Received 19 December 2024
Revised 29 May 2025
3 December 2025
6 April 2026
Accepted 1 May 2026

Capital providers' effects on the ESG performance scores of European industrial firms: frequentist and Bayesian approaches

Joachim Rojahn and Florian Zechser
Department of Economics, FOM Hochschule, Essen, Germany

Abstract

Purpose – This study aims to explore the effects of external capital providers, particularly the largest shareholders and debtholders, on environmental, social and governance (ESG) performance scores and three European industrial companies' ESG pillar scores.

Design/methodology/approach – The sample consists of 135 industrial services and goods companies that were members of the STOXX Europe 600 Index during the 2019–2023 period. This selection enables the exploration of the effects of external capital providers beyond the constraints of intense public scrutiny within the industry. The study uses regression-based analyses complemented by Bayesian approaches. Because the sample period begins after the adoption of the Sustainable Finance Disclosure Regulation and the European Green Deal, the results provide valuable insights for policymakers, regulators and minority shareholders.

Findings – The findings consistently show that ownership concentration negatively affects social and governance scores, whereas corporate ownership positively affects environmental performance, likely because of potential synergies. In addition, financial investors appear to respond more to ESG controversies than to actively shape the ESG efforts of portfolio companies. Finally, Bayesian analysis reveals a high probability of a positive debt–social score association.

Originality/value – While previous studies have primarily relied on frequentist methods to assess ESG determinants at the aggregate level, this study leverages Bayesian analyses to quantify the likelihood that the largest shareholders and debtholders affect ESG performance positively or negatively. Furthermore, it broadens the scope of ESG research by investigating the role of non-financial corporations as significant equity holders, a topic that has received limited attention.

Keywords Environmental social and governance, Ownership structure

Paper type Research paper

1. Introduction

Many investors perceive environmental, social and governance (ESG) information as crucial for investment decisions (Amel-Zadeh and Serafeim, 2018). However, compiling an ESG score is time-consuming because it is a multidimensional construct and each dimension can be decomposed into numerous measurable indicators (Widyawati, 2021). Thus, most investors rely on external providers' assessments (Cellier *et al.*, 2016; Drempetic *et al.*, 2020). Most ESG scores measure ESG performance by assessing how a firm manages its

Conflict of interest: The authors have no conflicts of interest to declare.

Review of Accounting and Finance
Vol. 25 No. 4, 2026
pp. 616-639
Emerald Publishing Limited
1475-7702
DOI 10.1108/RAF-12-2024-0560

environmental impact and interacts with employees, customers and other stakeholders and evaluating the ethical and governance standards in corporate decision-making. However, ESG performance scores vary considerably across firms (Drempetic *et al.*, 2020).

The ESG preferences of external capital providers may be a source of this variation, particularly the preferences of the largest shareholders and debtholders. For instance, the European Union's Sustainable Finance Disclosure Regulation (SFDR) and the European Green Deal specifically encourage financial institutional investors to promote sustainable financing (Horn, 2024). A literature review by Kavadis and Thomsen (2023) highlights that previous studies have predominantly identified financial ownership as a positive factor in ESG performance. Similarly, Khan's (2022) meta-study finds leverage to be a positive driver of ESG performance. However, the impact of family ownership remains inconclusive (Kavadis and Thomsen, 2023), and little research has examined the role of non-financial corporations holding substantial equity stakes in publicly listed firms.

Most studies in this research field follow a frequentist approach, relying on traditional statistical significance testing such as regression analysis (Velte, 2023). Frequentist techniques allow for inferences about which variables, *on average*, affect ESG performance. In contrast, Bayesian analysis enables the examination of ESG performance drivers at the *individual* firm level instead of focusing on an average firm (Hansen *et al.*, 2004; Mackey *et al.*, 2017). To illustrate, a firm's unique ESG performance may be shaped, among other factors, by its largest shareholder's investment motives, oversight resources, or its attitude toward ESG, with the last factor based on its perceived impact on corporate value. As many of these factors are intangible or inherently unobservable, Bayesian analysis, which offers probabilities of parameters exceeding or falling below zero rather than single-point estimates, can provide additional insights (Hansen *et al.*, 2004; Mackey *et al.*, 2017).

This study contributes to the literature that examines the extent to which different external capital providers influence a firm's ESG performance and its three-pillar scores in the following aspects. First, we complement the regression-based analyses with a Bayesian approach, which has recently attracted increasing attention in empirical finance research (Chakraborty *et al.*, 2022). However, based on the literature review in Section 3, we believe that this is the first study to apply a Bayesian approach to analyze the ESG performance factors.

Second, we investigate the influence of external capital providers on the ESG performance of European firms under harmonized regulations within the supersector of industrial services and goods (hereafter, industrials) according to the Industry Classification Benchmark (ICB). This supersector includes sectors, such as electronic and electrical equipment and industrial engineering, which tend to face less public pressure to improve their ESG efforts. Instead, their ESG performance is likely shaped by large investors. For example, in the absence of public attention, large shareholders may intervene if they consider a firm's ESG efforts to have no effect on value. Conversely, companies in industries that directly address retail consumers to a large extent may experience customer-driven pressure to uphold environmentally and socially responsible practices (Cordeiro *et al.*, 2021). Similarly, companies in ESG-sensitive industries, such as chemicals, are often subjected to political pressures and public debates to reduce their environmental damage (Garcia *et al.*, 2017; Kannenberg and Schreck, 2019). Furthermore, our sample firms exhibit diverse ownership structures in terms of both concentration and identity, with family owners or non-financial corporations included among the largest shareholders. Consequently, analyzing industrials provides a quasi-natural experimental setting to assess the impact of external capital providers on ESG performance beyond the constraints of intense public scrutiny. Our sample period begins in 2019, after the adoption of the SFDR and European Green Deal and

extends to 2023, when these regulations came into force. Unlike prior European studies, which focus on institutional and/or family owners and rely on frequentist methods (Velte, 2023; Kavadis and Thomsen, 2023), our study broadens the scope by incorporating rarely examined non-financial corporate shareholders and complementing regression-based analyses with a Bayesian framework. The findings may be relevant to policymakers, regulators and minority shareholders.

The remainder of this paper is organized as follows. Section 2 reviews related literature. Section 3 presents the hypotheses. Section 4 outlines the data and methodology. Section 5 presents the results of our analyses, while Section 6 discusses their implications. Finally, Section 7 concludes the paper.

2. Theoretical foundation

European firms are typically characterized by a high level of ownership concentration (Kirchmaier and Grant, 2005; Thomsen and Pedersen, 2000). Therefore, we follow previous research (Thomsen and Pedersen, 2000) and focus on the largest shareholders in our analysis. The influence of the largest shareholder on the ESG performance of a portfolio firm can be understood through several key theories, including agency theory, stakeholder theory, legitimacy theory and the resource-based view (RBV) (Velte, 2023). These frameworks collectively suggest that the largest shareholders possess both the ability and incentive to shape a firm's ESG performance, although the direction of this influence depends on their objectives.

Large investors may engage managers directly, exercise voting rights or threaten share divestment (Edmans, 2009). Moreover, the largest investors can contribute additional funding, and this capital allocation affects a firm's growth rate (Kölbel *et al.*, 2020). Incentives to promote ESG performance include encouraging management to pursue long-term objectives and mitigate reputational risks (Ellimäki *et al.*, 2023). Monitoring incentives are positively associated with both the size of the equity stake and length of the investment horizon (Shleifer and Vishny, 1986). Longer horizons facilitate sustainability strategies (Kordsachia *et al.*, 2022), and concentrated ownership extends horizons (Kavadis and Thomsen, 2023). Accordingly, large shareholders are generally expected to steer managerial decision-making toward ESG practices that reflect investor preferences for sustainable value creation.

Agency theory provides the foundation for this expectation, positing that concentrated ownership reduces Type I agency conflicts between managers and shareholders. The stakeholder theory complements this view by suggesting that large owners promote ESG initiatives to balance the interests of shareholders, employees, customers and communities, thereby strengthening their reputation and stakeholder support (Rees and Rodionova, 2015). Legitimacy theory explains that firms adopt ESG practices to conform to societal expectations and preserve their social license to operate. Thus, large shareholders who are sensitive to reputational risks are inclined to advocate transparent disclosures (Ellimäki *et al.*, 2023; Gega *et al.*, 2025). Finally, the RBV frames ESG performance as a strategic resource that generates competitive advantage (Bhandari *et al.*, 2022). From this perspective, large shareholders act as strategic resources that shape ESG capabilities, with various types of shareholders affecting strategy and effectiveness.

However, concentrated ownership may impair ESG performance when shareholder incentives conflict with sustainability objectives. In highly concentrated ownership structures, Type I agency conflicts between managers and shareholders are typically minor, whereas Type II agency conflicts – that is, principal–principal conflicts – occur frequently (Renders and Gaeremynck, 2012). With privileged access to information, large shareholders

may exploit firm resources, prioritize short-term profits over ESG investments (Kordsachia *et al.*, 2022), or collude with management for private benefits (Souguir *et al.*, 2024). Such behavior may lead to the withholding of ESG information, undermining reported performance, given rating agencies' reliance on public disclosure (Escrig-Olmedo *et al.*, 2019). Similarly, the absence of immediate ESG returns, short-term financial pressures, or market turbulence may lead large shareholders to prioritize profitability over stakeholder alignment, legitimacy-driven transparency or long-term resource development (Short and Ndlovu, 2025).

Beyond ownership concentration, debt ratio serves as an additional governance mechanism that influences ESG performance. From an agency theory perspective, higher leverage increases creditor monitoring because debtholders bear downside risks without participating in upside gains (Jensen and Meckling, 1976). Firms may voluntarily enhance ESG disclosures to mitigate the agency costs of debt. Stakeholder theory supports a positive debt–ESG link, as robust ESG practices signal reliability to lenders, lowering the cost of debt and improving financing access (Adeneye *et al.*, 2023). However, excessive leverage may constrain ESG performance because firms cannot afford discretionary ESG investments (Bani-Khaled *et al.*, 2025).

3. Literature review and hypotheses development

Drawing on the aforementioned theoretical frameworks, this section develops hypotheses on how ownership concentration and debt ratio influence ESG performance. Importantly, the largest shareholders cannot be considered a homogeneous class because their investments are undertaken for different motives that are likely to affect their preferences for ESG performance. Building on prior research, we differentiate institutional investors, family owners (Kavadis and Thomsen, 2023), and non-financial corporate shareholders as distinct ownership types. European empirical evidence on these ownership types is fragmented and relies almost exclusively on frequentist methods.

As institutional investors' client demand for ESG investments has been increasing (Amel-Zadeh and Serafeim, 2018), institutional investors are likely to promote ESG performance to fulfill their fiduciary duties. Agency theory suggests that their large equity stakes incentivize monitoring to align management with long-term ESG goals. However, institutional investors exhibit heterogeneity in investment horizons, monitoring propensity and motivation to commit to ESG criteria (Kavadis and Thomsen, 2023). Even fund labeling does not yield unambiguous conclusions, as the incentives and conduct of sustainable funds often resemble those focused solely on returns (Cremasco and Boni, 2024). A recent literature review by Velte (2023) examines the effects of institutional ownership on ESG and corporate social responsibility (CSR) reporting and performance, finding that long-term, sustainable and foreign institutional ownership are positive drivers. Similarly, a review conducted by Kavadis and Thomsen (2023) shows that most studies report a positive impact of institutional ownership on ESG and/or CSR metrics. Based on these insights, we hypothesize as follows:

H1. When the largest shareholder is a financial institutional investor, ESG performance is positively associated with the size of the financial institution's equity position.

Following Thomsen and Pedersen (2000), we classify firms in which individual investors hold the largest equity stakes as family firms. Decisions made by family owned firms are influenced by socio-emotional wealth (Gomez-Mejia *et al.*, 2010). Family owners often prioritize maintaining control over the firm and protecting their reputation, focusing on long-term goals (Souguir *et al.*, 2024). However, this long-term orientation does not necessarily

align with ESG concerns. If competitiveness is threatened, family owners may emphasize short-term profitability over ESG (Kavadis and Thomsen, 2023), and their less diversified portfolios make them cautious about risky ESG investments (Gega *et al.*, 2025; Rees and Rodionova, 2015). Theoretical perspectives highlight this tension. Agency theory points to principal–principal conflicts that can lead to private benefit-seeking, whereas the RBV suggests a reluctance to allocate resources to ESG if competitiveness is at risk.

Although long-term ownership is often positively associated with ESG performance, the evidence for family firms is mixed. Kavadis and Thomsen (2023) report that many studies find a negative effect. Thus, we hypothesize as follows:

H2. When the largest shareholder is an individual investor, ESG performance is negatively associated with the size of the individual investor's equity stake.

A common phenomenon in European stock markets is that non-financial corporations hold substantial equity stakes in publicly listed firms (Kirchmaier and Grant, 2005; Thomsen and Pedersen, 2000). Such investments are often strategic and aim to reduce contracting costs, mitigate information asymmetries (Fee *et al.*, 2006) and realize synergies or access technologies (Drees *et al.*, 2013). From an RBV perspective, corporate investors may support ESG when it generates synergies or strengthens competitive advantage, for instance, by enhancing stakeholder trust. However, similar to family owners, their less diversified portfolios make them reluctant to encourage risky ESG initiatives. Based on this reasoning, we hypothesize as follows:

H3. When the largest shareholder is a non-financial corporate investor, ESG performance is negatively associated with the size of the corporate investor's equity stake.

Agency theory suggests that debtholders act as external monitors, encouraging ESG disclosure to reduce the agency costs linked to information asymmetry and risk (Jensen and Meckling, 1976). Stakeholder theory states that firms with higher debt ratios may adopt stronger ESG practices to reassure creditors and other stakeholders concerned about reputational or regulatory risks (Adeneye *et al.*, 2023). Legitimacy theory further argues that debt-financed firms enhance ESG disclosures to meet societal expectations and safeguard their social licenses. Empirical evidence supports this view. A meta-study by Khan (2022) identifies leverage as one of the most frequently examined variables – after firm size – in explaining ESG performance and finds it to be a positive driver. Thus, we hypothesize as follows:

H4. The higher an issuer's debt ratio is, the higher its ESG performance score.

4. Sample, data and methodology

4.1 Sample selection

The initial sample comprises all firms that were classified as industrials and were members of the STOXX Europe 600 Index for at least one year from 2019 to 2023. The sample period covers more recent years to obtain as many observations as possible using the available ESG performance scores. Moreover, the sample period begins in 2019 to ensure comparability. This is because the scoring methodology of the ESG performance score used in this study – the London Stock Exchange Group (LSEG; formerly Refinitiv Eikon, Thomson Reuters and Asset4) ESG performance score – was modified in 2018 (Adeneye *et al.*, 2023). To avoid survivorship and newness biases, the firms are added to the sample in the year they first enter the index and remain part of the sample until they cease business activities during the

investigation period. All data items required for this study are sourced from the LSEG Workspace, Datastream and Worldscope databases. The initial sample includes 647 firm-year observations. From this sample, 37 observations are removed because of missing information, and an additional 41 firm-year observations are classified as outliers according to Cook's distance (23), applying a threshold of 4/n or because of negative common equity (18). These modifications lead to an unbalanced data set comprising 569 observations across 5 years and 135 firms.

4.2 Dependent variables

We follow previous research (Cicchiello *et al.*, 2022; Drempetic *et al.*, 2020; Ferrell *et al.*, 2016; Garcia *et al.*, 2017) and use the ESG performance scores provided by the LSEG, which are also widely utilized by investors (Rajesh and Rajendran, 2020). The LSEG ESG performance scores are exclusively based on publicly available information and comprise hundreds of ESG measures and data points, ranging from 0 to 100 (Rajesh and Rajendran, 2020; Widyawati, 2021).

However, a company's overall ESG performance score includes only a subset of the most relevant and comparable ESG measures per industry. These measures are grouped into ten categories, and the corresponding category scores are aggregated into the three pillar scores: ESG. Moreover, the environmental and social scores are relative scores benchmarked against the issuer's industry. To ensure comparability, this study relies on observations from the same ICB supersector. Finally, the ESG performance scores are extended by 23 material ESG controversies obtained from negative media stories, which yield the ESG combined scores (hereafter, ESG-COMB). This allows for the comprehensive evaluation of companies' sustainability impacts (Rajesh and Rajendran, 2020).

While aggregating the ESG dimensions ensures that users are not overwhelmed by information (Widyawati, 2021), disaggregation may shift factor salience (Crace and Gehman, 2022). To account for the multidimensional nature of the ESG construct, we perform additional analyses and successively replace ESG-COMB as the dependent variable with the three pillar scores: environmental (E-Score), social (S-Score) and governance (G-Score).

4.3 Explanatory variables

Following Thomsen and Pedersen (2000), we express ownership structure in terms of the fraction of shares held by the largest shareholder. We account for the potential heterogeneity among investor types and rely on investor-type descriptions assigned by the LSEG Ownership and Profiles module. We categorize the proportion of shares held by the largest shareholder into four categories: non-financial corporate ownership (CORP), which includes 78 firm-year observations; financial institutional ownership (FIN), with 320 firm-year observations; individual ownership (IND), comprising 94 firm-year observations; and all other entities (OTHERS), such as government agencies, which account for 77 firm-year observations. DEBT is defined as the sum of short- and long-term financial debts scaled by total assets.

4.4 Control variables

The set of control variables is derived from previous studies. Firm size (SIZE) is the natural logarithm of the firm's total assets and is often found to positively affect ESG performance (Borghesi *et al.*, 2014; Drempetic *et al.*, 2020; Garcia *et al.*, 2017). Larger firms are more likely to encounter Type I agency conflicts that can be mitigated by information disclosure (Jensen and Meckling, 1976), and may experience public pressure to comply with ESG criteria. ROA is measured as the earnings before interest and taxes divided by total assets. Profitable firms have resources to support ESG activities. However, greater profitability may

signal higher proprietary costs (Botosan and Stanford, 2005), reducing firms' willingness to issue extensive ESG reports to protect future margins. The MBR, defined as the market value of equity divided by the book value of equity, captures a stock's valuation level. A higher market-to-book ratio may signal Type I agency problems (Ferrell *et al.*, 2016), necessitating greater disclosure that can enhance ESG performance. Intensified ESG efforts may also help legitimize high ratios. The issuer's growth opportunities are measured by CAPEX, that is, the ratio of capital expenditures to total assets. High capital expenditures may signal Type I agency problems (Ferrell *et al.*, 2016) and create financing needs that encourage greater disclosure (Reitmaier and Schultze, 2017), potentially enhancing ESG performance. CASH is the ratio of cash and marketable securities to total assets. High cash reserves serve as another proxy for agency problems (Ferrell *et al.*, 2016), which can be reduced through ESG efforts. However, low cash reserves may also call for intensified ESG efforts if they indicate a demand for fresh money.

Moreover, we consider the country-level characteristics that may influence a firm's ESG performance. All sample firms are located in countries with strong democratic representation, where societal pressure encourages them to act responsibly (Daugaard and Ding, 2022). However, the European Union has driven regulatory measures to address ESG-related challenges more strongly than any other jurisdiction (Balp and Strampelli, 2022), which potentially affects ESG performance scores. Thus, we create a binary variable (NON-EU) that equals one if the firm's country of domicile is outside the European Union and zero otherwise. In 232 of our 569 firm-year observations, NON-EU takes the value of one. Finally, we include year dummies to account for time-specific influences, with 2019 serving as the reference category. Table 1 summarizes the variables used in the analysis.

Table 2 presents the descriptive statistics for the continuous variables.

4.5 Methodology

To reduce the risk of endogeneity, we use one-period lagged values (t–1) for our explanatory variables and continuous control variables (controls) and current year values (t) for the dependent variables. We include year dummies for 2020–2023 to account for time-specific influences common to all issuers, and a binary control variable (NON-EU) to capture jurisdictional differences. We test the model as specified in equation (1):

$$\begin{aligned} \mathrm{ESG-COMB}_{i,t} = f\big(&\mathrm{CORP}_{i,t-1},\ \mathrm{FIN}_{i,t-1},\ \mathrm{IND}_{i,t-1},\ \mathrm{OTHERS}_{i,t-1},\ \mathrm{DEBT}_{i,t-1},\ \mathrm{controls}_{i,t-1},\\ &\mathrm{NON-EU}_{i,t-1},\ \mathrm{year\ dummies}_{t}\big). \end{aligned} \tag{1}$$

We account for the multidimensional character of the ESG performance score and disaggregate ESG-COMB by using the E-Score, S-Score and G-Score, as summarized in equations (2)–(4):

$$\begin{aligned} \mathrm{E-Score}_{i,t} = f\big(&\mathrm{CORP}_{i,t-1},\ \mathrm{FIN}_{i,t-1},\ \mathrm{IND}_{i,t-1},\ \mathrm{OTHERS}_{i,t-1},\ \mathrm{DEBT}_{i,t-1},\ \mathrm{controls}_{i,t-1},\\ &\mathrm{NON-EU}_{i,t-1},\ \mathrm{year\ dummies}_{t}\big), \end{aligned} \tag{2}$$

$$\begin{aligned} \mathrm{S-Score}_{i,t} = f\big(&\mathrm{CORP}_{i,t-1},\ \mathrm{FIN}_{i,t-1},\ \mathrm{IND}_{i,t-1},\ \mathrm{OTHERS}_{i,t-1},\ \mathrm{DEBT}_{i,t-1},\ \mathrm{controls}_{i,t-1},\\ &\mathrm{NON-EU}_{i,t-1},\ \mathrm{year\ dummies}_{t}\big), \end{aligned} \tag{3}$$

Table 1. Variable definitions

Variable	Description
Dependent variables	
ESG-COMB	LSEG ESG performance combined score ranging from 0 to 100 and discounted by material ESG controversies obtained from negative media stories
E-SCORE	LESG environmental pillar score ranging from 0 to 100
S-SCORE	LESG social pillar score ranging from 0 to 100
G-SCORE	LESG governance pillar score ranging from 0 to 100
Independent variables	
CORP	Fraction of shares held by the largest shareholder in the case of non-financial corporate ownership
FIN	Fraction of shares held by the largest shareholder in the case of financial ownership
IND	Fraction of shares held by the largest shareholder in the case of individual ownership
OTHERS	Fraction of shares held by the largest shareholder who is not sorted into the categories CORP, FIN, or IND
DEBT	Total financial debt scaled by total assets
Control variables	
SIZE	Natural logarithm of the firm's total assets
ROA	Earnings before interest and taxes divided by total assets
MBR	Market value of equity divided by the book value of equity
CAPEX	Ratio of capital expenditures to total assets
CASH	Ratio of cash and marketable securities to total assets
NON-EU	Binary variable that equals One if the firm's country of domicile is outside the European Union and zero otherwise
YEAR dummies	Set of binary variables for 2020, 2021, 2022 and 2023 (2019 is the omitted reference year)

Source(s): Created by authors

$$G-\text{Score}_{i,t} = f(\text{CORP}_{i,t-1},\ \text{FIN}_{i,t-1},\ \text{IND}_{i,t-1},\ \text{OTHERS}_{i,t-1},\ \text{DEBT}_{i,t-1},\ \text{controls}_{i,t-1},\ \text{NON}-\text{EU}_{i,t-1},\ \text{year dummies}_{t}). \quad (4)$$

We perform traditional panel regressions. Random-effects models are selected instead of fixed-effects models for three reasons. First, we aim to understand why firms' ESG performance scores differ. Such differences would be difficult to identify if much of the information on Level-2 entities (i.e. the sample firms) is lost by applying de-meaning (Bell *et al.*, 2019), especially when analyzing a short panel. In addition, the ownership variables exhibit minimal within-firm variation over time. Second, unobserved variables, such as the largest shareholder's attitude toward ESG, are unlikely to remain unchanged over time. Third, to mitigate the potential small-sample bias inherent in the conventional Hausman specification test and following the approach of Talloen *et al.* (2019), we approximate the distribution of the Hausman test statistic through 5,000 bootstrap replications. Across all model specifications, the bootstrap procedure does not provide evidence against the null hypothesis.

Unreported regression diagnostics reveal heteroscedasticity and serial correlations in the residuals. Year dummies absorb common shocks, while Pesaran CD tests indicate no remaining cross-sectional dependence. To address the remaining issues, we calculate cluster-

Table 2. Sample descriptive statistics for continuous variables

Variable	Min.	Max.	Mean	SD
$ESG\text{-}COMB_t$	28.156	93.979	64.7	13.21
$E\text{-}SCORE_t$	3.598	98.746	63.661	20.121
$S\text{-}SCORE_t$	28.298	96.298	71.502	15.872
$G\text{-}SCORE_t$	12.901	96.649	66.525	17.832
$CORP_{t-1}$	0	0.947	0.044	0.124
FIN_{t-1}	0	0.46	0.063	0.073
IND_{t-1}	0	0.754	0.056	0.151
$OTHERS_{t-1}$	0	0.51	0.035	0.104
$DEBT_{t-1}$	0	0.977	0.404	0.193
$SIZE_{t-1}$	12.529	18.82	15.583	1.133
ROA_{t-1}	−0.366	0.284	0.076	0.064
MBR_{t-1}	0.091	15.981	2.05	2.026
$CAPEX_{t-1}$	0.002	0.223	0.029	0.022
$CASH_{t-1}$	0.001	0.873	0.131	0.103

Note(s): This table reports the descriptive sample statistics. All variables are defined in Table 1
Source(s): Created by authors

robust standard errors at the firm level (Petersen, 2009). Since the variance inflation factors in all model specifications are less than five, the reported results are not affected by multicollinearity.

We complement our traditional statistical significance testing with Bayesian statistical methods to gain more nuanced insights into the factors that drive ESG performance. A limitation of traditional regression analysis is that it only calculates point and interval estimates, whereas Bayesian models allow full probabilistic predictive inference (Hansen *et al.*, 2004; Mackey *et al.*, 2017). In other words, Bayesian analyses quantify the *probability* that a variable will have a positive or negative impact on ESG performance scores. In contrast, frequentist regressions provide information on whether an *effect* exists but offer limited insight into the magnitude of the hypothesized effects and the uncertainty surrounding them (Kruschke and Liddell, 2018). Additionally, Bayesian models enhance the reliability of parameter estimates, even with limited data, by borrowing strength across observations using a shared parameter distribution (Hansen *et al.*, 2004). By contrast, traditional statistical significance testing in short panels tends to yield weak confidence because parameter estimation relies on only a few observations per firm.

When performing the Bayesian analyses, we follow the guidelines suggested by Jebb and Woo (2015) and Kruschke (2015). Consistent with the panel regression specifications introduced above, we employ a linear model to examine the effects of ownership variables, debt and other covariates on ESG performance scores. Irrespective of the dependent variable's definition and given the nature of the value being modelled, we request the normal model's likelihood function and normal priors for the coefficients with a mean of 0 and variance of 100. We use relatively uninformative priors because, to the best of our knowledge, previous Bayesian research in this field is scarce, with little credible information justifying unequal outcome probabilities.

In any model specification, posterior distributions are generated using the Markov chain Monte Carlo methods (Gelfand and Smith, 1990) from four chains. Each chain comprises 625,000 draws from a Hamiltonian Monte Carlo (HMC) sampler, retaining every 20th draw after a burn-in period of 25,000 draws. We assess whether the HMC algorithm is

representative of the posterior distribution via visual inspection, including trace, density and autocorrelation plots, none of which are reported for the sake of parsimony. In terms of representativeness and convergence, each parameter's trace plot fails to reveal any trends and traverses the distribution quickly. Moreover, for each parameter, the autocorrelation diminishes quickly (i.e. the autocorrelation becomes negligible before the fifth leg), indicating reasonable stability and accuracy.

The numerical indicators support the visual inspections. The median acceptance rate for all models exceeds 0.95, implying that the chains explore the entire posterior domain. The bulk effective sample sizes fall within the interval of 115,924–119,564, well above the threshold of 10,000 (Kruschke, 2015). Finally, the Monte Carlo standard error for each parameter, except for CAPEX (approximately 10%), falls below 5% of the posterior standard deviation, indicating less sampling error variation (Toft *et al.*, 2007).

5. Results

5.1 Results for environmental, social and governance combined scores as the dependent variable

Table 3 presents our findings for equation (1), where ESG-COMB serves as the dependent variable. Columns 1 and 2 contain the results of the random-effects regression, and Columns 3–7 display the results using the Bayesian methodology. When presenting the results of the Bayesian models, we follow previous studies (Cordeiro *et al.*, 2021; Mackey *et al.*, 2017) and disclose the posterior mean of the distribution of the parameters (Column 3), the probability that these parameters would have a negative effect on the dependent variable (Column 4) and the corresponding 95% highest posterior density (HPD) interval (Column 5).

In a Bayesian framework, the prior distribution formalizes theoretical assumptions or initial uncertainty before data collection. By combining these priors with the observed data, we obtain the posterior distribution, which represents the updated probability of parameter values. The HPD interval identifies the most credible values within this distribution; a 95% HPD interval that includes zero indicates that the null value remains highly plausible and that there is insufficient evidence to conclude that the parameter differs meaningfully from zero (Kruschke, 2018).

Complementary Bayesian null hypothesis testing is performed using the Bayes factor, which provides a continuous measure of evidence by quantifying the relative support for competing models yielded by the data. Unlike the *p*-value – which evaluates the data only against a single reference value – the Bayes factor is inherently comparative (Wagenmakers *et al.*, 2018). For instance, a Bayes factor of 30 indicates that the data support a non-zero effect 30 times more strongly than the null hypothesis. Thresholds of 30 and 100 are typically interpreted as strong and decisive evidence, respectively (Kruschke and Liddell, 2018).

The results from both frequentist and Bayesian regressions provide strong support for *H2*. IND is a robust negative driver of ESG-COMB, supported by classical significance ($p < 0.05$) and a strong Bayes factor of 44. In contrast, *H1*, *H3* and *H4* are rejected, although the coefficient signs and Bayesian posterior means align with expectations. For the control variables, both methods indicate that SIZE (NON-EU) is a positive (negative) driver of ESG performance, with classical significance of $p < 0.01$ ($p < 0.1$) and decisive (strong) Bayesian evidence. Furthermore, both techniques show that the 2020 and 2021 year dummies are positively related to ESG-COMB, with classical significance ($p < 0.05$) and consistent Bayesian support (Bayes factors of 26 and 46). For the remaining variables, neither *p*-values nor posterior distributions provide clear evidence of statistical effects.

Table 3. Frequentist and Bayesian estimates with ESG-COMB as the dependent variable

	Random-effects panel regression		Bayesian estimation					
Variable	(1) Estimates	(2) Std. error	(3) Posterior mean	(4) Prob < 0	(5) 95% HPD interval		(6) BF < 0	(7) BF > 0
INTERCEPT	14.765	16.373	11.969	0.196	−15.231	39.465	0.244	4.100
$CORP_{t-1}$	−0.629	5.939	−1.170	0.568	−14.417	12.452	1.313	0.762
FIN_{t-1}	15.826	12.823	15.153	0.092	−7.153	37.516	0.101	9.926
IND_{t-1}	−13.304**	6.469	−13.939	0.978	−27.536	−0.245	43.577	0.023
$OTHERS_{t-1}$	−14.317	8.961	−13.544	0.914	−33.189	5.890	10.584	0.094
$DEBT_{t-1}$	3.125	4.229	3.185	0.189	−3.891	10.199	0.233	4.295
$SIZE_{t-1}$	3.017***	1.014	3.206	0.000	1.508	4.887	0.000	14,999.0
ROA_{t-1}	3.728	7.254	1.313	0.440	−16.222	18.260	0.785	1.274
MBR_{t-1}	−0.385	0.335	−0.287	0.753	−1.145	0.577	3.046	0.328
$CAPEX_{t-1}$	41.172	36.667	38.428	0.064	−11.934	87.036	0.068	14.701
$CASH_{t-1}$	8.257	5.648	9.291	0.072	−3.291	21.672	0.077	12.976
$NON\text{-}EU_{t-1}$	−4.000*	2.194	−4.095	0.972	−8.263	0.161	34.885	0.029
YEAR_2020	1.875**	0.876	1.780	0.038	−0.199	3.734	0.039	25.566
YEAR_2021	2.376**	1.020	2.216	0.021	0.100	4.366	0.022	45.765
YEAR_2022	1.424	1.294	1.297	0.116	−0.851	3.427	0.131	7.619
YEAR_2023	−0.200	1.233	−0.303	0.614	−2.315	1.800	1.594	0.627
Hausman test		24.68						
(*p*-value)		(0.099)						
R^2		0.114						
R^2 adj.		0.090						
Wald χ^2		48.876						
(*p*-value)		(<0.001)						
Firm-year obs.		569						
Acceptance rate					0.981			
Effective sample size					119,564			

Note(s): Columns 1 and 2 report unstandardized regression coefficients and clustered standard errors at the firm level of the random-effects panel regression for equation (1). The Hausman test follows a bootstrap procedure that relies on 5,000 repetitions to account for the potential small-sample bias of the conventional Hausman specification test. Columns 3–7 summarize the corresponding results of the Bayesian analysis and provide the posterior mean of the parameters, the probability of these parameters having a negative effect on the dependent variable, the corresponding 95% highest posterior density (HPD) interval and the Bayes factors (BF) for the parameters falling below and exceeding the null value. The results are based on 4 chains, each relying on 30,000 post-warm-up draws sampled using the Hamiltonian Monte Carlo algorithm. All the variables are defined in Table 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Created by authors

5.2 Results for the disaggregated environmental, social and governance pillar scores

The evidence for the determinants of the E-Score is presented in Table 4. Both traditional and Bayesian regressions show that the E-Score is positively associated with SIZE ($p < 0.01$, Bayes factor approaching infinity) and the year dummies (all p-values below 0.10 and the minimum Bayes factor across the dummy variables exceeding 146). Additionally, the traditional regression identifies NON-EU as a marginally statistically significant negative determinant of the E-Score. In the Bayesian framework, there is a posterior probability of approximately 96% that NON-EU negatively affects the E-Score, with the Bayes factor falling slightly below the threshold of 30. All hypotheses regarding the variables of interest are rejected. However, contrary to *H3*, traditional regression finds CORP to be a significantly positive factor influencing the E-Score.

The results with the S-Score as the dependent variable are reported in Table 5. Across both frequentist and Bayesian frameworks, FIN and IND emerge as relevant predictors, though they differ in their degree of empirical support. Specifically, FIN shows only marginal frequentist significance ($p < 0.10$), and the Bayesian analysis likewise yields substantial evidence with a Bayes factor of 27. In contrast, IND exhibits a more robust impact, achieving both classical statistical significance ($p < 0.01$) and strong Bayesian evidence (Bayes factor of 51). While the findings for IND align with *H2*, the results for FIN contradict the positive association proposed in *H1*. In the traditional regression, DEBT shows a positive but statistically nonsignificant association with the S-Score. In contrast, the Bayesian analysis reveals strong evidence of a positive effect: the Bayes factor is 41, and only 2.4% of the posterior draws are negative. Moreover, consistent with previously reported results, both methods identify SIZE and NON-EU as significant drivers of the S-Score.

The results for the determinants of the G-Score are summarized in Table 6. Both the traditional and Bayesian regressions show that the G-Score is positively related to SIZE. Moreover, both methods demonstrate inverse relationships between the G-Score and ownership concentration among the largest shareholders across all owner-type variables. Both IND and CORP exhibit strong frequentist evidence ($p < 0.01$) and decisive Bayesian support (Bayes factors $\gg 100$), while FIN shows only marginal frequentist support ($p < 0.10$) and substantial Bayesian evidence (Bayes factor above 24). The G-Score reflects, inter alia, an issuer's transparency in ESG reporting and its commitment to corporate governance principles. It is based on indicators such as the experiences of the supervisory board's members or the independence of an audit committee. Thus, our findings on the negative impact of ownership concentration correspond to Type II agency conflicts.

5.3 Robustness checks

First, we test whether our results suffer from endogeneity. For brevity, we rely on traditional approaches, namely the two-stage least squares (2SLS) regressions. We focus on endogeneity concerns related to our independent variables because it is unclear whether their effects on the dependent variables are causal or whether external capital providers select companies with ESG-Scores that align with their preferences (Adeneye *et al.*, 2023). We restrict the analyses to the independent variables for which the null value hypotheses in equations (1)–(3) are rejected. Because several variables in equation (4) are potentially endogenous, no further endogeneity tests are conducted.

Thus, we consider IND a potentially endogenous variable in equation (1). We choose the natural logarithm of (number of security analysts + 1) as the instrument because concentrated ownership is often associated with less analyst coverage, whereas analyst coverage does not significantly explain the dependent variable in equation (1). As shown in Table 7, the first-stage F-statistic of ln(number of security analysts + 1) comfortably exceeds the threshold of 10 (F-value ≈ 18.8) according to Stock *et al.* (2002). The second-stage results are broadly

Table 4. Frequentist and Bayesian estimates with E-SCORE as the dependent variable

	Random-effects panel regression		Bayesian estimation				
Variable	(1) Estimates	(2) Std. error	(3) Posterior mean	(4) Prob < 0	(5) 95% HPD interval		(6) BF < 0	(7) BF > 0
INTERCEPT	−27.254	25.400	−21.311	0.882	−56.432	14.123	7.439	0.134
$CORP_{t-1}$	18.209**	8.235	11.263	0.062	−3.176	25.694	0.066	15.210
FIN_{t-1}	−4.830	9.601	−6.886	0.745	−26.998	14.169	2.923	0.342
IND_{t-1}	−5.553	8.114	−3.883	0.653	−23.429	15.226	1.884	0.531
$OTHERS_{t-1}$	−20.680	17.122	−9.653	0.752	−37.770	18.164	3.026	0.330
$DEBT_{t-1}$	6.293	3.925	2.363	0.243	−4.322	8.937	0.320	3.122
$SIZE_{t-1}$	5.510***	1.531	5.274	0.000	3.021	7.476	0.000	INF
ROA_{t-1}	3.869	7.283	−0.858	0.565	−11.585	10.224	1.298	0.770
MBR_{t-1}	0.470	0.379	0.224	0.324	−0.741	1.216	0.480	2.084
$CAPEX_{t-1}$	54.124	57.408	42.311	0.026	−1.707	85.509	0.026	38.037
$CASH_{t-1}$	1.334	5.341	1.411	0.382	−7.785	10.449	0.619	1.615
$NON\text{-}EU_{t-1}$	−6.065*	3.546	−5.753	0.956	−12.468	0.787	21.901	0.046
YEAR_2020	1.131*	0.578	1.385	0.007	0.286	2.479	0.007	146.601
YEAR_2021	2.240**	0.918	2.109	0.005	0.472	3.703	0.005	183.332
YEAR_2022	2.796***	0.960	3.115	0.000	1.374	4.831	0.000	4,136.931
YEAR_2023	2.167**	1.014	2.463	0.004	0.624	4.292	0.004	233.375
Hausman test (*p*-value)	31.012 (0.052)							
R^2	0.180							
R^2 adj.	0.157							
Wald χ^2	102.165							
(*p*-value)	(<0.001)							
Firm-year obs.	569							
Acceptance rate					0,979			
Effective sample size					115,924			

Note(s): Columns 1 and 2 report unstandardized regression coefficients and clustered standard errors at the firm level of the random-effects panel regression for equation (1). The Hausman test follows a bootstrap procedure that relies on 5,000 repetitions to account for the potential small-sample bias of the conventional Hausman specification test. Columns 3–7 summarize the corresponding results of the Bayesian analysis and provide the posterior mean of the parameters, the probability of these parameters having a negative effect on the dependent variable, the corresponding 95% highest posterior density (HPD) interval and the Bayes factors (BF) for the parameters falling below and exceeding the null value. The results are based on 4 chains, each relying on 30,000 post-warm-up draws sampled using the Hamiltonian Monte Carlo algorithm. All the variables are defined in Table 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Created by authors

Table 5. Frequentist and Bayesian estimates with S-SCORE as the dependent variable

	Random-effects panel regression		Bayesian estimation					
Variable	(1) Estimates	(2) Std. error	(3) Posterior mean	(4) Prob < 0	(5) 95% HPD interval		(6) BF < 0	(7) BF > 0
INTERCEPT	36.015*	19.906	30.473	0.020	1.002	59.515	0.020	49.336
$CORP_{t-1}$	−9.351	8.657	−8.033	0.892	−20.903	4.723	8.276	0.121
FIN_{t-1}	−20.647*	11.809	−17.209	0.964	−35.958	1.637	26.900	0.037
IND_{t-1}	−17.099***	5.870	−15.873	0.981	−31.336	−1.055	50.993	0.020
$OTHERS_{t-1}$	−22.931**	11.206	−16.095	0.933	−37.056	5.416	14.002	0.071
$DEBT_{t-1}$	6.269	4.388	6.182	0.024	0.137	12.246	0.024	41.448
$SIZE_{t-1}$	2.589**	1.232	2.780	0.002	0.919	4.569	0.002	559.748
ROA_{t-1}	3.721	7.543	2.533	0.320	−8.075	13.194	0.470	2.130
MBR_{t-1}	−0.404	0.594	0.098	0.408	−0.710	0.914	0.691	1.448
$CAPEX_{t-1}$	−7.342	41.604	11.693	0.283	−28.374	51.444	0.395	2.529
$CASH_{t-1}$	1.382	5.508	3.647	0.210	−5.408	12.350	0.266	3.753
$NON\text{-}EU_{t-1}$	−10.987***	2.801	−10.641	1.000	−15.772	−5.543	59,999.000	0.000
YEAR_2020	0.632	0.660	0.560	0.166	−0.554	1.729	0.199	5.030
YEAR_2021	0.810	1.043	0.836	0.148	−0.730	2.418	0.174	5.760
YEAR_2022	1.954*	1.102	1.709	0.028	−0.019	3.488	0.029	34.336
YEAR_2023	0.517	1.146	0.694	0.241	−1.251	2.637	0.317	3.156
Hausman test		30.147						
(*p*-value)		(0.054)						
R^2		0.184						
R^2 adj.		0.162						
Wald χ^2		61.067						
(*p*-value)		(<0.001)						
Firm-year obs.		569						
Acceptance rate					0.959			
Effective sample size					117,042			

Note(s): Columns 1 and 2 report unstandardized regression coefficients and clustered standard errors at the firm level of the random-effects panel regression for equation (1). The Hausman test follows a bootstrap procedure that relies on 5,000 repetitions to account for the potential small-sample bias of the conventional Hausman specification test. Columns 3–7 summarize the corresponding results of the Bayesian analysis and provide the posterior mean of the parameters, the probability of these parameters having a negative effect on the dependent variable, the corresponding 95% highest posterior density (HPD) interval and the Bayes factors (BF) for the parameters falling below and exceeding the null value. The results are based on 4 chains, each relying on 30,000 post-warm-up draws sampled using the Hamiltonian Monte Carlo algorithm. All the variables are defined in Table 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Created by authors

Table 6. Frequentist and Bayesian estimates with G-SCORE as the dependent variable

	Random-effects panel regression		Bayesian estimation					
Variable	(1) Estimates	(2) Std. error	(3) Posterior mean	(4) Prob < 0	(5) 95% HPD interval		(6) BF < 0	(7) BF > 0
INTERCEPT	25.586*	15.263	23.591	0.081	−9.704	56.673	0.088	11.344
$CORP_{t-1}$	−28.192***	7.272	−26.591	0.999	−42.421	−10.248	1,845.154	0.001
FIN_{t-1}	−26.204*	13.396	−23.871	0.960	−51.061	2.332	24.258	0.041
IND_{t-1}	−59.710***	8.794	−58.615	1.000	−75.665	−41.524	INF	0.000
$OTHERS_{t-1}$	−53.262***	14.346	−50.963	1.000	−75.059	−26.249	29,999.0	0.000
$DEBT_{t-1}$	2.241	4.227	1.334	0.377	−6.872	9.758	0.605	1.654
$SIZE_{t-1}$	2.927***	0.941	3.051	0.002	0.951	5.066	0.002	475.190
ROA_{t-1}	3.372	9.318	2.464	0.400	−17.076	21.618	0.667	1.498
MBR_{t-1}	−0.487	0.313	−0.407	0.789	−1.453	0.626	3.735	0.268
$CAPEX_{t-1}$	−19.562	26.169	−15.775	0.706	−72.729	41.274	2.405	0.416
$CASH_{t-1}$	6.877	7.212	6.048	0.207	−8.623	20.595	0.262	3.823
$NON\text{-}EU_{t-1}$	2.344	2.529	2.402	0.179	−2.770	7.559	0.219	4.575
YEAR_2020	3.427***	0.913	3.386	0.001	1.285	5.481	0.001	1,211.121
YEAR_2021	2.212*	1.231	2.191	0.034	−0.144	4.544	0.035	28.777
YEAR_2022	0.982	1.401	0.980	0.213	−1.433	3.399	0.271	3.689
YEAR_2023	0.783	1.509	0.755	0.268	−1.653	3.121	0.365	2.737
Hausman test		8.9267						
(*p*-value)		(0.632)						
R^2		0.160						
R^2 adj.		0.137						
Wald χ^2		94.646						
(*p*-value)		(<0.001)						
Firm-year obs.		569						
Acceptance rate					0.984			
Effective sample size					116,501			

Note(s): Columns 1 and 2 report unstandardized regression coefficients and clustered standard errors at the firm level of the random-effects panel regression for equation (1). The Hausman test follows a bootstrap procedure that relies on 5,000 repetitions to account for the potential small-sample bias of the conventional Hausman specification test. Columns 3–7 summarize the corresponding results of the Bayesian analysis and provide the posterior mean of the parameters, the probability of these parameters having a negative effect on the dependent variable, the corresponding 95% highest posterior density (HPD) interval and the Bayes factors (BF) for the parameters falling below and exceeding the null value. The results are based on 4 chains, each relying on 30,000 post-warm-up draws sampled using the Hamiltonian Monte Carlo algorithm. All the variables are defined in Table 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Created by authors

consistent with those reported in Table 3. The Durbin–Wu–Hausman test does not indicate any endogeneity concerns, with a χ^2 test statistic of 1.85 ($p \approx 0.99$). Given that 2SLS is less efficient than one-stage regressions (Ebbes *et al.*, 2016), our statistical inference statements rely on previously reported one-stage regressions. Comparable findings emerge when IND is treated as a potentially endogenous variable in equation (3).

Similarly, we test for the endogeneity of CORP in explaining the E-Score using ln(number of security analysts + 1) as the instrument. The first-stage F-statistic is below the threshold of ten (F-value ≈ 6.2), while the Durbin–Wu–Hausman does not suggest any endogeneity concerns ($p \approx 0.999$). In the single-stage regression, CORP exhibits a positive and statistically significant association with the E-Score. However, when the model is re-estimated using 2SLS, the CORP is no longer statistically significant. Given the lack of stronger instruments, endogeneity cannot be entirely ruled out, although the relatively low within-variance of CORP may render such concerns less plausible. For brevity, we do not present the 2SLS estimation results separately. In the case of FIN, which is considered a potentially endogenous variable in equation (3), only weak instruments are detectable, similar to earlier findings for CORP. For instance, the first-stage F-statistic of ln(number of security analysts + 1) is just 3.2. Although endogeneity in FIN cannot be statistically ruled out, we address this issue from an economic perspective in Section 6.

Second, we account for the possibility that the E-Score and S-Score of our sample firms could not be readily compared across ICB subsectors. Instead of re-estimating the models for different subsamples, we exploit the benefit of the Bayesian approach, which allows an entire distribution to be grouped into different sub-distributions (Mackey *et al.*, 2017), such as for different sub-sectors. Table 8 shows the findings of the sub-distributions for the subsectors of "electronic and electrical equipment" and "industrials engineering," with the S-Score serving as the dependent variable. These findings do not differ substantially from the previously reported results. The findings with the E-Score as dependent variable are comparable to those reported in Table 8 (not reported for brevity). Finally, we examine whether our findings differ in terms of firm size. The results do not exhibit any size-related bias; therefore, we do not provide additional reporting.

6. Discussion

6.1 Synthesis of results

Contrary to previous results (Dyck *et al.*, 2019; Feng and Wu, 2021) and our *H1*, we find a negative association between financial ownership and both the social and governance scores based on traditional and Bayesian analyses. In the traditional regression, however, we observe a positive but nonsignificant effect on ESG-COMB. Given that the latter is based on the three-pillar scores but includes ESG controversies, it can be inferred that financial investors appear to be guided by the ESG score and ESG controversies rather than exerting pressure to improve it.

Consistent with our *H2*, both the frequentist and Bayesian results reveal a negative influence of individual ownership on ESG-COMB, as well as on the S-Score and G-Score. These findings correspond to the perception that family owners hesitate to engage in ESG investments (Gega *et al.*, 2025). Alternatively, the largest individual shareholders may not anticipate a positive ESG–firm value relationship.

Overall, we find little evidence that large shareholders exercise control or voting power during the investigation period to improve issuers' ESG performance in European industrial firms. However, contrary to our third hypothesis, the E-Score is positively associated with ownership concentration when corporate investors hold equity positions. A potential explanation is that corporate investments are often undertaken to gain access to the target's technology (Drees *et al.*, 2013). Thus, these findings allow us to conclude that large investors do not inherently oppose ESG but instead seek the benefits associated with it, although endogeneity concerns, while addressed, cannot be completely ruled out.

Table 7. The influence of IND on ESG-COMB: two-stage least squares (2SLS) regression

	First stage regression (1)		Second stage regression (2)	
	Dependent variable: IND		Dependent variable: ESG-COMB	
Variable	Estimates	Std. error	Estimates	Std. error
INTERCEPT	0.082	0.051	17.473	16.958
$CORP_{t-1}$	−0.072***	0.019	−7.301	8.785
FIN_{t-1}	−0.158***	0.025	3.660	18.926
$OTHERS_{t-1}$	−0.148**	0.058	−23.272*	−12.958
$DEBT_{t-1}$	0.011	0.007	3.581	4.443
$SIZE_{t-1}$	0.002	0.003	3.008***	1.056
ROA_{t-1}	−0.001	0.015	3.098	7.502
MBR_{t-1}	0.001	0.001	−0.303	0.355
$CAPEX_{t-1}$	0.045	0.049	38.446	38.002
$CASH_{t-1}$	0.031**	0.012	10.449*	6.272
$NON\text{-}EU_{t-1}$	−0.039	0.023	−5.121**	2.448
YEAR_2020	0.001	0.001	1.864**	0.870
YEAR_2021	−0.001	0.002	2.272**	1.009
YEAR_2022	0.001	0.002	1.431	1.295
YEAR_2023	0.001	0.002	−0.115	1.234
$LN(\text{number of analysts} + 1)_{t-1}$	−0.012***	0.003		
IND_{t-1} (fitted values)			−34.584*	20.839
F-Test excluded instrument (p-value)	18.776 (<0.001)			
χ^2 endogeneity test (p-value)			1.85 (0.999)	
R^2	0.130		0.104	

Note(s): Column 1 reports the first-stage regressions results with IND as an endogenous variable. The LN (number of analysts + 1) was used as the instrument. Column 2 presents the second-stage regression results. The regression coefficients are unstandardized, and standard errors are clustered at the firm level. All the variables are defined in Table 1. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Created by authors

The traditional regression analysis indicates that DEBT is a positive but nonsignificant factor in ESG-COMB. Complementarily, the Bayesian analysis, aligned with our fourth hypothesis, estimates an 18.9% probability of a negative impact.

Regardless of the models tested and techniques applied, our findings underscore the positive contribution of company size to ESG performance, thereby adding to the conventional wisdom that ESG performance scores are subject to size bias (Drempetic *et al.*, 2020). According to the Bayesian analysis, CAPEX is a positive factor of the E-Score, supported by strong evidence. Industrial firms may have acknowledged environmental performance as a key decision-making factor for potential investors, thus strengthening their efforts. Alternatively, industrial companies may have increasingly invested under ESG criteria, leading to improvements in environmental performance. However, a more comprehensive analysis requires detailed information on the nature of investments. The availability of such data is expected to increase once the Corporate Sustainability Directive of the European Union is fully implemented (Arvidsson and Dumay, 2022).

6.2 Methodological and practical implications

This study has both methodological and practical implications. First, our Bayesian analysis complements traditional regression by providing additional insights. The coefficient

Table 8. Determinants of S-Score for different ICB subsectors

Variable	All firms (1) Posterior mean	All firms (2) Prob < 0	Electronics and electrical equipment subsector (1) Posterior mean	Electronics and electrical equipment subsector (2) Prob < 0	Industrial engineering subsector (1) Posterior mean	Industrial engineering subsector (2) Prob < 0
INTERCEPT	30.473	0.020	31.447	0.030	30.488	0.036
$CORP_{t-1}$	−8.033	0.892	−7.775	0.833	−8.152	0.843
FIN_{t-1}	−17.209	0.964	−17.252	0.936	−17.115	0.933
IND_{t-1}	−15.873	0.981	−16.117	0.955	−15.845	0.951
$OTHERS_{t-1}$	−16.095	0.933	−16.132	0.903	−16.182	0.903
$DEBT_{t-1}$	6.182	0.024	5.892	0.152	6.299	0.141
$SIZE_{t-1}$	2.780	0.002	2.885	0.010	2.781	0.012
ROA_{t-1}	2.533	0.320	2.488	0.369	2.508	0.369
MBR_{t-1}	0.098	0.408	0.350	0.399	0.014	0.481
$CAPEX_{t-1}$	11.693	0.283	11.724	0.289	11.641	0.291
$CASH_{t-1}$	3.647	0.210	3.800	0.247	3.643	0.256
$NON\text{-}EU_{t-1}$	−10.641	1.000	−10.451	0.947	−10.547	0.944
YEAR_2020	0.560	0.166	−0.750	0.537	0.719	0.439
YEAR_2021	0.836	0.148	−1.640	0.531	1.240	0.435
YEAR_2022	1.709	0.028	−0.040	0.500	2.108	0.408
YEAR_2023	0.694	0.241	−0.591	0.511	0.660	0.489

Note(s): Column 1 reports the posterior mean of the parameters. Column 2 shows the probability of these parameters having a negative effect on the dependent variable. The results are segregated into ICB subsectors. All the variables are defined in Table 1
Source(s): Created by authors

estimates from the random-effects regressions broadly align with those obtained through Bayesian analysis, as the latter employs weakly informative priors and assumes a normal distribution to generate estimates. Nonetheless, Bayesian analysis helps mitigate some limitations of traditional regression methods. For instance, while traditional regressions indicate a negative but nonsignificant effect of financial ownership on the E-Score, our Bayesian approach quantifies the probability of a negative impact at 74.5%.

Second, our results illustrate that studies on the influence of the largest shareholders on ESG performance require differentiation by industry and ESG pillar scores. To illustrate this, we identify the negative impact of financial investors on the scores of all three ESG pillars of industrial firms, whereas previous studies have predominantly demonstrated the positive influence of financial investors (Velte, 2023).

Third, our findings allow us to conclude that financial investors seem to be guided by ESG scores instead of actively shaping portfolio firms' ESG performance. Specifically, they tend to avoid ESG controversies. However, controversial ESG data may be subject to selection bias in terms of geography and language, with companies in English- and French-speaking countries being overrepresented (Barkemeyer *et al.*, 2023).

Fourth, regardless of the identity of the largest shareholder, our Bayesian analyses reveal a high probability of a negative impact of ownership concentration on each of the three ESG pillar scores. Consequently, to counteract this lack of engagement, additional regulatory requirements and targeted incentives can be developed to encourage greater engagement in ESG investments. For instance, if ESG investments are considered risky, tax tools such as accelerated ESG investment depreciation (Tan *et al.*, 2024) could promote sustainability efforts.

7. Conclusions

This study aims to provide additional insights into the firm-specific determinants of ESG performance by applying traditional and Bayesian regressions. Our analysis relies on the ESG combined score provided by the LSEG. Moreover, we account for the multidimensional nature of the ESG construct and, in additional models, replace the ESG combined score as the dependent variable with each ESG pillar score. We analyze a sample of firms classified as industrials, in which public pressures to enhance ESG efforts are expected to be lower than in more ESG-sensitive industries, such as the energy sector. As one of the primary goals of the European Green Deal framework is to direct capital flows toward sustainable investments (Horn, 2024), we focus specifically on the effects of the largest shareholders and debtholders. We assume that the ESG performance of industrials is largely driven by the largest shareholder's investment motives, oversight resources and attitude toward ESG.

To obtain more nuanced insights into the influence of the largest shareholders and debtholders on ESG performance and pillar scores, we supplement traditional statistical significance testing with Bayesian analyses. One key advantage of Bayesian regression is its ability to quantify the probability that a variable will exert a positive or negative effect on ESG performance scores.

Regardless of the estimation technique applied or the identity of the largest shareholder, we consistently find negative associations between ownership concentration and the three ESG pillar scores. The sole exception is corporate ownership, which shows a positive association with environmental scores, likely because of synergies, although endogeneity remains a concern. Moreover, our findings suggest that financial investors are guided by ESG controversies rather than actively shaping the ESG performance of portfolio firms. Although corporate debt is not significant in traditional regressions, the Bayesian analysis estimates the probability of a negative impact at approximately 18.9% for the ESG combined score and only 2.4% for the social score. These findings are robust for different sub-distributions sorted by the ICB subsector and firm size.

Our analysis has a few limitations. The study reveals that the proportion of shares held by the largest shareholder negatively affects social and governance pillar scores. Subsequent research should address the question of whether this finding is attributable to Type II agency conflicts or the perceived non-beneficial impact of ESG on corporate value, among other factors. Moreover, our study relies exclusively on the ESG combined score and its pillars provided by the LSEG. Previous research has shown a lack of convergence in different ESG measurement approaches (Billio *et al.*, 2021; Dorfleitner *et al.*, 2015). Discrepancies across ESG measures stem from differences in the criteria used to assess ESG, the metrics applied in the evaluation and the weighting of these metrics (Berg *et al.*, 2022). Consequently, our findings are not necessarily generalizable. Finally, the explanatory power of our traditional regressions is limited, necessitating the inclusion of additional explanatory variables. For instance, our analysis does not consider managers' personality traits such as the Big Five. A recent study shows that managers' risk tolerance reduces the readability and disclosure volume of corporate sustainability reports (Mahmoudian *et al.*, 2021). Therefore, ESG performance may also be a function of such personality traits.

Acknowledgements

The authors gratefully acknowledge the editor and two anonymous reviewers for their helpful feedback.

Data availability

The data supporting the findings of this study are available from LSEG Workspace. The availability of the data is restricted under the license for this study.

References

Adeneye, Y.B., Kammoun, I. and Ab Wahab, S.N.A. (2023), "Capital structure and speed of adjustment: the impact of environmental, social and governance (ESG) performance", *Sustainability Accounting, Management and Policy Journal*, Vol. 14 No. 5, pp. 945-977, doi: 10.1108/SAMPJ-01-2022-0060.

Amel-Zadeh, A. and Serafeim, G. (2018), "Why and how investors use ESG information: evidence from a global survey", *Financial Analysts Journal*, Vol. 74 No. 3, pp. 87-103, doi: 10.2469/faj.v74.n3.2.

Arvidsson, S. and Dumay, J. (2022), "Corporate ESG reporting quantity, quality and performance: Where to now for environmental policy and practice?", *Business Strategy and the Environment*, Vol. 31 No. 3, pp. 1091-1110, doi: 10.1002/bse.2937.

Balp, G. and Strampelli, G. (2022), "Institutional investor ESG engagement: the European experience", *European Business Organization Law Review*, Vol. 23 No. 4, pp. 869-904, doi: 10.1007/s40804-022-00266-y.

Bani-Khaled, S., Azevedo, G. and Oliveira, J. (2025), "Environmental, social, and governance (ESG) factors and firm value: a systematic literature review of theories and empirical evidence", *AMS Review*, Vol. 15 Nos 1-2, pp. 228-260, doi: 10.1007/s13162-025-00303-2.

Barkemeyer, R., Revelli, C. and Douaud, A. (2023), "Selection bias in ESG controversies as a risk for sustainable investors", *Journal of Cleaner Production*, Vol. 405, p. 137035, doi: 10.1016/j.jclepro.2023.137035.

Bell, A., Fairbrother, M. and Jones, K. (2019), "Fixed and random effects models: making an informed choice", *Quality and Quantity*, Vol. 53 No. 2, pp. 1051-1074, doi: 10.1007/s11135-018-0802-x.

Berg, F., Kölbel, J.F. and Rigobon, R. (2022), "Aggregate confusion: the divergence of ESG ratings", *Review of Finance*, Vol. 26 No. 6, pp. 1315-1344, doi: 10.1093/rof/rfac033.

Bhandari, K.R., Ranta, M. and Salo, J. (2022), "The resource-based view, stakeholder capitalism, ESG, and sustainable competitive advantage: the firm's embeddedness into ecology, society, and governance", *Business Strategy and the Environment*, Vol. 31 No. 4, pp. 1525-1537, doi: 10.1002/bse.2967.

Billio, M., Costola, M., Hristova, I., Latino, C. and Pelizzon, L. (2021), "Inside the ESG ratings: (dis) agreement and performance", *Corporate Social Responsibility and Environmental Management*, Vol. 28 No. 5, pp. 1426-1445, doi: 10.1002/csr.2177.

Borghesi, R., Houston, J.F. and Naranjo, A. (2014), "Corporate socially responsible investments: CEO altruism, reputation, and shareholder interests", *Journal of Corporate Finance*, Vol. 26, pp. 164-181, doi: 10.1016/j.jcorpfin.2014.03.008.

Botosan, C.A. and Stanford, M. (2005), "Managers' motives to withhold segment disclosures and the effect of SFAS No. 131 on analysts' information environment", *The Accounting Review*, Vol. 80 No. 3, pp. 751-772, doi: 10.2308/accr.2005.80.3.751.

Cellier, A., Chollet, P. and Gajewski, J.F. (2016), "Do investors trade around social rating announcements?", *European Financial Management*, Vol. 22 No. 3, pp. 484-515, doi: 10.1111/eufm.12066.

Chakraborty, B., Chatterjee, M. and Bhattacharjee, T. (2022), "Impact of analyst report on the behavior of retail investors: a study during COVID-19 in India", *Journal of Financial Reporting and Accounting*, Vol. 21 No. 5, pp. 1188-1205, doi: 10.1108/JFRA-10-2021-0310.

Cicchiello, A.F., Marrazza, F. and Perdichizzi, S. (2022), "Non-financial disclosure regulation and environmental, social, and governance (ESG) performance: the case of EU and US firms", *Corporate Social Responsibility and Environmental Management*, Vol. 30 No. 3, pp. 1121-1128, doi: 10.1002/csr.2408.

Cordeiro, J.J., Profumo, G. and Tutore, I. (2021), "Family ownership and stockholder reactions to environmental performance disclosure: a test of secondary agency relationships", *Business Strategy and the Environment*, Vol. 30 No. 4, pp. 2091-2107, doi: 10.1002/bse.2734.

Crace, L. and Gehman, J. (2022), "What really explains ESG performance? Disentangling the asymmetrical drivers of the triple bottom line", *Organization and Environment*, Vol. 36 No. 1, pp. 150-178, doi: 10.1177/10860266221079408.

Cremasco, C. and Boni, L. (2024), "Is the European Union (EU) sustainable finance disclosure regulation (SFDR) effective in shaping sustainability objectives? An analysis of investment funds' behaviour", *Journal of Sustainable Finance and Investment*, Vol. 14 No. 4, pp. 1018-1036, doi: 10.1080/20430795.2022.2124838.

Daugaard, D. and Ding, A. (2022), "Global drivers for ESG performance: the body of knowledge", *Sustainability*, Vol. 14 No. 4, p. 2322, doi: 10.3390/su14042322.

Dorfleitner, G., Halbritter, G. and Nguyen, M. (2015), "Measuring the level and risk of corporate responsibility - An empirical comparison of different ESG rating approaches", *Journal of Asset Management*, Vol. 16 No. 7, pp. 450-466, doi: 10.1057/jam.2015.31.

Drees, F., Mietzner, M. and Schiereck, D. (2013), "Effects of corporate equity ownership on firm value", *Review of Managerial Science*, Vol. 7 No. 3, pp. 277-308, doi: 10.1007/s11846-012-0080-2.

Drempetic, S., Klein, C. and Zwergel, B. (2020), "The influence of firm size on the ESG score: Corporate sustainability ratings under review", *Journal of Business Ethics*, Vol. 167 No. 2, pp. 333-360, doi: 10.1007/s10551-019-04164-1.

Dyck, A., Lins, K.V., Roth, L. and Wagner, H.F. (2019), "Do institutional investors drive corporate social responsibility? International evidence", *Journal of Financial Economics*, Vol. 131 No. 3, pp. 693-714, doi: 10.1016/j.jfineco.2018.08.013.

Ebbes, P., Papies, D. and van Heerde, H.J. (2016), "Dealing with endogeneity: a nontechnical guide for marketing researchers", Homburg, C. Klarmann, M. and Vomberg, A. (Eds), *Handbook of Market Research*, Springer, pp. 1-37, doi: 10.1007/978-3-319-05542-8_8-1.

Edmans, A. (2009), "Blockholder trading, market efficiency, and managerial myopia", *The Journal of Finance*, Vol. 64 No. 6, pp. 2481-2513, doi: 10.1111/j.1540-6261.2009.01508.x.

Ellimäki, P., Aguilera, R.V., Hurtado-Torres, N.E. and Aragón-Correa, J.A. (2023), "The link between foreign institutional owners and multinational enterprises' environmental outcomes", *Journal of International Business Studies*, Vol. 54 No. 5, pp. 910-927, doi: 10.1057/s41267-022-00580-0.

Escrig-Olmedo, E., Fernández-Izquierdo, M.Á., Ferrero-Ferrero, I., Rivera-Lirio, J.M. and Muñoz-Torres, M.J. (2019), "Rating the raters: Evaluating how ESG rating agencies integrate sustainability principles", *Sustainability*, Vol. 11 No. 3, p. 915, doi: 10.3390/su11030915.

Fee, C.E., Hadlock, C.J. and Thomas, S. (2006), "Corporate equity ownership and the governance of product market relationships", *The Journal of Finance*, Vol. 61 No. 3, pp. 1217-1251, available at:www. jstor.org/stable/3699322

Feng, Z. and Wu, Z. (2021), "ESG disclosure, REIT debt financing and firm value", *The Journal of Real Estate Finance and Economics*, Vol. 67 No. 3, pp. 388-422, doi: 10.1007/s11146-021-09857-x.

Ferrell, A., Liang, H. and Renneboog, L. (2016), "Socially responsible firms", *Journal of Financial Economics*, Vol. 122 No. 3, pp. 585-606, doi: 10.1016/j.jfineco.2015.12.003.

Garcia, A.S., Mendes-Da-Silva, W. and Orsato, R. (2017), "Sensitive industries produce better ESG performance: evidence from emerging markets", *Journal of Cleaner Production*, Vol. 150, pp. 135-147, doi: 10.1016/j.jclepro.2017.02.180.

Gega, M., Höhler, J., Bijman, J. and Oude Lansink, A. (2025), "Firm ownership and ESG performance in European Agri-food companies: the mediating effect of risk-taking and time horizon", *Corporate Social Responsibility and Environmental Management*, Vol. 32 No. 1, pp. 1161-1181, doi: 10.1002/csr.3008.

Gelfand, A.E. and Smith, A.F.M. (1990), "Sampling-based approaches to calculating marginal densities", *Journal of the American Statistical Association*, Vol. 85 No. 410, pp. 398-409, doi: 10.1080/01621459.1990.10476213.

Gomez-Mejia, L.R., Makri, M. and Kintana, M.L. (2010), "Diversification decisions in family-controlled firms", *Journal of Management Studies*, Vol. 47, pp. 223-252, doi: 10.1111/j.1467-6486.2009.00889.x.

Hansen, M.H., Perry, L.T. and Reese, C.S. (2004), "A Bayesian operationalization of the resource-based view", *Strategic Management Journal*, Vol. 25 No. 13, pp. 1279-1295, doi: 10.1002/smj.432.

Horn, M. (2024), "The European green deal, retail investors and sustainable investments: a perspective article covering economic, behavioral, and regulatory insights", *Current Research in Environmental Sustainability*, Vol. 7, p. 10024, doi: 10.1016/j.crsust.2024.100241.

Jebb, A.T. and Woo, S.E. (2015), "A Bayesian primer for the organizational sciences: the 'two sources' and an introduction to BugsXLA", *Organizational Research Methods*, Vol. 18 No. 1, pp. 92-132, doi: 10.1177/1094428114553060.

Jensen, M.C. and Meckling, W.H. (1976), "Theory of the firm: managerial behavior, agency costs and ownership structure", *Journal of Financial Economics*, Vol. 3 No. 4, pp. 305-360, doi: 10.1016/0304-405X(76)90026-X.

Kannenberg, L. and Schreck, P. (2019), "Integrated reporting: Boon or bane? A review of empirical research on its determinants and implications", *Journal of Business Economics*, Vol. 89 No. 5, pp. 515-567, doi: 10.1007/s11573-018-0922-8.

Kavadis, N. and Thomsen, S. (2023), "Sustainable corporate governance: a review of research on long-term corporate ownership and sustainability", *Corporate Governance: An International Review*, Vol. 31 No. 1, pp. 198-226, doi: 10.1111/corg.12486.

Khan, M.A. (2022), "ESG disclosure and firm performance: a bibliometric and meta analysis", *Research in International Business and Finance*, Vol. 61, p. 101668, doi: 10.1016/j.ribaf.2022.101668.

Kirchmaier, T. and Grant, J. (2005), "Corporate ownership structure and performance in Europe", *European Management Review*, Vol. 2 No. 3, pp. 231-245, doi: 10.1057/palgrave.emr.1500043.

Kölbel, J.F., Heeb, F., Paetzold, F. and Busch, T. (2020), "Can sustainable investing save the world? Reviewing the mechanisms of investor impact", *Organization and Environment*, Vol. 33 No. 4, pp. 554-574, doi: 10.1177/1086026620919202.

Kordsachia, O., Focke, M. and Velte, P. (2022), "Do sustainable institutional investors contribute to firms' environmental performance? Empirical evidence from Europe", *Review of Managerial Science*, Vol. 16 No. 5, pp. 1409-1436, doi: 10.1007/s11846-021-00484-7.

Kruschke, J.K. (2015), *Doing Bayesian Data Analysis: A Tutorial with R, JAGS, and Stan*, 2nd Edition Academic Pres, Boston.

Kruschke, J.K. (2018), "Rejecting or accepting parameter values in Bayesian estimation", *Advances in Methods and Practices in Psychological Science*, Vol. 1 No. 2, pp. 270-280, doi: 10.1177/2515245918771304.

Kruschke, J.K. and Liddell, T.M. (2018), "The Bayesian new statistics: hypothesis testing, estimation, meta-analysis, and power analysis from a Bayesian perspective", *Psychonomic Bulletin and Review*, Vol. 25 No. 1, pp. 178-206, doi: 10.3758/s13423-016-1221-4.

Mackey, T.B., Barney, J.B. and Dotson, J.P. (2017), "Corporate diversification and the value of individual firms: a Bayesian approach", *Strategic Management Journal*, Vol. 38 No. 2, pp. 322-341, doi: 10.1002/smj.2480.

Mahmoudian, F., Nazari, J.A., Gordon, I.M. and Hrazdil, K. (2021), "CEO personality and language use in CSR reporting", *Business Ethics, the Environment and Responsibility*, Vol. 30 No. 3, pp. 338-359, doi: 10.1111/beer.12347.

Petersen, M.A. (2009), "Estimating standard errors in finance panel data sets: comparing approaches", *Review of Financial Studies*, Vol. 22 No. 1, pp. 435-480, doi: 10.1093/rfs/hhn053.

Rajesh, R. and Rajendran, C. (2020), "Relating environmental, social, and governance scores and sustainability performances of firms: an empirical analysis", *Business Strategy and the Environment*, Vol. 29 No. 3, pp. 1247-1267, doi: 10.1002/bse.2429.

Rees, W. and Rodionova, T. (2015), "The influence of family ownership on corporate social responsibility: an international analysis of publicly listed companies", *Corporate Governance: An International Review*, Vol. 23 No. 3, pp. 184-202, doi: 10.1111/corg.12086.

Reitmaier, C. and Schultze, W. (2017), "Enhanced business reporting: Value relevance and determinants of valuation-related disclosures", *Journal of Intellectual Capital*, Vol. 18 No. 4, pp. 832-867, doi: 10.1108/JIC-12-2016-0136.

Renders, A. and Gaeremynck, A. (2012), "Corporate governance, principal-principal agency conflicts, and firm value in European listed companies", *Corporate Governance: An International Review*, Vol. 20 No. 2, pp. 125-143, doi: 10.1111/j.1467-8683.2011.00900.x.

Shleifer, A. and Vishny, R.W. (1986), "Large shareholders and corporate control", *Journal of Political Economy*, Vol. 94 No. 3, Part 1, pp. 461-488, available at: www. jstor.org/stable/1833044

Short, J.A. and Ndlovu, G. (2025), "Environmental, social, and governance (ESG) scores and portfolio performance: evidence from South Africa", *Journal of Applied Economics*, Vol. 28 No. 1, p. 2464507, doi: 10.1080/15140326.2025.2464507.

Souguir, Z., Lassoued, N., Khanchel, I. and Bouzgarrou, H. (2024), "Environmental performance and corporate tax avoidance: greenwashing policy or eco-responsibility? The moderating role of ownership structure", *Journal of Cleaner Production*, Vol. 434, p. 140152, doi: 10.1016/j.jclepro.2023.140152.

Stock, J.H., Wright, J.H. and Yogo, M. (2002), "A survey of weak instruments and weak identification in generalized method of moments", *Journal of Business and Economic Statistics*, Vol. 20 No. 4, pp. 518-529, doi: 10.1198/073500102288618658.

Talloen, W., Loeys, T. and Moerkerke, B. (2019), "A bootstrap version of the Hausman test to assess the impact of cluster-level endogeneity beyond the random intercept model", *Multivariate Behavioral Research*, Vol. 54 No. 1, pp. 1-14, doi: 10.1080/00273171.2018.1482192.

Tan, C., Zou, F., Li, Y. and Sun, X. (2024), "Accelerated depreciation policy of fixed assets and corporate sustainable development: a perspective of ESG", *Applied Economics*, Vol. 57 No. 17, pp. 2144-2160, doi: 10.1080/00036846.2024.2322580.

Thomsen, S. and Pedersen, T. (2000), "Ownership structure and economic performance in the largest European companies", *Strategic Management Journal*, Vol. 21 No. 6, pp. 689-705, doi: 10.1002/(SICI)1097-0266(200006)21:6<689::AID-SMJ115>3.0.CO;2-Y.

Toft, N., Innocent, G.T., Gettinby, G. and Reid, S.W.J. (2007), "Assessing the convergence of Markov chain Monte Carlo methods: an example from evaluation of diagnostic tests in absence of a gold standard", *Preventive Veterinary Medicine*, Vol. 79 Nos 2-4, pp. 244-256, doi: 10.1016/j.prevetmed.2007.01.003.

Velte, P. (2023), "Which institutional investors drive corporate sustainability? A systematic literature review", *Business Strategy and the Environment*, Vol. 32 No. 1, pp. 42-71, doi: 10.1002/bse.3117.

Wagenmakers, E.J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q.F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J.N. and Morey, R.D. (2018), "Bayesian inference for psychology. Part I: theoretical advantages and practical ramifications", *Psychonomic Bulletin and Review*, Vol. 25 No. 1, pp. 35-57, doi: 10.3758/s13423-017-1343-3.

Widyawati, L. (2021), "Measurement concerns and agreement of environmental social governance ratings", *Accounting and Finance*, Vol. 61 No. S1, pp. 1589-1623, doi: 10.1111/acfi.12638.

Further reading

Driscoll, J.C. and Kraay, A.C. (1998), "Consistent covariance matrix estimation with spatially dependent panel data", *Review of Economics and Statistics*, Vol. 80 No. 4, pp. 549-560, doi: 10.1162/003465398557825.

Corresponding author
Joachim Rojahn can be contacted at: joachim.rojahn@gmx.de