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Market structure, ESG performance, and corporate efficiency: Insights from Brazilian publicly traded companies

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Abstract

Using a sample of Brazilian listed companies, our study investigates the directional cause–effect relationship between market structure, ESG performance, and firm efficiency under a Stochastic Structural Relationship Programming (SSRP) model. Our empirical evidence is threefold. First, our findings indicate that firms with better environmental performance are more efficient, whereas lower ESG performance and poorer corporate governance practices are associated with a higher level of efficiency. Second, our study suggests that market structure measures (i.e., competition, concentration, and market power) have heterogeneous impacts on various ESG indexes. Specifically, higher market competition is associated with a lower concentration, better ESG performance and environmental performance, but worse corporate governance performance, although market power can only enhance the environmental and governance performance of firms. Third, the market structure proxies employed in this study are significantly attributed to firm efficiency. Our findings provide practical implications for various stakeholders and suggest avenues for future studies that can build on our evidence.

KEYWORDS

Brazil, corporate efficiency, ESG, market structure, network data envelopment analysis, Stochastic Structural Relationship Programming

1 | INTRODUCTION

One can say that there are three main reasons why ESG growth has been accelerating in the last few years. First, due to new global challenges, such as climate risk, increased regulatory pressures, social and demographic shifts, and data security concerns, which represent new and increasing risks for firms, investors, and people in general. Second, due to the fact that a new generation of investors has been showing interest in putting their money where their values are, which means in those firms with stronger ESG agendas. Third, artificial intelligence and alternative data extraction techniques, such as machine learning and natural language processing, which help minimize the reliance on firms' voluntary ESG disclosures and increase the timeliness and precision of ESG data collection, have similarly contributed to the growth of ESG area in the contemporary working environment (MSCI, 2021).

In order to illustrate this fast ESG growth scenario, according to the reports by various international bodies, such as the US SIF

Abbreviations: CFP, Corporate Financial Performance; CISE, Index Governance Committee; ESG, Environmental, Social, and Governance; HHI, Herfindahl–Hirschman Index; ICO2, Carbon Efficient Index; IGCX, Special Governance Corporate Index; ISE, Corporate Sustainability Index; NDEA, network data envelopment analysis; PRI, Principles for Responsible Investment; SSRP, Stochastic Structural Relationship Programming.

Foundation, Eurosif, The Japan Sustainable Investment Forum, the Responsible Investment Association of Canada, and the Responsible Investment Association Australasia, ESG investing assets under management in 2021 reached \$17.1 trillion, €1.6 trillion, ¥42.6 trillion, CAD\$3.2 trillion, and AUD\$1.2 trillion, in the United States, Europe, Japan, Canada, and Australia/New Zealand, respectively, The United States and Europe experienced growth in ESG investments by 42% generally and 23% since 2018, while Japan and Australia/New Zealand experienced a general growth by 9.9% and 13% since 2019, respectively. Likewise, in Canada, since 2017, there has been an increasing trend in ESG-related investments by 48%. Moreover, the number of signatories to the Principles for Responsible Investment (PRI, 2021), an agreement to incorporate ESG issues into investment analysis and decision-making process, has grown by 28% as of March 2022. Thus, this magnitude of investment flow suggests that ESG is much more than a fad or a feel-good exercise.

Due to this meteoric rise of the ESG theme, as one can imagine, there already is a vast literature regarding the subject. However, most of this literature is mainly focused on the relationship between ESG performance and Corporate Financial Performance (CFP). According to a recent body of literature (e.g., Clément et al., 2023; Singhania & Saini, 2023; Wang et al., 2023), there is a substantial amount of published empirical academic studies analyzing the determinants and consequences of ESG performance. Notwithstanding, as in any other literature subject, there still are some gaps that are worth addressing and fulfilling. First, the number of publications from developing economies is significantly lower than that from developed economies—which also focus heavily on US firms (Hawn et al., 2018). Thus, further research is needed for developing economies (Alshehhi et al., 2018). Second, according to Do Prado et al. (2020), a significant gap and future opportunity for the ESG literature exists regarding the application of different measures of financial, social, and environmental performance besides the traditional and already saturated ones that have been used in most of the studies. Third, research studies continue to face the challenges of both establishing causality and taking endogeneity properly into account when focusing on aspects of ESG performance and CFP (Garcia-Castro et al., 2010; Ruggiero & Lehkonen, 2017). Consequently, additional methodologies and approaches to deal with these issues are clearly needed. Fourth, there is a lot more to be considered regarding general market characteristics and their effects on firms' ESG performance. Thus, this evolving nature of ESG and the potential for new empirical designs allow for additional causal interpretations and suggest a rich agenda for future work in this research area (Gillan et al., 2021; Koçak et al., 2022; Lu et al., 2023).

Based on these ESG literature gaps, the main objective of this research is to investigate and analyze the endogeneity and directional cause–effect relationships between Brazilian publicly traded firms' financial efficiency, market structure, and ESG performance. For that, this paper tries to innovate, first, by taking an emerging economy perspective, focusing on the Brazilian listed firms during the period from 2010 to 2019; second, by applying innovative data techniques, such as a two-stage network data envelopment analysis (NDEA) model to measure firms' efficiency; third, by applying a comprehensive measures for market structure, including three different proxies are the *Herfindahl–Hirschman Index* (*HHI*) to capture market concentration, the Panzar–Rosse *H*-statistic to capture competition, and the Lerner Index to capture market power; fourth, by using more relevant ESG stock indexes as proxies for ESG performance, the Carbon Efficient Index (ICO2) to capture firms' environmental dimension performance, the Special Governance Corporate Index (IGCX) to capture firms' corporate governance dimension performance, and the Corporate Sustainability Index (ISE) to capture firms' overall ESG performance; and fifth, by being the first, to our knowledge, to employ a Stochastic Structural Relationship Programming (SSRP) model in order to analyze the endogeneity and directional cause–effect relationships between all the above-mentioned variables.

This paper's main findings suggest a significant cause–effect relationship between firms' ESG proxies and their efficiency. This means that the higher the firm's environmental performance, the higher the firm's efficiency. In contrast, efficient firms in Brazil are associated with lower ESG performance and weaker corporate governance practices. Likewise, our empirical evidence indicates that marker structures are key determinants of firms' ESG scores and their efficiency. For instance, the degree of competition and concentration, which Brazilian listed firms face regarding their business sectors, play an important role in determining both firms' ESG performance and their efficiency. Crucially, we find that the higher the competition and the lower the concentration, the higher the firms' ESG performance, the higher the firms' environmental performance, and the lower the firms' corporate governance performance. Similarly, firm competition has a significant and positive association with firm efficiency. Moreover, regarding market power, as another proxy of market structure, we find that the higher the market power, the higher the firm's environmental performance, the higher the firm's corporate governance performance, and the lower the firms' ESG performance, while it is significantly attributed to firms' efficiency.

This paper adds to the ongoing debate regarding ESG literature in various ways. First, we contribute to existing knowledge by sufficiently addressing endogeneity and directional cause–effect relationships between market structure, ESG proxies and firm efficiency—an issue that has not been adequately addressed in previous ESG research. Second, this paper also adds to the literature by being the first one to address each business sector from the Brazilian stock exchange separately; by being the first one to use ESG stock indexes' yearly variation to measure ESG performance and practices; and by being the first one to study the relationship between market structure indicators and firms' environmental dimension of ESG performance through the ICO2.

The rest of the paper is divided into four sections. An overview of studies regarding the relationships between efficiency and ESG, market structure and ESG, and efficiency and market structure is presented in Section 2. The dataset is discussed in Section 3, which also presents the theoretical background and methodologies regarding the network data envelopment analyses model, the market structure indicators, and the ESG stock indexes and describes the novel SSRP approach. Section 4 analyzes and discusses the findings, while Section 5 presents the conclusions.

2 | LITERATURE REVIEW

2.1 | ESG and efficiency

The literature on a firm's efficiency and its ESG performance uses both data envelopment analysis (DEA) and stochastic frontier analysis (SFA) to measure efficiency. Table 1 summarizes the efficiency and ESG papers' main points. In relation to ESG, prior studies address both ESG in general (all its three dimensions together) and also each one of its dimensions (Environmental, Social, and Governance) separately. Regarding Governance, Janang et al. (2018) applied an SFA model to measure Malaysian listed firms' efficiency and found a positive relationship between the variables, meaning that better governance leads to higher efficiency. Conversely, Kahveci and Wolfs (2019) and Wang et al. (2018) found no relationship between these variables. Both studies applied a DEA model to measure the firm's efficiency. While Kahveci and Wolfs (2019) analyzed the Turkish listed companies, Wang et al. (2018) analyzed the Taiwanese ones.

Moving to the Environmental dimension, both Perez et al. (2011) and Chai et al. (2020) analyzed firms' energy consumption efficiency and returns. Perez et al. (2011), after applying an SFA model to measure listed European hotels' energy efficiency, found that it has no relationship with the hotels' returns. Contrary to that, Chai et al. (2020), after applying a DEA model to measure Chinese listed thermal power firms' energy efficiency, found that it is positively related to the firms' returns. Regarding the Social dimension, both Sotome and Takahashi (2014) and Uribe-Bohorquez et al. (2019) found negative results. Sotome and Takahashi (2014) applied a DEA model to measure Japanese listed firms' efficiency and found that the human resources system in Japan harms firms' efficiency. Uribe-Bohorquez et al. (2019) applied a DEA model to measure internationally listed firms' efficiency and found evidence that female directors decrease firms' efficiency.

Finally, addressing all the ESG dimensions together, Liu (2020), after applying a DEA model to measure Taiwanese listed companies' efficiency, found that the implementation of ESG practices increases firms' efficiency. In a different approach, Belu (2009) applied a DEA model with financial indicators as inputs and sustainability scores as outputs to rank large firms listed on the world's main stock exchanges. The results show that many firms are positioned well below ESG best practices in their respective industries. Then, regarding ESG disclosure, Loprevite et al. (2020) and Rahim (2021), after applying DEA models to measure firms' efficiency, found that ESG reports play a significant role in determining firms' efficiency. While Loprevite et al. (2020) analyzed Italian listed companies, Rahim (2021) analyzed Pakistan listed companies.

Thus, this paper adds to the literature by, first, addressing and analyzing each business sector from the Brazilian stock exchange separately, a concern that no study has had so far; second, by making use of ESG stock indexes' yearly variation to measure firms' ESG performance and practices, which none of the existing studies has done so far as well; and third, by applying a two-stage network DEA model to decompose and measure firms' efficiency, again, an approach has never been adopted in the literature to date. Based on the above

TABLE 1 Efficiency and ESG studies.

Authors and year	Period	Efficiency model	Business sector	ESG measure	ESG dimension	Relationship
Loprevite et al. (2020)	2016–2018	DEA	No differentiation	Overall disclosure index	ESG	Positive
Rahim (2021)	2021	DEA	No differentiation	Sustainability report dummy	ESG	Positive
Liu (2020)	2007–2016	DEA	No differentiation	World corporate citizen award	ESG	Positive
Belu (2009)	2008	DEA	No differentiation	SAM ratings	ESG	Negative
Chai et al. (2020)	2018–2019	DEA	Thermal power	DEA model for energy efficiency	Environmental	Positive
Perez et al. (2011)	2004–2007	SFA	Hotels	SFA model for energy efficiency	Environmental	No relationship
Janang et al. (2018)	2001–2012	SFA	Government linked	7 governance variables	Governance	Positive
Kahveci and Wolfs (2019)	2019	DEA	No differentiation	CGR from Turkey stock exchange	Governance	No relationship
Wang et al. (2018)	2008–2010	DEA	No differentiation	Shareholding ratio of directors	Governance	No relationship
Sotome and Takahashi (2014)	2006–2012	DEA	No differentiation	Toyo Keizai HR scores and HR variables	Social	Negative
Uribe-Bohorquez et al. (2019)	2006–2015	DEA	No differentiation	Blau index	Social	Negative

review of previous literature studies, and given the inconclusive findings of prior literature, we develop non-directional hypotheses for the potential impact of ESG indexes on firm efficiency as follows:

H1. There is a positive (negative) relationship between the high-level (low-level) environmental performance of firms (as a dimension of ESG) and firm efficiency.

H2. There is a positive (negative) relationship between strong (weak) corporate governance practices (as a dimension of ESG) and firm efficiency.

H3. There is a positive (negative) relationship between the high-level (low-level) ESG performance of firms and firm efficiency.

2.2 | Market structure and ESG

Most of the literature regarding market structure and ESG uses the HHI to measure competition and concentration, with only two studies using the Lerner Index, and just one using the Panzar–Rosse *H*-statistic. Concerning ESG, the studies are well diversified between addressing ESG in general and the Governance dimension separately. However, regarding the social dimension, we have found just one study that addresses it separately, and in relation to the environmental dimension, we have not found any study addressing it separately. Table 2 summarizes the market structure and ESG papers' main points. Regarding the only study that addresses the social dimension separately, Jiao and Shi (2014), after applying the HHI to US listed firms, found that, in more competitive markets, a firm's effort to cater to customers' social preferences is positively related to firms' value enhancing. Although there are no studies explicitly addressing the impact of the environmental dimension of ESG separately on the level of competition, previous literature studies have clearly indicated the impact on efficiency. CO_2 emissions have been widely used as an environmental performance indicator at the firm level by previous studies (Antunes, Neves, et al., 2023; Wanke et al., 2020; Wanke et al., 2023), and a number of studies have incorporated this environmental performance indicator as an undesirable output in the estimation of efficiency (Antunes, Tan, et al., 2023; Liu et al., 2022). In other words, large volumes of CO_2 emissions reduce the level of efficiency. The existing literature in the banking context revealed that firms with higher levels of efficiency occupy larger volumes of shares, which results in an increase in concentration and a reduction in competition (Tan & Floros, 2018). On the other hand, in a highly competitive environment, firms tend to focus on building their own competitive advantage; one of the ways of which to achieve this is through the reduction of CO_2 emissions (Palsson & Kovacs, 2014).

Moving to the Governance dimension, both Ammann et al. (2013) and Gempesaw (2021), by using the HHI to measure competition, found evidence that competition acts as a substitute for corporate governance practices, meaning that more competition may lead to less or weaker governance practices. The first study was applied to the European listed firms, while the second was applied to the US manufacturing listed firms. Moreover, by using both the HHI and the Lerner Index to measure the competition and market power of the Taiwanese non-financial listed firms, Tang and Chen (2020) found evidence that more competition and

TABLE 2 Market structure and ESG studies.

Authors and year	Period	Market structure indicator	Business sector	ESG measure	ESG dimension	Relationship
Sheikh (2018)	2003–2015	HHI; Lerner Index	No differentiation	MSCI KLD ratings	ESG	Negative
Acabado et al. (2020)	2013	HHI	No differentiation	CSRHub ratings	ESG	Negative
Kontesa et al. (2020)	2010–2016	HHI	Non-financial	Constructed CSR index	ESG	Negative
Flammer (2015)	1992–2005	HHI	No differentiation	MSCI KLD ratings	ESG	Negative
Chih et al. (2010)	2003–2005	Panzar–Rosse	Financial sector	DJSI and DJWI dummies	ESG	Positive
Declerck and M'Zali (2012)	1995–2009	HHI	No differentiation	MSCI KLD ratings	ESG	Negative
Fernández-Kranz and Santaló (2010)	1991–2005	HHI	No differentiation	MSCI KLD ratings	ESG	Negative
Lee et al. (2018)	2010–2013	HHI	No differentiation	CSRI from KCGS	ESG	Positive
Gempesaw (2021)	1990–2005	HHI	Manufacturing	G-index and E-index	Governance	Positive
Moradi et al. (2017)	2004–2012	HHI	No differentiation	4 governance variables	Governance	Positive
Tang and Chen (2020)	2003–2014	HHI; Lerner Index	Non-financial	9 governance variables	Governance	Positive
Chou et al. (2011)	1990–2005	HHI	No differentiation	G-index and E-index	Governance	Positive
Ammann et al. (2013)	2003–2007	HHI	No differentiation	GMI	Governance	Positive
Liu et al. (2018)	2001–2016	HHI	No differentiation	Constructed governance index	Governance	Positive
Jiao and Shi (2014)	1991–2009	HHI	No differentiation	MSCI KLD ratings	Social	Negative

low market power reduce the effect of corporate governance. In a similar path, Chou et al. (2011), after applying the HHI to US listed firms, found evidence that firms in more competitive markets and with low market power tend to have weaker corporate governance structures. Additionally, Moradi et al. (2017) applied the HHI to the Iranian listed firms and found evidence that more competition leads to less suitable corporate governance effectiveness.

Finally, the studies addressing all the ESG dimensions together have found very similar results. Acabado et al. (2020), Kontesa et al. (2020), Flammer (2015), Chih et al. (2010), and Declerck and M'Zali (2012) have found evidence that a more competitive environment increases firms' ESG practices. Most of the studies have applied the HHI to measure competition (Acabado et al., 2020; Declerck & M'Zali, 2012; Flammer, 2015; Kontesa et al., 2020), while just one (Chih et al., 2010) has applied the Panzar–Rosse *H*-statistic. Regarding the sampled firms, Flammer (2015) and Declerck and M'Zali (2012) analyzed the US listed firms; while Acabado et al. (2020) and Chih et al. (2010) analyzed the listed firms from all over the world, and Kontesa et al. (2020) analyzed a sample of Malaysian non-financial listed firms. Additionally, Fernández-Kranz and Santaló (2010) also found analogous results. The authors, after applying the HHI to US listed firms, found evidence that firms in more competitive markets have better ESG ratings. Contrary to those findings, Lee et al. (2018), after applying the HHI to Korean listed firms, found evidence that firms in a more competitive environment are less engaged in their social responsibility activities. Finally, Sheikh (2018) applied both the HHI and the Lerner Index to the US listed firms and found evidence that ESG practices only increase firms' value in competitive markets.

From a methodological perspective, we add to the extant literature by (i) using all three measures of competition and concentration together (HHI, Panzar–Rosse *H*-statistic, and Lerner Index) in order to avoid the limitations of a large number of prior studies that were either confined to just using the HHI or limited to using the Panzar–Rosse *H*-statistic and the Lerner Index and (ii) being the first study to analyze the environmental dimension of ESG separately through the ICO2. Based on the above literature, we have developed the following hypotheses:

H4. There is a positive (negative) relationship between a strong (weak) market structure and good (poor) corporate governance practices.

H5. There is a positive (negative) relationship between a strong (weak) market structure and a high-level (low-level) environmental performance.

H6. There is a positive (negative) relationship between a strong (weak) market structure and a high-level (low-level) ESG performance.

2.3 | Market structure and efficiency

The literature regarding the link between market structure and firm efficiency is highly concentrated on the banking industry, with only two studies analyzing different sectors. Moreover, the HHI is, again, the most utilized indicator of competition and concentration, and DEA is the only method to measure efficiency that has been applied in prior literature so far. Table 3 summarizes the previous market structure-to-efficiency studies. Beginning with the non-banking sector studies, both have applied the HHI to measure competition. Specifically, focusing on the context of container ports in Southeast Asia, Nguyen et al. (2020) found that competition has no relationship with efficiency. Contrary to that, Dai et al. (2019), after analyzing the market structure–efficiency nexus in the Chinese civil aviation industry, found evidence that stronger competition leads to higher efficiency.

Regarding the banking sector, both Le Long et al. (2020) and Viverita (2014) used the Lerner Index to measure competition and market power. The first study found that in a more competitive market, banks are more efficient in the Vietnamese context. In contrast, the second study analyzed Indonesian banks and found that market power improves efficiency. Moreover, Mohammed et al. (2019), by applying the Panzar–Rosse *H*-statistic to Malaysian banks, found evidence of a positive relationship between competition and efficiency, meaning that banks need to operate more efficiently to be more competitive. Furthermore, Alves et al. (2020) employed the HHI, the Panzar–Rosse *H*-statistic, and the Lerner Index to measure the competition of the Portuguese banks and found that production efficiency is the endogenous cornerstone variable that encompasses the feedback process among competition levels. Additionally, Rao Subramaniam et al. (2019), after applying the HHI to Southeast Asian banks, found that competition is

TABLE 3 Efficiency and market structure studies.

Authors and year	Period	Efficiency model	Market structure indicator	Business sector	Relationship
Le Long et al. (2020)	2010–2017	DEA	Lerner Index	Banking	Negative
Viverita (2014)	2002–2011	DEA	Lerner Index	Banking	Positive
Mohammed et al. (2019)	1997–2016	DEA	Panzar–Rosse	Banking	Positive
Alves et al. (2020)	2010–2016	DEA	HHI; Panzar–Rosse; Lerner Index	Banking	Positive
Rao Subramaniam et al. (2019)	2011–2016	DEA	HHI	Banking	Positive and negative
Titko et al. (2015)	2007–2013	DEA	HHI	Banking	No relationship
Dai et al. (2019)	2001–2015	DEA	HHI	Civil aviation	Negative
Nguyen et al. (2020)	2007–2017	DEA	HHI	Container ports	No relationship

positively related to technical efficiency but negatively related to scale efficiency. Finally, Titko et al. (2015) applied the HHI to the banks operating in the Baltic region and found that there is no empirical evidence that competition has an impact on efficiency. Based on our review of previous literature that shows inconclusive evidence on the market structure–efficiency nexus, we develop non-directional hypotheses to test in the current study as follows:

> **H7.** There is a positive (negative) association between strong (weak) market structure and firm efficiency.

3 | DATA AND METHODOLOGY

3.1 | The data

Regarding the data sample, we collected it from the Brazilian publicly traded companies and stock indexes, encompassing 381 listed firms and three ESG indexes, with available data for the period from 2010 to 2019. Regarding the accounting and financial variables used as the inputs and outputs for the NDEA model and for the market structure indicators calculation—HHI, Panzar–Rosse *H*-statistic, and Lerner Index—they were gathered from the Economatica platform. The variable selection is based on theoretical support from the literature as well as data availability. The variables from Economatica were all gathered in a million reais and inflation adjusted. Furthermore, regarding the ESG stock indexes, data were gathered from B3's website. We collected both the yearly variation, measured by the monthly nominal closing rates, and each index's methodology for the IGCX, ISE, and ICO2.

3.2 | Network Data Envelopment Analysis (NDEA)

DEA is a nonparametric model that was first introduced by Charnes et al. (1978) to evaluate the efficiency of different types of DMUs that are subject to many diverse inputs and outputs. Besides the studies reviewed above, there are other studies applying this methodology from different perspectives (Donthu et al., 2005; Gonzalez-Padro et al., 2014; Haugland et al., 2007; Luo, 2003; Rahman et al., 2016, among others). Many previous studies illustrate that DMUs can be formed by two-stage network structures that consume inputs in the first stage and use their respective outputs as the inputs of the second stage, which ultimately will produce the final outputs of the system (Barros & Peypoch, 2012; Briec & Peypoch, 2007; Halkos et al., 2014). It is noteworthy that the trade-off between maximizing the outputs of the first stage while minimizing the correspondent inputs for the second stage is a usual research topic within the ambit of the two-stage productive structure (Kao & Hwang, 2008; Liang et al., 2008; Zhu, 2011). These different perspectives on how to manage the intermediate resources within the ambit of two-stage structures gave birth to the idea of cooperative versus non-cooperative approaches (Cook, Liang, & Zhu, 2010; Cook, Zhu, et al., 2010). In the cooperative approach, both stages collaborate to achieve maximal overall efficiency, as assumed in this research.

In fact, different research studies have been carried out on DEA modeling focusing on the particular case of the two-stage productive structures in series (Cook, Liang, & Zhu, 2010; Halkos et al., 2014). A relevant issue when modeling network productive structures is the choice between additive and multiplicative approaches to decompose the overall efficiency. This choice is constrained not only by the assumption of the return to scale premises but also by whether or not the model admits the exogenous inputs and outputs—in this research, no exogenous inputs and outputs are being considered. Kao and Hwang (2008) demonstrated that the product of efficiencies from individual stages would make up the overall efficiency if there were no exogenous inputs and outputs allowed. The main issue is that the network productive structures under the multiplicative approach cannot be transformed into linear programming models (Charnes & Cooper, 1962). In dynamic models, when variables that are exogenously defined, such as carry overs and connections, are permitted, significant implications arise. This research differs from the previous studies (see the comprehensive literature review presented in Halkos et al., 2014) by considering a serial, cooperative two-stage network DEA model with multiplicative efficiency decomposition structure, which allows the use of the endogenously defined weights at each stage given that maximal attainable efficiency is defined first.

In this paper, the following multiplier form of the two-stage DEA model is proposed to assess the profit and balance sheet efficiency and the financial health efficiency levels regarding the Brazilian publicly traded companies. It differs from the previous models not only by considering the overall financial efficiency level as a product of the individual efficiencies for each stage but also by making explicit the return to scales parameters for each stage, which can be considered as variable or constant. Besides, the maximal overall efficiency levels are computed first, so that the maximal attainable individual efficiencies for each stage are directly bounded by the overall score in a cooperative fashion. In other words, balance and profit sheet and financial health stages cooperate to achieve the maximal overall efficiency scores and, this being the case, it is indifferent to run the overall efficiency model followed either by the balance and profit sheet efficiency or financial health efficiency models, as long as the overall efficiency values and the efficiency level values of each stage can be used to determine the remaining efficiency. The overall efficiency two-stage DEA model can be described as depicted in the model (1).

Overall efficiency:

$$
\begin{aligned}
& E_o = E_o^1 * E_o^2 = \max \sum\nolimits_{r=1}^{s} u_r y_{ro} - c_0 - c_1 \\
& s.t \\
& \sum\nolimits_{i=1}^{m} v_i x_{io} = 1, \\
& \sum\nolimits_{d=1}^{D} w_d z_{dj} - \sum\nolimits_{i=1}^{m} v_i x_{ij} - c_0 \le 0, j = 1, \ldots, N, \\
& \sum\nolimits_{r=1}^{s} u_r y_{rj} - \sum\nolimits_{d=1}^{D} w_d z_{dj} - c_1 \le 0, j = 1, \ldots, N, \\
& v_i, \ge \epsilon, i = 1, \ldots, m, \\
& w_d, \ge \epsilon, d = 1, \ldots, D, \\
& u_r \ge \epsilon, r = 1, \ldots, s, \\
& c_0, c_1 \text{ free in sign,}
\end{aligned}
\qquad (1)
$$

where N is the number of DMUs; m, D, and s are the number of inputs, intermediate variables, and outputs, respectively; and epsilon is an Archimedean value. Model (1) is an extension of the model presented in Kao and Hwang (2008) based on Sahoo et al. (2014), where two free-in-sign variables, c_0 and c_1, are used to represent the returns-to-scale assumption at each stage. Here, c_0 and c_1 are relative to the first (balance and profit sheet efficiency) and second (financial health efficiency) stages, respectively. To evaluate model (1) under the CRS assumption, for instance, both free-in-sign variables c_0 and c_1 must be set equal to zero. Once model (1) is solved, models (2) and (3) focus on the individual efficiencies E_0^1 and E_0^2, balance and profit sheet and financial health, respectively, both linked to E_0. In this research, for the sake of simplicity and comparability of results, both stages were either considered under the CRS or VRS assumptions.

Balance and profit sheet efficiency:

$$\begin{aligned} & E_o^1 = \max \sum_{d=1}^{D} w_d z_{do} - c_0 \\ & s.t \\ & \sum_{i=1}^{m} v_i x_{io} = 1, \\ & \sum_{r=1}^{s} u_r y_{ro} - E_o * \sum_{i=1}^{m} v_i x_{io} - c_0 - c_1 = 0, \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - c_0 - c_1 \le 0, j = 1, \ldots, N, \\ & \sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} - c_0 \le 0, j = 1, \ldots, N, \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} w_d z_{dj} - c_1 \le 0, j = 1, \ldots, N, \\ & v_i, \ge \epsilon, i = 1, \ldots, m, \\ & w_d, \ge \epsilon, d = 1, \ldots, D, \\ & u_r \ge \epsilon, r = 1, \ldots, s, c_0, \\ & c_1 \textit{ free in sign}. \end{aligned} \tag{2}$$

Financial health efficiency:

$$\begin{aligned} & E_o^2 = \max \sum_{r=1}^{s} u_r y_{ro} - c_0 \\ & s.t \\ & \sum_{d=1}^{D} w_d z_{do} = 1, \\ & \sum_{r=1}^{s} u_r y_{ro} - E_o * \sum_{i=1}^{m} v_i x_{io} - c_0 - c_1 = 0, \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - c_0 - c_1 \le 0, j = 1, \ldots, N, \\ & \sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} - c_0 \le 0, j = 1, \ldots, N, \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} w_d z_{dj} - c_1 \le 0, j = 1, \ldots, N, \\ & v_i, \ge \epsilon, i = 1, \ldots, m, \\ & w_d, \ge \epsilon, d = 1, \ldots, D, \\ & u_r \ge \epsilon, r = 1, \ldots, s, \\ & c_0, c_1 \textit{ free in sign}. \end{aligned} \tag{3}$$

The inputs, outputs, and intermediate variables within the scope of the two sub-structures of the dynamic network built for Brazilian listed companies are depicted in Figure 1. Total assets, provisions, and costs are the variables of the first stage, referred to as "balance and profit sheet" efficiency in Figure 1. This stage represents the profitability of Brazilian publicly traded firms. Due to total assets, costs, and provisions, this stage assesses firms' profitability both in terms of net income and equity. Furthermore, the efficiency of the future sub-structure known as "financial health" is influenced by the performance of this stage. Income and equity are the intermediate variables linking these two stages. The "financial health" stage, as its name already says, assesses firms' financial health in terms of how net income and equity translate into net interest income, which is basically the difference between firms' financial income and financial expense, or in other words, the difference between firms' interest generated and paid. The model's variables' descriptive statistics are presented in Table 4.

The aggregate empirical results of the NDEA model for the Brazilian publicly traded firms are provided in Figure 2. The structure

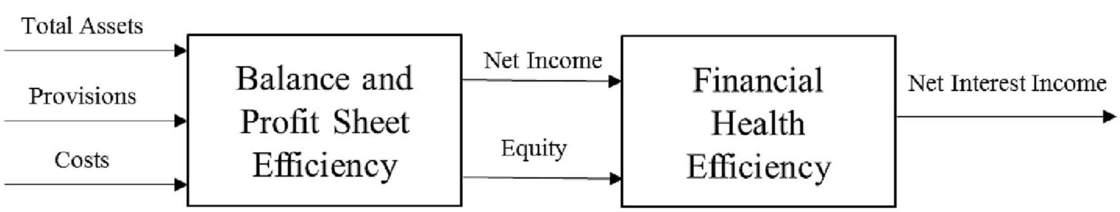

FIGURE 1 Network DEA model for Brazilian publicly traded firms.

TABLE 4 Descriptive statistics for the inputs, outputs, and intermediate variables for the NDEA model.

Variable type	Variable name	Min	Max	Mean	SD
Inputs	Total assets	0.44	1,892,392.53	34,918.45	175,382.61
	Provisions	−42,259.46	197,778.66	538.5	9652.75
	Costs	1	171,720.36	16,531.52	11,676.14
Intermediate variables	Net income	−53,053.96	59,899.87	620.35	3867.01
	Equity	−15,140.61	522,490.36	6781.92	30,573.32
Outputs	Net interest income	−43,845.57	60,217.91	310.89	5509.26

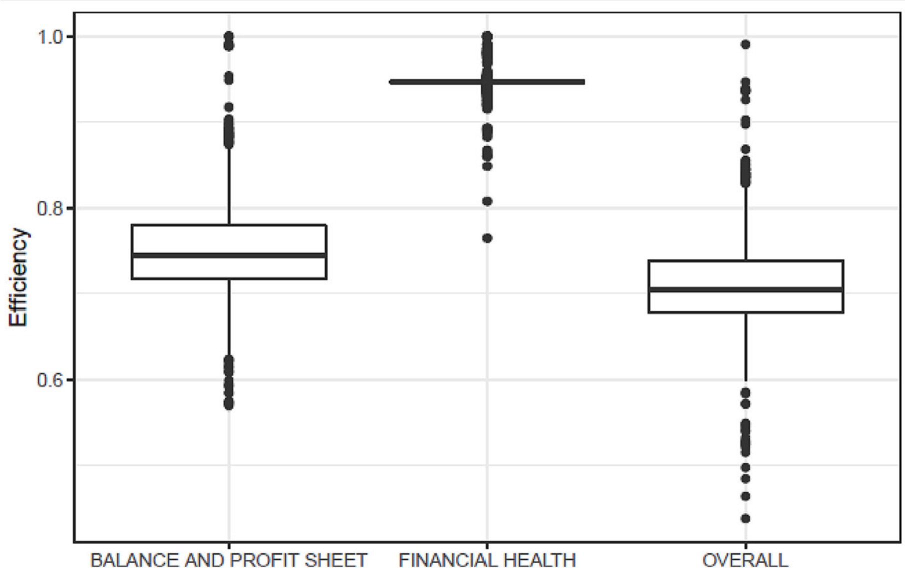

FIGURE 2 Aggregate results for the two-stage NDEA model.

of the production process, in particular, the two main stages of the production process, is depicted: balance and profit sheet efficiency (Stage 1) and financial health efficiency (Stage 2). The Brazilian listed firms are way more efficient regarding their financial health rather than their balance and profit sheet efficiency. Furthermore, they do not present high overall efficiencies. This can be understood from the perspective that Brazilian companies have a higher ability to use net income and equity capital in generating net interest income; in comparison, the ability to use total assets, provisions and costs to generate net income and equity is much lower. This indicates that cost control and effective use of assets in generating income and capital would be the priority that should be focused on by the Brazilian companies for future improvement.

3.3 | Market structure

3.3.1 | HHI

The HHI (or sometimes HHI score) measures the size of the company with respect to the business sector or the whole market. Empirical studies have widely used HHI as the measurement of concentration in different economic sectors (Sheikh, 2019). The sum of the squares of the market shares of the enterprises in the industry is used to calculate this index, with higher values indicating higher levels of concentration. Two alternative HHI metrics were computed in this paper to examine the market concentration of Brazilian publicly traded enterprises: HHI in terms of B3's whole market and HHI in terms of B3's business sectors. The distributions of these indexes are depicted in Figures 3 and 4.

As one can imagine, the results show that if we analyze the Brazilian stock exchange as a whole market, without considering the different business sectors, the concentration seems to be very low, which makes sense since we have seen that B3 presents a few numbers of firms, from different business sectors, that make half of B3's total market capitalization. However, when we analyze the second index, HHI, by business sectors, the concentration range is way higher, confirming that the Brazilian stock exchange presents highly concentrated business sectors. Regarding the 10 different business sectors B3 has, only two of them (Cyclical Consumption and Publicly Utility) have not presented HHI figures indicating a high concentration level. Finally, as one can perceive, the Oil, Gas, and Biofuels; Communications; Non-Cyclical Consumption; and Basic Materials sectors presented very high concentration rates, which is explained, as we have already seen, by the presence of the respective large companies—Petrobras, Telefonica Brasil, Ambev, and Vale.

In this paper, in order to assess competition besides concentration between Brazilian listed firms, we additionally employ the Panzar and Rosse (1987) *H*-statistic and Lerner (1934) Index. These two non-structural approaches benefit from the advantages of being able to measure firms' behavior in a direct manner.

3.3.2 | Panzar–Rosse *H*-statistic

The Panzar and Rosse (1987) *H*-statistic is estimated using the reduced revenue equation as illustrated below in Equation (4). ln, *i*, and *t* represent logarithm, time dimension, and a specific company. The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) were employed for us to choose between the fixed-effects and random-effects models. Since the results from the AIC and BIC were not conclusive in terms of whether each model was the best choice, we have chosen the fixed effects one due to the fact that it controls our sample for business sectors dummies and trend dummies as well.

$$\begin{aligned}\ln(TR_{it}) = {} & \\ & \propto + \beta_1 \ln(PL_{it}) + \beta_2 \ln(PF_{it}) + \beta_3 \ln(PC_{it}) + \gamma_1 \ln(EQAST_{it}) \\ & + \gamma_2 \ln(SIZE_{it}) + \gamma_3 \ln(LOANAST_{it}) + \epsilon_{it}.\end{aligned} \tag{4}$$

The dependent variable TR_{it} is total revenue, measured by the gross revenue to total assets ratio (Tan et al., 2021).

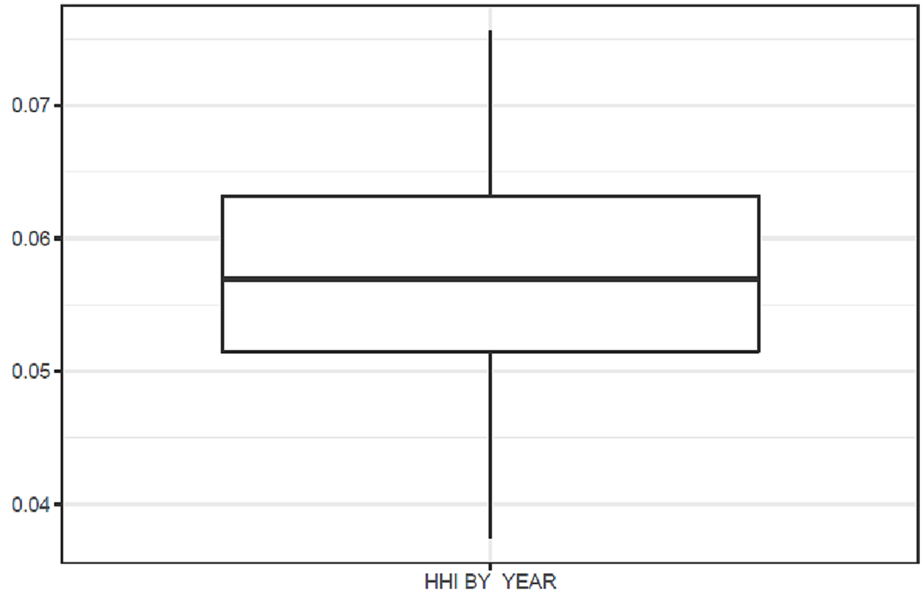

FIGURE 3 HHI results from B3 as a whole.

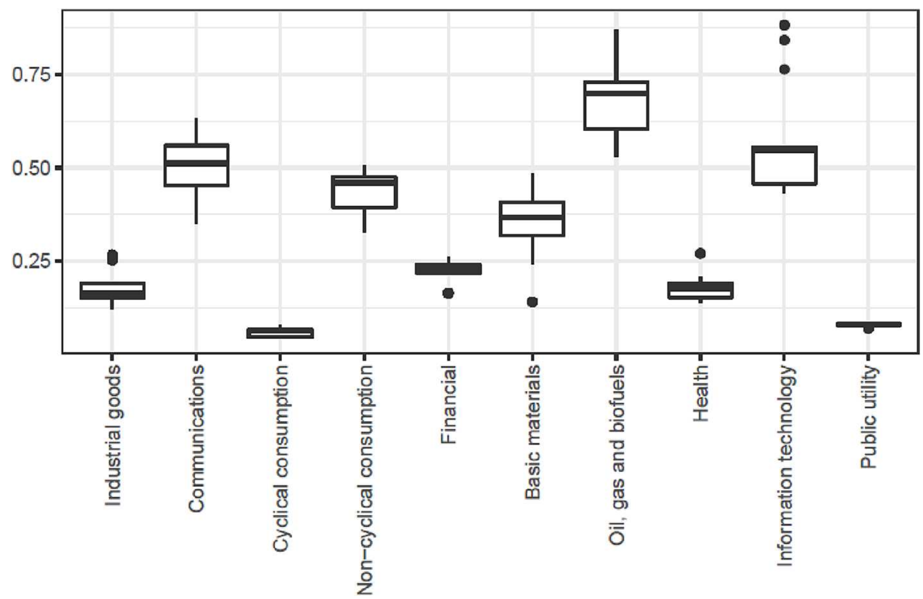

FIGURE 4 HHI results from B3's business sectors.

PL_{it}, PF_{it}, and PC_{it} are measured as follows:

- labor cost, proxied by the personnel expenses to total assets ratio $\left[\frac{(SBE+ERLST+ESRL)}{(TA)}\right]_{it}$;
- funding cost, represented by the interest expenses to total deposits ratio $\left[\frac{(EFO)}{(DEP)}\right]_{it}$ for banks, and interest expenses to total investments and cash $\left[\frac{(FE)}{(INV+CCE)}\right]_{it}$ for the rest of the firms;
- fixed capital cost, represented by the operating and administrative expenses to total assets ratio $\left[\frac{(OE+OOP+ADM+OWOP)}{(TA)}\right]_{it}$.

$EQAST_{it}$ is the total equity to total assets ratio, which reflects the firms' capitalization $\left[\frac{(EQTY)}{(TA)}\right]_{it}$; $SIZE_{it}$ is total assets, capturing the firms' size $[TA]_{it}$; $LOANAST_{it}$ is the total loans to total assets ratio, representing the firms' portfolio mix $\left[\frac{(TL)}{(TA)}\right]_{it}$ for banks, and total accounts payable and receivable to total assets ratio $\left[\frac{(ACCP+ACCR)}{(TA)}\right]_{it}$ for the rest of the firms. The *H*-statistic is calculated as the sum of the input prices coefficients β_1, β_2, and β_3 from Equation (4), with higher values indicating higher levels of competition. To be more specific, perfect competition will be reflected by the *H*-statistic taking the value of 1, and monopoly will be characterized by the value of 0, while the value between 0 and 1 indicates that there is monopolistic competition.

3.3.3 | Lerner Index

The Lerner Index, unlike the *H*-statistic, is a company-level measure of competition. It's the gap between the price and the marginal cost expressed as a percentage of the price (Fukuyama & Tan, 2022). The difference between the price and the marginal cost grows as the index rises, reflecting a wider gap between the price and the competitive price. As a result, the index is always used as a market power gauge. The estimation of a translog cost function using ordinary least squares (OLS) with company and time-fixed effects is required to calculate the Lerner Index, as below:

$$\ln(COST_{it}) = \beta_0 + \beta_1 \ln(Q_{it}) + \beta_2 1/2 \ln(Q_{it})2 + \gamma_1 \ln(P_{it}) + \gamma_2 \ln(P_{it}) \ln(Q_{it}) + \gamma_3 \ln(P_{it}) \ln(P_{it}) + \epsilon_{it} \quad (5)$$

where $COST_{it}$ stands for total costs $(\mathrm{OE+OOE+ADM+OWOP+SBE+ERLST+ESRL})_{it}$; Q_{it} denotes firm output $(\mathrm{NI+IFO+FI})_{it}$; and P_{it} represent different input prices. The marginal cost can be obtained by taking the differentiation of Equation (5) with respect to Q_{it} as below:

$$\mathrm{MC}_{TA} = COST_{it}/Q_{it}[\beta_1 + \beta_2 \ln(Q_{it}) + \gamma_2 \ln(P_{it})]. \quad (6)$$

The Lerner Index can be expressed as

$$\mathrm{LERNER}_{it} = (\mathrm{P}_{TA} - \mathrm{MC}_{TA})/\mathrm{P}_{TA}, \quad (7)$$

where $\mathrm{P}_{TA,it}$ denotes the price of assets, measured by the total revenues to total assets ratio for a company i at time $t\left(\left[\frac{(\mathrm{NI+IFO+FI})}{(\mathrm{TA})}\right]_{it}\right)$, and $\mathrm{MC}_{TA,it}$ denotes the marginal cost. The Lerner Index takes a value between 0 and 1, with higher values indicating a greater market power. Table 5 provides the descriptive statistics of the variables in the estimation of the Panzar–Rosse *H*-statistic and Lerner Index. Table 6 presents the results of the *H*-statistic based on the OLS estimator. It shows that the sum of the coefficients β_1, β_2, and β_3 is .45, suggesting that the Brazilian listed firms are operating in a state of quasi-monopoly or monopoly regarding their business sectors. The *H*-statistic result is depicted in Figure 5.

This can be interpreted as the Brazilian business sectors being characterized by being operated with either one large company dominating the market or with very few limited numbers of companies; in other words, the competition in the Brazilian business sectors is very low. The results of the Lerner Index are provided in Table 7, derived from the OLS estimation with the distributions of the Lerner Index presented in Figure 6. It shows that market power is high in the Brazilian stock exchange.

Due to the fact that market power is negatively correlated with the level of competition. We would conclude the results from the Lerner Index present the same condition regarding the environment that the Brazilian companies have operated in. As far as we are concerned, there have not yet been any studies investigating the level of market power across different economic sectors in Brazil. However, we find that a higher level of market power is evident in the Brazilian cement industry (Salvo, 2010) and the soybean processing industry (Costa & Cordeiro de Santana, 2015).

3.4 | B3's ESG indexes

3.4.1 | IGCX

Launched in 2001, the IGCX is a weighted average of a theoretical portfolio of stocks designed to measure the average stock performance, tracking changes in the prices of stocks listed for trading on the special corporate governance segments of B3 known as Level 1, Level 2, and Novo Mercado. Besides being listed for trading on any of the special corporate governance segments of B3, the eligible firms

TABLE 5 Descriptive statistics for the variables used in the *H*-statistic and in the Lerner Index calculations.

Variable name	Acronym	Min	Max	Mean	SD
Administrative expenses	ADM	−230.71	40,219.57	713.45	2748.33
Cash and cash equivalents	CCE	0.00	117,412.53	1140.07	4788.70
Deposits	DEP	0.00	221,581.41	19,768.92	40,051.43
Expenses from financial operations	EFO	0.00	195,741.94	16,440.74	37,356.16
Employee-related liabilities short term	ERLST	−0.24	5806.25	74.22	259.02
Employee- and social-related liabilities	ESRL	0.00	8082.46	147.63	521.68
Financial expenses	FE	−1300.53	75,245.95	754.9	2960.86
Financial income	FI	−1819.05	32,717.05	332.70	1390.23
Income from financial operations	IFO	0.00	217,595.88	2304.55	17,536.89
Investments	INV	0.00	43,893.57	443.09	1963.28
Net income	NI	−53,053.96	59,899.87	620.35	3867.01
Operational expenses	OE	−13,869.51	135,931.47	1229.59	5762.56
Other operational expenses	OOE	0.00	98,028.86	470.73	5314.55
Own operational expenses	OWOP	0.00	1855.63	15.82	118.25
Salaries and beneficiaries expenses	SBE	0.45	27,321.10	3692.32	7512.71
Total assets	TA	0.44	1,892,392.53	34,918.45	175,382.61

TABLE 6 OLS regression results for the *H*-statistic.

Variable name	Coefficient	SE	*t* value	*p* value
(Intercept)	2.673	0.040	66.338	**.000**
log PL	0.003	0.000	4.918	**.000**
log PF	0.006	0.000	6.585	**.000**
log PC	−0.456	0.012	−36.226	**.000**
log EQAST	0.089	0.008	11.073	**.000**
log SIZE	0.001	0.000	3.191	**.001**
log LOANAST	0.001	0.000	1.996	**.046**
Trend	−0.001	0.001	−1.136	.256
Trend Squared	0.000	0.000	0.708	.479
Dummy Communications	0.008	0.006	1.294	.195
Dummy Cyclical Consumption	0.007	0.002	2.848	**.004**
Dummy Non-Cyclical Consumption	0.006	0.003	1.966	**.049**
Dummy Financial	0.011	0.002	4.157	**.000**
Dummy Health	0.011	0.003	2.919	**.003**
Dummy Basic Materials	−0.0004	0.003	−0.127	.899
Dummy Information Technology	0.023	0.005	4.113	**.000**
Dummy Oil, Gas, and Biofuels	−0.005	0.004	−1.089	.276
Dummy Public Utility	0.002	0.003	0.982	.326

Note: Adjusted R^2: .4284. *F*-statistics: 117.4 on 17 and 2646 DF. Bold values indicate significance at .05 level. Individual fixed effects are controlled in the regression.

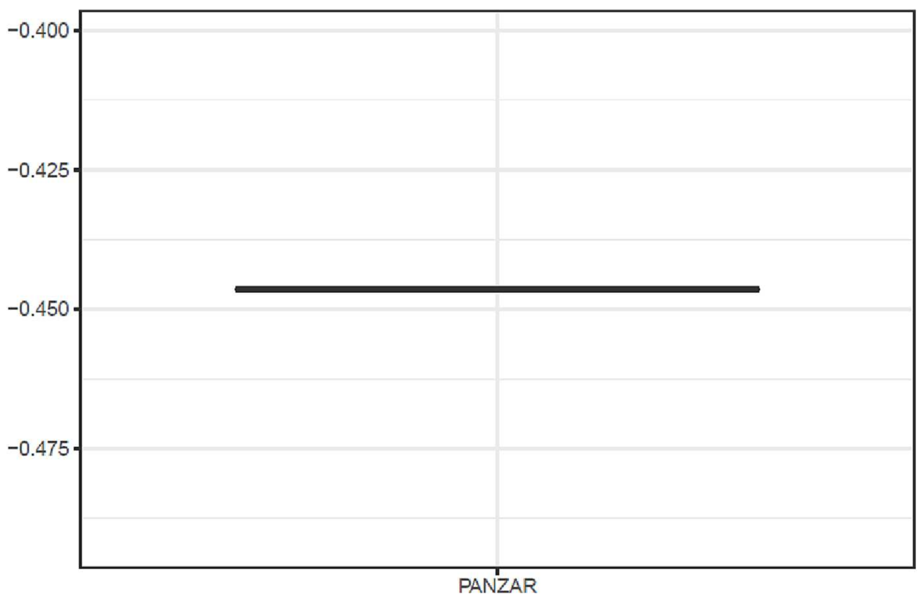

FIGURE 5 Panzar–Rosse *H*-statistic distribution.

must also have been actively traded in 50% of the trading sessions held over a period comprising the three previous portfolio cycles or all of the post-listing period, if shorter than the former; and must not constitute a "penny stock" (share of stock quoted at less than R$ 1.00). Regarding the yearly variation, measured by the monthly nominal closing rates, IGCX has moved from 7.629,88 points in 2010 to 18.179,46 points in 2019, presenting a 138.27% appreciation (IGCXB3, 2021).

3.4.2 | ISE

Launched in 2005, the ISE is the most famous and broadly utilized ESG index in the Brazilian stock exchange. It is a weighted average of a theoretical portfolio of stocks designed to measure the average stock performance, tracking changes in the prices of stocks of firms recognized for their commitment to corporate sustainability. The index portfolio comprises no more than 40 stocks selected by the

TABLE 7 OLS regression results for the Lerner Index.

Variable name	Coefficient	SE	*t* value	*p* value
(Intercept)	−9.28	182.10	−5.097	**.000**
log *Q*	87.42	17.35	5.039	**.000**
log Q^2	0.37	0.013	27.297	**.000**
log P	110.30	21.360	5.165	**.000**
log *Q*_log *P*	−10.50	**2.035**	−5.161	**.000**
log *P*_log *P*	−0.01	0.012	−0.953	.341
Trend	0.01	0.009	0.767	.443
Trend Squared	0.00	0.001	−0.754	.451
Dummy Communications	0.30	0.047	6.323	**.000**
Dummy Cyclical Consumption	0.03	0.018	1.638	.101
Dummy Non-Cyclical Consumption	0.14	0.026	5.371	**.000**
Dummy Financial	0.09	0.020	4.758	**.000**
Dummy Health	0.03	0.029	1.185	.236
Dummy Basic Materials	0.06	0.024	2.702	**.007**
Dummy Information Technology	0.01	0.043	0.166	.868
Dummy Oil, Gas, and Biofuels	0.09	0.036	2.441	**.015**
Dummy Public Utility	0.01	0.021	0.588	.557

Note: Adjusted R^2: .2649. *F*-statistics: 60.47 on 16 and 2625 DF. Bold values indicate significance at .05 level. Individual fixed effects are controlled in the regression.

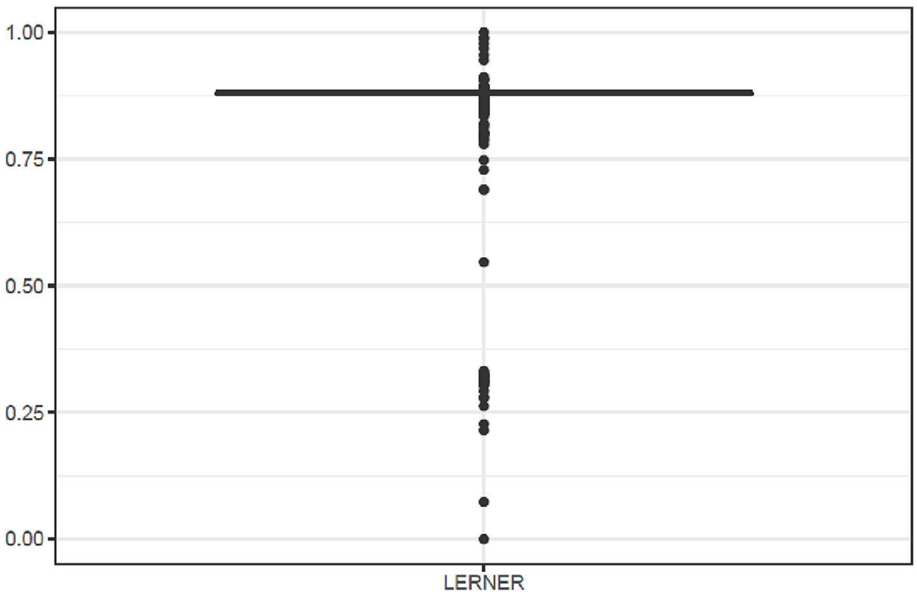

FIGURE 6 Lerner Index distribution.

Index Governance Committee (CISE). Different from the IGCX, which focuses on just one dimension of the ESG agenda (Governance) and different from the ICO2, which also focuses on just one dimension of the ESG agenda (Environmental), ISE is a broad sustainability index that tries to encompass all three ESG pillars—environmental, social, and governance. For that, firms' commitment to corporate sustainability is measured by seven different dimensions: environmental, economic-financial, general, corporate governance, climate change, product nature, and social. The index participation is voluntary, meaning that an invitation is made by B3 to the firms holding the 200 most liquid shares of stocks to compete for the ISE Portfolio. The firms that accept the invitation and want to be part of the index must first answer a questionnaire divided into the seven dimensions presented above and then send seven pieces of evidence that are drawn in each of the dimensions. Finally, CISE analyses all the answers and deliberates to choose the firms that will indeed compose ISE. Regarding the yearly variation, measured by the monthly nominal closing rates, ISE has moved from 2.087,30 points in 2010 to 4.140,26 points in 2019, presenting a 98.35% appreciation (ISEB3, 2021).

3.4.3 | ICO2

Launched in 2010, the ICO2 is a weighted average of a theoretical portfolio of stocks designed to measure the average performance of the stocks in the theoretical portfolio of the IBrX 100 (Brazil-100 Index), which represents the 100 most actively traded and best representative stocks of the Brazilian stock market, taking into account the greenhouse gas emissions of the issuing firms. Besides being part of the IBrX index, the eligible firms must also have formally joined the ICO2 initiative and report annual greenhouse gas emission inventories in accordance with the scope and timetable determined by B3. Regarding the yearly variation, measured by the monthly nominal closing rates, ICO2 has moved from 1.106,94 points in 2010 to 2.580,90 points in 2019, presenting a 133.16% appreciation (ICO2B3, 2021).

3.5 | SSRP model

The existing endogenous relationships among the Brazilian publicly traded firms' financial efficiency, market structure indicators and the performance of the chosen three Brazilian stock exchange ESG indexes (IGCX, ISE, and ICO2) will be disclosed by an innovative SSRP model under the structure of the neural network, while the potential cause–effect relationships among them will be identified.

- Indicator 1: Efficiency—Two-step NDEA Model
- Indicator 2: HHI (Business Sector)
- Indicator 3: HHI (Year)
- Indicator 4: Lerner Index
- Indicator 5: Panzar–Rosse *H*-statistic
- Indicator 6: IGCX—Corporate Governance Index
- Indicator 7: ISE—Corporate Sustainability Index
- Indicator 8: ICO2—Carbon Efficient Index

These residuals are then utilized to construct a full set of conditional residual distributions between each model's specified dependent variable pairings. These conditional residual distributions allow for the investigation of possible directional links between variables. The unique SSRP model is divided into two parts that allow endogeneity to be shown while also identifying key cause–effect linkages among the reminder variables. Next, we'll go over these steps.

3.5.1 | Step 1: Minimal endogenous relationship variance

The variances of each model and the covariances between models are used to explore the relevant importance of Indicators 1–8, through which not only the relationships among efficiency, market structure, and ESD indexes can be explained, but the potential endogenous relationships among the variables can be examined. Model (8) shows that a non-linear stochastic optimization problem is used to minimize the variances and the covariances of the residuals, in which the weights to the residual vector for each of the eight indicators are assigned with the values range between 0 and 1. In order to minimize the variance and the covariance of the pooled residuals, we optimize the values of *w*. Differential evolution (DE) is used to solve the model (8).

$$\min\left[Var\left(\sum_{i=1}^{8} w_i * R_i\right) + \left(2 * \sum_{i,j=1}^{8} Covar\left(w_i * w_j * R_i * R_j\right), i \neq j, j < i\right)\right], \quad (8)$$

subject to

$$\sum_{i=1}^{8} w_i = 1,$$

$$0 \le w_i \le 1 \ \ \forall i.$$

We bootstrapped 100 times the residuals of the MLP models, which will benefit from the ability to collect a distributional profile of *w*, so that the efficiency scores and contextual variables can be most accurately predicted.

3.5.2 | Step 2: Maximal information entropy for directional weighted residuals

In the context of precisely testable information, the principle of maximum entropy argues that the probability distribution with the biggest entropy best captures the current state of knowledge. Subsequently, we compute a full combinatorial set of conditional distributions of residuals (CR_k), based on previously 100 bootstrapped applications of the individual residuals, where $CR_k \sim f(R_i/R_j)$ for all i and j, $i \neq j$, and $K = i * j - i = 8 * 8 - 8 = 56$. The following non-linear integer programming model is solved by the DE to see whether there are significant differences among the conditional distributions of each residual pair with regard to the directions. For example, higher entropy can be yielded for the weights assigned to $f(R_i/R_j)$ for those assigned to $f(R_j/R_i)$ levels, compared with the unconditional residuals examined in Step 1 to disclose endogeneity. The model below describes this non-linear integer programming problem.

$$\max\left[\left(\sum_{i}^{8}\sum_{j}^{8} H\left(f\left(\frac{R_i}{R_j}\right) * w_i * w_j\right)\right) OR \left(\sum_{i}^{8}\sum_{j}^{8} H\left(g\left(R_i, R_j\right) * w_i * w_j\right)\right), \ \ i \neq j\right], \quad (9)$$

subject to

$$\sum\nolimits_{i=1}^{8} w_i = 1,$$

$$0 \le w_i \le 1, \ \forall i,$$

where $H(.)$ denotes the information entropy function; $g(R_i, R_j)$ denotes the unconditional marginals of the residuals from Indicators 1–8,

$\forall i,j,\ i \neq j$; $f(R_i/R_j)$ denotes the conditional distribution of the residuals from Indicators 1–8, $\forall i,j,\ i \neq j$.

The structural relationship among dependent variables defined in Indicators 1–8 for which information entropy is maximal is returned by this non-linear integer programming model. This ensures that the probabilistic weight profile produced in Step 1 is unique and consistent, with a low overall residual variance. As a result, the weights calculated in Step 1 served as the starting point for Step 2 optimization. The DE method was used to determine the best solutions for each *ij* pair in terms of maximal entropy. This model determines if a given *ij* pair's relationship is endogenous or if *i* causes *j*. (or the other way around). The pseudo-code for computing *f*(.) and *g*(.) estimations in the Step 2 optimization model is shown in Table 5.

4 | RESULTS AND DISCUSSION

4.1 | Relationship among performance and key attributes

Only one of Indicators 1–8 has a high relative value for achieving the least residual variance, the Panzar–Rosse *H*-statistic (cf. Figure 7). In fact, this indicator accounts for nearly 40% of the total median weights, thus indicating that B3's concentration and the state of quasi-monopoly and monopoly that firms operate regarding their business sectors play an important role in determining both firms' ESG performances and firms' efficiency. This indicates the government or regulatory authorities could propose and implement relevant policies to adjust the level of competitive conditions in the business sectors. Also, the Brazilian firms themselves could also play a key role in shaping the competitive environment in the Brazilian business sectors through engaging in relevant behavior, such as engaging in more innovation-related activities to expand their product range offered to the customer and/or engaging in cross-sector operation offering different types of products or services in different economic sectors (in case of increase the level of competition). Figure 8 shows the relative relevance of the major interaction pairings in explaining the overall residual variation, which supports this hypothesis, where the Panzar–Rosse *H*-statistic appears associated with both all the ESG indexes and the Efficiency indicator.

4.2 | Endogeneity

The 10 major indicator pairs' combined feedback effect on overall residual variance is roughly 5% (cf. Figure 8). When each of the eight indicators accounts for 12.50% of the total residual variation, the maximum feasible endogeneity effect is achieved. The maximum joint effect in this instance of equal weights is 87.50% = 2 * 43.75% = 2 * 12.50% * 12.50% * 28, where 28 is the number of possibilities selected two by two, as determined by the joint variations of Indicators 1 and 2. This preliminary analysis of the weights derived in Step 1 reveals that endogeneity is only modestly relevant for understanding the links between business efficiency, market structure, and ESG measures. This result indicates that the inter-relationships among business efficiency, market structure, and ESG measures are primarily driven by exogenous factors

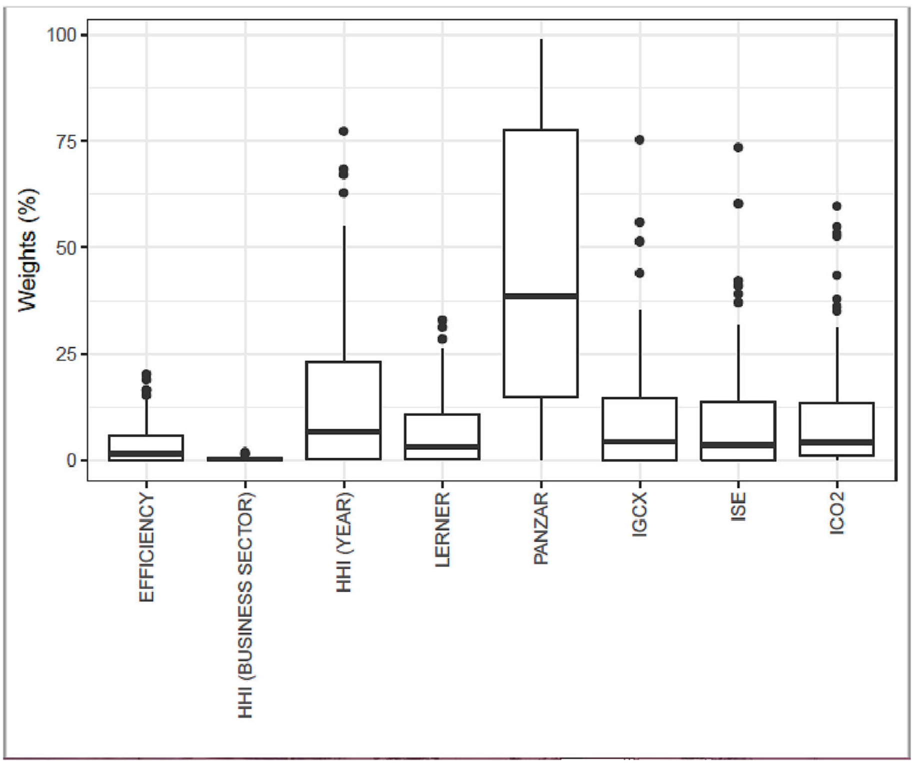

FIGURE 7 Relative importance of Indicators 1–8.

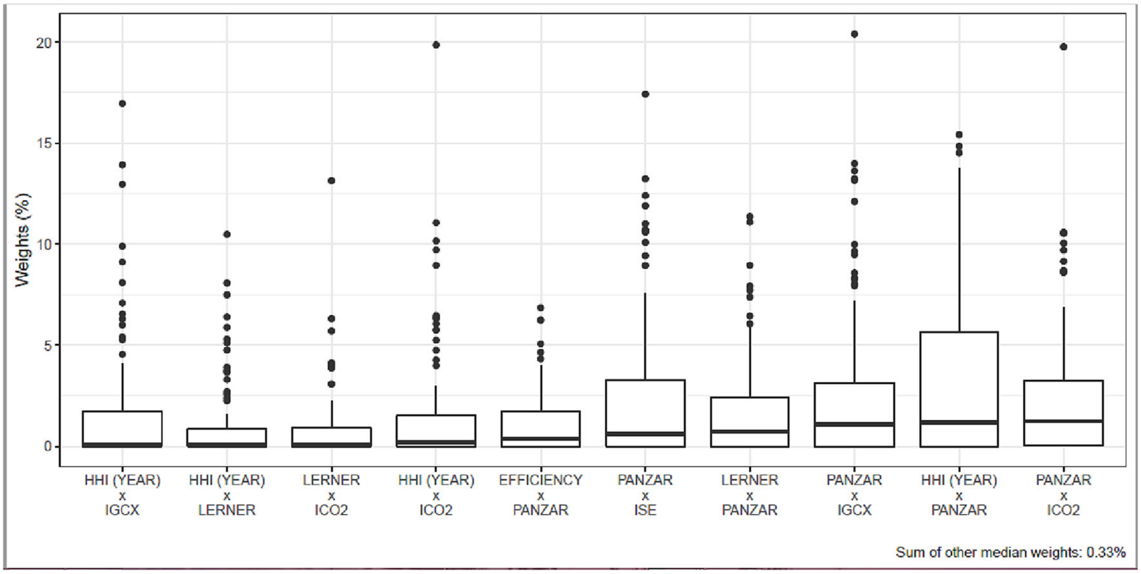

FIGURE 8 Endogeneity weights for pairs of Indicators 1–8: 10 major combinations.

TABLE 8 Information entropy of conditional distribution for .975 percentile.

Models	EFFICIENCY	HHI (BUSINESS SECTOR)	HHI (YEAR)	LERNER	PANZAR	IGCX	ISE	ICO2
EFFICIENCY		.663211;	.665961;	.665716;	.66201;	.664172;	.668814;	.662312;
HHI (BUSINESS SECTOR)	.665489;		.662869;	.662304;	.666753;	.665226;	.667078;	.666456;
HHI (YEAR)	.665067;	.665076;		.663513;	.664653;	.662855;	.662481;	.663625;
LERNER	.668727;	.669965;	.670915;		.670202;	.670972;	.669623;	.668455;
PANZAR	.663153;	.65558;	.660471;	.660078;		.662249;	.667498;	.66125;
IGCX	.662909;	.663478;	.663004;	.661454;	.665141;		.665927;	.663142;
ISE	.66348;	.66183;	.668246;	.665573;	.662383;	.659987;		.66608;
ICO2	.662625;	.661865;	.661625;	.661012;	.66023;	.65727;	.661797;	

such as government policies, macroeconomic conditions, and technological changes. In addition, while the findings suggest that endogeneity is only modestly relevant for understanding the links between business efficiency, market structure, and ESG measures, it is important to note that the degree of relevance may vary depending on the specific context. Thus, future research could explore the potential endogeneity issues in different contexts, such as different industries, regions, or time periods. Finally, policymakers could use this information to design policies that promote competition and ESG practices, as these could help improve business efficiency. For example, policymakers could encourage firms to adopt environmentally sustainable practices or provide incentives to promote competition in markets.

4.3 | Cause–effect associations

Tables 8 and 9 report on the conditional and unconditional distribution results utilized in the model (9), achieved for the .975 percentile. Based on the ideal weights obtained in Step 2 for the .975 percentile criterion, Figures 9 and 10 show the directional relationships among variables and their corresponding signs. When assuming a balanced bi-directional relationship among variables, the median predicted weight for each conditional distribution would be 0.0179 (1/56). Taking into account the .975 percentile criterion, where associations are strained to a 2.5 percent false positive rate, the state of quasi-monopoly and monopoly (captured by the Panzar–Rosse *H*-statistic) that Brazilian listed firms operate regarding their business sectors is a key indicator determining the firms' ESG performances and firms' efficiency. In other words, the Brazilian highly concentrated business sectors play a central role in both how firms will behave regarding their ESG practices and how efficient they will be. It is also interesting to notice that the cause–effect relationships between the Panzar–Rosse indicator, the ESG indexes, and the Efficiency indicator are exactly the same as between the HHI (Business Sectors) indicator and these variables as well, clearly confirming the important role of B3's business sectors' concentration and competition in their ESG practices and firms' efficiency.

With regard to the cause–effect relationships between ESG indexes and firms' Efficiency, the results point to a scenario where the

TABLE 9 Information entropy of unconditional distributions for .975 percentile.

Models	EFFICIENCY	HHI (BUSINESS SECTOR)	HHI (YEAR)	LERNER	PANZAR	IGCX	ISE	ICO2
EFFICIENCY								
HHI (BUSINESS SECTOR)	.352794;							
HHI (YEAR)	.323613;	.212722;						
LERNER	.45958;	.464126;	.316338;					
PANZAR	.299662;	.291696;	.32213;	.357804;				
IGCX	.198871;	.291608;	.340461;	.34502;	.295523;			
ISE	.306402;	.292429;	.184423;	.485068;	.292909;	.387857;		
ICO2	.404304;	.293834;	.255483;	.187981;	.33061;	.285104;	.217295;	

Note: Differently for the conditional distribution matrix, the unconditional distribution is a symmetric one.

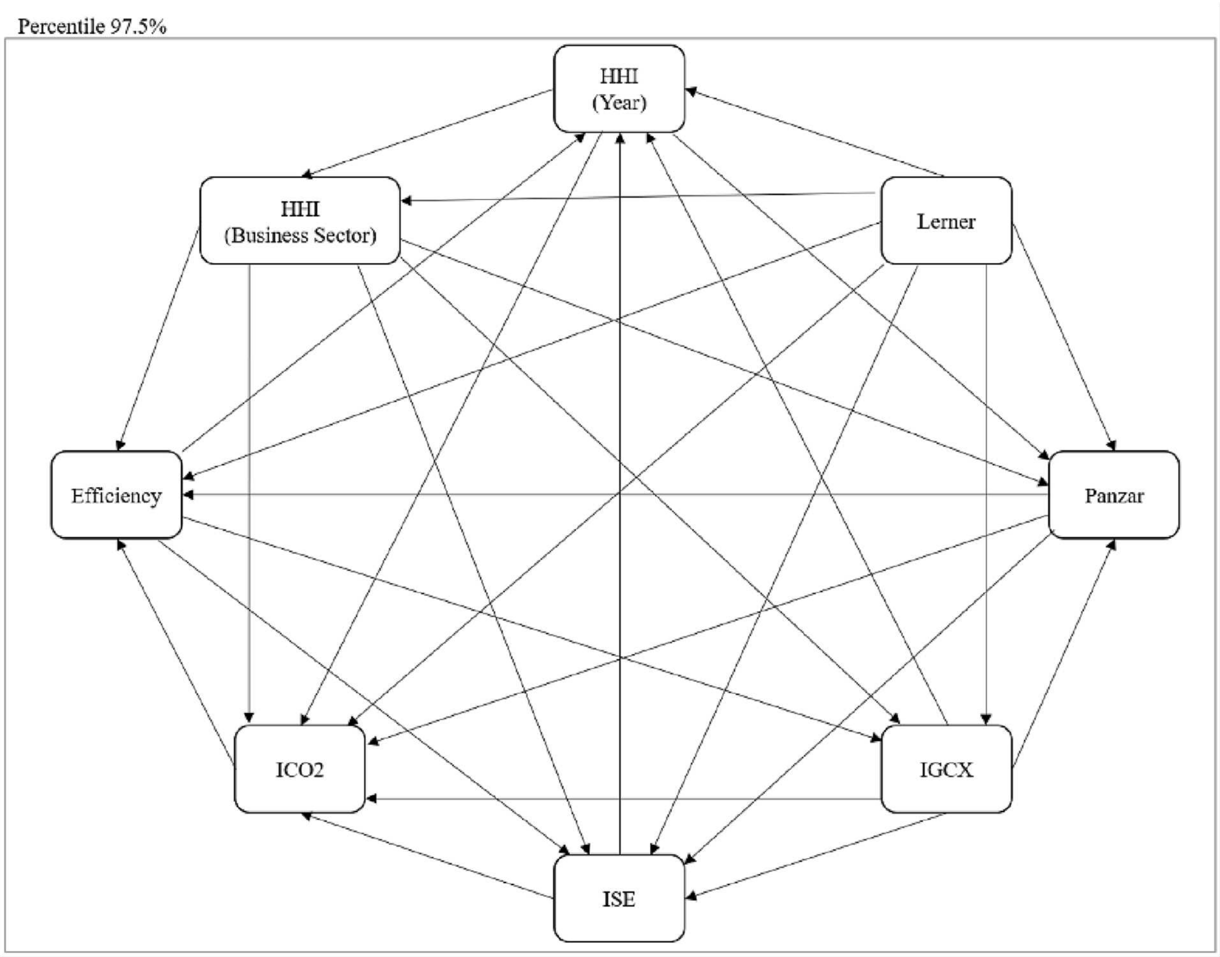

FIGURE 9 Cause and effect framework for selected attributes at .975 percentile.

lower the firms' ESG and governance performances (lower ISE and IGCX), the higher the firms' efficiency. This finding implies that the Brazilian listed firms are more concerned about their financial efficiency rather than their ESG and governance performances and practices and maybe see those practices just as sunk costs that can decay their financials once they are already efficient. Interesting to point out that these results go against a stream of existing literature regarding the subject (Janang et al., 2018; Kahveci & Wolfs, 2019; Liu, 2020; Loprevite et al., 2020; Rahim, 2021; Wang et al., 2018). On the other hand, the ICO2 is the only ESG index that presented a positive relationship with efficiency—the higher the ICO2, the higher the firms' efficiency. This result shows firms' tendency to care about greenhouse gas emissions and other environmental practices in an effort to be more financially efficient. This result is in line with Chai et al. (2020), whereas it goes against Perez et al. (2011). These results give empirical credibility to our H1 to H3, confirming a significant association between

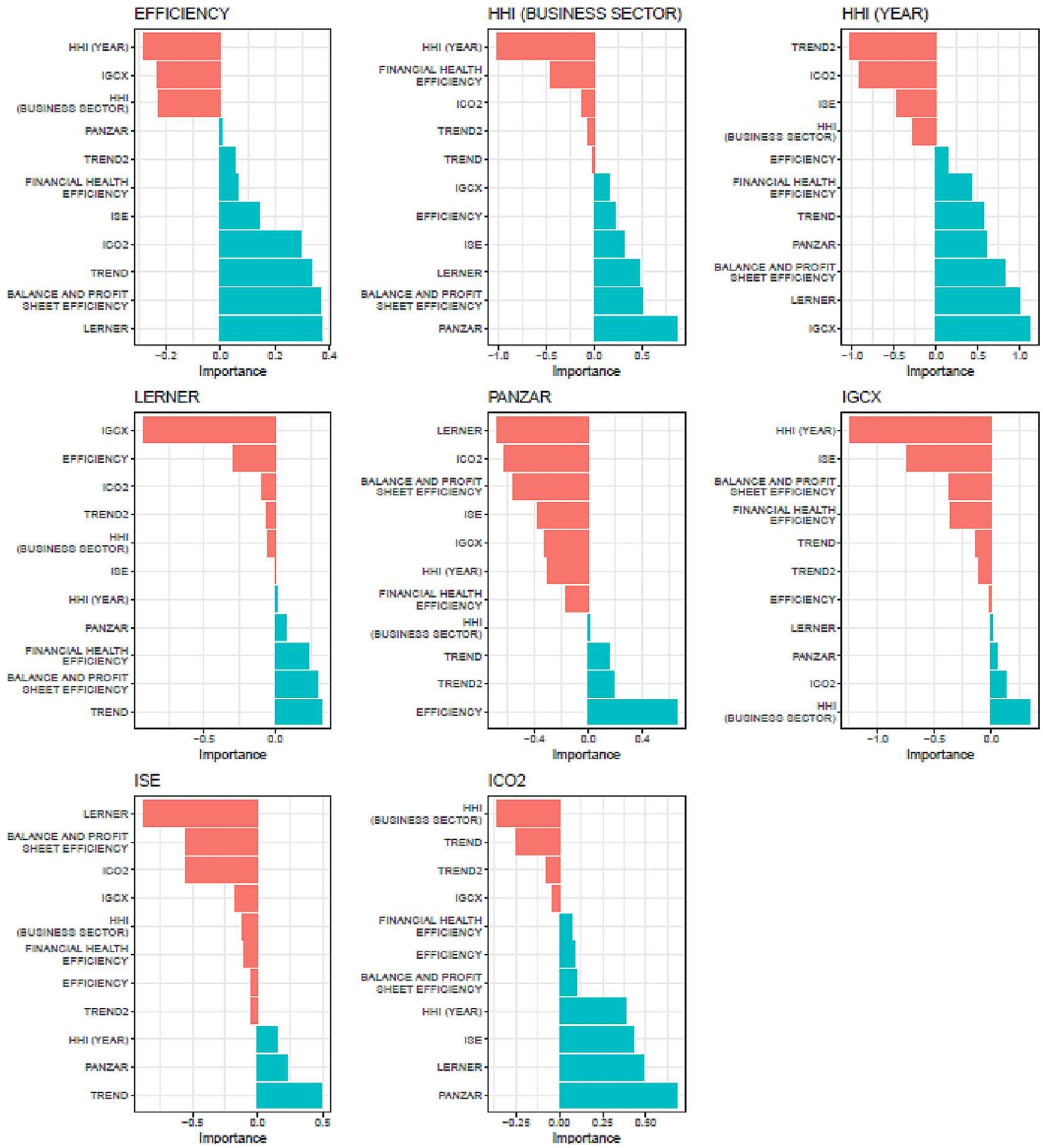

FIGURE 10 Results of Olden's sensitivity analysis.

environmental performance (positive), governance performance, and total ESG score (negative) on the one hand and firm efficiency on the other hand. All links and signals of cause–effect relationships between ESG indexes and firm efficiency are presented in Table 10.

Regarding the directional cause–effect relationships between ESG indexes and marker structure indicators (i.e., Panzar–Rosse and HHI), the results also show that the lower the competition and the higher the concentration, the higher IGCX. and that the higher the IGCX, the lower the competition, which means that competition and corporate governance practices are two substitute variables. These results are in line with a body of existing literature regarding the subject (Ammann et al., 2013; Chou et al., 2011; Gempesaw, 2021; Liu et al., 2018; Moradi et al., 2017; Tang & Chen, 2020). This result is supported by our non-directional H4.

On the other hand, the results show that the higher the competition and the lower the concentration, the higher the ISE and ICO2, and the lower the competition and the higher the concentration, the lower ISE and ICO2, which means that the Brazilian listed firms' ESG performance (ISE) and environmental performance (ICO2) are influenced by the degree of concentration and competition they face and can be perceived as a competitive advantage. The results concerning competition, concentration, and ESG performance are in line with most of the existing literature on the topic (Acabado et al., 2020; Chih et al., 2010; Declerck & M'Zali, 2012; Fernández-Kranz & Santaló, 2010; Flammer, 2015; Kontesa et al., 2020; Sheikh, 2018) and go against just one study (Lee et al., 2018). The significant and positive impact of competition on ISE (ESG) and ICO2 (environmental performance) is also in line with our non-directional H5 and H6,

TABLE 10 Link and signal of cause–effect relationships.

From	To	Link	Signal
EFFICIENCY	HHI (YEAR)	.0130	+
EFFICIENCY	IGCX	.0028	–
EFFICIENCY	ISE	.0003	–
HHI (BUSINESS SECTOR)	EFFICIENCY	.0029	–
HHI (BUSINESS SECTOR)	ICO2	.0070	–
HHI (BUSINESS SECTOR)	IGCX	.0027	+
HHI (BUSINESS SECTOR)	ISE	.0003	–
HHI (BUSINESS SECTOR)	PANZAR	.0148	+
HHI (YEAR)	HHI (BUSINESS SECTOR)	.0127	–
HHI (YEAR)	ICO2	.0315	+
HHI (YEAR)	PANZAR	.0660	–
PANZAR	EFFICIENCY	.0151	+
PANZAR	ICO2	.0367	+
PANZAR	ISE	.0014	+
ICO2	EFFICIENCY	.0072	+
IGCX	HHI (YEAR)	.0120	+
IGCX	ICO2	.0067	–
IGCX	ISE	.0002	–
IGCX	PANZAR	.0140	–
ISE	HHI (YEAR)	.0012	–
ISE	ICO2	.0007	+
LERNER	EFFICIENCY	.0103	+
LERNER	HHI (BUSINESS SECTOR)	.0101	+
LERNER	HHI (YEAR)	.0451	+
LERNER	ICO2	.0250	+
LERNER	IGCX	.0096	+
LERNER	ISE	.0009	–
LERNER	PANZAR	.0524	–

confirming a positive association between the level of competition and both firms' environmental performance and the total ESG score.

Moreover, regarding the cause–effect relationships between ESG indexes and the Lerner Index, the results are quite interesting since, regarding governance (IGCX) and ESG (ISE) performances, the relationships' directions and signs are in line with both the Panzar–Rosse *H*-statistic and the HHI (Business Sectors) indicators, and also with the previous-mentioned literature, meaning that the higher the market power (which can be interpreted as less competition), the higher IGCX and the lower ISE. However, regarding the environmental dimension (ICO2), the results show that the higher the market power, the higher ICO2, which means that some Brazilian listed firms are indeed concerned about the environment, specifically about their greenhouse gas emissions, and that they are trying to use their market power to influence other firms to act the same green way.

Our previous findings regarding the positive impact of competition on ICO2 can be explained by the fact that, as we discussed earlier, firms operating in a highly competitive environment are more concerned about building competitive advantage, which can be achieved by improving the performance of the environmental dimension of ESG (Palsson & Kovacs, 2014). On the other hand, the positive impact of market power on ICO2 can be explained from the perspective that firms with higher levels of market power would have higher revenue and/or lower marginal cost (based on the formula we used to estimate the Lerner Index), this can be achieved by an improvement in the level of efficiency, while the reduction of greenhouse gas emissions (i.e., the improvement in the environmental dimension of ESG) would facilitate the achievement of financial efficiency (Antunes, Tan, et al., 2023; Liu et al., 2022).

Moving to the directional cause–effect relationships between firms' efficiency and Panzar–Rosse and HHI (Business Sectors) indicators, the results show that the higher the competition and the lower the concentration, the higher the firms' efficiency, and the lower the competition and the higher the concentration, the lower the firms' efficiency. This means that Brazilian listed firms' efficiency is also influenced by the degree of concentration and competition they face.

This finding indicates that H7 has been statistically accepted. These results are in line with most of the existing literature about the topic (Dai et al., 2019; Mohammed et al., 2019; Rao Subramaniam et al., 2019), going against only Titko et al. (2015) and Nguyen et al. (2020) that found no relationship between these variables. This is in accordance with the quiet-life hypothesis in the banking industry (Tan & Anchor, 2017), which argues that managers with higher levels of market power are less careful in managing their expenses and their working efforts are reduced, which eventually results in a lower level of efficiency.

Moreover, regarding the cause–effect relationship between firms' efficiency and the Lerner Index, the directional sign points to a scenario similar to the one between ICO2 and the Lerner Index, meaning that the higher the market power, the higher the firms' efficiency, which makes sense since the Lerner Index measures the distance between price and marginal cost, and the larger this distance is, the more efficient the firm has to be. This result is in line with Viverita (2014) and goes against Le Long et al. (2020).

5 | CONCLUSION

This paper aims to examine the cause–effect relationships between the level of competition, firms' ESG indexes, and their efficiency in the Brazilian context. To do so, we use a two-stage NDEA to evaluate the firm's efficiency; the market structure was evaluated by employing three different indicators, the HHI in order to capture concentration, the Panzar–Rosse *H*-statistic to capture competition, and the Lerner Index to capture market power; and lastly, ESG practices were evaluated by the yearly variation (measured by the monthly nominal closing rates) of three different ESG stock indexes, the IGCX, the ISE, and the ICO2. Finally, this paper has applied an innovative SSRP method aiming to unveil both the existing endogenous relationships between all the above-mentioned variables and their directional cause–effect relationships.

The main findings of this paper suggest that the degree of competition and concentration that the Brazilian listed firms face regarding their business sectors play an important role in determining both their ESG performance and efficiency. That being said, the lower the firms' ESG performance and the poorer corporate governance practices, the higher the firms' efficiency, while firms with high levels of environmental performance are more financially efficient. Moving to the cause–effect relationships between market structure, firms' ESG performances, and their efficiency, the results show that the higher the competition and the lower the concentration, the higher the firms' ESG performance, the higher firms' environmental performance, and the lower firms' corporate governance performance. Moreover, regarding market power, the results show that the higher the market power, the higher firms' environmental performance, the higher the corporate governance performance, and the lower the ESG performance. Additionally, market structure proxies (i.e., market compaction and power) are positively attributed to firms' efficiency.

Our empirical evidence generates several policy implications that could help firms improve their business strategies: (1) *Focus on improving environmental performance*: As the findings suggest a positive link between the environmental performance of firms and their financial efficiency, firms could consider implementing environmentally friendly practices and technologies in order to enhance their financial efficiency in the long run. This could include reducing energy and resource consumption, adopting renewable energy sources, and implementing waste reduction and recycling programs. (2) *Improve corporate governance practices*: The findings suggest that a firm's efficiency is subject to poor corporate governance performance. Hence, firms could consider implementing better governance practices such as transparent reporting and independent board oversight while maintaining a focus on improving their financial efficiency. (3) *Increase competition*: As higher competition is associated with higher ESG performance and firm efficiency, firms could consider strategies to increase competition in their market. This could involve differentiating their products or services, expanding into new markets, or forming strategic partnerships with other firms to gain a competitive advantage. (4) *Reduce market power*: The findings suggest that higher market power is associated with lower ESG performance. Firms could consider strategies to reduce their market power, such as entering into collaborations or partnerships to increase competition or implementing more transparent pricing practices.

Our evidence also generates important implications for investors, regulators, and the Brazilian stock exchange. For example, investors will notice that if they are looking forward to putting their money in more ESG-minded firms, firms from highly competitive business sectors and presenting low market power can be good options for them. Besides, our study informs regulators and the authorities of the Brazilian stock exchange that market competition is a crucial factor for both firms' financial efficiency and their ESG practices. Thus, our evidence calls for these governing authorities in Brazil to implement more flexible rules, regulations, and fees both for the already listed firms and also for the not yet listed ones in order to persuade them to become and stay public-traded firms since, as we have already seen in our findings, the Brazilian stock market is a highly concentrated one due to the low number of listed firms.

Finally, for future research, applying this new approach regarding the cause–effect relationships between firms' efficiency, market structure, and ESG performance to different countries around the world, including not only emerging markets but also advanced and low-income economies, would be highly interesting, both for comparisons and analyzes across countries themselves and also between markets with different levels of development. Additionally, future studies could try to apply different ESG performance indicators besides ESG stock indexes and could also try to add indicators measuring specifically the ESG social dimension since our paper makes use of indexes that focus on the ESG as a whole (ISE); on the governance dimension (IGCX); and on the environmental dimension (ICO2), leaving a blank space for the social dimension.

CONFLICT OF INTEREST STATEMENT

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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