance, firm value).

We take a deeper dive by focusing on the internal stakeholders of the firm, specifically the staff. To do so we use WORKFORCE, a social sub-score from ESG ratings referring particularly to the workforce. WORKFORCE measures a company's success towards job satisfaction, a healthy and safe workplace, while maintaining diversity, and equal opportunities, and development opportunities for its staff. This category should provide a specific contribution to explain technical efficiency. A few studies have addressed specific stakeholders (Pfajfar, 2022) and employee-friendly firms (Cao and Rees, 2020). Pfajfar (2022) finds a positive relationship between employee-focused firms and CSR performance. In a paper closer to ours, Cao and Rees (2020) document that employee-friendly firms invest more efficiently. Previous studies have shown that employee-friendly policies can improve the firm's operational and financial performance. However, agency theory claims that entrenched managers might not always act in the best interest of organizations. Managers might want to retain staff not to have the trouble of recruiting and motivating more skilled and productive workers. This might be achieved just by paying higher wages, at the cost of technical efficiency (Bertrand and Mullainathan, 1999). So, retained staff might not be productivity-oriented, nor engaged in maximizing the output.

Hypotheses 2a b: There is a (a) stronger - (b) weaker - relationship between employee-oriented CSR and technical efficiency as compared to other social and governance practices.

In a similar vein, the relationship between CSR and technical efficiency might be the result of two countervailing forces. On one hand motivated and engaged employees might drive the firm toward producing the maximum output for a given set of inputs. On the other hand, entrenched managers might engage in lower wage bargaining effort, poised to improve social relations with less productive employees to enjoy private benefits, while maintaining a positive social climate (Cronqvist et al., 2009). This stance might add to firm inefficiency.

Hypotheses 3: The relationship between employee-oriented CSR and technical efficiency is non-linear.

3. Data, Method and Variables

3.1. Data

We obtained data from three Refinitiv/Thomson Reuters databases, spanning 2005 to 2019: Eikon, I/B/E/S, and Worldscope/Datastream. Eikon is the leading corporate social responsibility database (Villiers et al., 2022). It gathers information from annual reports, corporate sustainability reports, NGOs, and news sources for large, publicly traded companies.

The data on CSR obtained from Eikon are supplemented with data collected from Worldscope/Datastream. We use the latter source to gather firms' accounting data, four-digits SIC sectors, and ownership variables. We collect information on analyst coverage from I/B/E/S. Firms from the financial industry are excluded from the investigation. In addition, we also remove firm-year observations in which the number of employees, fixed assets, sales or cost of goods sold are missing. We exclude firm-year observations presenting negative value added.

3.2. Method

We compare a firm's actual value added (VA_{it}) to the value added of a hypothetical fully-efficient firm. In that regard, our work differs from earlier studies that address the average function of an outcome (most of times a financial performance indicator, e.g. Tobin's Q or return on assets). Deterministic production functions fit a frontier function above the data, assuming no statistical noise (Coelli et al., 1998).

Our econometric approach is stochastic, a mix of the two above regression models. Stochastic frontier analysis (SFA) allows pinpointing a frontier function at which most efficient firms are operating for a given set of inputs. Unlike OLS, one interesting feature of stochastic frontier models is that the two-sided, zero-mean regression error term is supplemented with a one-sided error term. While the symmetric component is associated with random variation (noise) of the boundary across firms (as in the former OLS approach), the (new) one-sided component aims at capturing inefficiency (Kumbhakar and Lovell, 2003). SFA judiciously incorporates both noise and inefficiency into the model specification (Fried et al., 2008).

To put it another way, the frontier function is estimated in conjunction with a technical (in)efficiency term. Technical efficiency[4] refers to operating at the production function. The inefficiency term equals zero for firms attaining the highest level of output, but it is strictly positive for other firms that are inefficient, i.e., fail to reach the highest level of output given their inputs.

So, our first step is to estimate the production function. We explore the method developed by Battese and Coelli (1995) to simultaneously estimate the frontier production function and the inefficiency model, thereby avoiding the biases of the two-step procedure (Wang and Schmidt, 2002)[5].

3.3. Variables

Economic value added (VA_{it}) is our dependent variable (output). Along the lines of Lieberman and Dhawan (2005), value added is computed as the difference between resources and the cost of goods sold[6]. We consider two input variables capital and labor, proxied by total fixed assets (K_{it}) and the number of employees (L_{it}), respectively. We assume the stochastic production frontier model to take a Cobb-Douglas (model (1) of table 3) or a translog form (models (2)-(4) of table 3). Following Díaz and Sanchez (2005) and Taymaz (2005), we also

4 The technical efficiency (TE) of a firm may be defined as the ratio of its output to that of a fully efficient firm employing the same inputs. TE resembles a firm's scaling factor relative to the frontier: 0<TE≤1.

5 The Battese and Coelli (1995) model can be written as $Y_{it} = f(X_{it};\beta) \times \exp\,(v_{it} - u_{it})$, where i and t denote firms and period, respectively, Y represents output, X is the set of inputs; β is a parameter vector, v_{it} is a two-sided random error, assumed to be iid $N(0, \sigma_v^2)$; u_{it} stands for a non-negative random variable representing the inefficiency which is assumed to be distributed independently and obtained by truncation at zero following $N(0, \sigma_u^2)$.
Along the lines of Lieberman and Dhawan (2005), we use a log transformation to make the model linear with respect to the parameters of the production function: $\ln(Y_{it}) = \ln\big(f(X_{it};\beta)\big) + v_{it} - u_{it}$
Battese and Coelli (1995) specify TE (u_{it}) as a function of firm-specific, time-varying factors: $u_{it} = \sum_{j=1}^{M} \delta_j \times Z_{ijt} + W_{it}$, with Z_{ijt} denoting a vector of variables that may produce effects over firm efficiency and W_{it} standing for a random variable defined by the truncation of the normal distribution with zero mean and variance σ^2. In this setting, technical efficiency is represented by: $TE_{it} = \exp\big(-\sum_{j=1}^{M}(\delta_j \times Z_{ijt} + W_{it})\big)$. The production function coefficients (β), the inefficiency model parameters (δ), and the variance parameters ($\sigma_S^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma_S^2}$) are estimated in tandem using the maximum likelihood estimator.

6 In a robustness check, value added was computed as sales minus cost of goods sold, minus selling and general administrative expenses.

enter industry (two-digit SIC code) fixed effects and time fixed effects. The inclusion of time dummies (and a time trend t, in models (3) and (4)) in the production frontier allows for shifts of the frontier over time, which captures technical change. Industry-level variables seek to capture industry-specific heterogeneity in the innovative environment. The translog function[7] for model (4) can be written as:

$$\ln(VA_{it}) = \alpha_0 + \alpha_1 * \ln(Fixed\ Assets_{it}) + \alpha_2 * \ln(Employees_{it}) + \alpha_3 * \ln(Fixed\ Assets_{it})^2 + \alpha_4 * \ln(Employees_{it})^2 + \alpha_5 * \ln(Employees_{it}) * \ln(Fixed\ Assets_{it}) + \alpha_6 * t + Industry\_FE + Year\_FE + (v_{it} - u_{it}) \quad (1)$$

In a more succinct form, let $Fixed\ Assets_{it} = K_{it}\ and\ k_{it} = \ln(K_{it}); Employees_{it} = L_{it}\ and\ l_{it} = ln(L_{it})$; equation (1) can be rewritten as:

$$\ln(VA_{it}) = \alpha_0 + \alpha_1 * k_{it} + \alpha_2 * l_{it} + \alpha_3 * k_{it}^2 + \alpha_4 * l_{it}^2 + \alpha_5 * l_{it} * k_{it} + \alpha_6 t + Industry\_FE + Year\_FE + (v_{it} - u_{it}) \quad (2)$$

In our setting the inefficiency component varies along time. So, an initially inefficient firm might become more efficient over time. One concern with the inefficiency component is endogeneity and the omission of relevant variables. Hence, to analyze the determinants of the systematic inefficiency component, we follow previous literature and add other covariates (CONTROLS) that could be related to both firm inefficiency and CSR performance.

$$u_{it} = ß_0 + ß_1 * CSR_{it} + \sum_{j=1}^{M} ß_j * CONTROLS_{ijt} + W_{it} \quad (3)$$

Size is proxied by the logarithm of total assets. On the one hand, size might enhance efficiency if firm operation is associated with large fixed costs. On the other hand, larger firms might become inefficient in a fast-changing ecosystem. For example, in large firms with higher headcount might add to complexity, requiring extra layers of administrative control (organizational form) and other frictions, thereby elevating inefficiency (Cohen et al., 2012). We expect the logarithm of the ratio of the number of employees to total fixed assets to control for this effect. Ln(Age) is also used in extant studies to proxy for firm growth.

7 In our empirical model, we use a logarithmic transformation of value added. First and foremost, this allows transforming a non-linear specification into a linear model. Correspondingly, frontier parameters resemble input elasticities. Second, it helps lessen the influence of extreme observations and skewness on the final results. Third, it lessens the influence of heteroskedasticity on statistical inference.

Along the lines of Jensen (1986) we include Leverage in the model. The degree of leverage reduces managers' capacity to divert funds from the firm or to realize poor investments and more indebted firms might be subjected to greater external monitoring by creditors. On the other hand, more indebted firms might have less leeway to adapt technology to improve efficiency, because they might lack the required funding flexibility as they become more dependent on external funding.

Foreign sales aim to capture product market competition. The underlying rationale is that market competition induces management effort and limits their capacity to capture private benefits from the firm. In a similar vein, Global is a binary variable taking the value of 1 in case the firm obtains revenues outside the U.S. As a measure of revenue diversification, we enter the Herfindahl-Hirschman index (HHI) based on the revenues of the firm at each four-digit SIC code division. The number of financial analysts following the firm is used as an additional proxy for external monitoring of firm's management.

We enter Insider Holdings and Holdings of the Controlling Shareholder (Blockholder) in order to control for the presence of agency conflicts between management and shareholders (Jensen and Meckling, 1976). Morck, Shleifer, and Vishny (1988) establish an association between the holdings of managers and firms' Q. To proxy an external governance mechanism, we enter the number of Analysts issuing forecasts for the firm. Along the lines of finance and accounting literature the controls are lagged for one period.

The average firm has around $4 billion in total assets and a leverage ratio of approximately 23%. The median firm does not sell outside the U.S., it is followed by two analysts and the percentage of closely held shares is about 23%. The median net sales growth over a 5-year period attains 6%.

4. Results

Table 3 presents the results for running Cobb-Douglas trans-logarithmic (translog) production functions, which model the relationship between value added (output) and labour (ln employees) and capital (ln fixed assets). We enter industry fixed effects in all specifications. The estimates for labour and capital are statistically significant at 1% level and their values suggest that the increase in either productivity factor leads to an increase in the output, although with declining returns-to-scale. We conduct a z-test to ascertain whether all firms operate at the maximum possible output (efficient frontier). The results of the z-test document the existence of technical inefficiency effects ($\sigma_u^2 \neq 0$), calling for the inefficiency component to be included in a model to account for systematic inefficiencies across firms.

We enter time fixed effects in models 1 and 2 of table 3, to avoid a specific year biasing the results. Moreover, in models 3 and 4 we replace time fixed effects by a time trend. The estimated coefficient of the time trend (model 3) has a negative value suggesting that technological progress is decreasing over time. However, entering the square of the time trend (model 4) the estimated coefficients suggest a non-linear, inverse U-shaped relationship between technological progress and value-added over time.

In order to gain further insights on its determinants, we regress the inefficiency component on the social pillar score (SOCIAL), workforce subscore (WORKFORCE), the governance score (GOVERNANCE) and a set of covariates[8]. We run a two-step procedure along the lines of Jondrow et al. (1982). In model 1 of table 4 we enter WORKFORCE and Size in the second step. Model 2 adds the SOCIAL score and firm CONTROLS. While using also translog functions to estimate the efficient production frontier, models 3 to 7 enter industry-specific elasticities in the first step in estimating various translog production functions for robustness. We run models 1-7 entering industry fixed effects and a time trend, except in model 5 in which we replace the time trend by year fixed effects. To save space, table 4 presents the results for the second stage, i.e. the inefficient component, as depicted in equation (3).

The results across models 1-7 suggest that firms ranking higher in the social pillar of ESG are less inefficient (the estimates for SOCIAL are statistically significant at 1%, ranging -0.254 to -0.223). Most importantly, WORKFORCE is also statistically significant at 1% and adds to the contribution of the SOCIAL score when we enter them in the same run. When entered alone, i.e. in models 1 and 3, WORFORCE contributes more to reduce inefficiency than SOCIAL score. This is suggested by the higher estimate of WORFORCE sub-score (-0.352) as compared to the higher estimate of SOCIAL score (- 0223). To the best of our knowledge these are novel results, although in line namely with Cao and Rees (2020) who documented the benefits of employee-friendly practices in firm investment efficiency. Also, by focusing on the social pillar and delving deeper in social sub scores, our study contributes to a burgeoning strand of literature on micro-level research on Corporate Social Responsibility (Jones et al., 2019). In fig.1 we depict the evolution of the contribution of the social pillar using the results from five-year window runs. Interestingly the influence of socially responsible practices on firm inefficiency

[8] In an auxiliary test, we also examine whether the additional covariates entered in model (4) are jointly significant. The test confirms the relevance of squared and interaction terms to represent the production function of the analyzed firms.

shows a decreasing trend over time. This finding illustrates that firms' commitment to social responsibility has persisted for some time and is a resource with diminishing marginal returns as documented in other setups addressing limited resources (Flammer, 2015).

In H1 we hypothesized that firms adopting CSR practices are less inefficient. Overall, our findings suggest that CSR practices are negatively correlated with technical efficiency. H2a is also confirmed, as we find that employee-oriented social practices, proxied by WORKFORCE sub score, contribute to a stronger decrease in inefficiency, as compared to average social practices. These results are underpinned by legitimacy theory and extant studies documenting that some sectors are more visible and aim at higher standards (Garcia et al., 2017; Zaiane and Ellouze, 2022).

In what pertains the control variables our results suggest that Size, and Insider holdings reduce inefficiency. The former underpinned by economies of scale and the latter according with agency theory. In terms of governance, the Governance score loads negatively and so does external monitoring from gatekeepers (proxied by the number of Analysts), suggesting that both internal and external systems and processes are effective in reducing technical inefficiency. Holdings of controlling shareholders (Blockholders) load positively, suggesting an opposite effect, i.e. contributing to technical inefficiency. Diversification appears to have mixed effects on technical efficiency. Firms selling their products and services abroad (Foreign Sales), more subject to global screening by customers appear to be less efficient[9].

Finally, H3 is also confirmed as table 5 depicts. To save space, the estimation results concerning the efficient frontier are omitted. The results of the second stage document a U-shaped relationship between social responsibility and inefficiency. Low CSR scores or high CSR scores may be sup-optimal. To determine the optimal value of CSR represents an avenue for future research, requiring a finer-grained analysis, namely at the industry level or the firm business model. In fact, we run our specification with the WORFORCE sub-score for the Fama-French 17 industries classification, popular among finance research academics and practitioners[10]. Our results show that the inefficiency of more labour dependent industries (restaurants; hotels; agriculture; caregiving), but also some specialized ones (mining; transportation; consumer durables) is more affected by employee-oriented social practices (proxied by WORKFORCE).

[9] A large number of studies has documented the effects of diversification (Gulamhussen et al., 2017).

[10] See e.g. Bohjraj et al. (2003) for a detailed application of the Fama-French algorithm. The results are available form the authors upon request.

In all, our results underpin the importance of social and governance performance as drivers of technical efficiency, as hypothesized. We ran additional sensitivity tests to enrich our analysis and the previous results are confirmed[11].

5. Final Remarks

The burgeoning literature on corporate social responsibility mostly highlights its benefits in terms of financial performance. Our paper differs from past studies as we are interested in analyzing the influence of corporate social responsibility on technical efficiency. Technical efficiency is defined as the maximization of output given a set of inputs. We circumvent hurdles from previous studies on efficiency regarding measurement problems, self-selection bias, missing variables, or simultaneity, by using Cobb-Douglas production functions in a two-step procedure running a stochastic frontier model. This model allows us to simultaneously estimate firm efficiency scores and the significance of various factors that can determine firm efficiency. Our sample focusses on a large number of U.S. companies spanning 2004 to 2016, yielding a final sample of 12 389 firm-year observations.

Our findings suggest that good social practices boost firm technical efficiency. This relationship is economically substantive and is confirmed by a number of robustness tests, including endogeneity and multicollinearity checks. Chen et al. (2023) also find that the social and the environmental dimension of CSR lessen firms' restraints. More employee-friendly firms focusing on their workforces' loyalty and productivity are the ones appropriating greater benefits from social responsibility practices. We witness decreasing returns of workforce-friendly policies over time, as in other limited resources in the economy.

The positive effect on technical efficiency is non-linear suggesting an optimal point, apart from which the effect lessens. The reduction of technical inefficiency appears to be more relevant in labour-intensive sectors or for those with more specialized workforces. These sectors accrue greater benefits in terms of technical efficiency from CSR investment.

Are the aspects identified in our study persistent over time and in other jurisdictions?

[11] First, we winsorize dependent and independent variables from the stochastic frontier equation at the 1% and 99% tails inside each industry-year cell. Second, we employ alternative measures of value added and of fixed assets. Value added was also calculated as the difference between net sales and the sum of the cost of goods sold and selling, general and administrative expense. Net property, plant and equipment and net tangible assets were also used as proxies for fixed assets. Finally, we run the Battese and Coelli (1995) one-step procedure entering only firms for which CSR scores are available.

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Table 1 – Descriptive Statistics

Variable	Nr. Observ.	Mean	Std. Dev.	p10	p25	p50	p75	p90	Units
ln(Value added)	12 752	13.75	1.59	11.83	12.79	13.79	14.78	15.76	millions
WORKFORCE	12 956	42.20	7.01	0.94	4.08	14.46	38.38	68.18	ratio
SOCIAL	11 475	41.14	21.15	16.51	24.27	37.31	55.64	72.64	ratio
GOVERNANCE	11 475	47.68	22.69	17.20	29.31	47.77	65.71	78.45	ratio
ln(Size)	12 953	15.16	1.53	13.14	14.15	15.14	16.19	17.27	millions
Ln(Tangible Assets)	12 829	0.53	0.42	0.09	0.19	0.40	0.82	1.12	millions
ln(Employees)	12 667	8.88	1.73	6.61	7.84	8.99	10.04	11.05	thousands
ln(Employees/Fixed Assets)	12 573	5.25	1.54	3.67	4.25	4.91	5.95	7.57	ratio
ln(Fixed Assets)	12 829	14.13	1.98	11.53	12.91	14.22	15.52	16.75	millions
ln(Nr. Analysts)	12 095	1.95	0.72	1.10	1.39	1.95	2.48	2.89	number
ROA	12 698	0.08	0.14	-0.04	0.04	0.08	0.14	0.21	number
Market-to-book-value	12 893	4.47	6.58	1.15	1.71	2.79	4.74	8.41	ratio
ln(Net Profit Margin)	12 955	4.36	2.27	-9.39	1.72	6.09	11.36	19.25	millions
Leverage	12 949	0.23	0.17	0.00	0.09	0.22	0.34	0.46	ratio
Asset Turnover	12 952	0.92	0.72	0.27	0.44	0.74	1.18	1.81	ratio

Table 2 – Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1 WORKFORCE	1.0000											
2 SOCIAL	0.7925	1.0000										
3 GOVERNANCE	0.3571	0.3710	1.0000									
4 ln(Size)	0.5153	0.4649	0.3380	1.0000								
5 ln(Tangible Assets)	0.0477	0.0253	0.1670	0.1737	1.0000							
6 ln(Employees/Fixed Assets)	0.0755	0.0157	0.1432	0.3387	0.6346	1.0000						
7 ln(Nr. Analysts)	0.2533	0.3174	0.1375	0.3112	-0.0380	0.0306	1.0000					
8 ROA	0.1103	0.0916	0.0868	0.0569	-0.0136	-0.1368	0.0769	1.0000				
9 Market-to-book-value	0.0833	0.1017	-0.0605	-0.1394	-0.2330	-0.2330	0.1922	0.3982	1.0000			
10 ln(Net Profit Margin)	0.1552	0.1173	0.1061	0.2255	0.0138	0.1568	0.1150	0.6865	0.2240	1.0000		
11 Leverage	0.0202	0.0242	0.0621	0.2668	0.1782	0.2514	0.0557	-0.1802	-0.0233	-0.0822	1.0000	
12 Asset turnover	-0.0291	0.0447	0.0531	-0.2134	-0.0061	-0.4807	-0.0480	0.3594	0.1555	-0.1868	-0.2408	1.0000
13 Earnings per Share	0.4043	0.3562	0.1757	0.5653	0.0004	0.0643	0.6250	0.2188	0.1948	0.2429	-0.0445	-0.0688

Table 3: Stochastic Frontier Analysis

We estimate frontier functions using value-added as the outcome variable. The estimation is run on U.S. listed firms and covers the period 2005-2019. Several frameworks are considered: (1) Cobb-Douglas specification with year and two-digit SIC fixed effects (PF1); (2) trans-log specification with year and two-digit SIC fixed effects (PF2); (3) trans-log specification (no squared input variables) with two-digit SIC fixed effects and a trend variable (PF3); and (4) trans-log specification (with squared input variables) with two-digit SIC fixed effects and a trend variable (PF4). We present t-statistics clustered at the firm level in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted (***), (**), and (*), respectively.

	1	2	3	4
Production Frontier				
ln(Employees)	0.398***	0.045**	0.053**	0.57***
	(-56.64)	(-2.00)	(-2.33)	(-13.14)
ln(Fixed Assets)	0.406***	0.216***	0.221***	-0.408***
	(-64.08)	(-16.18)	(-16.59)	(-9.05)
ln(Fixed Assets)*ln(Employees)		0.024***	0.024***	-0.024***
		(-16.25)	(-15.99)	(-6.47)
trend			-0.015***	0.013*
			(-9.84)	(-1.93)
ln(Fixed Assets)2				0.037***
				(-15.43)
ln(Employees)2				0.01***
				(-4.55)
trend2				-0.002***
				(-4.48)
constant	4.963***	7.69***	7.88***	9.845***
	(-30.04)	(-32.9)	(-33.4)	(-36.14)
Distributions of u and v				
Mu	-749.288**	-758.955***	-762.229**	-751.519***
	(-2.47)	(-2.93)	(-2.17)	(-3.41)
Sigma u	5.996***	6.022***	6.031***	6.002***
	(-14.8)	(-17.67)	(-13.13)	(-20.47)
Sigma v	-1.375***	-1.432***	-1.425***	-1.437***
	(-51.69)	(-53.83)	(-53.43)	(-53.75)
Number of observations	13 302	13 302	13 302	13 302
Log likelihood	-14 272	- 14 139	-14 190	-14 055
Sigma u	20.0	20.3	20.4	20.1
Sigma v	0.5	0.5	0.5	0.5
z-test	-35.682	-38.863	-38.832	-38.083
	(0.000)	(0.000)	(0.000)	(0.000)
lambda	39.9	41.6	41.6	41.3

Table 4 – Determinants of the systematic inefficiency term

We regress the inefficient term against the WORKPORCE score and a set of control covariates. In the simple variant. only ln(Size)$_{-1}$is included in the equation, whereas extended versions also include the SOCIAL score, the GOVERNANCE score and a number of firm control variables. Technical efficiency is estimated by means of different production function to ensure the robustness of the results. We present t-statistics clustered at the firm level in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted (***), (**), and (*), respectively.

	1	2	3	4	5	6	9
Mu							
WORKFORCE	-0.352***	-0.091**	-0.351***	-0.113**	-0.116***	-0.102**	-0.107**
	(-13.11)	(-2.02)	(-12.66)	(-2.55)	(-2.62)	(-2.25)	(-2.37)
ln (Size)$_{-1}$	-0.627***	-0.647***	-0.640***	-0.640***	-0.640***	-0.650***	-0.645***
	(-63.62)	(-48.37)	(-63.89)	(-47.74)	(-47.60)	(-51.12)	(-48.56)
SOCIAL		-0.239***		-0.227***	-0.231***	-0.254***	-0.223***
		(-4.00)		(-3.88)	(-3.93)	(-4.35)	(-3.78)
LEVERAGE$_{-1}$		0.031***		0.029***	0.029***	0.031***	0.031***
		(9.50)		(9.12)	(9.09)	(9.62)	(9.63)
ln(Employees/Fixed Assets)$_{-1}$		0.010		0.010	0.010	0.041***	0.020***
		(1.46)		(1.15)	(1.13)	(10.60)	(3.04)
GOVERNANCE$_{-1}$		-0.001***		-0.001**	-0.001**	-0.001***	-0.001***
		(-3.20)		(-2.26)	(-2.05)	(-2.85)	(-2.84)
DIVERSIFICATION$_{-1}$		0.021***		0.022***	0.021***	0.020***	0.020***
		(8.99)		(9.39)	(9.17)	(8.87)	(8.61)
ln (Age)$_{-1}$		0.000		-0.004	-0.004	0.000	-0.001
		(-0.03)		(-1.27)	(-1.38)	(-0.11)	(-0.36)
INSIDER OWNERSHIP$_{-1}$		-0.008***		-0.005	-0.005	-0.009***	-0.009***
		(-2.68)		(-1.64)	(-1.62)	(-2.80)	(-2.97)
Foreign Sales$_{-1}$		0.054**		0.056**	0.056**	0.069***	0.068***
		(2.39)		(2.42)	(2.43)	(3.07)	(3.06)
Global$_{t-1}$		-0.024		-0.016	-0.018	-0.035*	-0.038**
		(-1.26)		(-0.89)	(-0.96)	(-1.86)	(-2.02)
ln(Analysts)$_{t-1}$		-0.148***		-0.148***	-0.158***	-0.152***	-0.158***
		(-12.30)		(-12.57)	(-11.94)	(-12.37)	(-11.83)
Blockholder$_{-1}$		0.015***		0.012***	0.012***	0.016***	0.017***
		(4.95)		(4.03)	(4.10)	(5.37)	(5.58)
constant	12.712***	12.901***	12.024***	12.346***	12.459***	12.660***	12.890***
	(13.45)	(43.73)	(69.74)	(45.75)	(44.02)	(58.45)	(51.34)
Distributions of u and v							
Usigma	-4.083	-1.165	-1.024	-1.386	-1.404	-1.073	-1.099
Vsigma	-0.926	-3.334	-3.208	-2.846	-2.863	-32.837	-30.738
Number of observations	12 389	6 950	12 389	6 950	6 950	6 950	6 950
Log likelihood	-7647.8	-4434.6	-7074.0	-4091.3	-4059.7	-4397.0	-4331.8
Sigma u	0.56	0.13	0.19	0.19	0.17	0.00	0.01
Sigma v	0.26	0.53	0.57	0.48	0.48	0.55	0.54
Production Function	PF3	PF3	PF5	PF5	PF6	PF4	PF7

Table 5 – Non-linear effects

We regress the inefficient term against the WORKPORCE and SOCIAL scores, controlling for size. WORKFORCE q represents the quartiles of the variable. We present t-statistics clustered at the firm level in parentheses. Statistical significance at the 1%, 5%, and 10% level is denoted (***), (**), and (*), respectively.

	(1)	(2)
WORKFORCEq	-0.121 ***	
	(-3.76)	
SOCIAL	-0.327 ***	-0.185 ***
	(-6.49)	(-3.43)
$\ln Size_{-1}$	-63.734 ***	-63.531***
	(-59.96)	(-59.88)
WORKFORCE		-0.032
		(-0.34)
$WORKFORCE^2$		-0.270 ***
		(-2.83)
Constant	12.060 ***	11.974 ***
	(66.09)	(65.33)
Distributions of u and v		
Sigma u	-1.206 ***	-1.203 ***
	(-43.15)	(-44.51)
Sigma v	-3.162 ***	-3.166 ***
	(-19.83)	(-21.13)
Number of observations	10 959	10 959
Log likelihood	-9 276	-9 254
Sigma u	0.21	0.21
Sigma v	0.55	0.55
Production Function	PF5	PF5

Figure 1 – Five-year rolling windows

We present the results of 5-year rolling windows runs, to check for stability of the estimates of WORKFORCE.