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The impact of board gender diversity on green building practices: Moving beyond traditional linear and logistic specifications

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Abstract

This article examines the relationship between sustainability and gender equality by analyzing how the percentage of women on the board of directors (still less than 50% in most cases) influences a company's commitment to green building practices. For this analysis, we estimate 30 competing multivariate pooled and panel data logistic specifications, including the gender diversity factor in both its traditional and polynomial forms. This methodological innovation (the polynomial form) allows for the examination of gender diversity's relationship with other variables beyond conventional models that assume constant effects, thus enabling a more realistic depiction of impacts that vary with the degree of diversity. Our dataset includes companies listed on the Euro Stoxx 300 and Standard & Poor's 500 for the period 2010–2021. The findings indicate that, in both indices, an increased percentage of women on the board (and a higher Blau diversity index) correlates with a greater propensity for sustainable building practices, up to a threshold nearing parity. The impacts are more significant in Europe than in the U.S., where board gender diversity appears to have a lesser influence on green building initiatives. The specification that best models the relationship between sustainable building practices and gender diversity, along with other relevant factors, is a multivariate panel data logistic model with the gender diversity factor included as a cubic polynomial for companies listed on the Euro Stoxx 300. A similar model, but with the gender factor in a quadratic polynomial form, was selected for companies listed on the Standard & Poor's 500. Therefore, the impact function of gender diversity on sustainable building practices is not constant but depends on the existing degree of board gender diversity, with the shape of the impact function differing between Europe and the U.S. Additionally, the study finds that other board characteristics—larger boards, longer tenures of directors, and higher compensation for senior executives—are associated with an increased propensity towards green practices in both the European and U.S. contexts. Conversely, linking CEO compensation to shareholder returns reduces this propensity. Moreover, the number of non-executive directors and the overlap between the Chairperson and CEO positions do not significantly impact this propensity.

KEYWORDS
board gender diversity, green buildings, multivariate panel data logistic model, polynomial logistic specification, sustainable buildings

1 | INTRODUCTION

In recent decades, environmental sustainability has become a fundamental goal for society at large and for both public and private organizations. In this regard, the United Nations adopted the 2030 Agenda for Sustainable Development in September 2015. However, commitment to these goals has not been uniform across the globe. Europe, through its Sustainable Development Observatory, aims to position itself as the global leader in sustainability. It was not until 2021 that a world reference country such as the United States joined the 2015 Paris Agreement on reducing greenhouse gas emissions. In contrast, Europe had already made a significant move in 2020 by adopting the European Green Deal, through which member states commit to implementing a set of policy initiatives to achieve climate neutrality (zero emissions) by 2050.

In this context, companies have been actively working to reduce their ecological footprint and promote responsible practices in social, environmental, and corporate governance. Consequently, adopting sustainable or green buildings has emerged as a key strategy to tackle the prevailing economic and ecological challenges. The green building concept is multifaceted, incorporating a comprehensive approach to sustainability (Gou & Xie, 2017; Samer, 2013). It covers the entire lifecycle of a building (Akomea-Frimpong et al., 2022; Ding et al., 2018), from selecting a location that minimizes environmental impact to integrating eco-friendly design principles, employing sustainable construction processes, and choosing materials that can be recycled post-demolition. These initiatives aim to reduce energy and water usage, cut down on resource consumption, lower pollution levels, harness renewable energy, and facilitate waste recycling. Additionally, green buildings prioritize occupant well-being, featuring indoor air quality, optimal lighting, and regulated temperature and humidity to ensure comfort and health.

On the other hand, gender diversity on boards of directors has received much attention in debates on corporate governance and business decision-making (Amorelli & García-Sánchez, 2021; Velte, 2017). It has been argued that the inclusion of women in leadership positions, a target of Sustainable Development Goal 5, not only promotes gender equality but can also significantly impact strategic business policymaking and the management of economic, social, or environmental risk positively (Pletzer et al., 2015; Terjesen et al., 2016; Valls Martínez & Soriano Román, 2022).

Gender policies differ significantly across the globe. In November 2022, the European Parliament passed a law mandating gender balance on corporate boards, stipulating that by 2026, at least 40% of non-executive directors must be from the less represented gender, with a requirement of 33% for all director positions. In contrast, in the U.S., California is the only state that has enacted a similar law (Williams, 2022). Senate Bill 826, enacted in 2018, required that by the end of 2021, boards with four or fewer members must include at least one woman, those with five members must have at least two women, and boards with six or more members must have at least three women. Failure to comply would result in a fine of $100,000 for a first offense and $300,000 for subsequent offenses. As a consequence, the representation of women on California's corporate boards exceeded 33% by 2022, effectively doubling the figures from 2018 and indicating the law's effectiveness. Nevertheless, the law was deemed unconstitutional in 2022 and became unenforceable, leading to a decline in the number of women represented on boards.

The results show that the presence of women on boards of directors, in terms of board gender diversity, leads to greater company commitment to adopting sustainable building practices. Furthermore, the study reveals that the influence of gender diversity on this commitment varies, depending on the level of gender diversity within the board. These insights contribute substantially to the understanding of corporate sustainability and board gender diversity. The results are particularly informative for various economic stakeholders: (i) companies and their shareholders, in making informed decisions about board composition; (ii) investors, in selecting investment portfolios based on sustainable and gender-diverse criteria, favoring companies that encourage gender diversity in senior management; and (iii) policymakers, by providing evidence to support the promotion of women in top management roles.

Certainly, the need to make progress towards sustainable business practices is becoming increasingly urgent in the context of the current climate crisis. Companies are facing regulatory and societal pressures to reduce their ecological footprint, and one of the most promising strategies for doing so is the adoption of green buildings. However, the question of how board characteristics, particularly gender diversity, influence the implementation of these sustainable practices is still an open question. Specifically, the potential link between the representation of women on boards of directors and companies' engagement in green building practices remains underexplored, with the notable exception of preliminary research by Valls Martínez et al. (2024), which focused primarily on linear impacts. This article seeks to bridge this research gap by (i) examining how the composition and characteristics of the board, particularly the gender distribution among directors, influence a company's inclination to integrate green buildings into their operations; and (ii) introducing methodological innovations aimed at better capturing the complexities of this relationship, based on multivariate panel data logistic regression models in which the gender diversity variable is introduced as a polynomial term (up to the third degree). In doing so, our research provides a more sophisticated understanding of how gender diversity influences corporate decision-making regarding sustainability. It is important to note that, as with all the other related papers published to date, this article is methodologically conditioned by an aspect of reality that is not usually considered: female participation rarely exceeds 50%.

To achieve our objective, we analyze companies listed in the Euro Stoxx 300 and Standard & Poor's (S&P) 500 indexes over the period from 2010 to 2021. Our analysis utilizes not only traditional multivariate logistic regression models—a novel approach for studies of this nature—but also expands them by incorporating the gender diversity factor into multivariate panel data logistic models through quadratic and cubic polynomials. As outlined above, this methodology facilitates a more nuanced understanding of the relationship between boardroom gender diversity and a company's inclination towards green building practices, moving beyond the limitations of conventional linear models, panel data specifications or logistic models. Our methodological proposal is a hybrid of logistic regression models and panel data specifications that (i) encompasses the methods previously used in the literature on the topic and (ii) considers the percentage of women on the board of directors in polynomial form, with polynomials of up to the third degree; by so doing, the impact of female board representation on companies' propensity to engage in green building practices is allowed to go from being fixed and independent of the specific percentage of women on the board (as in the existing literature) to being flexible and dependent on this percentage, which in reality makes much more sense. The findings indicate that, while the presence of women on boards is crucial for companies in both markets to engage in sustainable building practices, the best fitting model varies between contexts. Moreover, the positive impact of increased female representation in the boardroom on green building practices is notably more pronounced in Europe.

The current study makes significant contributions to the literature through the following advancements: First, this article is pioneering in its analysis of the impact of board gender diversity on companies' decisions regarding green or sustainable building practices and considering that female participation rarely exceeds 50%, conducting this analysis across both the European and U.S. markets. Second, it investigates the effects of other corporate governance characteristics on the propensity of companies to adopt green building practices. Third, it represents the first use of quadratic and cubic multivariate panel data logistic models in gender studies, offering a solution to the limitations inherent in traditional linear models, especially under the assumption that in practice female participation on boards of directors rarely exceeds 50%.

This research is particularly relevant in the context of recent European policies that impose gender quotas on corporate boards, such as the European Union Gender Balance Directive, which is due to be implemented by 2026. At the same time, the adoption of the European Green Deal requires companies to achieve carbon neutrality by 2050, making sustainable building practices a priority. Our study connects these two critical aspects—gender and sustainability—providing valuable insights for regulators, investors, and companies looking to meet stakeholder demands on both fronts.

After this introduction, Section 2 reviews the literature on the topic and establishes the theoretical framework. Section 3 describes the quantitative methodology employed in this research. Section 4 presents the results obtained. Section 5 discusses key lessons learned from the research. Finally, Section 6 concludes the article.

2 | LITERATURE REVIEW AND THEORETICAL FOUNDATION

Green buildings play a vital role in advancing sustainability by offering enhanced energy efficiency, improved indoor air quality, and effective waste management (Siddiq et al., 2023). Therefore, promoting the construction of green buildings is essential for mitigating environmental impacts. However, research exploring the intersection of green buildings and gender has yet to examine significant aspects such as esthetic preferences, perceptions of safety and well-being, and environmental sensitivity. This body of research sheds light on how gender influences individuals' interactions with green building practices and their perceptions of environmental sustainability.

Gender differences are currently evident in various domains, notably in the selection of green products (Brough et al., 2016). Previous studies have identified both psychological and physiological gender differences in the use of green and ecological spaces (Bolte et al., 2019; Kaczynski et al., 2009; Markevych et al., 2017; Schipperijn et al., 2010; Wu, Furuoka, et al. 2022; Wu, Richard, et al., 2022; Wu, Xu, et al., 2022). Börjesson (2012) suggests that women tend to associate the physical environment with security more than men do. Accordingly, Morris et al. (2019) argue that women, motivated by a desire for safety and outdoor enjoyment, show a stronger preference for natural environments and derive more satisfaction from green and ecological spaces. This preference influences women to favor ecological designs, both indoors and outdoors. Hamilton (2021) underscores the significant effect of gender on environmentally responsible behaviors. Further research by Pillay and Pahlad (2014) and Sang et al. (2016) investigates the gender dynamics within green spaces. Pillay and Pahlad (2014) highlight differences in how men and women value and use these spaces. Sang et al. (2016) observe that women engage more actively in urban green spaces and express a greater appreciation for their esthetic qualities. Topcu (2019) examines gender experiences in urban green spaces, emphasizing women's enhanced sensitivity to spatial characteristics and selective use of these areas.

Regarding environmental aspects, socialization theory suggests that women's life experiences cultivate greater sensitivity to environmental issues (Ibrahim et al., 2009), leading to increased concern for climate change compared to men (Choi & Park, 2014; Eliwa et al., 2023; Nielsen & Huse, 2010; Valls Martínez et al., 2019). Similarly, social role theory demonstrates heightened sensitivity towards stakeholder concerns, including environmental aspects (Bernardi & Threadgill, 2010; Liao et al., 2019).

In the corporate sector, according to resource dependency theory, which views companies as open systems, greater diversity on the board of directors enhances a company's ability to acquire necessary resources and fulfill social and environmental responsibilities (Valls Martínez et al., 2020). Consequently, firms with more gender diversity are characterized by carrying out proactive and effective environmental practices (Naveed, Khalid, & Voinea, 2023; Naveed, Khalid, Voinea, Roijakkers, et al., 2023). Thus, the inclusion of women on corporate boards is linked to the promotion of eco-friendly innovations and the endorsement of corporate sustainability initiatives (Lin et al., 2022). As a result, gender diversity on boards correlates with higher levels of corporate social responsibility, managerial transparency, and engagement in sustainable initiatives, all of which contribute to the advancement of and support for environmentally friendly buildings (Wahyudi & Mayasari, 2023). Moreover, upper echelons theory suggests that the demographic characteristics and experiences of board members shape their values and behaviors (Hambrick & Mason, 1984). Therefore, the presence of women on boards enhances the cognitive diversity of these executive bodies, increasing the likelihood of integrating environmental innovations (García-Sánchez et al., 2023; Konadu et al., 2022).

Recent scientific literature has extensively investigated the impact of board gender diversity on various environmental aspects within companies (Singhania et al., 2023). Previous research has established a positive correlation between gender diversity on boards of directors and firms' environmental policies (Li et al., 2017). Additionally, García-Sánchez et al. (2023) highlight that companies with gender diversity on the board of directors are more proactive in investing in climate change innovation. This proactive stance leads to enhanced eco-innovation within firms (Naveed, Khalid, & Voinea, 2023, Naveed, Khalid, Voinea, Roijakkers, et all., 2023), resulting in increased use of renewable energies and improved waste management practices (Atif et al., 2021; Gull et al., 2023). Moreover, other authors have confirmed that gender diversity on the board of directors contributes to the reduction of CO_2 emissions (Konadu et al., 2022; Valls Martínez, Martín Cervantes, et al., 2022; Valls Martínez, Santos Jaén, et al., 2022; Valls Martínez, Soriano Román, et al., 2022). Studies also show that gender diversity is associated with better disclosure of a company's biodiversity conservation initiatives (Issa & Zaid, 2023).

Turning to some alternative perspectives or sub-topics related to the relationship between green building practices and board gender diversity, a notable gender gap can be observed in pro-environmental behavior, with women generally showing more engagement in eco-friendly practices than men. Studies indicate that women tend to be more involved in green consumption, and households where women play a significant role are more likely to adopt environmentally sustainable behaviors, such as using energy-efficient products (Li et al., 2019). This gender gap is also reflected in the green building sector, where women's stronger environmental concerns translate into more pro-environmental behavior at the household level (Kennedy & Kmec, 2018). Additionally, men tend to be more averse to adopting green behaviors due to societal stereotypes that associate eco-friendly behavior with femininity, creating a barrier to more widespread green consumption among men (Brough et al., 2016).

Moreover, the relationship between women and sustainable cities is closely intertwined with gender-sensitive urban planning, social equity, and environmental sustainability. Research indicates that cities designed with gender equality in mind provide safer, more accessible public spaces, especially for women seeking to balance work and family responsibilities. Sustainable city initiatives often neglect gender considerations, yet women's participation in urban planning is crucial for creating inclusive, livable environments. Studies suggest that addressing urban design issues such as safety, lighting, and accessibility can enhance women's experiences in cities, fostering greater involvement in sustainability efforts (Kiper et al., 2016). In addition, it is essential for women to play a role in waste management and environmental conservation in order to achieve urban sustainability goals (Malekabadi et al., 2014).

Furthermore, the intersection of gender, green building, and social housing is central to the creation of inclusive, sustainable communities. Gender-sensitive designs in social housing address the specific needs of women, relating to energy consumption and household routines; conversely, poor design can place economic pressure on women and increase energy use, as seen in slum rehabilitation housing in Mumbai (Sunikka-Blank et al., 2019). Green social housing initiatives utilize low-carbon technologies and renewable energy to make housing both affordable and environmentally friendly, while the additional incorporation of gender perspectives ensures that housing designs meet the needs of both men and women equally, promoting social equity (Shepherd, 2009).

In summary, the presence of women on corporate boards enhances the cognitive diversity of these executive bodies due to women's heightened sensitivity towards ethical and environmental issues (Issa, 2023), thereby making the incorporation of environmental innovations more likely. This, in turn, aligns with the proactive stance exhibited by companies with gender diverse boards of directors, leading to enhanced eco-innovation, increased use of renewable energies, and improved waste management practices. Consequently, gender diversity on boards of directors plays a crucial role in driving sustainability efforts within organizations, including the promotion of green building practices.

Based on the above, we propose the following general hypothesis, which will be itemized into specific hypotheses in Section 3.3.5: The gender composition of boards of directors, specifically the percentage of women, significantly increases the likelihood that companies will commit to green building practices.

In our review of the literature, we encountered some conflicting findings regarding the impact of gender diversity on corporate sustainability. Most studies suggest that higher levels of board gender diversity are positively correlated with stronger environmental performance, including the adoption of sustainable practices (two good examples are Bernardi & Threadgill, 2010, and Atif et al., 2021). However, other research, such as the article by Liao et al. (2019), has found that the influence of gender diversity diminishes after reaching a certain threshold, at which point environmental commitment either plateaus or starts to decline. Our study builds on these contradictory results by proposing a non-linear relationship between board diversity and green building practices. By considering gender diversity as a (quadratic and cubic) polynomial regressor in 30 multivariate panel data logistic regression specifications, we demonstrate that the relationship between gender diversity and sustainability is not constant, and that the effects of increasing female board representation vary depending on the existing level of diversity. This approach helps resolve some of the inconsistencies in previous research by highlighting the threshold effects in the relationship between board composition and corporate sustainability.

As outlined in the introductory section, our methodological approach significantly differs from the methods used in the literature cited above. We do not force the relationship between the percentage of women on the board of directors and the company's commitment to green building practices to be represented by linear regressions (Amorelli & García-Sánchez, 2020; Fernández-Feijoo et al., 2014) or inverted U-shaped (Valls Martínez et al., 2020) regression specifications. Above all, this is because there is no need to fix the shape of the relationship when it is possible to use flexible specifications for which the aforementioned rigid relationships are specific cases. In other words, we want the impacts of female board representation on the company's commitment to green building practices to emerge from a general flexible specification so that these impacts depend on the specific percentage of women on the board rather than being fixed (in absolute or percentage terms), regardless of the percentage in question. In addition, it is worth mentioning that when the response value is probabilistic in nature, a linear regression relationship cannot be applied because the response variable usually takes values outside the interval [0, 1]. Something similar can be said about panel data models with fixed or random effects used to monitor omitted variables and overcome unobservable heterogeneity among firms (Boulouta, 2013; Miralles-Quiros, Miralles-Quiros & Guia Arraiano, 2017, 2017b; Orazalin & Baydauletov, 2020; Oino & Liu, 2022; Ren et al., 2024; Tingbani et al., 2020) or endogeneity if models suffer from self-selection bias, which is not the case in our study. In the case of endogeneity, instrumental variables are recommended, but the conventional instrumental variable estimator, although consistent, is not efficient in the presence of heteroscedasticity (Baum et al., 2003). This limitation can be overcome by using, for example, the two-step estimator of Arellano and Bond (1991), which is based on the generalized method of moments (GMM) (Hansen, 1982).

In the related literature, logistic and Tobit models have also been widely used when the response variable is a categorical variable, using probability scores as the predicted values of the response variable. Studies taking this approach include those by Al-Qahtani & Elgharbawy (2020) and García-Sánchez et al. (2023), who state that the only reason for using these kinds of models is the categorical nature of the dependent variable.

The advantage of our methodological proposal—embodied in 30 competing multivariate pooled and panel data logistic specifications, including the gender diversity factor in both its traditional and polynomial forms—is that it hybridizes logistic and panel data specifications to deal with the probabilistic nature of the variable together with the unobservable heterogeneity among firms, without imposing rigid specifications on the relationship between the percentage of women on the board of directors and the company's commitment to green building practices. On the contrary, our methodological approach allows this relationship to be flexible enough to include the one that actually exists. It is, therefore, a proposal that encompasses the other specifications used in the literature on the issue without imposing any of them a priori.

However, all methodologies have advantages and disadvantages, and ours is no exception: it shares with linear regression and linear discriminant analysis a low prediction variance (which is a strength) at the expense of non-negligible bias errors, which translates into underfitting and prediction inaccuracies. In this sense, our proposal is not at a disadvantage with respect to the methodologies commonly used in the literature. There are also other kind of limitations besides the methodological ones that are never mentioned in the literature but that undoubtedly condition the analysis. We refer to (i) the fact that the percentage of women on the board of directors never exceeds 67%, and (ii) the high year-to-year variability of this percentage. These are two important practical limitations which have never been raised in the related literature, but which should be taken into account when selecting the model to be used and interpreting the results. The former is a methodological challenge for the future and must be solved by researchers; the latter—especially worrying because it suggests that the information contained in the reports provided by the firms[1] may not be trustworthy—must be solved by companies, and while this problem remains unsolved, the results of the research carried out on the issue will be subject to skepticism.

3 | DATASET AND METHODOLOGY

3.1 | The dataset

Given the main objective of this study—to explore the relationship between board gender diversity and a company's commitment to green building practices in the European and U.S. markets—the dataset used gathers comprehensive information from various perspectives (including gender and environmental) on companies listed in the

[1]Including the largest and most prestigious publicly traded firms in the world.

TABLE 1 Sample description.

Panel A. Percentage composition by sector						
	Euro Stoxx 300 index			S&P 500 index		
Sector	% of the total number of firms	% of firms committed to green building practices	% of women on corporate boards	% of the total number of firms	% of firms committed to green building practices	% of women on corporate boards
1. Basic materials	9.97	41.95	30.74	4.96	51.56	25.61
2. Consumer cyclicals	13.44	41.19	31.06	14.19	57.10	25.47
3. Consumer non-cyclicals	5.96	52.48	32.14	7.56	57.69	25.30
4. Energy	5.03	47.90	31.49	4.71	53.91	25.77
5. Financials	13.44	48.74	31.50	13.14	60.18	24.92
6. Healthcare	7.57	41.90	30.97	12.23	58.48	25.28
7. Industrials	18.51	47.95	30.65	13.69	56.09	25.00
8. Technology	4.35	35.92	31.60	6.59	54.71	25.83
9. Telecom services	13.74	43.38	31.56	16.85	55.01	25.06
10. Utilities	7.99	45.50	30.33	6.07	56.67	25.14

Panel B. Euro Stoxx 300: Percentage composition by country			
Country	%	Country	%
Austria	3.38	Luxembourg	1.90
Belgium	5.54	Netherlands	8.71
Finland	5.87	Portugal	1.52
France	28.61	Spain	8.45
Germany	24.77	Switzerland	0.42
Republic of Ireland	1.18	United Kingdom	0.76
Italy	8.88		

Panel B. S&P 500: Percentage composition by country			
Bermuda	0.19	Switzerland	0.70
Republic of Ireland	2.06	United Kingdom	0.93
Israel	0.12	United States of America	95.81
Netherlands	0.19		

Euro Stoxx 300 and S&P 500 indexes from 2010 to 2021. To ensure the robustness and validity of the results, only observations with complete data for all variables included in the study were considered (Liao et al., 2019). The final sample comprises 2366 observations in the European market and 5158 in the U.S. market. The dataset was sourced from the Thomson Reuters Eikon database, a dependable resource extensively used by both practitioners and scholars (Kyaw et al., 2017; Mazur et al., 2021; Oehler et al., 2017; Pérez-Cornejo et al., 2020).

Table 1 displays the composition of the sample by sector for each index and by country for both stock exchange indexes. Most of the European companies listed in the Euro Stoxx 300 are from France and Germany, with Italy, the Netherlands, and Spain being substantially less represented; the representation of the remaining countries is significantly smaller. The S&P 500 primarily consists of companies located in the United States, with other countries making up a marginal percentage.

There are no major differences in the percentage of women on the board of directors among the different economic sectors. Specifically, in the Euro Stoxx 300, the range is 1.81 percentage points, with the non-cyclical consumer industry having the highest percentage (32.14%) and the utilities sector the lowest (30.33%). In the S&P 500, the range is only 0.91 percentage points, with technology having the highest value (25.83%) and financials the lowest (24.92%). Regarding the commitment to green building practices, the differences are more significant. In the Euro Stoxx 300, the percentages vary from 35.92% to 52.48%, a range of 16.56 percentage points; in the S&P 500, however, the sectoral percentages are closer, ranging from

TABLE 2 Definition of variables.

Abbreviation	Variable	Definition
GRB	Green Buildings	Dummy variable: 1 if the company reports on environmentally friendly or green sites/offices, 0 otherwise.
BGD	Board gender diversity	Percentage of women on board of directors.[a]
BLAU	Blau index	Blau index of gender diversity.
CSRC	CSR committee	Dummy variable: 1 if the company has a Corporate Social Responsibility (CSR) committee or team, 0 otherwise.
CSRR	CSR reporting	Dummy variable: 1 if the company discloses Corporate Social Responsibility (CSR) reporting, 0 otherwise.
AUD	Audit committee Independence	Percentage of independent board members on the audit committee.
BSZ	Board size	The total number of board members.
BSK	Board skills	Percentage of board members who have either an industry-specific background or a solid financial background.
BTN	Average board tenure	The average number of years each board member has been on the board.
NEM	Non-executive board members	Percentage of non-executive board members.
IBM	Independent board members	Percentage of independent board members.
DUA	Duality	Dummy variable: 1 if the CEO also serves as the board chair or if the board chair has previously served as the company's CEO, 0 otherwise.
SEC	Senior executive compensation	Logarithm of total compensation for all senior executives, expressed in thousands of U.S. dollars.
CEOC	CEO compensation	Dummy variable: 1 if the Chief Executive Officer (CEO)'s compensation is linked to total shareholder return, 0 otherwise.
BMC	Board members compensation	Logarithm of total compensation for board members, measured in thousands of U.S. dollars.
NEC	Net employment Creation	Employment growth over the last year.
ESG	ESG score	Environmental, Social and Governance (ESG) score assigned by Thomson Reuters Eikon.
CO_2	CO_2 emission	Logarithm of estimated tons of CO_2 emissions.
SIZE	Company size	Logarithm of total assets.
ROA	Return on assets	Earnings before interest expense and taxes divided by total assets.

[a]Obviously, BGD ranges from 0 to 1. Extreme values indicate a board composed exclusively of one gender (no diversity), while central values suggest a more balanced representation of men and women, with maximum diversity achieved at BGD = 0.5.

51.56% to 60.18%, a spread of 8.62 percentage points. Nonetheless, it can be observed that the percentage of women on boards is generally not very heterogeneous across the different sectors.

3.2 | Variable description

Table 2 presents the description of the variables included in the empirical study along with the abbreviations used in subsequent results tables. The dependent variable, Green Buildings (GRB), is a dichotomous variable assigned a value of 1 if the company reports its buildings as sustainable, and 0 otherwise. One of the two independent variables of interest in this study, Board Gender Diversity (BGD) represents the percentage of board members who are women.

As mentioned in the introductory section, although the relationship between gender diversity on the board of directors and a firm's propensity for green building practices has not yet been analyzed, the relationship between gender diversity on boards and corporate social responsibility (CSR) has been extensively studied. This literature has highlighted potential endogeneity problems in the econometric specifications used to model such a relationship (Francoeur et al., 2019; Valls Martínez & Soriano Román, 2022), prompting the adoption of measures to ensure the robustness of the results. Among these measures, the most utilized is the replacement of BGD with the Blau heterogeneity index (BLAU, the second of the most significant independent variables). Considering that a company's commitment to green building practices falls within the realm of CSR, it is conceivable that similar endogeneity issues could impact the econometric specification relating GRB and BGD. Therefore, to validate the findings concerning this relationship, the study will employ a comparative analysis with results obtained when BGD is replaced by BLAU, in accordance with methodologies utilized in prior research (Mohiuddin et al., 2014; Reguera-Alvarado et al., 2017; Sial et al., 2018).

BLAU is a suitable metric for measuring diversity, as it meets four key criteria: it indicates complete homogeneity when its value is zero, with higher values denoting greater diversity; it remains non-negative; and it is dimensioned (Miller & del Triana, 2009). The Blau index formula, $1-\sum_{j=1}^{N} p_j^2$ (Blau, 1977), where j denotes the category index (in this context, 2, representing women and men) and $p_{j,}\ j=1,2$, represents the proportion of board members in each category, allows for the quantification of a group's diversity. Thus, BLAU ranges from 0, indicating a board composed exclusively of one gender, to 0.5, reflecting equal representation of both men and women.

Collaterally, to explore the impact of other characteristics of the company's board of directors and top management on its inclination towards green building practices, the study included the following variables as regressors: Board size (BSZ), board skills (BSK), average board tenure (BTN), the percentage of non-executive board members (NEM), the percentage of independent board members (IBM), the duality between chairman and CEO (DUA), board members' compensations (BMC), the percentage of independent board members on the audit committee (AUD), senior executive compensation (SEC), and CEO compensation (CEOC).

In addition, companies with a stronger commitment to social responsibility are expected to exhibit a greater propensity for sustainable and green building practices. Therefore, the following explanatory variables were also considered: the presence of a CSR committee (CSRC), CSR reporting (CSRR), CO_2 emissions (CO_2), and the company's ESG score assigned by Eikon (ESG).

Finally, company size (SIZE), return on assets (ROA) and net employment creation (NEC) were used as control variables. In addition, given that a company's industry and location can significantly influence its sustainability practices due to factors such as legislation and stakeholder pressure, sector and country dummy variables were included to control for this effect (Cuadrado Ballesteros et al., 2015; Kyaw et al., 2017).

3.3 | Methodology

In this methodological section, we will first introduce the fundamentals of multivariate logistic modeling. Subsequently, we will delineate our approach to model selection and validation, along with the methodology employed to assess the predictive efficacy of the chosen models.

3.3.1 | Training, validating, and testing

We have employed a comprehensive validation approach. Initially, both databases (Euro Stoxx 300 and S&P 500) were randomly divided into two sets: The first set comprises 75% of the companies listed in the respective stock index, while the second set consists of the remaining 25% of companies. It is important to note that, due to the panel data nature of our analysis, the number of observations in the first and second subsets may not precisely represent 75% and 25%, respectively, of the total observations. The second subset, referred to as the test set, is reserved for use after the model has been trained and validated. Meanwhile, the first subset, known as the training set, is utilized for variable selection, model estimation, and model adequacy checking.

Once the model has been selected and estimated, the first set is divided into 10 subsets (folds), and a 10-fold cross-validation[2] is conducted to assess the goodness of fit and various error metrics (for detailed cross-validation procedures, see Fernández-Avilés & Montero, 2024). If the goodness of fit and error metrics are deemed acceptable, they are computed using the test set. If the results are consistent with those observed in the cross-validation procedure, the final model is estimated using the complete database to leverage all available information. This final estimation is expected to refine the model selected during the estimation phase, although its efficacy can only be validated in real-world applications. While the utilization of a single test set might be perceived as a limitation, this is mitigated by the large training sets employed for both the Euro Stoxx 300 and S&P 500 (Molinaro et al., 2005).

After completing the above steps, the model coefficients can be interpreted (the explanatory perspective) and the model is ready to be used for prediction (the predictive perspective).

3.3.2 | Multivariate logistic models

The decision to employ a specific type of model or specification within such a type implicitly implies two aspects: (i) formulating a relationship between the response variable (in our case, GRB) and the set of its presumed drivers or regressors; and (ii) determining how the regressors impact the response variable.

In our case, estimating the probability that a company is committed to green (or environmentally friendly) practices as a function of several variables, including the variable of focus (BGD or BLAU, depending on the model), cannot be achieved with a traditional linear model, as probabilities are bounded in the interval [0, 1], and linear models may produce estimates below 0 or beyond 1. Hence, traditional linear models are unsuitable for modeling a dichotomous (or polytomous) response variable of a probabilistic nature. Instead, considering that in reality female participation on boards of directors rarely exceeds 50%, generalized linear models, particularly multivariate logistic models (MLM), are employed. These models use the multivariate logistic function to model the probability of 'success' (YES or 1) for the ith observation.

[2]For those not familiar with resampling techniques, an n-fold cross-validation consists of the following steps:
i. Split the training set into n subsets, where n is the hyperparameter of the procedure.
ii. For each subset i, where $i = 1,2, ..., n$:
- Estimate the model using the data from the remaining subsets.
- Evaluate this model using the data included in the ith subset through the corresponding metrics.

iii. Compute the average of these metrics to globally evaluate the selected model.

$$P_{1i} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}} + \epsilon_i, \tag{1}$$

such that the probability of 'failure' (NO or 0) is given by:

$$P_{0i} = 1 - \frac{1}{1+e^{-(\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}} + \epsilon_i = \frac{e^{-(\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}}{1+e^{-(\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}} + \epsilon_i, \tag{2}$$

where β_0 is the intercept, $x_{1i}, x_{2i}, \ldots, x_{pi}$ are the values of the p explanatory variables in the ith observation, $\beta_1, \beta_2, \ldots \beta_p$ are their associated coefficients, and ϵ_i is an error term.

The quotient $\frac{P_{1i}}{P_{0i}}$ is known as the odds ratio:

$$\frac{P_{1i}}{P_{0i}} = e^{\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi}} + \varepsilon_i, \tag{3}$$

where ε_i is an error term.

The logarithm of the odds ratio is a linear combination of the explanatory variables, allowing us to leverage the well-known literature on linear models:

$$ln \frac{P_{1i}}{P_{0i}} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_p x_{pi} + e_i, \tag{4}$$

where $ln \frac{P_{1i}}{P_{0i}}$ is known as the logit function and e_i is an error term.

It is noteworthy that in the logistic framework, the interpretation of the estimated coefficients $\widehat{\beta}_j$, $j = 0, 1, 2, \ldots, p$, is not straightforward; however, the terms $e^{\widehat{\beta}_j}$ are interpretable. Specifically, the impact of a unitary increment in the jth explanatory variable, $j = 0, 1, 2, \ldots, p$, on the response variable, (P_{1i}/P_{0i}), is given by $100 \times (e^{\beta_1} - 1)\%$, which remains constant regardless of the value of X_j. As an example, let us assume that X_1 is the covariate of interest (in our case BGD or BLAU) and consider $\widehat{\beta}_1 = 0{,}1$ and $e^{-(\beta_0+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})} = 2$ (ceteris paribus). Then, a change of one unity in BGD result in a percent increment of $100 \times (e^{\beta_1} - 1)\% = 10{,}52\%$ in the odds ratio. That is, irrespective of the percentage of women in the board of directors, an increment of 1% unit in such a percentage would result in an increment by 10.52% of the probability of supporting green building practices against not supporting them. It is also noteworthy that the increment of the probability that a company adopts green building practices, P_{1i}, when BGD augments in one unity, is governed by the expression $\frac{\partial P_{1i}}{\partial X_{ji}} = \frac{-\beta_1 e^{-(\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}}{\left(1+e^{-(\beta_0++\beta_1 x_{1i}+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}\right)^2}$,[3] in our example $\frac{\partial P_{1i}}{\partial X_{1i}} = \frac{-\beta_1 e^{-(\beta_1 x_{1i}+2)}}{\left(1+e^{-(\beta_1 x_{1i}+2)}\right)^2}$, which do varies depending on the percentage of women in the board room. For example, in the case that the percentage increases from 5% to 6% the estimated probability of adopting green practices would augment by approximately 0,006 (from 0.924 to 0.930). However, In the case of increasing from 20% to 21%, the probability of adopting green building practices would augment only by 0,001 (from 0.982 to 0.983).

In some cases, the odds ratio is also of interest:

$$\psi_{10|ij} = \frac{\frac{P_{1i}}{P_{0i}}}{\frac{P_{1j}}{P_{0j}}} = e^{\beta_{11}(x_{1i}-x_{1j})} + \omega_i, \tag{5}$$

which indicates the relative situation of the two values of the response variable (YES/NO or 1/0) for two different values of the explanatory variable of interest (ceteris paribus).

Another option is to include the variable of interest in the logistic function in polynomic terms.[4] In these cases, the logistic model is not linear with respect to the variables. Consequently, the impact of a specific variation of this variable on P_{1i}, P_{0i}, the odds ratio, and the logit depends on the level of that variable.

Assuming that the variable of interest is X_1, in the case of a second-degree polynomial (the quadratic case), we have:

$$P_{1i} = \frac{1}{1+e^{-(\beta_0+\beta_{11} x_{1i}+\beta_{12} x_{1i}^2+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}} + \epsilon_i, \tag{6}$$

$$P_{0i} = \frac{e^{-(\beta_0+\beta_{11} x_{1i}+\beta_{12} x_{1i}^2+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}}{1+e^{-(\beta_0+\beta_{11} x_{1i}+\beta_{12} x_{1i}^2+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})}} + \epsilon_i, \tag{7}$$

$$\frac{P_{1i}}{P_{0i}} = e^{\beta_0+\beta_{11} x_{1i}+\beta_{12} x_{1i}^2+\beta_2 x_{2i}+\ldots+\beta_p x_{pi}} + \varepsilon_i, \tag{8}$$

$$ln \frac{P_{1i}}{P_{0i}} = \beta_0 + \beta_{11} x_{1i} + \beta_{12} x_{1i}^2 + \beta_2 x_{2i} + \ldots + \beta_p x_{pi} + e_i, \tag{9}$$

and the impact of a unitary increment in $X_j \neq X_1$ on the odds ratio continues to be constant with a value of β_j, $j \neq 1$. However, a unitary increment in the variable we are interested in, X_1, has an impact on the odds ratio of $100 \times \left(e^{\beta_{11}+\beta_{12}(2x_{1i}+1)} - 1\right)\%$, which is not constant but depends on the value of X_j. In other words, there is no longer a constant impact, but a percentage impact function: $IF(x_{1i})$.[5]

In order to illustrate the above considerations, let X_1 be BGD and assume $\widehat{\beta}_{11} = 0{,}01$, $\widehat{\beta}_{12} = 0{,}025$, and $e^{-(\beta_0+\beta_2 x_{2i}+\ldots+\beta_p x_{pi})} = 2$ (ceteris paribus). Then, the non-constant impact of a change in BGD of one unity (which can be approximated by $100 \times (e^{\beta_{11}+\beta_{12} x_{1i}} - 1)\%$) is by 26.49% when the percent of women in the director board raises from 5% to 6%, but is by 341.49% when that percent is 29%, for example. The increment of the probability of adopting green building practices, P_{1i}, when BGD augments in one unity is also dependent on the percentage of women already taking part of the board of directors. Such

[3] In fact, this expression provides the increment of the probability for the company to adopt green building practices when BGD experiences an infinitesimal change. However, for the sake of clarity, we prefer to use increments of a unity instead of infinitesimal unities and this is the reason for the increments in the probability that a company is committed to green building practices to be approximations (they differ from the real value in the second or third decimal place). This clarification applies to all the cases where the impact of a change in the covariate of interest on the response variable is not constant but depends on the level of the covariate (in this research to the quadratic and cubic cases).

[4] Meaning the inclusion of either a single polynomial term of any degree, or several polynomial terms simultaneously.

[5] The estimation method remains unaffected, as a simple variable transformation can revert the model to its linear form.

an increment is given by the expression the expression $\frac{\partial P_{1i}}{\partial X_j} = \frac{-(\beta_{11}+\beta_{12})\, e^{-\left(\beta_0+\beta_{11}x_{1i}+\beta_{21}x_{1i}^2+\beta_2x_{2i}+\ldots+\beta_px_{pi}\right)}}{\left(1+e^{-\left(\beta_0+\beta_{11}x_{1i}+\beta_{21}x_{1i}^2+\beta_2x_{2i}+\ldots+\beta_px_{pi}\right)}\right)^2}$, in our example $\frac{\partial P_{1i}}{\partial X_1} = \frac{-(0{,}01+0{,}025)\, e^{-\left(0{,}01x_{1i}+0{,}025x_{1i}^2+2\right)}}{\left(1+\left(0{,}01x_{1i}+0{,}025x_{1i}^2+2\right)\right)^2}$. Therefore, for example, when the percentage of women in the board increases from 5% to 6% the estimated probability of adopting green practices would augment by 0,015 (from 0.935 to 0.9500). In the case of an increment from 20% to 21%, the augment in the above probability would be practically null.

The odds quotient is given by:

$$\Psi_{10|ij} = \frac{\frac{P_{1i}}{P_{0i}}}{\frac{P_{1j}}{P_{0j}}} = e^{\beta_{11}\left(x_{1i}-x_{1j}\right)+\beta_{12}\left(x_{1i}^2-x_{1j}^2\right)}, \tag{10}$$

which reflects the relative situation of the two options of the response variable (YES and NO) for two different values of the explanatory variable of interest (ceteris paribus).

Analogously, in the cubic case (third-degree polynomial):

$$P_{1i} = \frac{1}{1+e^{-\left(\beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2+\beta_{13}x_{1i}^3+\beta_2x_{2i}+\ldots+\beta_px_{pi}\right)}} + \epsilon_i, \tag{11}$$

$$P_{0i} = \frac{e^{-\left(\beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2++\beta_{13}x_{1i}^3+\beta_2x_{2i}+\ldots+\beta_px_{pi}\right)}}{1+e^{-\left(\beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2+\beta_{13}x_{1i}^3+\beta_2x_{2i}+\ldots+\beta_px_{pi}\right)}} + \epsilon_i, \tag{12}$$

$$\frac{P_{1i}}{P_{0i}} = e^{\beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2+\beta_{13}x_{1i}^3+\beta_2x_{2i}+\ldots+\beta_px_{pi}} + \varepsilon_i, \tag{13}$$

$$ln\frac{P_{1i}}{P_{0i}} = \beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2+\beta_{13}x_{1i}^3+\beta_2x_{2i}+\ldots+\beta_px_{pi}+e_i, \tag{14}$$

where the impact of a unitary increment in $X_j \neq X_1$ on the odds ratio continues to be constant at the value β_j, $j \neq 1$. However, a unitary increment in the variable of interest, X_1, has a non-constant impact on the odds ratio; on the contrary, it depends on the value of X_j. The percentage impact function is given by: $IF(x_{1i}) = 100 \times \left(e^{\beta_{11}+\beta_{12}(1+x_{1i})+\beta_{13}\left(1+3x_{1i}+3x_{1i}^2\right)} - 1\right)\%$.

For instance, in the case that the covariate of interest, X_1, is BGD, letting $\widehat{\beta}_{11}, \widehat{\beta}_{12}$, and $\widehat{\beta}_{13}$ to take the values 0,0001, 0,0003 and 0,001, respectively, and assuming $e^{-\left(\beta_0+\beta_2x_{2i}+\ldots+\beta_px_{pi}\right)} = 1$ (ceteris paribus), the impact on the odds ratio of an unitary increment in BGD (given by the impact function above presented) is of 9.90% when the percentage of women in the board is of 5%. However, the odds multiplies by 13.85 when the percentage is 29%.

As with the case of polynomials of lower degree, the variation of probability of adopting green practices is far from being constant when BGD experiences unitary increments. For example, it is 29.30% when the percentage of women in the board is 5%, but it would be practically null if the female participation would be 40%.

The odds quotient is given by:

$$\Psi_{10|ij} = \frac{\frac{P_{1i}}{P_{0i}}}{\frac{P_{1j}}{P_{0j}}} = e^{\beta_{11}\left(x_{1i}-x_{1j}\right)+\beta_{12}\left(x_{1i}^2-x_{1j}^2\right)+\beta_{13}\left(x_{1i}^3-x_{1j}^3\right)}, \tag{15}$$

It is worth noting that as the degree of the polynomial increases, so does its flexibility to fit the training dataset. However, this also raises the risk of overfitting, meaning the polynomial may not generalize well to new datasets (bad generalization). For this reason, logistic models beyond the cubic case are not considered.[6]

3.3.3 | Competing multivariate panel data logistic models

Three different types of multivariate panel data logistic models (MPDLM) are considered to analyze the relationship between GRB and the explanatory variables listed in Section 3.2 (although the focus is on BGD or BLAU, depending on the model): Traditional multivariate panel data logistic models (TMPDLM), quadratic multivariate panel data logistic models (QMPDLM), and cubic multivariate logistic models (CMPDLM). As seen in Section 3.3.2., the general form of the logit for such models is:

$$\text{In TMPDLM}: ln\frac{P_{1i}}{P_{0i}} = \beta_0+\beta_1x_{1i}+\beta_2x_{2i}+\ldots+\beta_px_{pi}+e_i, \tag{16}$$

$$\text{In QMPDLM}: ln\frac{P_{1i}}{P_{0i}} = \beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2+\beta_2x_{2i}+\ldots+\beta_px_{pi}+e_i, \tag{17}$$

$$\text{In CMPDLM}: ln\frac{P_{1i}}{P_{0i}} = \beta_0+\beta_{11}x_{1i}+\beta_{12}x_{1i}^2+\beta_{13}x_{1i}^3+\beta_2x_{2i}+\ldots+\beta_px_{pi}+e_i, \tag{18}$$

where X_1 represents the variable of interest (BGD or BLAU).

For each of these three cases, five specifications are considered. Initially, using TMPDLM to outline these specifications, BGD is chosen as the variable of interest. In TMLM1, the data are pooled. However, due to potential endogeneity problems between BGD and GRB, as well as concerns about omitted variables (Adams, 2016; Boulouta, 2013; Reguera-Alvarado et al., 2017; Valls Martínez & Soriano Román, 2022), the remaining four models adopt panel data approaches. Other well-known advantages of using panel data include the ability to handle unobserved heterogeneity, increase estimation precision (due to increased information and degrees of freedom), and address issues related to under-specification or omitted relevant variables, among others.

The choice between fixed or random effects in the panel data models depends on whether the unobserved transversal heterogeneity (β_{0i} in the models listed below) is correlated with the explanatory variables. This decision is the responsibility of the researcher. However, when uncertainty arises regarding the appropriate specification,

[6]Another possibility is to model the logit function non-parametrically by using a splines approach.

statistical tests, such as the Hausman test (Hausman, 1978), can assist in decision-making. In light of the aforementioned considerations and the results of the Hausman tests, fixed effects models were ultimately selected.

In particular, TMPDLM2 represents a panel data model with fixed effects, where the variable representing gender diversity on the board of directors is BGD. In TMPDLM3, BGD is replaced with BLAU (Blau, 1977; Valls Martínez & Soriano Román, 2022). TMPDLM4 is a residual panel data model, involving two steps: first, BGD is estimated as a function of the remaining predictors, and the residuals are computed; second, a TMPDLM2 model is estimated where BGD is substituted with the residuals obtained in the previous step (Elsayih et al., 2018; Haque, 2017; Valls Martínez, Martín Cervantes, et al., 2022; Valls Martínez, Santos Jaén, et al., 2022; Valls Martínez, Soriano Román, et al., 2022). This approach allows for considering the direct influence of BGD once the indirect influence exerted by the other regressors through gender diversity has been removed. TMPDLM5 is a winsorized version of TMPDLM2 at the 1% level, aiming to eliminate potential distortion caused by extreme values of the explanatory variables (Haque, 2017; Luo et al., 2012).

These five specifications are also estimated for the quadratic case. Previous studies have indicated that the relationship between CSR and board gender diversity is not linear but quadratic (Amorelli & García-Sánchez, 2020; Fernández-Feijoo et al., 2014). Thus, if the relationship between CSR and board gender diversity follows an inverted U-shaped pattern, a higher percentage of women on the board would initially increase CSR, but up to a certain level, after which it would begin to decrease (Valls Martínez, Martín Cervantes, et al., 2022, Valls Martínez, Santos Jaén, et al., 2022, Valls Martínez, Soriano Román, et al., 2022). Therefore, the quadratic term is introduced in the five traditional specifications to assess whether this relationship also applies to the propensity for green buildings.

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Finally, the QMPDLM are extended with a cubic term on the variable representing board gender diversity to uncover new insights. As far as we know, this is the first instance of using a CMPDLM in the literature on the topic.

Summarizing, the multivariate panel data logistic models (MPDLM) considered in our study are:

- Pooled models (in the specification 1):

$$\mathrm{TMLM(P)}: ln\frac{P_{1it}}{P_{0it}} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_p x_{pit} + e_{it}, \tag{19}$$

$$\mathrm{QMLM(P)}: ln\frac{P_{1it}}{P_{0it}} = \beta_0 + \beta_{11} x_{1it} + \beta_{12} x_{1it}^2 + \beta_2 x_{2it} + \ldots + \beta_p x_{pit} + e_{it}, \tag{20}$$

$$\mathrm{CMLM(P)}: ln\frac{P_{1it}}{P_{0it}} = \beta_0 + \beta_{11} x_{1ti} + \beta_{12} x_{1it}^2 + \beta_{13} x_{1it}^3 + \beta_2 x_{2it} + \ldots + \beta_p x_{pit} + e_{it}, \tag{21}$$

where $i = 1, \ldots, N; t = 1, \ldots, T$, there is assumed to be no unobserved individual heterogeneity, and the model underlies the usual assumptions for cross section analysis.

- Fixed effects (FE) models (in specifications 2–5)[7]:

$$\mathrm{TMPDLM(FE)}: ln\frac{P_{1it}}{P_{0it}} = \beta_{0i} + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_p x_{pit} + e_{it}, \tag{22}$$

$$\mathrm{QMPDLM(FE)}: ln\frac{P_{1it}}{P_{0it}} = \beta_{0i} + \beta_{11} x_{1it} + \beta_{12} x_{1it}^2 + \beta_2 x_{2it} + \ldots + \beta_p x_{pit} + e_{it}, \tag{23}$$

$$\begin{aligned}\mathrm{CMPDLM(FE)}: ln\frac{P_{1it}}{P_{0it}} = {} & \beta_{0i} + \beta_{11} x_{1ti} + \beta_{12} x_{1it}^2 + \beta_{13} x_{1it}^3 + \beta_2 x_{2it} \\ & + \ldots + \beta_p x_{pit} + e_{it},\end{aligned} \tag{24}$$

where $i = 1, \ldots, N; t = 1, \ldots, T$, β_{0i} is the non-observable time-invariant specific effect of each cross-sectional unit, X variables are not time-invariant, and e_{it} denotes spheric random error terms which verify $E(X_{it} \cdot e_{it}) = 0$ for all explanatory variables (thus ensuring efficient and consistent estimates).

- Random effects (RE) models (also in specifications 2–5)[8,9]:

$$\mathrm{TMPDLM(RE)}: ln\frac{P_{1it}}{P_{0it}} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_p x_{pit} + \beta_{0i}\, e_{it}, \tag{25}$$

$$\begin{aligned}\mathrm{QMPDLM(RE)}: ln\frac{P_{1it}}{P_{0it}} = {} & \beta_0 + \beta_{11} x_{1it} + \beta_{12} x_{1it}^2 + \beta_2 x_{2it} + \ldots \\ & + \beta_p x_{pit} + \beta_{0i} + e_{it},\end{aligned} \tag{26}$$

$$\begin{aligned}\mathrm{CMPDLM(RE)}: ln\frac{P_{1it}}{P_{0it}} = {} & \beta_0 + \beta_{11} x_{1ti} + \beta_{12} x_{1it}^2 + \beta_{13} x_{1it}^3 + \beta_2 x_{2it} \\ & + \ldots + \beta_p x_{pit} + \beta_{0i} + e_{it},\end{aligned} \tag{27}$$

[7]The rationale behind the fixed effects panel data model lies in the presence of unobserved cross-sectional heterogeneity that is time-invariant, possesses a random nature, and is correlated with the explanatory variables.

[8]As mentioned above, the assumptions behind the random effects panel data model include the existence of unobserved cross-sectional heterogeneity that is time-invariant, possesses a random nature, and is not correlated with the explanatory variables.

[9]In the random effects case, there is only one intercept, and the N specific intercepts corresponding to the N individuals (in our case, companies) are included in the composed perturbation term. It is noteworthy that such N specific intercepts can be estimated, along with the coefficients of the explanatory variables in the fixed effects model. However, in the random effects model, these intercepts are considered random variables not correlated with the explanatory variables and are therefore added to the error term.

where $i = 1, \ldots, N; t = 1, \ldots, T$, and $\beta_{0i} + e_{it}$ is a composed error term where β_{0i} is a random time-invariant group term for the ith cross-sectional unit, unlike e_{it}, which is random but time-variant.

3.3.4 | Model estimation: Variables selection, adequacy assessment, goodness-of-fit measures and classification metrics

The five specifications of TMLM, QMLM, and CMLM were estimated using maximum likelihood and within-groups estimators, except for the pooled strategies. Computation was performed using the Stata v.16 statistical software.

For variable selection, the preselection phase involved considering zero-variance and pairwise correlation criteria, as well as the correlation between variables/linear combinations of variables. Subsequently, a filter-type method with a sequential forward selection algorithm determined the final set of explanatory variables from the initially pre-selected ones (refer to Montero & Velasco-López, 2024 for details).

To assess the significance of the logistic model, a Chi-square test and a likelihood ratio test for nested models based on the change in deviance[10] were employed. Additionally, the Z statistic and the Wald chi-test were used to determine the individual significance of each predictor introduced in the logistic regression model.

The adequacy of the selected model is verified to ensure that the major assumptions of the model are met, including the type of relationship between the response and the regressors, the significance of all theoretical regressors included in the model, and the assumptions made on the error term. Model inadequacies can have serious consequences, particularly instability, where two samples may yield different specifications leading to opposing conclusions.

As for assessing goodness-of-fit, the literature on generalized linear models often employs a combination of tests and measures.[11] These include the Hosmer-Lemeshow goodness-of-fit test[12] (applicable when there is at least one quantitative explanatory variable), McFadden's and Cox and Snell's pseudo-R^2, along with Nagelkerke's correction of the Cox and Snell's measure (Cox & Snell, 1989; McFadden, 1974; Nagelkerke, 1991).[13] Additionally, the Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978) are utilized to rank candidate models based on their fit to the data and assist in decision-making. Lower values in both cases indicate a better-fitting model.

When the focus is on determining which of two groups an element, object, individual, or company is classified into (in our case, in favor of or not in favor of green buildings) based on the available information contained in the explanatory variables, the evaluation of goodness-of-fit follows a different approach. Firstly, a decision rule based on a probability value is required to predict whether an element, object, or individual (in our case, companies) should be assigned to one group or the other. For instance, a company will be classified as belonging to group 1 (in favor of green buildings) if $\hat{p} > 0.8$; otherwise, it will be classified in group 2 (not in favor of green buildings). Clearly, determining the value of $\hat{p}$ that discriminates between the two groups is a crucial decision made based on the number of cases correctly and incorrectly classified by the model. Using classification terminology, this decision is based on the sensitivity and specificity of the model, which can be visualized in the receiver operating characteristic (ROC) curve and its area under the curve (AUC); for further details, refer to Casero-Alonso and Durban (2024).

According to Montero and Velasco-López (2024), sensitivity, or the true positive rate, is defined as the number of true positives divided by the sum of false positives and false negatives.[14] It measures the probability that a positive real case will be classified correctly. Conversely, specificity is the probability that a real negative case will be correctly classified, while accuracy represents the proportion of correct predictions or classifications (TP + TN/Total). Precision answers the question: when a classifier says "yes," what is the proportion of correct predictions? (TP/(TP + TN)). The ROC curve displays sensitivity against 1-specificity for various selected cut-off values (ranging between 0 and 1). Sensitivity represents the true positive rate, while 1-specificity corresponds to the rate of false positives (i.e., the number of false negatives divided by the sum of the true negatives and the false positives). A higher AUC value, ranging between 0 and 1, indicates greater discriminatory power of the model,[15] making it useful for comparing different logistic models. The Gini index, well-known in the statistics literature on concentration, can be computed as $2AUC - 1$. $G = 1$ implies $AUC = 0$, and $G = 0$ when $AUC = 1/2$. AUC = 1/2. Finally, the Jaccard index measures the similarity between the actual classes of the response variable and those predicted by the model: $J = TP + TN/2\,Total - (FP + FN))$.

3.3.5 | Research hypotheses

The specific research hypotheses guiding our research are the following[16]:

Hypothesis 1. The percentage of women on the board

[10]These tests are very popular when dealing with generalized linear models, particularly in the analysis of logistic models.

[11]These measures exclude the traditional R^2, as it is not applicable in the logistic regression context.

[12]The lower the p-value, the worse the goodness-of-fit.

[13]As is well known, numerous options exist for calculating an R^2-type goodness-of-fit measure for logistic regression, but unfortunately, no consensus has been reached on which is the most effective. Among these, McFadden's and Nagelkerke's pseudo-R^2 are the most frequently used in software related to this topic, which is why we have chosen them. For all such measures, a higher value indicates better goodness-of-fit.

[14]In our case:

- A true positive (TP) occurs when the model correctly predicts a building as sustainable.
- A true negative (TN) occurs when the model correctly predicts a building as not sustainable.
- A false positive (FP) occurs when the model incorrectly predicts a building as sustainable.
- A false negative (FN) occurs when the model incorrectly predicts a building as not sustainable.

[15]The AUC for a random classifier is 0.5 because the ROC curve coincides with the diagonal in such a case.

[16]Under the assumption that in reality the female percentage on boardrooms rarely exceeds 50%.

of directors (BGD) significantly increases the odds ratio (the probability that a company is committed to green building practices divided by the probability of NOT) through a traditional multivariate pooled or panel data logistic model (ceteris paribus).

Hypothesis 2. Gender diversity on the board of directors (BLAU) significantly increases the odds ratio (the probability that a company is committed to green building practices divided by the probability of NOT) through a traditional multivariate pooled or panel data logistic model (ceteris paribus).

Hypothesis 3. The percentage of women on the board of directors (BGD) significantly increases the odds ratio (the probability that a company is committed to green building practices divided by the probability of NOT) through a quadratic multivariate pooled or panel data logistic model where gender diversity enters as a second-degree polynomial (ceteris paribus).

Hypothesis 4. Gender diversity on the board of directors (BLAU) significantly increases the odds ratio (the probability that a company is committed to green building practices divided by the probability of NOT) through a quadratic multivariate pooled or panel data logistic model where gender diversity enters as a second-degree polynomial (ceteris paribus).

Hypothesis 5. The percentage of women on the board of directors (BGD) significantly increases the odds ratio (the probability that a company is committed to green building practices divided by the probability of NOT) through a traditional multivariate pooled or panel data logistic model where such gender diversity enters as a third-degree polynomial (ceteris paribus).

Hypothesis 6. Gender diversity on the board of directors (BLAU) significantly increases the odds ratio (the probability that a company is committed to green or environmentally friendly building practices divided by the probability of NOT) through a traditional multivariate logistic model where such gender diversity enters as a third-degree polynomial (ceteris paribus).

It is worth noting that BGD can also be interpreted as an indicator of gender diversity because, based on the database this study relies on, which indicates that the percentage of women on boards of directors rarely exceeds 50%, an increase in the percentage of women implies an increase in gender diversity. Consequently, the above six hypotheses can be formulated in terms of gender diversity regardless of whether BGD or BLAU is used.

4 | RESULTS

4.1 | Univariate descriptive statistics and bivariate correlations

Table 3 presents the descriptive statistics of the continuous variables in the Euro Stoxx 300 and S&P 500 indexes, while Table 4 outlines the percentage distribution of the dichotomous variables. Several notable insights emerge from the analysis of both tables.

Firstly, there is a higher percentage of companies committed to green buildings in the U.S. (56.57%) compared to Europe (45.01%). Interestingly, this contrasts with the fact that European companies boast a slightly higher ESG score than their U.S. counterparts (66.64% and 62.49%, respectively), despite similar levels of CO_2 emissions in both regions. This finding is intriguing given the stricter environmental legislation in Europe compared to the U.S. (Valls Martínez, Martín Cervantes, et al., 2022; Valls Martínez, Santos Jaén, et al., 2022; Valls Martínez, Soriano Román, et al., 2022).

Secondly, concerning social responsibility, Europe exhibits a greater proportion of companies with CSR committees and those that disclose CSR reports compared to the U.S. Specifically, over 80% of European companies have CSR committees, whereas the percentage falls below 70% in the U.S. Moreover, more than 90% of companies listed in the Euro Stoxx 300 disclose CSR reports, surpassing their counterparts in the S&P 500 by 10 percentage points.

Another notable distinction is that nearly all members of the audit committee in companies listed in the S&P 500 are independent, whereas in companies listed in the Euro Stoxx 300, this percentage barely exceeds two thirds. This disparity could stem from American companies' efforts to legitimize their position in the eyes of stakeholders (Harjoto & Jo, 2015; Petersen & Vredenburg, 2009).

Regarding corporate governance factors, European companies exhibit greater gender diversity on their boards of directors. Specifically, the percentage of women on boards of directors is 31.12% for Euro Stoxx-listed companies and 25.25% for those listed in the S&P 500. Notably, in both cases, the maximum percentage of women hovers around two-thirds of the total board members, with some boards comprising only men. It's worth considering that many European countries have legislation mandating a certain quota of women on company boards (Valls Martínez & Soriano Román, 2022). Importantly, the percentage of women on boards fluctuates significantly over time for most companies, both in Europe and the U.S. Moreover, boards of Euro Stoxx 300-listed companies have more members and more non-executive members compared to those in the S&P 500, facilitating the inclusion of more women. Conversely, board members of U.S. companies typically have extensive backgrounds, longer tenures, higher independence rates, and larger compensations. Concerning CEOs, they often hold the position of Chairperson to a greater extent, with their compensation primarily tied to shareholder returns.

Lastly, in financial and performance terms, companies listed in the Euro Stoxx 300 and the S&P 500 are similar in size on average.

TABLE 3 Descriptive statistics of the continuous explanatory variables.

Variable	Mean	Median	SD	Minimum	Maximum
Panel A. Euro Stoxx 300					
BGD	31.1241	33.3333	10.5091	0.0000	64.2857
BLAU	0.4067	0.4444	0.1005	0.0000	0.5000
AUD	68.0727	66.6700	25.5521	0.0000	100.0000
BSZ	13.3579	13.0000	4.2792	3.0000	22.0000
BSK	24.8410	23.0769	17.7902	0.0000	87.5000
BTN	7.3086	6.9673	2.7197	0.2885	18.3000
NEM	92.9461	100.0000	10.7281	33.3333	100.0000
IBM	59.6175	57.8947	25.9779	0.0000	100.0000
SEC	14.7103	8.8231	18.9680	0.0365	248.0740
BMC	1.9879	1.2418	5.6012	0.0003	181.0968
NEC	3.5954	1.5494	21.7845	−67.4248	412.2273
ESG	66.6401	70.4317	17.9188	5.6323	94.8156
CO_2	12.3494	12.2705	2.8264	4.2613	19.0189
SIZE	23.5157	23.3847	1.7929	18.8032	28.5427
ROA	4.4718	3.9035	5.8832	−32.0467	58.8637
Panel B. S&P 500					
Variable	**Mean**	**Median**	**SD**	**Minimum**	**Maximum**
BGD	25.2552	25.0000	9.6535	0.0000	62.5000
BLAU	0.3589	0.3750	0.0943	0.0000	0.5000
AUD	99.1265	100.0000	3.8019	66.6667	100.0000
BSZ	10.8026	11.0000	2.2326	1.0000	24.0000
BSK	55.6744	54.5454	18.4012	0.0000	100.0000
BTN	8.7194	8.4091	3.1766	0.7500	29.4444
NEM	87.1958	88.8889	5.7202	50.0000	100.0000
IBM	85.3800	87.5000	7.5053	20.0000	100.0000
SEC	38.5431	31.3896	30.3943	0.7638	900.1443
BMC	3.1261	2.8780	2.5808	0.0384	51.1931
NEC	6.4659	3.2001	21.0161	−75.9278	379.7619
ESG	62.4904	65.5837	16.3934	11.7331	92.6173
CO_2	12.5471	12.3196	2.2389	0.0000	18.7449
SIZE	23.5776	23.5503	1.5136	18.1614	28.8503
ROA	6.5260	5.4657	7.4218	−74.7924	55.2244

TABLE 4 Percentage distribution in the dichotomous variables.

	Euro Stoxx 300		S&P 500	
Variable	Value 0	Value 1	Value 0	Value 1
GRB	54.99	45.01	43.33	56.67
CSRC	18.22	81.78	30.90	69.10
CSRR	6.64	93.36	22.00	78.00
DUA	85.29	14.71	32.61	67.39
CEOC	63.40	36.60	11.05	88.95

However, the latter exhibit higher returns on assets and generate more employment.

In summary, companies listed in the Euro Stoxx 300 boast a higher percentage of women on their boards of directors, which tend to be larger and include more non-executive members compared to those listed in the S&P 500. Additionally, Euro Stoxx-listed companies exhibit slightly higher ESG scores. However, a greater proportion of American firms are committed to green buildings, and they also demonstrate higher profitability and create more net employment. This could be attributed to the fact that in 90% of cases, CEO compensation in American companies is tied to total shareholder return, compared to only 30% of cases in European-listed companies.

Focusing on statistical aspects, Tables 5 and 6 display the bivariate Pearson correlations among the continuous explanatory variables for companies listed in the Euro Stoxx 300 and S&P 500, respectively. It is observed that the highest correlations are −0.4164 and 0.3397 in the Euro Stoxx 300 and S&P 500, respectively, indicating the absence of collinearity issues that might impact the estimations of the candidate multivariate panel data logistic models utilized to gauge the propensity of the companies listed in the aforementioned indexes for involvement in green building initiatives.

Table 7 illustrates the mean values of each explanatory variable for listed companies categorized as committed (group 1) and not committed (group 0) to green building, across both the Euro Stoxx 300 and the S&P 500 indexes. The between-group differences for these variables must be significant for them to be included in the competing models.

Upon examination, it is observed that in the European case, only AUD and BSK are not statistically significant. Although AUD is significant at the 0.075 level, it is retained in the set of explanatory variables due to its widespread usage in empirical studies. Similarly, in the American case, only NEC and AUD lack statistical significance, yet AUD is retained in the explanatory variables set.

Notably, in the European case, SEC, ESG, IBM, BGD, BSZ, and NEC exhibit the largest differences, although they are relatively small. The American case demonstrates similar patterns, albeit with more pronounced differences.

Furthermore, it is noteworthy that the percentage of women on the board of directors is slightly but significantly higher in companies with green buildings, both in the European and U.S. markets. These companies tend to have slightly larger boards, with board members serving slightly longer tenures. Moreover, executive and board member compensation tends to be more generous, and they exhibit a lower return on assets in Europe (not in the U.S.). Additionally, companies with green buildings emit less CO_2 and possess higher ESG scores.

4.2 | Results from logistic modeling

In light of Tables A1–A12 in the Appendix, which present the complete results obtained from the 30 competing multivariate logistic models, it can be concluded that (i) gender plays a significant role in decision-making regarding green building practices, and (ii) both the general hypothesis and the six specific hypotheses raised in Section 2 and Subsection 3.3.5, respectively, are supported by empirical evidence. The details justifying these two assertions are provided below.

In Europe (Tables A1–A6), the model showing the best goodness-of-fit is CMPDLM2, although CMPDLM3, which represents gender diversity with BLAU instead of BGD, is also a strong alternative.

Based on the estimations using the training set data, CMPDLM2 yields the most favorable results for pseudo R^2, McFadden's R^2, and Cox and Snell's R^2. It also has the lowest values for AIC and BIC. Additionally, it performs best in the LR and Wald tests. However, as mentioned earlier, the outcomes for CMPDLM3 closely resemble those for CMPDLM2. These findings are further supported by the 10-fold cross-validation procedure, which favors CMPDLM2 as the preferred strategy, although CMPDLM3 remains a viable option.

From the perspective of classification metrics, disregarding CMPDLM1 due to its high AIC and BIC values, all competing models demonstrate similar performance in terms of percentage of concordant pairs, MAE, and AUC. Similarly, the training set-based results for classification metrics are corroborated by the test set results obtained through 10-fold cross-validation.

In the U.S. dataset (Tables A7–A12), CMPDLM5 emerges as the best fit for the training data. It exhibits the lowest AIC and the highest pseudo R^2, McFadden's R^2, and Cox and Snell's R^2. Despite being the best in terms of AIC, CMPDLM5 is not the top performer in terms of BIC; notably, the BIC value for QMPDLM5 is even lower than that of CMPDLM5, suggesting it as a strong alternative. Analysis of classification metrics (MAE, percentage of concordant pairs, and AUC) also favors CMPDLM5. Results from both goodness-of-fit and classification metrics, obtained through 10-fold cross-validation on the test set, confirm CMPDLM5 as the superior model for the U.S. dataset. Additionally, QMPDLM5, with its low BIC value and similar performance to CMPDLM5 in terms of MAE, could be considered as the second-best option. Notably, the coefficient significance for cubed BGD in CMPDLM5 is low for the training set and null for the total set, which explains the similarity in results between the two.

While the complete results for the 30 competing models are available in the Appendix, Tables 8 (for the training sample) and 9 (for the total sample) present the outcomes for the two best-performing models selected for each index.

Regarding the significance of gender drivers, in Europe, in the case of CMPDLM2, BGD significantly influences GRB when using cubic polynomials (although the first and second powers of BGD are not significant). However, in CMPDLM3, the alternative strategy, where gender diversity in the board of directors is measured by the Blau index, the coefficients for BLAU, BLAU2, and BLAU3 are all significant at the 1% significance level. Therefore, our results suggest that the relationship between BGD or BLAU and the odds ratio for propensity to green building practices extends beyond traditional linear and quadratic shapes. More flexible forms, such as cubic polynomials, should be considered.

Figures 1 and 2 display, respectively, the odds ratio versus BGD and the GRB impact function for CMPDLM2-EURO STOXX 300. It can be observed that the odds ratio (Figure 1) increases following a logistic shape up to approximately 37% of women on the board of directors, after which it progressively decreases. As for the impact function (Figure 2), they are positive and increase up to BGD = 20%. They remain positive for values of BGD between 20% and 37%, but their magnitude decreases with the value of BGD. For values of BGD between 37% and 64%, the impacts become increasingly negative.

When BLAU is used as the representative of gender diversity on the board of directors (the alternative to CMPDLM2), the situation is as follows: Figure 3 indicates that (i) the odds ratio slightly decreases

TABLE 5 Pearson correlations between the continuous explanatory variables in the Euro Stoxx 300.

Variable	BGD	BLAU	AUD	BSZ	BSK	BTN	NEM	IBM	SEC	BMC	NEC	ESG	CO_2	SIZE
AUD	0.1489*** (0.0000)	0.1420*** (0.0000)												
BSZ	0.1491*** (0.0000)	0.1801*** (0.000)	−0.0735*** (0.0003)											
BSK	0.0168 (0.4135)	0.0108 (0.6011)	−0.0090 (0.6626)	−0.1701*** (0.0003)										
BTN	−0.1984*** (0.0000)	−0.1711*** (0.0000)	0.0011 (0.9590)	−0.1081*** (0.0000)	0.0740*** (0.0003)									
NEM	−0.0811*** (0.0000)	−0.0813*** (0.0001)	−0.1256*** (0.0000)	0.0825*** (0.0001)	−0.4008*** (0.0000)	−0.1473*** (0.0000)								
IBM	0.0456** (0.0264)	0.0240 (0.2425)	−0.4164*** (0.0000)	−0.1100*** (0.0000)	−0.1200*** (0.0000)	−0.0636*** (0.0020)	0.1299*** (0.0000)							
SEC	0.0712*** (0.0005)	0.0541*** (0.0085)	0.0282 (0.1698)	0.2811*** (0.0000)	−0.0596*** (0.0037)	−0.0607*** (0.0032)	0.1804*** (0.0000)	0.0572*** (0.0054)						
BMC	0.0396* (0.0540)	0.0550*** (0.0074)	−0.0188 (0.3601)	0.1815*** (0.0000)	0.0082 (0.6903)	−0.0031 (0.8811)	−0.0127 (0.5381)	−0.0047 (0.8181)	0.1514*** (0.0000)					
NEC	−0.0314 (0.1266)	−0.0553*** (0.0071)	0.0378* (0.0661)	−0.1311*** (0.0000)	0.0966*** (0.0000)	0.0274 (0.1833)	0.0154 (0.1833)	0.0383* (0.0626)	−0.0545*** (0.0081)	−0.0910*** (0.0000)				
ESG	0.3976*** (0.0000)	0.3951*** (0.0000)	0.0806*** (0.0001)	0.2362*** (0.0000)	0.0450** (0.0284)	−0.2668*** (0.0000)	−0.2668*** (0.0000)	0.2640*** (0.0000)	0.3191*** (0.0000)	0.3123*** (0.0000)	−0.0659*** (0.0013)			
CO_2	0.0262 (0.2031)	0.0513** (0.0125)	0.0032 (0.8781)	0.3096*** (0.0000)	−0.1609*** (0.0000)	0.0076 (0.7131)	0.0076 (0.7131)	0.1092*** (0.0000)	0.2488*** (0.0000)	0.2298*** (0.0000)	−0.0448** (0.0294)	0.4188*** (0.0000)		
SIZE	0.0262 (0.2034)	0.0178 (0.3866)	0.0223 (0.2772)	0.0279 (0.1745)	0.0224 (0.2763)	−0.0404** (0.0494)	−0.0404** (0.0494)	−0.0360* (0.0603)	0.0145 (0.4821)	0.0588*** (0.0042)	−0.0118 (0.5658)	0.0336 (0.1024)	−0.0068 (0.7403)	
ROA	−0.0010 (0.9595)	−0.0060 (0.7709)	0.0131 (0.5242)	−0.0290 (0.1580)	−0.0014 (0.9446)	0.0245 (0.2337)	0.0245 (0.2337)	−0.0317 (0.1231)	−0.0155 (0.4507)	−0.0290 (0.1579)	0.0208 (0.3124)	−0.0272 (0.1700)	0.0157 (0.4441)	−0.3951*** (0.0000)

Note: *p*-value in parentheses. Number of observations: 2366. ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively.

TABLE 6 Pearson correlations between the continuous variables in the S&P 500.

Variable	BGD	BLAU	AUD	BSZ	BSK	BTN	NEM	IBM	SEC	BMC	NEC	ESG	CO_2	SIZE
AUD	−0.0141 (0.3102)	−0.0257* (0.0654)												
BSZ.	0.0384*** (0.0057)	0.0729*** (0.000)	0.0073 (0.6020)											
BSK	0.0350** (0.0118)	0.0354** (0.0110)	0.0081 (0.5612)	−0.1062*** (0.0000)										
BTN	−0.0690*** (0.0000)	−0.0424*** (0.0023)	−0.1757*** (0.0000)	−0.0138*** (0.3201)	0.0474*** (0.0007)									
NEM	0.1131*** (0.0000)	0.1399*** (0.0000)	0.2302*** (0.0000)	0.2379*** (0.0000)	−0.2047*** (0.0000)	−0.1592*** (0.0000)								
IBM	0.1400*** (0.0000)	0.1719*** (0.0000)	0.2431*** (0.0000)	0.1983*** (0.0000)	−0.1766*** (0.0000)	−0.2539*** (0.0000)	0.5879*** (0.0000)							
SEC	0.0917*** (0.0000)	0.0951*** (0.0000)	−0.0338** (0.0151)	0.1493*** (0.0000)	−0.0018 (0.8983)	−0.0470*** (0.0007)	−0.0894*** (0.0000)	−0.0320** (0.0214)						
BMC	0.0085 (0.5409)	0.0197 (0.1579)	−0.0365*** (0.0088)	0.2646*** (0.0000)	0.0220 (0.1148)	0.0460*** (0.0010)	−0.0815*** (0.0000)	0.0830*** (0.0000)	0.1231*** (0.0000)					
NEC	−0.0533*** (0.0001)	−0.0631*** (0.000)	0.0063 (0.6494)	−0.0774*** (0.0000)	−0.0217 (0.1199)	0.0072 (0.6051)	−0.0293** (0.0354)	−0.0154 (0.2703)	−0.0060 (0.6655)	−0.0119 (0.3914)				
ESG	0.3397*** (0.0000)	0.3613*** (0.0000)	0.0603*** (0.0000)	0.2100*** (0.0000)	0.0790*** (0.0000)	−0.1710*** (0.0000)	0.2617*** (0.0000)	0.3188*** (0.0000)	0.2068*** (0.0000)	0.1539*** (0.0000)	−0.1027*** (0.0000)			
CO_2	0.0174 (0.2103)	0.0201 (0.1490)	0.0123 (0.3778)	0.1756*** (0.0000)	−0.1507*** (0.0000)	−0.2324*** (0.0000)	0.2089*** (0.0000)	0.2148*** (0.0000)	0.0295** (0.0343)	0.0464*** (0.0009)	−0.0656** (0.0000)	0.2221*** (0.0000)		
SIZE	0.0547*** (0.0001)	0.0546*** (0.0001)	−0.0121 (0.3857)	0.0569*** (0.0000)	−0.0067 (0.6291)	0.0151 (0.2770)	0.0008 (0.9546)	0.0216 (0.1217)	0.0604*** (0.0000)	0.0259* (0.0631)	−0.0327** (0.0187)	0.0247* (0.0760)	0.0431*** (0.0020)	
ROA	−0.0086 (0.5349)	−0.0083 (0.5534)	−0.0015 (0.9119)	−0.0289** (0.0378)	0.0183 (0.1880)	0.0135 (0.3319)	−0.0294** (0.0345)	−0.0122 (0.3822)	0.0023 (0.8690)	0.0005 (0.9730)	0.0254* (0.0680)	0.0081 (0.5592)	−0.0235* (0.0916)	−0.2695*** (0.0000)

Note: *p*-value in parentheses. Number of observations: 5158. ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively.

TABLE 7 Between group differences for listed companies committed (group 1) and not committed (group 0) to green building, by explanatory variable.

Panel A: Euro Stoxx 300 index			
Continuous variable	**Mean group 1**	**Mean group 0**	**Difference (*t*-test)**
BGD	32.4647	30.0267	2.4380*** (0.0000)
BLAU	0.4223	0.3939	0.0284*** (0.0000)
AUD	67.2691	68.7305	−1.4614^{ns} (0.1664)
BSZ	14.2272	12.6464	1.5808*** (0.0000)
BSK	24.5411	25.0866	−0.5455^{ns} (0.4582)
BTN	7.5051	7.1478	0.3573*** (0.0015)
NEM	93.4438	92.5386	0.9052** (0.0411)
IBM	61.1493	58.3634	2.7859*** (0.0094)
SEC	19.1889	11.0440	8.1449*** (0.0000)
BMC	2.5774	1.5053	1.07201*** (0.0000)
NEC	4.8701	2.5520	2.3181*** (0.0100)
ESG	70.1871	63.7364	6.4507*** (0.0000)
CO_2	11.9851	12.6476	−0.6625*** (0.0000)
SIZE	23.6239	23.4271	0.1968*** (0.0078)
ROA	4.1496	4.7356	−0.5860** (0.0159)
Dichotomous variable	**% group 1**	**% group 0**	**Pearson Chi^2**
CSRC	88.73	76.10	62.7736*** (0.000)
CSRR	98.31	89.32	76.4622*** (0.000)
DUA	16.15	13.53	3.2097* (0.073)
CEOC	33.99	38.74	5.6912** (0.017)
Panel B: S&P 500 index			
Continuous variable	**Mean group 1**	**Mean group 0**	**Difference (*t*-test)**
BGD	26.6035	23.4918	3.1117*** (0.0000)
BLAU	0.3744	0.3386	0.0358*** (0.0000)
AUD	99.2403	98.9775	0.2628** (0.0139)
BSZ	11.3421	10.0971	1.2450*** (0.0000)
BSK	56.7723	54.2385	2.5338*** (0.0000)
BTN	8.8872	8.4999	0.3873*** (0.0000)
NEM	87.4726	86.8339	0.6387*** (0.0001)
IBM	85.8823	84.7230	1.1593*** (0.0000)
SEC	44.0470	31.3449	12.7021*** (0.0000)
BMC	3.5254	2.6039	0.9215*** (0.0000)
NEC	6.0602	6.9964	−0.9362^{ns} (0.1129)
ESG	67.0097	56.5801	10.4296*** (0.0000)
CO_2	12.4126	12.7229	−0.3103*** (0.0000)
SIZE	23.6319	23.5065	0.1254*** (0.0018)
ROA	6.400	6.629	−0.229^{ns} (0.2644)
Dichotomous variable	**% group 1**	**% group 0**	**Pearson Chi^2**
CSRC	90.25	9.75	342.4034*** (0.000)
CSRR	12.21	87.79	376.8070***(0.000)
DUA	32.06	67.94	0.9402^{ns} (0.332)
CEOC	9.75	90.25	11.6076*** (0.001)

Note: *p*-value in parentheses. ***, ** and * indicate a significance of less than 1%, less than 5%, and less than 10%, respectively. ns denotes not significant.

TABLE 8 Selected multivariate panel data logistic models for Euro Stoxx 300 and S&P 500: Training sample.

PANEL A. Training sample				
	Euro Stoxx 300		S&P 500	
Variable	CMPDLM2	CMPDLM3	CMPDLM5	QMPDLM5
BGD^3	−0.000051** (0.041)	–	0.0000463* (0.053)	-
BGD^2	0.0021242^{ns} (0.310)	–	−0.0046244** (0.021)	−0.0008281** (0.012)
BGD	0.0482516^{ns} (0.349)	–	0.1536582*** (0.003)	0.0625336*** (0.001)
$BLAU^3$	–	−134.1463*** (0.000)	–	–
$BLAU^2$	–	105.0079*** (0.001)	–	–
BLAU	–	−16.22751** (0.019)	–	–
CSRC	0.659538*** (0.002)	0.6378957*** (0.003)	0.2996148*** (0.006)	0.2983533*** (0.007)
CSRR	2.75657*** (0.000)	2.7533*** (0.000)	0.7167124*** (0.000)	0.6909334*** (0.000)
AUD	−0.012322*** (0.000)	−0.011338*** (0.000)	0.0240819* (0.053)	0.0228063* (0.066)
BSZ	0.1476718*** (0.000)	0.154222*** (0.000)	0.2289698*** (0.000)	0.228883*** (0.000)
BSK	−0.0071866* (0.079)	−0.006823* (0.095)	0.0124784*** (0.000)	0.0119732*** (0.000)
BTN	0.2282707*** (0.000)	0.217623*** (0.000)	0.0762542*** (0.000)	0.078174*** (0.000)
NEM	–	–	–	–
IBM	0.0196896*** (0.000)	0.019418*** (0.000)	–	–
DUA	–	–	–	–
SEC	0.0299518*** (0.000)	0.0292567*** (0.000)	0.010932*** (0.000)	0.0106577*** (0.000)
CEOC	−1.00564*** (0.000)	−0.994485*** (0.000)	−0.659156*** (0.000)	−0.646656*** (0.000)
BMC	–	–	0.287628*** (0.000)	0.2868867*** (0.000)
NEC	0.0130787*** (0.000)	0.0137339*** (0.000)	–	–
ESG	–	–	0.0218964*** (0.000)	0.0229222*** (0.000)
CO_2	−0.319619*** (0.000)	−0.319023*** (0.000)	−0.172105*** (0.000)	−0.171929*** (0.000)
SIZE	0.6876989*** (0.001)	0.6618258*** (0.001)	0.1825355* (0.066)	0.1934839** (0.050)
ROA	–	–	−0.0153552* (0.098)	–
Observations	1661	1661	3572	3572
Hausman test	72.93 (0.0000)	94.29 (0.0000)	31.89 (0.0067)	31.24 (0.0051)
McFadden's R^2	0.272	0.272	0.239	0.238
Nagelkerke R^2	0.394	0.394	0.349	0.347
Cox & Snell	0.242	0.242	0.223	0.222
LR χ^2	460.51*** (0.0000)	459.50*** (0.0000)	901.00*** (0.0000)	894.58*** (0.0000)
Wald χ^2	282.03*** (0.0000)	278.08*** (0.0000)	539.30*** (0.0000)	566.99*** (0.0000)
AIC	1149.714	1150.723	2770.669	2773.092
BIC	1230.942	1231.951	2869.563	2859.625
Mean absolute error	0.3999137	0.3997169	0.5166784	0.5169127
Percent concordant	57.78	57.96	44.70	44.56
True positives	49	52	65	60
False negatives	717	714	1988	1993
True negatives	946	946	1546	1546
False positives	10	10	5	5
Sensitivity	6.40	6.79	3.17	2.92
Specificity	98.95	98.95	99.68	99.68
AUC-ROC	0.7549	0.7527	0.7601	0.7594
PANEL B. 10-folds validation				
I. Mean values of the 10 estimations				
McFadden's R^2	0.273	0.271	0.238	0.238

(Continues)

TABLE 8 (Continued)

PANEL B. 10-folds validation				
Nagelkerke R^2	0.396	0.395	0.350	0.347
Cox & Snell	0.243	0.242	0.223	0.222
AIC	1036.290	1037.217	2494.964	2496.936
BIC	1115.934	1116.861	2592.072	2581.993
Mean absolute error	0.3998059	0.3996268	0.5165940	0.5168404
Percent concordant	57.85	57.94	44.68	44.58
True positives	45.5	47.1	57.9	54.6
False negatives	643.9	642.3	1789.8	1793.1
True negatives	851.1	850.9	1391.3	1391.2
False positives	9.3	9.5	4.6	4.5
Sensitivity	6.60	6.83	3.13	2.96
Specificity	98.92	98.89	99.67	99.68
AUC-ROC	0.7551	0.7528	0.7603	0.7596
II. Mean values of the validation				
Mean absolute error	0.4028771	0.4025929	0.5173595	0.5175202
Percent concordant	57.51	57.90	44.58	44.39
True positives	5.0	5.7	6.2	5.5
False negatives	71.6	70.9	199.1	199.8
True negatives	94.2	94.4	154.5	154.5
False positives	1.4	1.5	0.6	0.6
Sensitivity	6.60	7.60	3.03	2.69
Specificity	98.46	98.25	99.61	99.61
AUC-ROC	0.7500	0.7471	0.7566	0.7560
PANEL C. Prediction in the test sample				
Mean absolute error	0.4212494	0.4189957	0.5044406	0.5043914
Percent concordant	55.90	55.90	46.59	46.46
True positives	20	20	43	41
False negatives	279	279	827	829
True negatives	340	340	681	681
False positives	5	5	3	3
Sensitivity	6.69	6.69	4.94	4.71
Specificity	98.55	98.55	99.56	99.56
AUC-ROC	0.7360	0.7419	0.7582	0.7588

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

when the BLAU index ranges from 0 to 0.10 (indicating situations of minimum diversity); (ii) it then strongly increases following a logistic pattern until BLAU = 0.43 (where two-thirds of the board members are women/men and the other third are men/women); and (iii) finally, it sharply decreases in the interval [0.43–0.50], where 0.50 indicates maximum diversity in the case of two categories (the majority of members are women or men).

As observed, the impact function of BLAU is compatible with that of BGD. When the percentage of women on the board of directors is low (indicating low diversity), the odds are approximately at unity. With an increase in the percentage of women (indicating increased gender diversity), there is a significant rise in the odds, up to around 35% of women. However, beyond 35%, the odds decrease as the percentage of women increases.

In the U.S., (see Figure 4), where the winning model is CMPDLM5 and the alternative is QMPDLM5, only the linear and quadratic terms of BGD are significant. This indicates that an inverted quadratic function best represents how BGD impacts the odds for GRB.

Figures 5 and 6 depict the odds ratio vs. BGD and the impact function, respectively, for the S&P 500 when using CMPDLM5. As

TABLE 9 Selected multivariate logistic models for Euro Stoxx 300 and S&P 500: Total sample.

	Euro Stoxx 300		S&P 500	
Variables	**CMPDLM2**	**CMPDLM3**	**CMPDLM5**	**QMPDLM5**
BGD^3	−0.0000439** (0.025)	–	0.0000186^{ns} (0.332)	–
BGD^2	0.0019985^{ns} (0.227)	–	−0.0026246* (0.099)	−0.001106*** (0.000)
BGD	0.0331434^{ns} (0.417)	–	0.1131578*** (0.005)	0.0768995*** (0.000)
$BLAU^3$	–	−126.3327*** (0.000)	–	–
$BLAU^2$	–	100.8017*** (0.000)	–	–
BLAU	–	−16.82001*** (0.003)	–	–
CSRC	0.8780972*** (0.000)	0.8721324*** (0.000)	0.3210325*** (0.001)	0.3187912*** (0.001)
CSRR	2.773291*** (0.000)	2.735163*** (0.000)	0.6635947*** (0.000)	0.6514519*** (0.000)
AUD	−0.009833*** (0.000)	−0.008852*** (0.000)	0.0204168* (0.046)	0.0197676* (0.052)
BSZ	0.1405553*** 0.000)	0.147709*** (0.000)	0.1974982*** (0.000)	0.1978722*** (0.000)
BSK	−0.0073634** (0.028)	−0.0065965** (0.049)	0.0106942*** (0.000)	0.0105207*** (0.000)
BTN	0.2313086*** (0.000)	0.2227852*** (0.000)	0.0665358*** (0.000)	0.0670361*** (0.000)
NEM	–	–	–	–
IBM	0.0165182*** (0.000)	0.0161192*** (0.000)	–	–
DUA	–	–	–	–
SEC	0.0309799*** (0.000)	0.0293403*** (0.000)	0.0091807*** (0.000)	0.0090733*** (0.000)
CEOC	−0.926970*** (0.000)	−0.895995*** (0.000)	−0.762677*** (0.000)	−0.760639*** (0.000)
BMC	–	–	0.342654*** (0.000)	0.341775*** (0.000)
NEC	0.0117874*** (0.000)	0.0126109*** (0.000)	–	–
ESG	–	–	0.0227088*** (0.000)	0.023234*** (0.000)
CO_2	−0.295971*** (0.000)	−0.292034*** (0.000)	−0.189201*** (0.000)	−0.189034*** (0.000)
SIZE	0.756376*** (0.000)	0.7453796*** (0.000)	0.1012844^{ns} (0.217)	0.112181^{ns} (0.170)
ROA	–	–	−0.0137651* (0.077)	–
Observations	2302	2302	5124	5124
Hausman test	73.39 (0.0000)	195.68 (0.0000)	37.90 (0.0009)	38.58 (0.0004)
McFadden's R^2	0.264	0.266	0.237	0.237
Nagelkerke R^2	0.379	0.381	0.344	0.343
Cox & Snell	0.234	0.235	0.220	0.219
LR χ^2	612.26*** (0.0000)	616.01*** (0.0000)	1273.13*** (0.0000)	1269.10*** (0.0000)
Wald χ^2	377.59*** (0.0000)	375.29*** (0.0000)	845.01*** (0.0000)	846.42*** (0.0000)
AIC	1624.333	1620.587	3997.769	3997.801
BIC	1710.456	1706.71	4102.436	4089.385
Mean absolute error	0.4064810	0.4060745	0.5130382	0.5131383
Percent concordant	56.85	57.19	45.23	45.29
True positives	60	67	106	108
False negatives	1005	998	2817	2815
True negatives	1285	1286	2227	2228
False positives	16	15	8	7
Sensitivity	5.63	6.29	3.63	3.69
Specificity	98.77	98.85	99.64	99.69
AUC-ROC	0.7519	0.7522	0.7601	0.7598

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

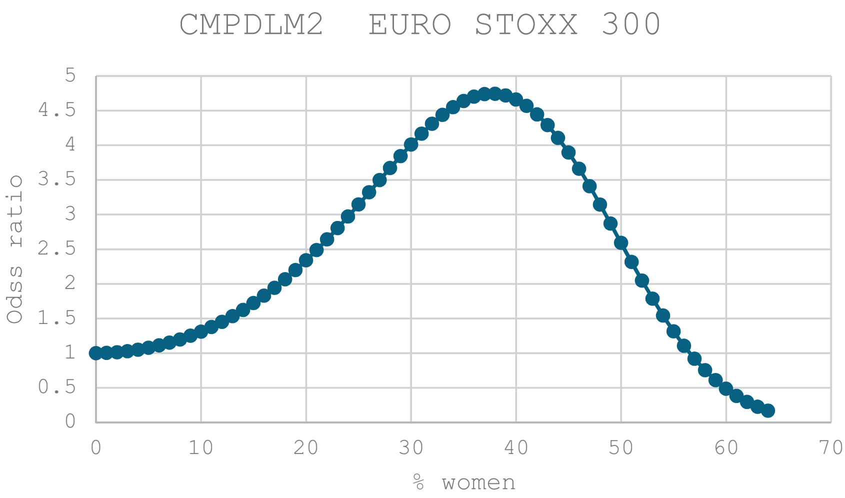

FIGURE 1 Odds ratio versus board gender diversity: CMPDLM2 EURO STOXX 300.

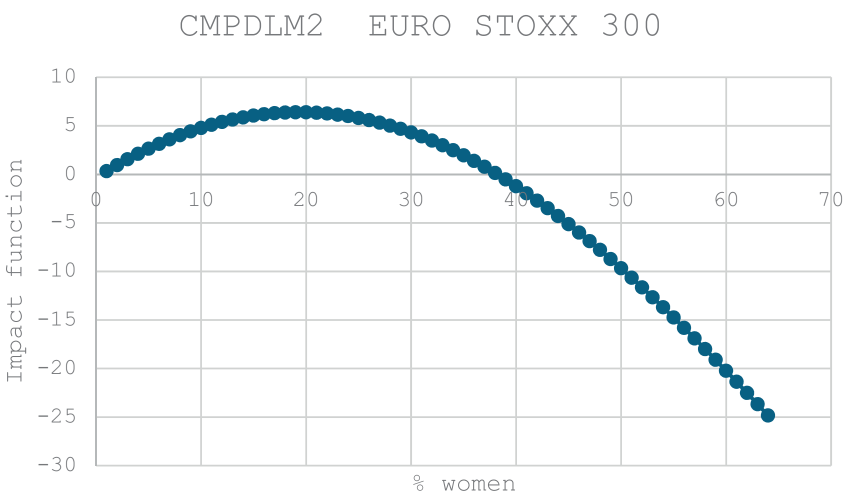

FIGURE 2 Board gender diversity impact function: CMPDLM2 EUROSTOXX 300.

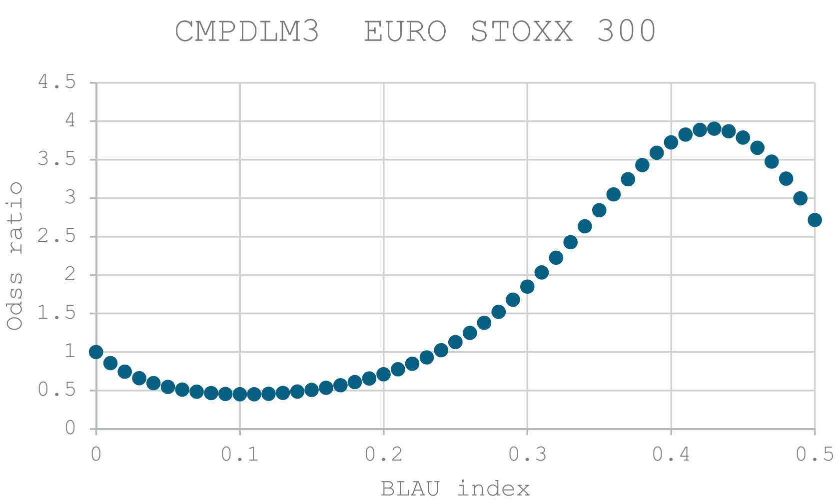

FIGURE 3 Odds ratio versus BLAU index: CMPDLM3 EURO STOXX 300.

expected, the corresponding plots for the quadratic alternative QMPDLM5 are virtually identical and, to save space, are not presented here.

The potential endogeneity problem has also been approached from the instrumental variable's (IV) perspective, in order to check for robustness and strengthen causal inferences. The IV analysis has been

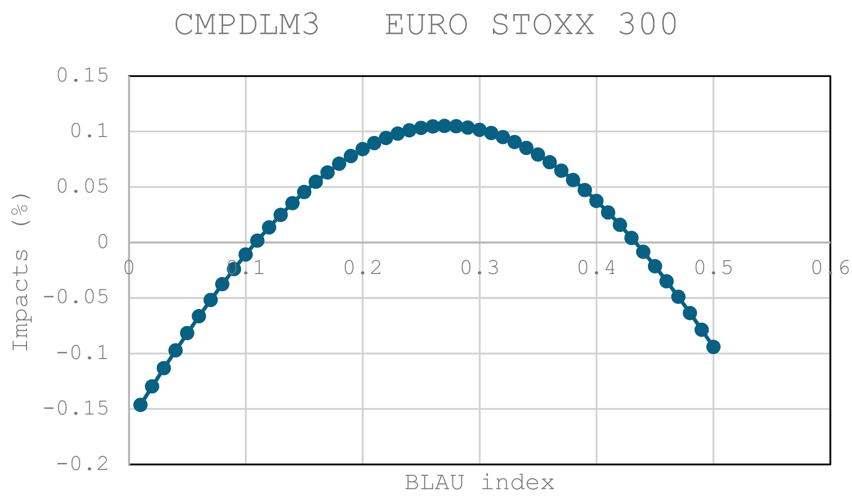

FIGURE 4 BLAU impact function (%) on the odds ratio: CMPDLM3 EURO STOXX 300.

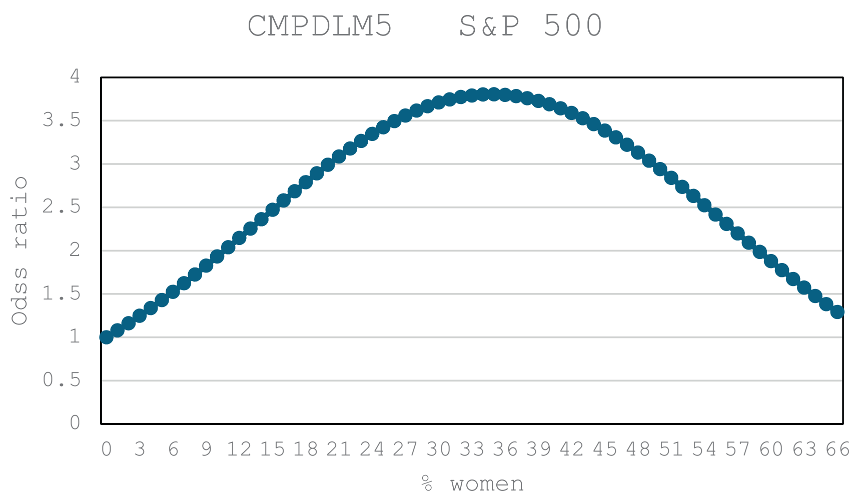

FIGURE 5 Odds ratio versus board gender diversity: CMPDLM5 S&P 500.

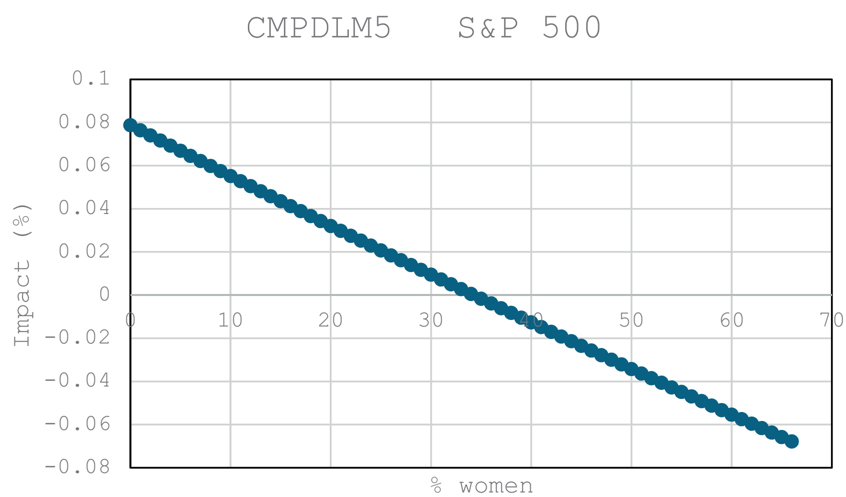

FIGURE 6 Board gender diversity impact function (%) on the odds ratio: CMPDLM5 S&P 500.

limited to BGD in the specifications selected for the European and American indices, and considering the covariates finally included in these models. Specifically, a two-stage regression with instrumental variables has been applied to models CMPDLM2 in the case of the Euro Stoxx 300 and CMPDLM5 when addressing the S&P 500. The results obtained are shown in Appendix B.

In addition to gender diversity, various factors related to the composition of the board of directors exert significant influence on the odds ratio in both the Euro Stoxx 300 and the S&P 500 indexes. Notably, larger board sizes, extended director tenure, and higher executive compensation are consistently associated with increased odds ratios across both indexes. Conversely, CEO compensation tied to shareholder returns tends to decrease the odds ratio. However, variables such as NEM and DUA do not demonstrate significant effects in either index.

Differences emerge when examining specific board-related variables between the Euro Stoxx 300 and the S&P 500. For instance, while AUD and BSK display significance, they exhibit negative coefficients in the Euro Stoxx 300 but positive coefficients in the S&P 500. Similarly, IBM shows a significant positive coefficient in the Euro Stoxx 300 but lacks significance in the S&P 500. Conversely, BMC is nonsignificant in the Euro Stoxx 300 but demonstrates a positive and significant coefficient in the S&P 500.

In terms of sustainability-related variables, consistent patterns emerge across both indexes, as expected. Variables such as CSRC and CSRR exhibit significant positive coefficients, indicating their favorable impact on the odds ratio. Conversely, CO_2 demonstrates a significant negative coefficient, suggesting its adverse association with the odds ratio.

5 | DISCUSSION

Based on the results obtained from the 30 competing models, as detailed in Tables A1–A12 (see Appendix A), several key insights emerge. The first underscores the disparity between Europe and the U.S. in terms of modeling GRB behavior and predicting a company's inclination towards environmentally friendly or green practices. Not only do the preferred models differ between the two regions, but also the significance of the powers of gender diversity variables. Specifically, the most effective models for the Euro Stoxx 300 show significant importance of gender proxies (BGD and BLAU) when cubed. Conversely, in the optimal specification for the S&P 500, BGD's significance is evident when cubed, but not when squared.

Linear models examining the influence of women's representation (or gender diversity) on corporate boards on continuous variables such as financial performance, corporate social responsibility, or other indicators typically utilize the gender variable without transformation or, in some instances, with quadratic terms. This approach allows researchers to assess whether the relationship between the response variable and the gender diversity driver or the proportion of women on corporate boards is linear, U-shaped, or inverted U-shaped (Bernardi & Threadgill, 2010; Fernández-Feijoo et al., 2014; Liao et al., 2018; Valls Martínez, Martín Cervantes, et al., 2022; Valls Martínez, Santos Jaén, et al., 2022; Valls Martínez, Soriano Román, et al., 2022). It is noteworthy that, as far as we know, the application of these drivers as cubic polynomials has not previously been explored in the literature concerning the impact of gender diversity or the presence of women on corporate boards on economic or ESG-related outcomes. Additionally, the non-linear incorporation of gender dispersion or the presence of women on corporate boards in a multivariate logistic panel data model using quadratic polynomials is also a novel approach in the literature. Hence, this study surpasses traditional (or, in the best of cases, quadratic) linear specifications and can be regarded as pioneering research in this crucial and contemporary area for modern societies, thereby opening a compelling new avenue for investigation.

The second insight reveals that gender variables significantly influence companies' decisions regarding the adoption of environmentally friendly or green sites/offices, both in Europe and the U.S. This finding aligns with existing literature indicating that the inclusion of women on corporate boards correlates with increased corporate social responsibility (Barrientos Báez et al., 2018; Ben-Amar et al., 2017; Francoeur et al., 2019; Furlotti et al., 2019; Rao & Tilt, 2016; Sial et al., 2018; Velte, 2017) and sustainable practices, such as reduced CO_2 emissions (García Martín & Herrero, 2020; Nuber & Velte, 2021; Valls Martínez, Martín Cervantes, et al., 2022; Valls Martínez, Santos Jaén, et al., 2022; Valls Martínez, Soriano Román, et al., 2022).

However, it is worth noting that numerous studies establish a positive linear relationship between the percentage of women on the board of directors and the implementation or disclosure of corporate social responsibility practices (Aslam et al., 2018; Ben-Amar et al., 2017; Bernardi & Threadgill, 2010; Boulouta, 2013; Dienes & Velte, 2016; Francoeur et al., 2019; Giannarakis, 2014; Giannarakis et al., 2014; Kyaw et al., 2017; Liao et al., 2018; Liao et al., 2019; Sial et al., 2018; Zhang et al., 2013). This relationship leads to the conclusion that boards composed exclusively of women are considered optimal. Evidently, this finding, resulting from the use of an inadequate specification (the linear one), challenges the assertions of researchers advocating for gender diversity on boards of directors. It creates a paradoxical situation, as it suggests that boards comprised solely of women are considered the optimal scenario, contrary to the intended goals of gender diversity advocacy.

Aligned with ethical principles and the rationale that diverse management teams are more effective economically, socially, and environmentally (Amorelli & García-Sánchez, 2021; Bassett-Jones, 2005; Wu, Furuoka, et al., 2022; Wu, Richard, et al., 2022; Wu, Xu, et al., 2022), recent studies have identified a quadratic-linear relationship between gender proxies (such as the percentage of women on the board, Blau index, Shannon index, etc.) and the variable under investigation. For instance, Valls Martínez, Martín Cervantes, et al. (2022), Valls Martínez, Santos Jaén, et al. (2022), and Valls Martínez, Soriano Román, et al. (2022) demonstrated an inverted U-shaped relationship between the percentage of women on corporate boards and companies' ESG scores in Europe, evident across both developed and emerging markets. Similarly, Valls Martínez et al. (2020) emphasized a similar relationship in both American and European markets. Likewise, Xie et al. (2024) reported a non-linear relationship between the percentage of women on the board and firm performance, as measured by Tobin's Q. In essence, the quadratic relationship suggests that optimal performance is achieved with gender-diverse boards of directors.

The results obtained in this article are consistent with previous literature.[17] In both the Euro Stoxx 300 and S&P 500, the odds ratio curves (depicted in Figures 1, 3, and 5) show a maximum around 35–37% for BGD and 45% for BLAU in Europe.

On the other hand, within the sphere of corporate social responsibility, a significant portion of the literature advocates for the existence of a critical mass of women on boards of directors (Broome et al., 2011; Torchia et al., 2011). This concept suggests that there must be a minimum number of women (typically two or three) for them to exert a positive influence on decisions related to corporate social responsibility (Fernández-Feijoo et al., 2014; Gong et al., 2021; Liao et al., 2018; Toukabri & Jilani, 2023; Yang et al., 2019; Yarram & Adapa, 2021). Figure 3 shows that in Europe,[18] the odds ratio begins to increase from a BLAU index value of 0.10.

The third insight concerns the magnitude of the impacts, which are more significant in Europe compared to the U.S., with distinct differences in the shape of their impact functions. Moreover, the impacts in the U.S. are relatively minimal, indicating that gender diversity on corporate boards is not exactly a key variable in determining whether a company chooses environmentally friendly locations or offices in the U.S.

What factors contribute to the divergence in the magnitude of the impact functions between the U.S. and Europe? It could be attributed to a complex set of regulations, cultural attitudes, and regional initiatives.

Regarding the regulatory environment, in Europe, the regulatory framework is robust and well-established in terms of both gender equality and sustainability (Valls Martínez & Soriano Román, 2022). The European Union (EU) Gender Equality Directive and the EU Gender Equality Action Plan 2020–2025 are clear examples of how gender equality in the workplace is actively promoted. Additionally, the EU is known for its stringent environmental regulations, such as the European Green Deal, which sets ambitious targets for emission reductions and the promotion of sustainable practices. This regulatory environment creates a favorable context for companies to adopt both gender equality and sustainable practices (Memon et al., 2022; Nicolò et al., 2022). In contrast, in U.S. gender equality policies and environmental regulations can vary significantly between states and administrations. While there are federal laws such as Title VII of the Civil Rights Act of 1964 and the Equal Pay Act of 1963, implementation and approach to the effective inclusion of women in boards of directors can be inconsistent. Regarding environmental legislation, the Environmental Protection Agency (EPA) plays a crucial role, but its policies can change with each administration, leading to greater variability in the implementation of sustainable practices (Dobson et al., 2018; Ma et al., 2022).

When analyzing cultural attitudes towards gender diversity, in Europe, the business culture in many European countries tends to be more collaborative and community-centered, fostering greater inclusion of women in leadership roles. This can influence the adoption of sustainable practices, as gender diversity in senior management has been associated with greater sensitivity to environmental and social issues (Valls Martínez, Martín Cervantes, et al., 2022, Valls Martínez, Santos Jaén, et al., 2022, Valls Martínez, Soriano Román, et al., 2022). Additionally, there is greater awareness and education about gender equality and sustainability, which can translate into more inclusive and sustainable corporate policies (Criado-Gomis et al., 2020). However, in the U.S., business culture often emphasizes competition and individual performance, which can affect the implementation of gender diversity and sustainability policies. Although there are strong social movements, such as the #MeToo movement and environmental activism, the response and adoption of these initiatives can be more fragmented and vary widely between industries and regions (Beck & Arduini, 2023; Kassinis et al., 2016).

Regarding sustainability initiatives carried out in both regions, it is worth noting that European sustainability initiatives are broad and well-funded. Programs like Horizon 2020 and Horizon Europe support research and innovation in sustainability, and many European companies are aligned with the UN Sustainable Development Goals (SDGs). Moreover, the pressure and expectations on companies to report and act on environmental and social issues are significant, encouraging companies to adopt more sustainable practices (Graham, 2019; Zaccone, 2023). In contrast, in the U.S., sustainability initiatives can vary considerably. Some states, like California, have strict and advanced environmental regulations (Valls Martínez et al., 2020), while others may be more lenient. At the corporate level, many large companies adopt sustainability policies, but these are often driven more by public perception and market demands than by strict regulation (Nadeem et al., 2017). This can lead to a more uneven adoption of sustainable practices (Ben-Amar et al., 2017).

Another potential explanation lies in the absence of quota legislation in the U.S., where behavioral distinctions between men and women may diminish as women ascend to traditionally male-dominated positions, such as board membership (Croson & Gneezy, 2009; Sial et al., 2018). In other words, women may adapt their behavior and way of thinking to align with those of men in order to remain in positions of power (Adams & Funk, 2012; Adams & Ragunathan, 2017).

The fourth insight pertains to the quality of the database and its usability for researching such a pressing issue in modern societies: the importance of gender diversity on company boards and their engagement with environmentally friendly sites or offices. The tables in the appendices demonstrate that the specificity results are commendably high in both Europe and the U.S. across various models. However, the results for sensitivity leave much to be desired. What causes this unfortunate situation? The definition of the GRB variable is crucial for interpreting the obtained results. Specifically, it addresses whether a company reports on environmentally friendly or green sites or offices. For a response to be considered affirmative (true), the company must explicitly report on environmentally friendly sites or offices; these sites should be operational spaces for the company's activities; the company must have obtained LEED/BREEAM certifications for its

[17]Considering that, in reality, the female participation in the boards of directors rarely exceeds 50%.

[18]In the U.S., models that use BLAU as a driver for gender diversity have been shown not to be the best ones.

buildings; significant refurbishments aimed at enhancing the environmental aspects of sites/buildings/offices must have been conducted; and the building must be operational at least by the end of the fiscal year. If the building is under construction, then the response should be "false." Surprisingly, a significant number of responses alternate between 'true' and 'false', which is puzzling since if the criteria are met one year, they are likely met in subsequent years as well. This inconsistency leads us to suspect that many "false" responses might actually be "true." Unfortunately, this issue is quite common in annual surveys that include questions necessitating detailed company knowledge, which the respondent might not possess. This is regrettable, given that this information is reported by companies listed in the EURO STOXX 300 and the S&P 500 and is expected to be reliable and, thus, valuable for researchers.

Two additional factors influencing the above results are: (i) the percentage of women never exceeds 67%; and (ii) there is considerable annual variability in the percentage of women on the board of directors. Instances have been observed where, in year t, the percentage of women is 50%, only to drop to zero in year $t+1$, and vice versa. Such fluctuations lead us to suspect the accuracy of some data reported by the companies.

6 | FUTURE RESEARCH LINES

The consequences of the increasing participation of women on company boards, especially in large corporations, is a hot topic in the current literature on gender economy. However, this field often lacks sophisticated quantitative methodologies. This article aims to address this gap by assessing the impact of gender diversity on socio-economic variables, with a specific focus on green building practices. It does so by enhancing multivariate logistic models with quadratic and cubic terms for gender diversity, seeking to achieve more reliable and precise insights in the context that female participation on company boards of directors rarely exceeds 50%. Nonetheless, this approach is merely an initial step in a complex analysis.

Every methodology has its advantages and disadvantages. Linear models such as linear regression, linear discriminant analysis, and logistic regression generally have lower prediction variance but can suffer from considerable bias errors, leading to underfitting and substantial prediction inaccuracies. Conversely, algorithms like decision trees, k-neighbors, naïve Bayes, and support vector machines offer lower bias at the cost of higher prediction variance, yet they excel in adaptability and flexibility to capture diverse patterns. Applying these machine learning algorithms to the dataset explored in this study, and comparing their efficacy with that of enhanced multivariate logistic models that incorporate a polynomial gender diversity component, represents a compelling research direction. Although these alternative models may risk overfitting, pairing them with resampling techniques could provide robust results, unaffected by the resampling process. Additionally, employing p-splines within a logistic framework offers a novel perspective, promising further insights into the dynamics at play under the assumption that female participation in the boardrooms rarely exceeds 50%.

In addition, we recommend verifying the favorable results by using data from companies listed on major stock indices worldwide, in addition to the Euro Stoxx and S&P 500.

Finally, special attention must be paid to the information provided by the companies, especially those listed on stock exchange indexes, as the quality of the models employed is contingent upon the reliability of their input data; without accurate data, the outcomes will remain open to question.

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REFERENCES

Adams, R. B. (2016). Women on boards: The superheroes of tomorrow? *Leadership Quarterly*, *27*(3), 371–386. https://doi.org/10.1016/j.leaqua.2015.11.001

Adams, R., & Funk, P. (2012). Beyond the glass ceiling: Does gender matter? *Management Science*, *58*(2), 219–235. https://doi.org/10.1287/mnsc.1110.1452

Adams, R., & Ragunathan, V. (2017). Lehman sisters. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3046451

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Akomea-Frimpong, I., Kukah, A. S., Jin, X., Osei-Kyei, R., & Pariafsai, F. (2022). Green finance for green buildings: A systematic review and conceptual foundation. *Journal of Cleaner Production*, *356*, 131869. https://doi.org/10.1016/j.jclepro.2022.131869

Al-Qahtani, M., & Elgharbawy, A. (2020). The effect of board diversity on disclosure and management of greenhouse gas information: Evidence from the United Kingdom. *Journal of Enterprise Information Management*, *33*(6), 1557–1579. https://doi.org/10.1108/JEIM-08-2019-0247

Amorelli, M. F., & García-Sánchez, I. M. (2020). Critical mass of female directors, human capital, and stakeholder engagement by corporate social reporting. *Corporate Social Responsibility and Environmental Management*, *27*(1), 204–221. https://doi.org/10.1002/csr.1793

Amorelli, M. F., & García-Sánchez, I. M. (2021). Trends in the dynamic evolution of board gender diversity and corporate social responsibility. *Corporate Social Responsibility and Environmental Management*, *28*(2), 537–554. https://doi.org/10.1002/csr.2079

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297.

Aslam, S., Abdul, M., Makki, M., Mahmood, S., & Amin, S. (2018). Gender diversity and managerial ownership response to corporate social responsibility initiatives: Empirical evidence from Australia. *Journal of Managerial Sciences*, *12*(2), 131–151.

Atif, M., Hossain, M., Alam, M. S., & Goergen, M. (2021). Does board gender diversity affect renewable energy consumption? *Journal of*

Corporate Finance, *66*, 101665. https://doi.org/10.1016/j.jcorpfin.2020.101665

Barrientos Báez, A., Báez-García, A. J., Flores-Muñoz, F., & Gutiérrez-Barroso, J. (2018). Gender diversity, corporate governance and firm behavior: The challenge of emotional management. *European Research on Management and Business Economics*, *24*(3), 121–129. https://doi.org/10.1016/j.iedeen.2018.07.001

Bassett-Jones, N. (2005). The paradox of diversity management, creativity and innovation. *Creativity and Innovation Management*, *14*(2), 169–175. https://doi.org/10.1111/j.1467-8691.00337.x

Baum, C., Schaffer, M., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal*, *3*(1), 1–31.

Beck, T., & Arduini, S. (2023). Gender equality in the role of independent directors. Is it linked to sustainability? *International Conference on Gender Research*, *6*(1), 9–15. https://doi.org/10.34190/icgr.6.1.1037

Ben-Amar, W., Chang, M., & McIlkenny, P. (2017). Board gender diversity and corporate response to sustainability initiatives: Evidence from the carbon disclosure project. *Journal of Business Ethics*, *142*(2), 369–383. https://doi.org/10.1007/s10551-015-2759-1

Bernardi, R., & Threadgill, V. (2010). Women directors and corporate social responsibility. *EJBO: Electronic Journal of Business Ethics and Organizational Studies*, *15*(2), 15–21.

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. Free Press.

Bolte, G., Nanninga, S., & Dandolo, L. (2019). Sex/gender differences in the association between residential green space and self-rated health—A sex/gender-focused systematic review. *International Journal of Environmental Research and Public Health*, *16*(23), 4818. https://doi.org/10.3390/ijerph16234818

Börjesson, M. (2012). Valuing perceived insecurity associated with use of and access to public transport. *Transport Policy*, *22*, 1–10. https://doi.org/10.1016/j.tranpol.2012.04.004

Boulouta, I. (2013). Hidden connections: The link between board gender diversity and corporate social performance. *Journal of Business Ethics*, *113*, 185–197. https://doi.org/10.1007/s10551-012-1293-7

Broome, L. L., Conley, J. M., & Krawiec, K. D. (2011). Does critical mass matter? Views from the boardroom. *Seattle University Law Review*, *34*, 1049–1080. http://www.heinonline.org.proxy.library.vanderbilt.edu/HOL/Page?handle=hein.journals/sealr34&div=48&collection=journals&set_as_cursor=13&men_tab=srchresults

Brough, A. R., Wilkie, J. E. B., Ma, J., Isaac, M. S., & Gal, D. (2016). Is eco-friendly unmanly? The green-feminine stereotype and its effect on sustainable consumption. *Journal of Consumer Research*, *43*(4), 567–582. https://doi.org/10.1093/jcr/ucw044

Casero-Alonso, V., & Durban, M. (2024). Modelos lineales generalizados. In G. Fernández-Avilés & J. M. Montero (Eds.), *Fundamentos de Ciencia de Datos con R* (pp. 262–278). McGraw-Hill.

Choi, H. J., & Park, J.-H. (2014). The relationship between learning transfer climates and innovation in public and private organizations in Korea. *International Journal of Manpower*, *35*(7), 956–972. https://doi.org/10.1108/IJM-07-2012-0101

Cox, D. R., & Snell, E. J. (1989). *Analysis of binary data (second)*. Chapman & Hall.

Criado-Gomis, A., Iniesta-Bonillo, M.-A., Cervera-Taulet, A., & Ribeiro-Soriano, D. (2020). Women as key agents in sustainable entrepreneurship: A gender multigroup analysis of the SEO-performance relationship. *Sustainability*, *12*(3), 1244. https://doi.org/10.3390/su12031244

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, *47*(2), 448–474. https://doi.org/10.1257/jel.47.2.448

Cuadrado Ballesteros, B., García Rubio, R., & Martínez Ferrero, J. (2015). Effect of the composition of the board of directors on corporate social responsibility. *Spanish Accounting Review*, *18*(1), 20–31. https://doi.org/10.1016/j.rcsar.2014.02.003

Dienes, D., & Velte, P. (2016). The impact of supervisory board composition on CSR reporting. Evidence from the German two-tier system. *Sustainability*, *8*(1), 1–20. https://doi.org/10.3390/su8010063

Ding, Z., Fan, Z., Tam, V. W. Y., Bian, Y., Li, S., Illankoon, I. M. C. S., & Moon, S. (2018). Green building evaluation system implementation. *Building and Environment*, *133*, 32–40. https://doi.org/10.1016/j.buildenv.2018.02.012

Dobson, J., Hensley, D., & Rastad, M. (2018). Toward gender diversity on corporate boards: Evaluating government quotas (EU) versus shareholder resolutions (US) from the perspective of third wave feminism. *Philosophy of Management*, *17*(3), 333–351. https://doi.org/10.1007/s40926-017-0077-7

Eliwa, Y., Aboud, A., & Saleh, A. (2023). Board gender diversity and ESG decoupling: Does religiosity matter? *Business Strategy and the Environment*, *32*(7), 4046–4067. https://doi.org/10.1002/bse.3353

Elsayih, J., Tang, Q., & Lan, Y. C. (2018). Corporate governance and carbon transparency: Australian experience. *Accounting Research Journal*, *31*(3), 405–422. https://doi.org/10.1108/ARJ-12-2015-0153

Fernández-Avilés, G., & Montero, J. M. (2024). *Fundamentos de Ciencia de Datos con R*. McGraw-Hill.

Fernández-Feijoo, B., Romero, S., & Ruíz-Blanco, S. (2014). Women on boards: Do they affect sustainability reporting? *Corporate Social Responsibility and Environmental Management*, *21*(6), 351–364. https://doi.org/10.1002/csr.1329

Francoeur, C., Labelle, R., Balti, S., & El Bouzaidi, S. (2019). To what extent do gender diverse boards enhance corporate social performance? *Journal of Business Ethics*, *155*, 343–357. https://doi.org/10.1007/s10551-017-3529-z

Furlotti, K., Mazza, T., Tibiletti, V., & Triani, S. (2019). Women in top positions on boards of directors: Gender policies disclosed in Italian sustainability reporting. *Corporate Social Responsibility and Environmental Management*, *26*(1), 57–70. https://doi.org/10.1002/csr.1657

García Martín, C. J., & Herrero, B. (2020). Do board characteristics affect environmental performance? A study of EU firms. *Corporate Social Responsibility and Environmental Management*, *27*(1), 74–94. https://doi.org/10.1002/csr.1775

García-Sánchez, I.-M., Monteiro, S., Piñeiro-Chousa, J.-R., & Aibar-Guzmán, B. (2023). Climate change innovation: Does board gender diversity matter? *Journal of Innovation & Knowledge*, *8*(3), 100372. https://doi.org/10.1016/j.jik.2023.100372

Giannarakis, G. (2014). Corporate governance and financial characteristic effects on the extent of corporate social responsibility disclosure. *Social Responsibility Journal*, *10*(4), 569–590. https://doi.org/10.1108/SRJ-02-2013-0008

Giannarakis, G., Konteos, G., & Sariannidis, N. (2014). Financial, governance and environmental determinants of corporate social responsible disclosure. *Management Decision*, *52*(10), 1928–1951. https://doi.org/10.1108/MD-05-2014-0296

Gong, M., Zhang, Z., Jia, M., & Walls, J. L. (2021). Does having a critical mass of women on the board result in more corporate environmental actions? Evidence from China. *Group and Organization Management*, *46*(6), 1106–1144. https://doi.org/10.1177/1059601121998892

Gou, Z., & Xie, X. (2017). Evolving green building: Triple bottom line or regenerative design? *Journal of Cleaner Production*, *153*, 600–607. https://doi.org/10.1016/j.jclepro.2016.02.077

Graham, J. (2019). Corporate sustainability: The impact of corporate leadership gender on year over year performance. In *Proceedings of the Informing Science + Information Technology Education Conference*, 149–183. https://doi.org/10.28945/4213

Gull, A. A., Atif, M., & Hussain, N. (2023). Board gender composition and waste management: Cross-country evidence. *The British Accounting Review*, *55*(1), 101097. https://doi.org/10.1016/j.bar.2022.101097

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Management*, *9*(2), 193–206. https://doi.org/10.2307/258434

Hamilton, E. M. (2021). Green building, green behavior? An analysis of building characteristics that support environmentally responsible behaviors. *Environment and Behavior*, *53*(4), 409–450. https://doi.org/10.1177/0013916520942601

Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(3), 1029–1054.

Haque, F. (2017). The effects of board characteristics and sustainable compensation policy on carbon performance of UK firms. *The British Accounting Review*, *49*(3), 347–364. https://doi.org/10.1016/j.bar.2017.01.001

Harjoto, M. A., & Jo, H. (2015). Legal vs. normative CSR: Differential impact on analyst dispersion, stock return volatility, cost of capital, and firm value. *Journal of Business Ethics*, *128*(1), 1–20. https://doi.org/10.1007/s10551-014-2082-2

Hausman, J. A. (1978). Specification test in econometrics. *Econometrica*, *46*(6), 1251–1271. https://doi.org/10.1007/978-981-10-5466-2_5

Ibrahim, N., Angelidis, J., & Tomic, I. M. (2009). Managers' attitudes toward codes of ethics: Are there gender differences? *Journal of Business Ethics*, *90*(S3), 343–353. https://doi.org/10.1007/s10551-010-0428-y

Issa, A. (2023). Shaping a sustainable future: The impact of board gender diversity on clean energy use and the moderating role of environmental, social and governance controversies. *Corporate Social Responsibility and Environmental Management*, *30*(6), 2731–2746. https://doi.org/10.1002/csr.2512

Issa, A., & Zaid, M. A. A. (2023). Firm's biodiversity initiatives disclosure and board gender diversity: A multi-country analysis of corporations operating in Europe. *Business Strategy and the Environment*, *32*(7), 4991–5007. https://doi.org/10.1002/bse.3404

Kaczynski, A. T., Potwarka, L. R., Smale, B. J. A., & Havitz, M. E. (2009). Association of Parkland Proximity with neighborhood and Park-based physical activity: Variations by gender and age. *Leisure Sciences*, *31*(2), 174–191. https://doi.org/10.1080/01490400802686045

Kassinis, G., Panayiotou, A., Dimou, A., & Katsifaraki, G. (2016). Gender and environmental sustainability: A longitudinal analysis. *Corporate Social Responsibility and Environmental Management*, *23*(6), 399–412.

Kennedy, E., & Kmec, J. (2018). Reinterpreting the gender gap in household pro-environmental behaviour. *Environmental Sociology*, *4*, 299–310. https://doi.org/10.1080/23251042.2018.1436891

Kiper, T., Korkut, A., & Topal, T. (2016). Women friendly city approach in spatial planning. *Idil Journal of Art and Language*, *5*, 1777–1796. https://doi.org/10.7816/IDIL-05-26-11

Konadu, R., Ahinful, G. S., Boakye, D. J., & Elbardan, H. (2022). Board gender diversity, environmental innovation and corporate carbon emissions. *Technological Forecasting and Social Change*, *174*, 121279. https://doi.org/10.1016/j.techfore.2021.121279

Kyaw, K., Olugbode, M., & Petracci, B. (2017). Can board gender diversity promote corporate social performance? *Corporate Governance: The International Journal of Business in Society*, *17*(5), 789–802. https://doi.org/10.1108/CG-09-2016-0183

Li, J., Zhang, J., Zhang, D., & Ji, Q. (2019). Does gender inequality affect household green consumption behaviour in China? *Energy Policy*, *135*, 111071. https://doi.org/10.1016/j.enpol.2019.111071

Li, J., Zhao, F., Chen, S., Jiang, W., Liu, T., & Shi, S. (2017). Gender diversity on boards and Firms' environmental policy. *Business Strategy and the Environment*, *26*(3), 306–315. https://doi.org/10.1002/bse.1918

Liao, L., Lin, T. P., & Zhang, Y. (2018). Corporate board and corporate social responsibility assurance: Evidence from China. *Journal of Business Ethics*, *150*(1), 211–225. https://doi.org/10.1007/s10551-016-3176-9

Liao, Z., Zhang, M., & Wang, X. (2019). Do female directors influence firms' environmental innovation? The moderating role of ownership type. *Corporate Social Responsibility and Environmental Management*, *26*(1), 257–263. https://doi.org/10.1002/csr.1677

Lin, X., Yu, L., Zhang, J., Lin, S., & Zhong, Q. (2022). Board gender diversity and corporate green innovation: Evidence from China. *Sustainability*, *14*(22), 15020. https://doi.org/10.3390/su142215020

Luo, L., Lan, Y., & Tang, Q. (2012). Corporate incentives to disclose carbon information: Evidence from the CDP global 500 report. *Journal of International Financial Management & Accounting*, *23*(2), 93–120. https://doi.org/10.1111/j.1467-646X.2012.01055.x

Ma, Z., Shu, G., Wang, Q., & Wang, L. (2022). Sustainable governance and green innovation: A perspective from gender diversity in China's listed companies. *Sustainability*, *14*(11), 6403. https://doi.org/10.3390/su14116403

Malekabadi, R., Jalalabadi, L., & No, Z. (2014). The impact of women on urban sustainability (case study: Three districts of Tehran). *World Academy of Science, Engineering and Technology, International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering*, *8*, 1185–1188.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M. J., Lupp, G., Richardson, E. A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J., & Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, *158*, 301–317. https://doi.org/10.1016/j.envres.2017.06.028

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, *38*, 101690. https://doi.org/10.1016/j.frl.2020.101690

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In *Frontiers in econometrics* (pp. 105–142). Academic Press.

Memon, A., Akram, W., & Abbas, G. (2022). Women participation in achieving sustainability of microfinance institutions (MFIs). *Journal of Sustainable Finance & Investment*, *12*(2), 593–611. https://doi.org/10.1080/20430795.2020.1790959

Miller, T., & del Triana, M. C. (2009). Demographic diversity in the boardroom: Mediators of the board diversity–firm performance relationship. *Journal of Management Studies*, *46*(5), 755–786. https://doi.org/10.1111/j.1467-6486.2009.00839.x

Miralles Quirós, M. M., Miralles-Quirós, M. M., & Guía Arraiano, I. (2017). Are firms that contribute to sustainable development valued by investors? *Corporate Social Responsibility and Environmental Management*, *24*(1), 71–84. https://doi.org/10.1002/csr.1392

Miralles Quirós, M. M., Miralles-Quirós, M. M., & Guía Arraiano, I. (2017b). Sustainable development, sustainability leadership and firm valuation: Differences across Europe. *Business Strategy and the Environment*, *26*(7), 1014–1028. https://doi.org/10.1002/bse.1964

Mohiuddin, M., Parveen, R., Rahman, M. I., & Su, Z. (2014). Motivational factors influencing social entrepreneurship in Bangladesh. In *Building businesses in emerging and developing countries: Challenges and opportunities*. Routledge. https://doi.org/10.4324/9780203080665-18

Molinaro, A. M., Simon, R., & Pfeiffer, R. M. (2005). Prediction error estimation: A comparison of resampling methods. *Bioinformatics*, *21*(15), 3301–3307. https://doi.org/10.1093/bioinformatics/bti499

Montero, J. M., & Velasco-López, J. (2024). Herramentas para el análisis en ciencia de datos. In G. Fernández-Avilés & J. M. Montero (Eds.), *Fundamentos de Ciencia de Datos con R* (pp. 153–170). McGraw-Hill.

Morris, S., Guell, C., & Pollard, T. M. (2019). Group walking as a "lifeline": Understanding the place of outdoor walking groups in women's lives. *Social Science & Medicine*, *238*, 112489. https://doi.org/10.1016/j.socscimed.2019.112489

Nadeem, M., Zaman, R., & Saleem, I. (2017). Boardroom gender diversity and corporate sustainability practices: Evidence from Australian securities exchange listed firms. *Journal of Cleaner Production*, *149*, 874–885. https://doi.org/10.1016/j.jclepro.2017.02.141

Nagelkerke, N. J. D. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, *78*(3), 691–692. https://doi.org/10.1093/biomet/78.3.691

Naveed, K., Khalid, F., & Voinea, C. L. (2023a). Board gender diversity and corporate green innovation: An industry-level institutional perspective. *Corporate Social Responsibility and Environmental Management*, *30*(2), 755–772. https://doi.org/10.1002/csr.2386

Naveed, K., Khalid, F., Voinea, C. L., Roijakkers, N., & Fratostiteanu, C. (2023b). Board gender diversity and corporate environmental commitment: A subnational perspective. *Business Strategy and the Environment*, *32*(7), 4970–4990. https://doi.org/10.1002/bse.3403

Nicolò, G., Zampone, G., Sannino, G., & De Iorio, S. (2022). Sustainable corporate governance and non-financial disclosure in Europe: Does the gender diversity matter? *Journal of Applied Accounting Research*, *23*(1), 227–249. https://doi.org/10.1108/JAAR-04-2021-0100

Nielsen, S., & Huse, M. (2010). The contribution of women on boards of directors: Going beyond the surface. *Corporate Governance: An International Review*, *18*(2), 136–148. https://doi.org/10.1111/j.1467-8683.2010.00784.x

Nuber, C., & Velte, P. (2021). Board gender diversity and carbon emissions: European evidence on curvilinear relationships and critical mass. *Business Strategy and the Environment*, *30*(4), 1958–1992. https://doi.org/10.1002/bse.2727

Oehler, A., Horn, M., & Wendt, S. (2017). Brexit: Short-term stock price effects and the impact of firm-level internationalization. *Finance Research Letters*, *22*, 175–181. https://doi.org/10.1016/j.frl.2016.12.024

Oino, I., & Liu, J. (2022). Do female board members influence corporate social responsibility performance? *IIM Kozhikode Society & Management Review*, *11*(2), 195–206. https://doi.org/10.1177/22779752211073643

Orazalin, N., & Baydauletov, M. (2020). Corporate social responsibility strategy and corporate environmental and social performance: The moderating role of board gender diversity. *Corporate Social Responsibility and Environmental Management*, *27*(4), 1664–1676. https://doi.org/10.1002/csr.1915

Pérez-Cornejo, C., de Quevedo-Puente, E., & Delgado-García, J. B. (2020). Reporting as a booster of the corporate social performance effect on corporate reputation. *Corporate Social Responsibility and Environmental Management*, *27*(3), 1252–1263. https://doi.org/10.1002/csr.1881

Petersen, H. L., & Vredenburg, H. (2009). Morals or economics? Institutional investor preferences for corporate social responsibility. *Journal of Business Ethics*, *90*(1), 1–14. https://doi.org/10.1007/s10551-009-0030-3

Pillay, S., & Pahlad, R. (2014). A gendered analysis of community perceptions and attitudes towards green spaces in a Durban metropolitan residential area: Implications for climate change mitigation. *Agenda*, *28*(3), 168–178. https://doi.org/10.1080/10130950.2014.932125

Pletzer, J. L., Nikolova, R., Kedzior, K. K., & Voelpel, S. C. (2015). Does gender matter? Female representation on corporate boards and firm financial performance - a meta-analysis. *PLoS One*, *10*(6), 1–20. https://doi.org/10.1371/journal.pone.0130005

Rao, K., & Tilt, C. (2016). Board composition and corporate social responsibility: The role of diversity, gender, strategy and decision making. *Journal of Business Ethics*, *138*(2), 327–347. https://doi.org/10.1007/s10551-015-2613-5

Reguera-Alvarado, N., de Fuentes, P., & Laffarga, J. (2017). Does board gender diversity influence financial performance? Evidence from Spain. *Journal of Business Ethics*, *141*(2), 337–350. https://doi.org/10.1007/s10551-015-2735-9

Ren, X., Li, J., Wang, X., & Lei, X. (2024). Female directors and CSR: Does the presence of female directors affect CSR focus? *International Review of Financial Analysis*, *92*, 103101. https://doi.org/10.1016/j.irfa.2024.103101

Samer, M. (2013). Towards the implementation of the green building concept in agricultural buildings: A literature review. *Agricultural Engineering International: CIGR Journal*, *15*(2), 25–46.

Sang, Å. O., Knez, I., Gunnarsson, B., & Hedblom, M. (2016). The effects of naturalness, gender, and age on how urban green space is perceived and used. *Urban Forestry & Urban Greening*, *18*, 268–276. https://doi.org/10.1016/j.ufug.2016.06.008

Schipperijn, J., Ekholm, O., Stigsdotter, U. K., Toftager, M., Bentsen, P., Kamper-Jørgensen, F., & Randrup, T. B. (2010). Factors influencing the use of green space: Results from a Danish national representative survey. *Landscape and Urban Planning*, *95*(3), 130–137. https://doi.org/10.1016/j.landurbplan.2009.12.010

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Shepherd, K. (2009). Green build for social housing. *Renewable Energy Focus*, *10*, 48–50. https://doi.org/10.1016/S1755-0084(09)70235-2

Sial, M. S., Zheng, C., Cherian, J., Gulzar, M. A., Thu, P. A., Khan, T., & Khuong, N. V. (2018). Does corporate social responsibility mediate the relation between boardroom gender diversity and firm performance of Chinese listed companies? *Sustainability*, *10*(10), 1–18. https://doi.org/10.3390/su10103591

Siddiq, N. A., Hendinata, L. K., Fikri, A. I. R., Prilia, R., & Asnawi, A. (2023). Looking for green building literacy in Indonesia: Where are we now? A Survey on Undergraduate Students. 030003. https://doi.org/10.1063/5.0122311

Sila, V., Gonzalez, A., & Hagendorff, J. (2016). Women on board: Does boardroom gender diversity affect firm risk? *Journal of Corporate Finance*, *36*, 26–53. https://doi.org/10.1016/j.jcorpfin.2015.10.003

Singhania, S., Singh, J., & Aggrawal, D. (2023). Gender diversity on board and corporate sustainability: A quantitative review based on bibliometric mapping. *International Journal of System Assurance Engineering and Management*, *14*(1), 267–286. https://doi.org/10.1007/s13198-022-01789-w

Sunikka-Blank, M., Bardhan, R., & Haque, A. (2019). Gender, domestic energy and design of inclusive low-income habitats: A case of slum rehabilitation housing in Mumbai, India. *Energy Research & Social Science*, *49*, 53–67. https://doi.org/10.1016/J.ERSS.2018.10.020

Terjesen, S., Barbosa Couto, E., & Morais Francisco, P. (2016). Does the presence of independent and female directors impact firm performance? A multi-country study of board diversity. *Journal of Management and Governance*, *20*(3), 447–483. https://doi.org/10.1007/s10997-014-9307-8

Tingbani, I., Chithambo, L., Tauringana, V., & Papanikolaou, N. (2020). Board gender diversity, environmental committee and greenhouse gas voluntary disclosures. *Business Strategy and the Environment*, *29*, 2194–2210. https://doi.org/10.1002/bse.2495

Topcu, U. (2019). Reflections of gender on the urban green space. *Archnet-IJAR: International Journal of Architectural Research*, *14*(1), 70–76. https://doi.org/10.1108/ARCH-04-2019-0071

Torchia, M., Calabrò, A., & Huse, M. (2011). Women directors on corporate boards: From tokenism to critical mass. *Journal of Business Ethics*, *102*(2), 299–317. https://doi.org/10.1007/s10551-011-0815-z

Toukabri, M., & Jilani, F. (2023). The power of critical mass to make a difference: How gender diversity in board affect US corporate carbon performance. *Society and Business Review*, *18*(4), 592–617. https://doi.org/10.1108/SBR-11-2021-0224

Valls Martínez, M. C., Cruz Rambaud, S., & Parra Oller, I. M. (2019). Gender policies on board of directors and sustainable development. *Corporate Social Responsibility and Environmental Management*, *26*(6), 1539–1553. https://doi.org/10.1002/csr.1825

Valls Martínez, M. C., Martín Cervantes, P. A., & Cruz Rambaud, S. (2020). Women on corporate boards and sustainable development in the American and European markets: Is there a limit to gender policies? *Corporate Social Responsibility and Environmental Management*, *27*(6), 2642–2656. https://doi.org/10.1002/csr.1989

Valls Martínez, M. C., Martín Cervantes, P. A., & Miralles Quirós, M. M. (2022). Sustainable development and the limits of gender policies on corporate boards in Europe. A comparative analysis between developed and emerging markets. *European Research on Management and Business Economics*, *28*(1), 1–15. https://doi.org/10.1016/j.iedeen.2021.100168

Valls Martínez, M. C., Montero, J.-M., Sánchez Pacheco, M. E., & Zambrano Farías, F. J. (2024). The influence of corporate governance on the sustainability of American company buildings. In M. C. del Valls Martínez & J. M. Santos-Jaén (Eds.), *Environmentally sustainable production: Research for sustainable development* (pp. 365–385). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-52656-5_18

Valls Martínez, M. C., Santos Jaén, J. M., Soriano Román, R., & Martín Cervantes, P. A. (2022). Are gender and cultural diversities on board related to corporate CO_2 emissions? *Journal of Cleaner Production*, *363*, 1–17. https://doi.org/10.1016/j.jclepro.2022.132638

Valls Martínez, M. C., & Soriano Román, R. (2022). Women in monitoring positions and market risk. Are the stocks of companies with gender diverse boards less volatile? *Frontiers in Psychology*, *13*(November), 1–19. https://doi.org/10.3389/fpsyg.2022.1049175

Valls Martínez, M. C., Soriano Román, R., & Martín Cervantes, P. A. (2022). Should risk-averse investors target the portfolios of socially responsible companies? *Oeconomia Copernicana*, *13*(2), 1–36. https://doi.org/10.24136/oc.2022.014

Velte, P. (2017). Do women on board of directors have an impact on corporate governance quality and firm performance? A literature review. *International Journal of Sustainable Strategic Management*, *5*(4), 302. https://doi.org/10.1504/ijssm.2017.10010121

Wahyudi, I., & Mayasari, D. (2023). Does board gender diversity Moderatively affect the relationship between business characteristics and corporate sustainability performance? *Journal of Economics, Finance and Management Studies*, *6*(6), 2449–2463. https://doi.org/10.47191/jefms/v6-i6-04

Williams, N. (2022). Making mandates last: Increasing female representation on corporate boards in the U.S. *Michigan Journal of Gender & Law*, *29*(29.2), 211. https://doi.org/10.36641/mjgl.29.2.making

Wu, J., Xu, Z., Jin, Y., Chai, Y., Newell, J., & Ta, N. (2022). Gender disparities in exposure to green space: An empirical study of suburban Beijing. *Landscape and Urban Planning*, *222*, 104381. https://doi.org/10.1016/j.landurbplan.2022.104381

Wu, J., Richard, O. C., Triana, M. C., & Zhang, X. (2022). The performance impact of gender diversity in the top management team and board of directors: A multiteam systems approach. *Human Resource Management*, *61*(2), 157–180. https://doi.org/10.1002/hrm.22086

Wu, Q., Furuoka, F., & Lau, S. C. (2022). Corporate social responsibility and board gender diversity: A meta-analysis. *Management Research Review*, *45*(7), 956–983. https://doi.org/10.1108/MRR-03-2021-0236

Xie, F., Guo, Y., Daniel, S. J., & Liu, Y. (2024). The dynamic relation between board gender diversity and firm performance: The moderating role of shareholder activism. *Review of Quantitative Finance and Accounting*, *62*(1), 225–246. https://doi.org/10.1007/s11156-023-01201-z

Yang, W., Yang, J., & Gao, Z. (2019). Do female board directors promote corporate social responsibility? An empirical study based on the critical mass theory. *Emerging Markets Finance and Trade*, *55*(15), 3452–3471. https://doi.org/10.1080/1540496X.2019.1657402

Yarram, S. R., & Adapa, S. (2021). Board gender diversity and corporate social responsibility: Is there a case for critical mass? *Journal of Cleaner Production*, *278*, 123319. https://doi.org/10.1016/j.jclepro.2020.123319

Zaccone, M. C. (2023). Unlocking sustainable governance: The role of women at the corporate apex. *Business Ethics, the Environment & Responsibility*, *33*(4), 746–762. https://doi.org/10.1111/beer.12637

Zhang, J. Q., Zhu, H., & Ding, H. (2013). Board composition and corporate social responsibility: An empirical investigation in the post Sarbanes-Oxley era. *Journal of Business Ethics*, *114*(3), 381–392. https://doi.org/10.1007/s10551-012-1352-0

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APPENDIX A

TABLE A1 Traditional logistic regressions in the Euro Stoxx 300 index: Training sample.

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−6.327238*** (0.000)	–	–	–	–
BGD	0.024599*** (0.000)	0.0273145*** (0.000)	-	0.0247295*** (0.001)	0.0279004*** (0.000)
BLAU	–	–	4.095663*** (0.000)	-	-
CSRC	0.47679** (0.018)	0.4901627** (0.017)	0.5022258** (0.016)	0.5172756** (0.018)	0.4565946** (0.025)
CSRR	2.711132*** (0.000)	2.883079*** (0.000)	2.797874*** (0.000)	2.652795*** (0.000)	2.70592*** (0.000)
AUD	−0.0120858*** (0.000)	−0.0122355*** (0.000)	−0.0130141*** (0.000)	−0.0100013*** (0.000)	−0.0121656*** (0.000)
BSZ	0.1607289*** (0.000)	0.1614847*** (0.000)	0.1543945*** (0.000)	0.1611874*** (0.000)	0.1531697*** (0.000)
BSK	–	–	–	−0.0079672** (0.050)	–
BTN	0.1943498*** (0.000)	0.2120301*** (0.000)	0.2170458*** (0.000)	0.2154361*** (0.000)	0.2143114*** (0.000)
NEM	–	–	–	–	–
IBM	0.0191799*** (0.000)	0.020358*** (0.000)	0.0209635*** (0.000)	0.0172979*** (0.000)	0.0200674*** (0.000)
DUA	–	–	–	–	–
SEC	0.0303959*** (0.000)	0.0293209*** (0.000)	0.0305969*** (0.000)	0.0264111*** (0.000)	0.0326517*** (0.000)
CEOC	−1.129664*** (0.000)	−1.119718*** (0.000)	−1.145963*** (0.000)	−0.9929199*** (0.000)	−1.137814*** (0.000)
BMC	–	–	–	–	–
NEC	0.0121336*** (0.001)	0.01164*** (0.000)	0.0119257*** (0.000)	0.01187*** (0.000)	−0.0129564** (0.041)
ESG	0.0096014* (0.090)	–	–	0.0129072** (0.030)	–
CO_2	−0.343722*** (0.000)	−0.3122397*** (0.000)	−0.3142103*** (0.000)	−0.3404202*** (0.000)	−0.3077775*** (0.000)
SIZE	0.0784083* (0.067)	0.6371603*** (0.001)	0.6276951*** (0.002)	0.6207048*** (0.002)	0.6302603*** (0.002)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	1722	1661	1661	1661	1661
Hausman test	–	72.93 (0.0000)	102.79 (0.0000)	63.72 (0.0000)	242.67 (0.0000)
Pseudo R^2	0.253	–	–	–	–
McFadden's R^2 (adjust)	0.221	0.254	0.264	0.254	0.246
Nagelkerke R^2	0.393	0.368	0.380	0.371	0.359
Cox & Snell	0.293	0.226	0.233	0.228	0.220
LR χ^2	597.70*** (0.0000)	425.02*** (0.0000)	441.63*** (0.0000)	429.29*** (0.0000)	413.28*** (0.0000)
Wald χ^2	374.03*** (0.0000)	270.16*** (0.0000)	275.73*** (0.0000)	272.32*** (0.0000)	268.52*** (0.0000)
AIC	1838.496	1179.211	1162.602	1178.937	1190.943
BIC	2029.289	1244.193	1227.584	1254.749	1255.925
Mean absolute error	0.3401944	0.4031886	0.4015891	0.4024429	0.4042615
Percent concordant	74.91	57.78	58.07	58.01	57.61
True positives	520	50	55	53	46
False negatives	246	716	711	713	720

(Continues)

TABLE A1 (Continued)

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
True negatives	770	945	945	946	946
False positives	186	11	11	10	10
Sensitivity	67.89	6.53	7.18	6.92	6.01
Specificity	80.54	98.85	98.85	98.95	98.95
AUC-ROC	0.8238	0.7414	0.7457	0.7426	0.7504
PANEL B. 10-folds validation					
I. Mean values of the 10 estimations					
Pseudo R^2	0.254	–	–	–	–
McFadden's R^2 (adjust)	0.219	0.253	0.263	0.253	0.246
Nagelkerke R^2	0.394	0.369	0.381	0.372	0.360
Cox & Snell	0.294	0.226	0.234	0.228	0.221
AIC	1658.504	1062.455	1047.479	1062.330	1073.035
BIC	1844.538	1126.17	1111.195	1136.664	1136.751
Mean absolute error	0.3390611	0.4031202	0.4015175	0.4023461	0.4041953
Percent concordant	74.94	57.95	58.15	58.01	57.65
True positives	469.7	47.7	50.6	48.3	42.6
False negatives	219.7	641.7	638.8	641.1	646.8
True negatives	691.7	850.4	850.6	850.7	850.9
False positives	168.7	10.0	9.8	9.7	9.5
Sensitivity	68.13	6.92	7.34	7.01	6.18
Specificity	80.39	98.83	98.86	98.87	98.90
AUC-ROC	0.8244	0.7416	0.7458	0.7430	0.6854
II. Mean values of the validation					
Mean absolute error	0.3465506	0.4059263	0.4043096	0.4053337	0.4068571
Percent concordant	73.80	57.66	58.02	57.93	57.46
True positives	50.9	5.1	5.8	5.5	4.5
False negatives	25.7	71.5	71.1	71.2	72.1
True negatives	76.2	94.3	94.4	94.4	94.5
False positives	19.4	1.3	1.2	1.2	1.1
Sensitivity	66.33	6.77	7.64	7.29	6.05
Specificity	79.64	98.59	98.68	98.72	98.81
AUC-ROC	0.8075	0.7361	0.7412	0.7387	0.7456
PANEL C. Prediction in the test sample					
Mean absolute error	0.3644668	0.4208732	0.4203364	0.4206004	0.4219363
Percent concordant	70.96	55.90	55.90	55.90	55.90
True positives	197	19	20	19	19
False negatives	102	280	279	280	280
True negatives	260	341	340	341	341
False positives	85	4	5	4	4
Sensitivity	65.89	6.35	6.69	6.35	6.35
Specificity	75.36	98.84	98.55	98.84	98.84
AUC-ROC	0.7817	0.7404	0.7392	0.7426	0.7367

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better.

TABLE A2 Traditional logistic regressions in the Euro Stoxx 300 index: Total sample.

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
Intercept	−6.963673*** (0.000)	–	–	–	–
BGD	0.0193924*** (0.000)	0.0251041*** (0.000)	–	0.0207743*** (0.001)	0.0255828*** (0.000)
BLAU	–	–	3.54894*** (0.000)	–	–
CSRC	0.6248005*** (0.000)	0.7750606*** (0.000)	0.7573108*** (0.000)	0.7448872*** (0.000)	0.7457371*** (0.000)
CSRR	2.58319*** (0.000)	2.838747*** (0.000)	2.798833*** (0.000)	2.440666*** (0.000)	2.586361*** (0.000)
AUD	−0.0089833*** (0.000)	−0.0094237*** (0.000)	−0.0101424*** (0.000)	−0.0074761*** (0.001)	−0.0092825*** (0.000)
BSZ	0.1512332*** (0.000)	0.1512897*** (0.000)	0.1465727*** (0.000)	0.1482356*** (0.000)	0.1411689*** (0.000)
BSK	–	–	–	−0.0085474** (0.010)	-
BTN	0.2020813*** (0.000)	0.2196416*** (0.000)	0.2214758*** (0.000)	0.2273013*** (0.000)	0.2224588*** (0.000)
NEM	–	–	–	–	–
IBM	0.0156986*** (0.000)	0.017138*** (0.000)	0.0176874*** (0.000)	0.0135753*** (0.000)	0.0166366*** (0.000)
DUA	–	–	–	–	–
SEC	0.0305122*** (0.000)	0.0303922*** (0.000)	0.0312672*** (0.000)	0.0268509*** (0.000)	0.0335234*** (0.000)
CEOC	−1.057219*** (0.000)	−1.027301*** (0.000)	−1.047291*** (0.000)	−0.9370965*** (0.000)	−1.03699*** (0.000)
BMC	-	-	-	-	-
NEC	0.0109634*** (0.000)	0.0106595*** (0.000)	0.0107877*** (0.000)	0.0108861** (0.000)	−0.0114378** (0.024)
ESG	0.0129248*** (0.007)	–	–	0.0170844*** (0.001)	–
CO_2	−0.3210831*** (0.000)	−0.2886525*** (0.000)	−0.2909087*** (0.000)	−0.3198331*** (0.000)	−0.2816651*** (0.000)
SIZE	0.0941779*** (0.009)	0.7145495*** (0.000)	0.715997*** (0.000)	0.6921745*** (0.000)	0.6978793*** (0.000)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	2366	2302	2302	2302	2302
Hausman test	–	–	–	42.87 (0.0001)	866.51 (0.0000)
Pseudo R^2	0.239	–	–	–	–
McFadden's R^2 (adjust)	0.216	0.250	0.258	0.253	0.241
Nagelkerke R^2	0.375	0.359	0.368	0.365	0.348
Cox & Snell	0.280	0.222	0.227	0.225	0.215
LR χ^2	777.75*** (0.0000)	576.51*** (0.0000)	593.19*** (0.0000)	292.91*** (0.0000)	556.62*** (0.0000)
Wald χ^2	491.57*** (0.0000)	364.29*** (0.0000)	369.75*** (0.0000)	370.02*** (0.0000)	361.53*** (0.0000)
AIC	2548.646	1654.086	1637.409	1647.902	1673.981
BIC	2750.56	1722.984	1706.308	1728.284	1742.879
Mean absolute error	0.348888	0.4087937	0.4075557	0.4080547	0.4100517
Percent concordant	74.30	57.27	57.48	57.40	57.06
True positives	710	69	74	71	64
False negatives	255	996	991	994	1001
True negatives	1048	1286	1286	1287	1286
False positives	253	15	15	14	15
Sensitivity	66.67	6.48	6.95	6.67	6.00
Specificity	80.55	98.85	98.85	98.92	98.85
AUC-ROC	0.8154	0.7429	0.7459	0.7442	0.7487

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better.

TABLE A3 Quadratic logistic regressions in the Euro Stoxx 300 index: Training sample.

PANEL A. Training sample	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−7.660976*** (0.000)	–	–	–	–
BGD^2	−0.0021567*** (0.000)	−0.0020845*** (0.000)	–	−0.0023005*** (0.000)	−0.0021703*** (0.000)
BGD	0.1489659*** (0.000)	0.1434862*** (0.000)	–	0.0147123* (0.056)	0.0147253*** (0.000)
$BLAU^2$	–	–	−5.395297^{ns} (0.216)	–	–
BLAU	–	–	7.233826*** (0.007)	–	–
CSRC	0.6301578*** (0.002)	0.6419943*** (0.003)	0.508474** (0.015)	0.5265016** (0.016)	0.5343098** (0.010)
CSRR	2.928479*** (0.000)	2.764615*** (0.000)	2.802963*** (0.000)	2.677794*** (0.000)	2.634018*** (0.000)
AUD	−0.0125865*** (0.000)	−0.0122265*** (0.000)	−0.0128683*** (0.000)	−0.0109916*** (0.000)	−0.0133583*** (0.000)
BSZ	0.1579007*** (0.000)	0.1506891*** (0.000)	0.1556033*** (0.000)	0.1580077*** (0.000)	0.1749206*** (0.000)
BSK	–	−0.0070226* (0.086)	–	−0.0084509** (0.039)	–
BTN	0.1879025*** (0.000)	0.2222911*** (0.000)	0.2145246*** (0.000)	0.2203108*** (0.000)	0.2255223*** (0.000)
NEM	–	–	–	–	–
IBM	0.0213632*** (0.000)	0.0205021*** (0.000)	0.02136*** (0.000)	0.0184474*** (0.000)	0.0221664*** (0.000)
DUA	–	–	–	–	–
SEC	0.0324943*** (0.000)	0.0291823*** (0.000)	0.0303013*** (0.000)	0.0269399*** (0.000)	0.036779*** (0.000)
CEOC	−1.018156*** (0.000)	−1.006067*** (0.000)	−1.126051*** (0.000)	−0.9682657*** (0.000)	−1.043872*** (0.000)
BMC	–	–	–	–	−0.1256443** (0.027)
NEC	0.0132785*** (0.001)	0.0125938*** (0.000)	0.0117681*** (0.000)	0.0117844*** (0.001)	−0.0141431** (0.027)
ESG	–	–	–	0.0100239* (0.096)	–
CO_2	−0.3466693*** (0.000)	−0.3252381*** (0.000)	−0.3187283*** (0.000)	−0.3445141*** (0.000)	−0.3224459*** (0.000)
SIZE	0.0772713* (0.075)	0.6884426*** (0.001)	0.6480765*** (0.001)	0.6901659*** (0.001)	0.7458105*** (0.000)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	1722	1661	1661	1661	1661
Hausman test	–	72.93 (0.0000)	190.39 (0.0000)	–	1896.85 (0.0000)
Pseudo R^2	0.266	–	–	–	
McFadden's R^2 (adjust)	0.234	0.271	0.264	0.264	0.264
Nagelkerke R^2	0.409	0.391	0.382	0.384	0.383
Cox & Snell	0.306	0.240	0.234	0.236	0.235
LR χ^2	628.44*** (0.0000)	456.41*** (0.0000)	443.18*** (0.0000)	447.10*** (0.0000)	444.79*** (0.0000)
Wald χ^2	384.44*** (0.0000)	280.85*** (0.0000)	276.54*** (0.0000)	274.94*** (0.0000)	278.84*** (0.0000)
AIC	1807.750	1151.818	1163.045	1163.128	1163.436
BIC	1998.544	1227.631	1233.442	1244.356	1239.249
Mean absolute error	0.33219	0.4000335	0.4013168	0.4003712	0.4012907
Percent concordant	75.73	58.13	58.07	58.01	58.48
True positives	537	55	56	54	62
False negatives	229	711	710	712	704
True negatives	767	946	944	945	945

TABLE A3 (Continued)

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
False positives	189	10	12	11	11
Sensitivity	70.10	7.18	7.31	7.05	8.09
Specificity	80.23	98.95	98.74	98.85	98.85
AUC-ROC	0.8327	0.7523	0.7461	0.7508	0.7539
PANEL B. 10-folds validation					
I. Mean values of the 10 estimations					
Pseudo R^2	0.267	–	–	–	–
McFadden's R^2 (adjust)	0.243	0.270	0.263	0.263	0.263
Nagelkerke R^2	0.411	0.393	0.383	0.386	0.384
Cox & Snell	0.307	0.241	0.235	0.237	0.236
AIC	1630.865	1038.004	1048.012	1048.228	1048.503
BIC	1816.899	1112.338	1117.037	1127.872	1122.838
Mean absolute error	0.3305913	0.3999286	0.4012399	0.4002600	0.4011925
Percent concordant	75.71	58.08	58.17	58.04	58.41
True positives	482.4	48.8	51.5	49.1	53.9
False negatives	207.0	640.6	637.9	640.3	635.5
True negatives	691.0	851.4	850.0	850.4	851.3
False positives	169.4	9.0	10.4	10.0	9.1
Sensitivity	69.98	7.08	7.47	7.12	7.82
Specificity	80.31	98.95	98.79	98.84	98.94
AUC-ROC	0.8333	0.7524	0.7463	0.7511	0.7541
II. Mean values of the validation					
Mean absolute error	0.3383068	0.4029449	0.4040456	0.4032876	0.4041537
Percent concordant	74.45	58.10	57.97	57.74	58.25
True positives	52.1	5.8	5.7	5.2	6.1
False negatives	24.5	70.8	70.9	71.4	70.5
True negatives	76.0	94.4	94.3	94.4	94.3
False positives	19.6	1.2	1.3	1.2	1.3
Sensitivity	67.91	7.65	7.47	6.84	8.08
Specificity	79.55	98.67	98.55	98.68	98.58
AUC-ROC	0.8197	0.7473	0.7415	0.7447	0.7501
PANEL C. Prediction in the test sample					
Mean absolute error	0.3626159	0.4208439	0.4205897	0.4207273	0.4201448
Percent concordant	70.65	56.21	56.06	55.90	56.83
True positives	197	22	21	19	26
False negatives	102	277	278	280	273
True negatives	258	340	340	341	340
False positives	87	5	5	4	5
Sensitivity	65.89	7.36	7.03	6.35	8.70
Specificity	74.78	98.55	98.55	98.84	98.55
AUC-ROC	0.7789	0.7370	0.7375	0.7392	0.7410

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A4 Quadratic logistic regressions in the Euro Stoxx 300 index: Total sample.

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
Intercept	−7.969573*** (0.000)	–	–	–	–
BGD^2	−0.0016041*** (0.000)	−0.0016383*** (0.000)	–	−0.001815*** (0.000)	−0.0017562*** (0.000)
BGD	0.1122403*** (0.000)	0.114995*** (0.000)	–	0.0122479* (0.056)	0.1205399*** (0.000)
$BLAU^2$	–	–	-2.632768^{ns} (0.461)	–	–
BLAU	–	–	5.05503** (0.018)	–	–
CSRC	0.7639192*** (0.000)	0.8596287*** (0.000)	0.7550269*** (0.000)	0.7122641*** (0.000)	0.7518314*** (0.000)
CSRR	2.936612*** (0.000)	2.787996*** (0.000)	2.80867*** (0.000)	2.478486*** (0.000)	2.621719*** (0.000)
AUD	−0.0095637*** (0.000)	−0.0096599*** (0.000)	−0.0100809*** (0.000)	−0.0082722*** (0.000)	−0.0108649*** (0.000)
BSZ	0.1526068*** (0.000)	0.1430399*** (0.000)	0.1472861*** (0.000)	0.1459177*** (0.000)	0.1739335*** (0.000)
BSK	–	−0.0072035** (0.031)	–	−0.0089514*** (0.008)	–
BTN	0.1906667*** (0.000)	0.2240514*** (0.000)	0.2193915*** (0.000)	0.2264334*** (0.000)	0.23091*** (0.000)
NEM	–	–	–	–	–
IBM	0.0183253*** (0.000)	0.0173286*** (0.000)	0.0179261*** (0.000)	0.0144463*** (0.000)	0.0192373*** (0.000)
DUA	–	–	–	–	–
SEC	0.0324984*** (0.000)	0.0301875*** (0.000)	0.0311504*** (0.000)	0.0276651*** (0.000)	0.0388625*** (0.000)
CEOC	−0.9407014*** (0.000)	−0.9236621*** (0.000)	−1.037312*** (0.000)	−0.9191225*** (0.000)	−0.9477298*** (0.000)
BMC	–	–	–	–	−0.1626778*** (0.001)
NEC	0.0117983*** (0.000)	0.0113664*** (0.000)	0.0107129*** (0.000)	0.0106306*** (0.000)	0.0123395** (0.016)
ESG	–	–	–	0.0148278*** (0.003)	–
CO_2	−0.3168096*** (0.000)	−0.3014749*** (0.000)	−0.2936043*** (0.000)	−0.3237391*** (0.000)	−0.2973886*** (0.000)
SIZE	0.0926412** (0.010)	0.7576845*** (0.000)	0.7256772*** (0.000)	0.7386175*** (0.000)	0.8101181*** (0.000)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	2366	2302	2302	2302	2302
Hausman test	–	106.33 (0.0000)	49.62 (0.0000)	54.76 (0.0000)	123.25 (0.0000)
Pseudo R^2	0.245	–	–	–	–
McFadden's R^2 (adjust)	0.222	0.263	0.257	0.260	0.256
Nagelkerke R^2	0.383	0.376	0.369	0.374	0.368
Cox & Snell	0.286	0.232	0.227	0.230	0.227
LR χ^2	797.87*** (0.0000)	607.37*** (0.0000)	593.73*** (0.0000)	602.71*** (0.0000)	556.62*** (0.0000)
Wald χ^2	499.93*** (0.0000)	376.25*** (0.0000)	370.17*** (0.0000)	378.20*** (0.0000)	373.99*** (0.0000)
AIC	2528.526	1627.227	1638.862	1633.891	1641.906
BIC	2730.439	1707.608	1713.502	1720.014	1722.288
Mean absolute error	0.3442997	0.4065261	0.4074674	0.4066981	0.4073585
Percent concordant	74.60	57.10	57.52	57.14	57.40
True positives	725	66	75	66	73
False negatives	340	999	990	999	992
True negatives	1040	1285	1286	1286	1285

TABLE A4 (Continued)

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
False positives	261	16	15	15	16
Sensitivity	68.08	6.20	7.04	6.20	6.85
Specificity	79.94	98.77	98.85	98.85	98.77
AUC-ROC	0.8214	0.7501	0.7461	0.7490	0.7517

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A5 Cubic logistic regressions in the Euro Stoxx 300 index: Training sample.

PANEL A. Training sample

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau Panel Data	Model 4 Residual Panel Data	Model 5 Winsorized Panel Data
Intercept	−7.050117*** (0.000)	–	–	–	–
BGD^3	−0.0000584** (0.015)	−0.000051** (0.041)	–	−0.0001303*** (0.000)	−0.0000622** (0.023)
BGD^2	0.0027119^{ns} (0.177)	0.0021242^{ns} (0.310)	–	−0.0033462*** (0.000)	0.0028449^{ns} (0.204)
BGD	0.0367508^{ns} (0.461)	0.0482516^{ns} (0.349)	–	0.0477035*** (0.000)	0.0367858^{ns} (0.491)
$BLAU^3$	–	–	−134.1463*** (0.000)	–	–
$BLAU^2$	–	–	105.0079*** (0.001)	–	–
BLAU	–	–	−16.22751** (0.019)	–	–
CSRC	0.6331468*** (0.002)	0.659538*** (0.002)	0.6378957*** (0.003)	0.5318111** (0.015)	0.5605727*** (0.000)
CSRR	2.941599*** (0.000)	2.75657*** (0.000)	2.7533*** (0.000)	2.570537*** (0.000)	2.617983*** (0.000)
AUD	−0.0127664*** (0.000)	−0.0123222*** (0.000)	−0.0113387*** (0.000)	−0.0108544*** (0.000)	−0.0135397*** (0.000)
BSZ	0.1549183*** (0.000)	0.1476718*** (0.000)	0.154222*** (0.000)	0.1564611*** (0.000)	0.1739837*** (0.000)
BSK	–	−0.0071866* (0.079)	−0.006823* (0.095)	−0.0081461** (0.047)	–
BTN	0.1941181*** (0.000)	0.2282707*** (0.000)	0.217623*** (0.000)	0.2284226*** (0.000)	0.2332455*** (0.000)
NEM	–	–	–	–	–
IBM	0.0206247*** (0.000)	0.0196896*** (0.000)	0.019418*** (0.000)	0.017728*** (0.000)	0.0214164*** (0.000)
DUA	-	-	-	-	-
SEC	0.0334062*** (0.000)	0.0299518*** (0.000)	0.0292567*** (0.000)	0.0290489*** (0.000)	0.0375735*** (0.000)
CEOC	−1.028936*** (0.000)	−1.00564*** (0.000)	−0.9944855*** (0.000)	−0.9606102*** (0.000)	−1.034658*** (0.000)
BMC	–	–	–	–	−0.1370494** (0.016)
NEC	0.0136799*** (0.000)	0.0130787*** (0.000)	0.0137339*** (0.000)	0.0125364*** (0.001)	0.0150582** (0.019)
ESG	–	–	–	0.0125431** (0.040)	–
CO_2	−0.3411215*** (0.000)	−0.3196198*** (0.000)	−0.3190236*** (0.000)	−0.3480363*** (0.000)	−0.3156164*** (0.000)
SIZE	0.0768671* (0.077)	0.6876989*** (0.001)	0.6618258*** (0.001)	0.6981972*** (0.001)	0.757133*** (0.000)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–

(Continues)

TABLE A5 (Continued)

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau Panel Data	Residual Panel Data	Winsorized Panel Data
Number of observations	1722	1661	1661	1661	1661
Hausman test	–	72.93 (0.0000)	94.29 (0.0000)	23.95 (0.0659)	999.25 (0.0000)
Pseudo R^2	0.268	–	–	–	
McFadden's R^2 (adjust)	0.236	0.272	0.272	0.271	0.266
Nagelkerke R^2	0.413	0.394	0.394	0.394	0.387
Cox & Snell	0.308	0.242	0.242	0.242	0.237
LR χ^2	634.45*** (0.0000)	460.51*** (0.0000)	459.50*** (0.0000)	460.15*** (0.0000)	449.90*** (0.0000)
Wald χ^2	385.00*** (0.0000)	282.03*** (0.0000)	278.08*** (0.0000)	284.08*** (0.0000)	279.95*** (0.0000)
AIC	1803.742	1149.714	1150.723	1152.073	1160.326
BIC	1999.986	1230.942	1231.951	1238.715	1241.554
Mean absolute error	0.3308944	0.3999137	0.3997169	0.399696	0.4009567
Percent concordant	75.84	57.78	57.96	57.90	58.19
True positives	534	49	52	53	57
False negatives	232	717	714	713	709
True negatives	772	946	946	944	945
False positives	184	10	10	12	11
Sensitivity	69.71	6.40	6.79	6.92	7.44
Specificity	80.75	98.95	98.95	98.74	98.85
AUC-ROC	0.8346	0.7549	0.7527	0.7568	0.7571
PANEL B. 10-folds validation					
I. Mean values of the 10 estimations					
Pseudo R^2	0.269	-	-	-	-
McFadden's R^2 (adjust)	0.237	0.273	0.271	0.270	0.265
Nagelkerke R^2	0.414	0.396	0.395	0.395	0.388
Cox & Snell	0.309	0.243	0.242	0.243	0.238
AIC	1627.455	1036.290	1037.217	1038.513	1045.847
BIC	1818.835	1115.934	1116.861	1123.467	1125.491
Mean absolute error	0.3296771	0.3998059	0.3996268	0.3995808	0.4008595
Percent concordant	75.80	57.85	57.94	58.09	58.38
True positives	481.3	45.5	47.1	50.8	54.0
False negatives	208.1	643.9	642.3	638.6	635.4
True negatives	693.4	851.1	850.9	849.5	840.8
False positives	167.0	9.3	9.5	10.9	9.6
Sensitivity	69.82	6.60	6.83	7.37	7.84
Specificity	80.59	98.92	98.89	98.73	98.88
AUC-ROC	0.8349	0.7551	0.7528	0.7569	0.7572
II. Mean values of the validation					
Mean absolute error	0.3369364	0.4028771	0.4025929	0.4026424	0.4038934
Percent concordant	74.62	57.51	57.90	57.58	57.90
True positives	52.4	5.0	5.7	5.1	5.6
False negatives	24.2	71.6	70.9	71.5	71.0
True negatives	76.0	94.2	94.4	94.2	94.2

TABLE A5 (Continued)

PANEL B. 10-folds validation					
False positives	19.6	1.4	1.5	1.4	1.4
Sensitivity	68.36	6.60	7.60	6.72	7.42
Specificity	79.46	98.46	98.25	98.48	98.47
AUC-ROC	0.8218	0.7500	0.7471	0.7514	0.7532
PANEL C. Prediction in the test sample					
Mean absolute error	0.3623169	0.4212494	0.4189957	0.4208632	0.4198986
Percent concordant	70.19	55.90	55.90	55.74	55.90
True positives	197	20	20	19	20
False negatives	102	279	279	280	279
True negatives	255	340	340	340	340
False positives	90	5	5	5	5
Sensitivity	65.89	6.69	6.69	6.35	6.69
Specificity	73.91	98.55	98.55	98.55	98.55
AUC-ROC	0.7784	0.7360	0.7419	0.7381	0.7429

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A6 Cubic logistic regressions in the Euro Stoxx 300 index: Total sample.

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−7.490482*** (0.000)	–	–	–	–
BGD^3	−0.0000492*** (0.009)	−0.0000439** (0.025)	–	−0.0001102*** (0.000)	−0.0000621*** (0.007)
BGD^2	0.0024768^{ns} (0.121)	0.0019985^{ns} (0.227)	–	−0.0025995*** (0.000)	0.0032247** (0.084)
BGD	0.019363^{ns} (0.626)	0.0331434^{ns} (0.417)	–	0.0413962*** (0.000)	0.121266^{ns} (0.783)
$BLAU^3$	–	–	−126.3327*** (0.000)	–	–
$BLAU^2$	–	–	100.8017*** (0.000)	–	–
BLAU	–	–	−16.82001*** (0.003)	–	–
CSRC	0.7765978*** (0.000)	0.8780972*** (0.000)	0.8721324*** (0.000)	0.7326846*** (0.000)	0.7790892*** (0.000)
CSRR	2.934091*** (0.000)	2.773291*** (0.000)	2.735163*** (0.000)	2.368*** (0.000)	2.58878*** (0.000)
AUD	−0.0097389*** (0.000)	−0.0098338*** (0.000)	−0.0088522*** (0.000)	−0.0081493*** (0.000)	−0.011119*** (0.000)
BSZ	0.1502825*** (0.000)	0.1405553*** (0.000)	0.147709*** (0.000)	0.1434456*** (0.000)	0.1735386*** (0.000)
BSK	–	−0.0073634** (0.028)	−0.0065965** (0.049)	−0.0088377*** (0.009)	–
BTN	0.1977289*** (0.000)	0.2313086*** (0.000)	0.2227852*** (0.000)	0.2355013*** (0.000)	0.2403681*** (0.000)
NEM	–	–	–	–	–
IBM	0.017533*** (0.000)	0.0165182*** (0.000)	0.0161192*** (0.000)	0.0135294*** (0.000)	0.0183655*** (0.000)
DUA	–	–	–	–	–
SEC	0.0331528*** (0.000)	0.0309799*** (0.000)	0.0293403*** (0.000)	0.0300562*** (0.000)	0.0395183*** (0.000)
CEOC	−0.9452103*** (0.000)	−0.9269706*** (0.000)	−0.8959959*** (0.000)	−0.9118705*** (0.000)	−0.9350491*** (0.000)
BMC	–	–	–	–	−0.1756673*** (0.000)
NEC	0.0120756*** (0.000)	0.0117874*** (0.000)	0.0126109*** (0.000)	0.0112158*** (0.000)	0.0130369** (0.011)

(Continues)

TABLE A6 (Continued)

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
ESG	–	–	–	0.0172897*** (0.001)	–
CO_2	−0.3113925*** (0.000)	−0.2959714*** (0.000)	−0.2920342*** (0.000)	−0.3260741*** (0.000)	−0.2891869*** (0.000)
SIZE	0.0931574** (0.010)	0.756376*** (0.000)	0.7453796*** (0.000)	0.7290028*** (0.000)	0.8208516*** (0.000)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	2366	2302	2302	2302	2302
Hausman test	–	73.39 (0.0000)	195.68 (0.0000)	64.20 (0.0000)	90.27 (0.0000)
Pseudo R^2	0.247	–	–	–	–
McFadden's R^2 (adjust)	0.224	0.264	0.266	0.265	0.258
Nagelkerke R^2	0.386	0.379	0.381	0.382	0.372
Cox & Snell	0.288	0.234	0.235	0.235	0.229
LR χ^2	804.44*** (0.0000)	612.26*** (0.0000)	616.01*** (0.0000)	617.34*** (0.0000)	599.99*** (0.0000)
Wald χ^2	502.52*** (0.0000)	377.59*** (0.0000)	375.29*** (0.0000)	383.90*** (0.0000)	376.83*** (0.0000)
AIC	2523.949	1624.333	1620.587	1621.258	1636.605
BIC	2731.632	1710.456	1706.71	1713.122	1722.728
Mean absolute error	0.3432862	0.4064810	0.4060745	0.4062178	0.4070699
Percent concordant	74.47	56.85	57.19	57.40	57.52
True positives	725	60	67	72	75
False negatives	340	1005	998	993	990
True negatives	1037	1285	1286	1286	1286
False positives	264	16	15	15	15
Sensitivity	68.08	5.63	6.29	6.76	7.04
Specificity	79.71	98.77	98.85	98.85	98.85
AUC-ROC	0.8225	0.7519	0.7522	0.7524	0.7543

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A7 Traditional logistic regressions in the S&P 500 index: Training sample.

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−6.513929*** (0.000)	–	–	–	–
BGD	0.0187667*** (0.000)	0.0172434*** (0.000)	–	0.0171582*** (0.000)	0.018339*** (0.000)
BLAU	–	–	2.110345*** (0.000)	–	–
CSRC	0.3598284*** (0.000)	0.3069224*** (0.005)	0.2956383*** (0.007)	0.3234361*** (0.003)	0.3084305*** (0.005)
CSRR	0.6511649*** (0.000)	0.6902783*** (0.000)	0.6821744*** (0.000)	0.7098563*** (0.000)	0.6971578*** (0.000)
AUD	–	0.021851* (0.052)	0.0226436** (0.044)	0.0206843* (0.066)	0.0216214* (0.082)
BSZ	0.2680176*** (0.000)	0.2663034*** (0.000)	0.2648931*** (0.000)	0.263842*** (0.000)	0.2333055*** (0.000)
BSK	0.0102583*** (0.000)	0.0119171*** (0.000)	0.011887*** (0.000)	0.0119289*** (0.000)	0.0120556*** (0.000
BTN	0.0808467*** (0.000)	0.082044*** (0.000)	0.07967*** (0.000)	0.081285*** (0.000)	0.0827245*** (0.000)
NEM	–	–	–	–	–
IBM	–	–	–	–	–
DUA	–	–	–	–	–
SEC	0.0119152*** (0.000)	0.0104448*** (0.000)	0.0103989*** (0.000)	0.0105225*** (0.000)	0.0107365*** (0.000)
CEOC	−0.6556011*** (0.000)	−0.6393615*** (0.000)	−0.6430102*** (0.000)	−0.614355*** (0.000)	−0.642191*** (0.000)
BMC	0.1732026*** (0.000)	0.153591*** (0.000)	0.1537438*** (0.000)	0.1512598*** (0.000)	0.2858802*** (0.000)
NEC	–	–	–	–	–
ESG	0.0233809*** (0.000)	0.0246271*** (0.000)	0.024193*** (0.000)	0.0275901*** (0.000)	0.0234035*** (0.000)
CO_2	−0.1575225*** (0.000)	−0.1684099*** (0.000)	−0.1680182*** (0.000)	−0.1738679*** (0.000)	−0.1715595*** (0.000)
SIZE	−0.009078* (0.096)	0.233799** (0.013)	0.2226863** (0.018)	0.2411636** (0.010)	0.2046776** (0.037)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	3604	3572	3572	3572	3572
Hausman test	–	27.46 (0.0108)	26.53 (0.0144)	28.02 (0.0090)	30.55 (0.0039)
Pseudo R^2	0.1945	–	–	–	–
McFadden's R^2 (adjust)	0.182	0.232	0.234	0.232	0.237
Nagelkerke R^2	0.313	0.339	0.340	0.339	0.345
Cox & Snell	0.233	0.216	0.218	0.216	0.220
LR χ^2	957.95*** (0.0000)	871.06*** (0.0000)	876.08*** (0.0000)	870.74*** (0.0000)	888.18*** (0.0000)
Wald χ^2	647.62*** (0.0000)	578.49*** (0.0000)	581.53*** (0.0000)	578.40*** (0.0000)	593.09*** (0.0000)
AIC	4024.104	2794.609	2789.595	2794.934	2777.490
BIC	4197.418	2874.961	2869.947	2875.286	2857.841
Mean absolute error	0.3717633	0.5176507	0.5177183	0.5176939	0.516699
Percent concordant	71.48	44.64	44.62	44.59	44.56
True positives	1631	64	64	63	59
False negatives	422	1989	1989	1990	1994
True negatives	945	1545	1544	1544	1547
False positives	606	6	7	7	4
Sensitivity	79.44	3.12	3.12	3.07	2.87

(Continues)

TABLE A7 (Continued)

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Specificity	60.93	99.61	99.55	99.55	99.74
AUC-ROC	0.7865	0.7453	0.7462	0.7453	0.7578
PANEL B. 10-folds validation					
I. Mean values of the 10 estimations					
Pseudo R^2	0.195	-	-	-	-
McFadden's R^2 (adjust)	0.182	0.232	0.233	0.232	0.236
Nagelkerke R^2	0.314	0.339	0.329	0.339	0.345
Cox & Snell	0.234	0.217	0.230	0.217	0.221
AIC	3624.123	2516.053	2511.537	2516.343	2500.774
BIC	3792.661	2595.035	2590.518	2595.324	2579.756
Mean absolute error	0.3713506	0.5175622	0.5176298	0.5176053	0.5166306
Percent concordant	71.54	44.61	44.59	44.62	44.64
True positives	1469.7	56.6	56.3	57.1	55.7
False negatives	378.1	1791.1	1791.4	1790.6	1792.0
True negatives	850.7	1390.5	1390.0	1390.3	1392.3
False positives	545.2	5.4	6.2	5.6	3.6
Sensitivity	79.54	3.06	3.05	3.09	3.02
Specificity	79.94	99.61	99.56	99.60	99.74
AUC-ROC	0.7868	0.7456	0.746	0.7456	0.7580
II. Mean values of the validation					
Mean absolute error	0.3749919	0.5183896	0.5184572	0.5184348	0.5172824
Percent concordant	70.66	44.58	44.50	44.58	44.53
True positives	161.1	6.2	5.9	6.2	5.9
False negatives	44.2	199.1	199.4	199.1	199.4
True negatives	93.6	154.5	154.5	154.5	154.6
False positives	61.5	0.6	0.6	0.6	0.5
Sensitivity	78.44	3.04	2.89	3.04	2.89
Specificity	60.33	99.61	99.61	99.61	99.67
AUC-ROC	0.7779	0.7418	0.7428	0.7415	0.7548
PANEL C. Prediction in the test sample					
Mean absolute error	0.3754492	0.5059358	0.5058336	0.5060116	0.5044814
Percent concordant	71.11	46.91	46.85	46.85	46.53
True positives	682	48	47	47	42
False negatives	188	822	823	823	828
True negatives	423	681	681	681	681
False positives	261	3	3	3	3
Sensitivity	78.39	5.52	5.40	5.40	4.83
Specificity	61.84	99.56	99.56	99.56	99.56
AUC-ROC	0.7785	0.7335	0.7356	0.7332	0.7547

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better.

TABLE A8 Traditional logistic regressions in the S&P 500 index: Total sample.

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−5.631659*** (0.000)	–	–	–	–
BGD	0.0172912*** (0.000)	0.0170547*** (0.000)	–	0.0167921*** (0.000)	0.0181155*** (0.000)
BLAU	–	–	2.200946*** (0.000)	–	–
CSRC	0.3754129*** (0.000)	0.3374614*** (0.000)	0.3236042*** (0.000)	0.354141*** (0.000)	0.3352427*** (0.000)
CSRR	0.5962079*** (0.000)	0.6455724*** (0.000)	0.6339065*** (0.000)	0.6654112*** (0.000)	0.6618165*** (0.000)
AUD	–	0.0195502** (0.034)	0.0202638** (0.029)	0.0183668** (0.047)	0.0186575* (0.067)
BSZ	0.2441187*** (0.000)	0.2404115*** (0.000)	0.2400267*** (0.000)	0.2378727*** (0.000)	0.2023997*** (0.000)
BSK	0.0089374*** (0.000)	0.0105649*** (0.000)	0.0105853*** (0.000)	0.0105689*** (0.000)	0.0105755*** (0.000)
BTN	0.0709742*** (0.000)	0.0706598*** (0.000)	0.0685611*** (0.000)	0.0699542*** (0.000)	0.0726935*** (0.000)
NEM	–	–	–	–	–
IBM	–	–	–	–	–
DUA	–	–	–	–	–
SEC	0.0107814*** (0.000)	0.0091848*** (0.000)	0.0091418*** (0.000)	0.0092504*** (0.000)	0.0091278*** (0.000)
CEOC	−0.7364343*** (0.000)	−0.7390538*** (0.000)	−0.747315*** (0.000)	−0.7145072*** (0.000)	−0.7500302*** (0.000)
BMC	0.2034799*** (0.000)	0.1918989*** (0.000)	0.192339*** (0.000)	0.1897048*** (0.000)	0.3400737*** (0.000)
NEC	–	–	–	–	–
ESG	0.0248915*** (0.000)	0.0248612*** (0.000)	0.0243595*** (0.000)	0.0277806*** (0.000)	0.0236857*** (0.000)
CO_2	−0.1799669*** (0.000)	−0.1866314*** (0.000)	−0.1859224*** (0.000)	−0.1920548*** (0.000)	−0.188439*** (0.000)
SIZE	–	0.1504695* (0.055)	0.1369938* (0.082)	0.1579411** (0.044)	0.1259327^{ns} (0.122)
ROA	−0.0071848^{ns} (0.119)	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	5158	5124	5124	5124	5124
Hausman test	–	37.88 (0.0000)	46.26 (0.0000)	47.37 (0.0000)	33.68 (0.0013)
Pseudo R^2	0.191	–	–	–	–
McFadden's R^2 (adjust)	0.182	0.228	0.230	0.227	0.234
Nagelkerke R^2	0.308	0.331	0.333	0.330	0.339
Cox & Snell	0.230	0.212	0.213	0.212	0.217
LR χ^2	1346.30*** (0.0000)	1218.49*** (0.0000)	1228.87*** (0.0000)	1217.68*** (0.0000)	1253.00*** (0.0000)
Wald χ^2	917.57*** (0.0000)	815.95*** (0.0000)	820.44*** (0.0000)	815.67*** (0.0000)	839.72*** (0.0000)
AIC	5768.167	4046.403	4036.026	4047.218	4011.898
BIC	5951.520	4131.445	4121.068	4132.26	4096.94
Mean absolute error	0.3738496	0.5144979	0.5144702	0.5145482	0.5130021
Percent concordant	71.83	45.21	45.27	45.25	45.29
True positives	2317	104	108	106	108
False negatives	606	2819	2815	2817	2815
True negatives	1388	2228	2227	2228	2228
False positives	847	7	8	7	7
Sensitivity	79.27	3.56	3.69	3.63	3.69
Specificity	62.10	99.69	99.64	99.69	99.69
AUC-ROC	0.7858	0.7425	0.7436	0.7426	0.7570

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A9 Quadratic logistic regressions in the S&P 500 index: Training sample.

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−7.520402*** (0.000)	–	–	–	–
BGD^2	−0.0007673*** (0.006)	−0.0007196** (0.013)	–	−0.0007349** (0.025)	−0.0008281** (0.012)
BGD	0.061661*** (0.000)	0.0570091*** (0.001)	–	0.0204369*** (0.000)	0.0625336*** (0.001)
$BLAU^2$	–	–	−6.497592* (0.073)	–	–
BLAU	–	–	6.29554*** (0.009)	–	–
CSRC	0.3365852*** (0.001)	0.2916925*** (0.008)	0.2925157*** (0.008)	0.3181569*** (0.004)	0.2983533*** (0.007)
CSRR	0.6623883*** (0.000)	0.6784966*** (0.000)	0.6933193*** (0.000)	0.7111294*** (0.000)	0.6909334*** (0.000)
AUD	0.0179252* (0.089)	0.0231348** (0.040)	0.0235835** (0.036)	0.0211445* (0.060)	0.0228063* (0.066)
BSZ	0.2709296*** (0.000)	0.2626964*** (0.000)	0.2619669*** (0.000)	0.2583615*** (0.000)	0.228883*** (0.000)
BSK	0.0094801*** (0.000)	0.0118371*** (0.000)	0.0120893*** (0.000)	0.0119191*** (0.000)	0.0119732*** (0.000)
BTN	0.0723948*** (0.000)	0.0777866*** (0.000)	0.075907*** (0.000)	0.0789709*** (0.000)	0.078174*** (0.000)
NEM	−0.0137208* (0.084)	–	–	–	–
IBM	–	–	–	–	–
DUA	–	–	–	–	–
SEC	0.011319*** (0.000)	0.0103577*** (0.000)	0.0105022*** (0.000)	0.0102809*** (0.000)	0.0106577*** (0.000)
CEOC	−0.6622948*** (0.000)	−0.642446*** (0.000)	−0.6524288*** (0.000)	−0.6083901*** (0.000)	−0.6466567*** (0.000)
BMC	0.1776005*** (0.000)	0.1539238*** (0.000)	0.153126*** (0.000)	0.1478752*** (0.000)	0.2868867*** (0.000)
NEC	–	–	–	–	–
ESG	0.0236138*** (0.000)	0.0243285*** (0.000)	0.0237501*** (0.000)	0.0281681*** (0.000)	0.0229222*** (0.000)
CO_2	−0.1572667*** (0.000)	−0.168299*** (0.000)	−0.1683368*** (0.000)	−0.1746375*** (0.000)	−0.1719296*** (0.000)
SIZE	−0.0091797* (0.093)	0.2235899** (0.018)	0.2200343** (0.020)	0.2353281** (0.012)	0.1934839** (0.050)
ROA	–	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	3604	3572	3572	3572	3572
Hausman test	–	31.11 (0.0053)	29.00 (0.0105)	26.11 (0.0251)	31.24 (0.0051)
Pseudo R^2	0.1970	–	–	–	–
McFadden's R^2 (adjust)	0.184	0.233	0.234	0.233	0.238
Nagelkerke R^2	0.317	0.341	0.342	0.340	0.347
Cox & Snell	0.236	0.218	0.218	0.217	0.222
LR χ^2	970.22*** (0.0000)	877.27*** (0.0000)	879.44*** (0.0000)	875.81*** (0.0000)	894.58*** (0.0000)
Wald χ^2	653.71*** (0.0000)	582.68*** (0.0000)	580.19*** (0.0000)	584.31*** (0.0000)	566.99*** (0.0000)
AIC	4017.836	2790.407	2788.235	2791.860	2773.092
BIC	4209.720	2876.940	2874.767	2878.393	2859.625
Mean absolute error	0.3702848	0.5178205	0.5178412	0.5177551	0.5169127
Percent concordant	71.89	44.59	44.53	44.59	44.56
True positives	1630	63	61	62	60
False negatives	423	1990	1992	1991	1993
True negatives	961	1544	1544	1545	1546
False positives	590	7	7	6	5

TABLE A9 (Continued)

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Sensitivity	79.40	3.07	2.97	3.02	2.92
Specificity	61.96	99.55	99.55	99.61	99.68
AUC-ROC	0.7872	0.7466	0.7471	0.7469	0.7594
PANEL B. 10-folds validation					
I. Mean values of the 10 estimations					
Pseudo R^2	0.198	-	-	-	-
McFadden's R^2 (adjust)	0.183	0.233	0.234	0.233	0.238
Nagelkerke R^2	0.318	0.341	0.342	0.341	0.347
Cox & Snell	0.234	0.218	0.219	0.218	0.222
AIC	3618.849	2512.406	2510.474	2513.734	2496.936
BIC	3805.640	2597.463	2595.531	2598.791	2581.993
Mean absolute error	0.3699143	0.5177288	0.5177507	0.5176662	0.5168404
Percent concordant	71.76	44.58	44.56	44.59	44.58
True positives	1466.6	56.0	55.5	55.8	54.6
False negatives	381.1	1791.7	1792.2	1791.9	1793.1
True negatives	859.0	1389.9	1389.7	1390.5	1391.2
False positives	533.9	6.0	6.2	5.4	4.5
Sensitivity	79.37	3.03	3.00	3.02	2.96
Specificity	61.67	99.57	99.56	99.61	99.68
AUC-ROC	0.7877	0.7469	0.7474	0.7472	0.7596
II. Mean values of the validation					
Mean absolute error	0.3737413	0.5185781	0.5185913	0.5184965	0.5175202
Percent concordant	70.91	44.47	44.47	44.55	44.39
True positives	160.9	5.9	5.9	6.1	5.5
False negatives	44.4	199.4	199.4	199.2	199.8
True negatives	94.6	154.4	154.4	154.5	154.5
False positives	60.5	0.7	0.7	0.6	0.6
Sensitivity	78.34	2.90	2.90	2.99	2.69
Specificity	61.02	99.54	99.54	99.61	99.61
AUC-ROC	0.7784	0.7433	07438	0.7436	0.7560
PANEL C. Prediction in the test sample					
Mean absolute error	0.3731628	0.5058900	0.5059791	0.5059790	0.5043914
Percent concordant	71.88	46.72	46.65	46.78	46.46
True positives	693	45	45	46	41
False negatives	177	825	825	824	829
True negatives	424	681	680	681	681
False positives	260	3	4	3	3
Sensitivity	79.66	5.17	5.17	5.29	4.71
Specificity	61.99	99.56	99.42	99.56	99.56
AUC-ROC	0.7809	0.7371	0.7370	0.7362	0.7588

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better.

TABLE A10 Quadratic logistic regressions in the S&P 500 index: Total sample.

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
Intercept	−6.956764*** (0.000)	–	–	–	–
BGD^2	−0.0009239*** (0.000)	−0.000955*** (0.000)	–	−0.0008995*** (0.001)	−0.0011066*** (0.000)
BGD	0.0684308*** (0.000)	0.0695109*** (0.000)	–	0.0205218*** (0.000)	0.0768995*** (0.000)
$BLAU^2$	–	–	−6.38981** (0.032)	–	–
BLAU	–	–	6.303608*** (0.001)	–	–
CSRC	0.3521772*** (0.000)	0.3149668*** (0.001)	0.3180177*** (0.001)	0.3436244*** (0.000)	0.3187912*** (0.001)
CSRR	0.6027214*** (0.000)	0.627483*** (0.000)	0.6438815*** (0.000)	0.6672429*** (0.000)	0.6514519*** (0.000)
AUD	0.0183021** (0.035)	0.0208591** (0.024)	0.020806** (0.025)	0.0188672** (0.041)	0.0197676* (0.052)
BSZ	0.2448005*** (0.000)	0.2366635*** (0.000)	0.2372281*** (0.000)	0.232081*** (0.000)	0.1978722*** (0.000)
BSK	0.0083679*** (0.000)	0.0105256*** (0.000)	0.0108047*** (0.000)	0.0106352*** (0.000)	0.0105207*** (0.000)
BTN	0.062418*** (0.000)	0.0654535*** (0.000)	0.0650637*** (0.000)	0.067417*** (0.000)	0.0670361*** (0.000)
NEM	−0.0110752* (0.095)	–	–	–	–
IBM	–	–	–	–	–
DUA	–	–	–	–	–
SEC	0.0102631*** (0.000)	0.009101*** (0.000)	0.0092732*** (0.000)	0.0089837*** (0.000)	0.0090733*** (0.000)
CEOC	−0.7461694*** (0.000)	−0.7487478*** (0.000)	−0.7594507*** (0.000)	−0.7123672*** (0.000)	−0.7606396*** (0.000)
BMC	0.2091098*** (0.000)	0.1933015*** (0.000)	0.1924534*** (0.000)	0.1857864*** (0.000)	0.341775*** (0.000)
NEC	–	–	–	–	–
ESG	0.0248357*** (0.000)	0.0246223*** (0.000)	0.0239928*** (0.000)	0.0285481*** (0.000)	0.023234*** (0.000)
CO_2	−0.1793488*** (0.000)	−0.1864923*** (0.000)	−0.1861065*** (0.000)	−0.1930413*** (0.000)	−0.1890347*** (0.000)
SIZE	–	0.1384168* (0.079)	0.1348037* (0.087)	0.1506461* (0.055)	0.112181^{ns} (0.170)
ROA	−0.0073186^{ns} (0.113)	–	–	–	–
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	5158	5124	5124	5124	5124
Hausman test	–	55.09 (0.0000)	48.23 (0.0000)	55.09 (0.0000)	38.58 (0.0004)
Pseudo R^2	0.194	–	–	–	–
McFadden's R^2 (adjust)	0.184	0.230	0.230	0.229	0.237
Nagelkerke R^2	0.312	0.334	0.334	0.333	0.343
Cox & Snell	0.233	0.214	0.214	0.213	0.219
LR χ^2	1367.40*** (0.0000)	1233.84*** (0.0000)	1233.71*** (0.0000)	1228.35*** (0.0000)	1269.10*** (0.0000)
Wald χ^2	926.46*** (0.0000)	822.78*** (0.0000)	817.79*** (0.0000)	825.26*** (0.0000)	846.42*** (0.0000)
AIC	5753.062	4033.053	4033.192	4038.549	3997.801
BIC	5956.059	4124.637	4124.776	4130.133	4089.385
Mean absolute error	0.3719712	0.5146119	0.5145921	0.5145752	0.5131383
Percent concordant	72.06	45.23	45.21	45.23	45.29
True positives	2325	105	105	104	108
False negatives	598	2818	2818	2819	2815
True negatives	1392	2228	2227	2229	2228
False positives	843	7	8	6	7
Sensitivity	79.54	3.59	2.04	3.56	3.69
Specificity	62.28	99.69	99.64	99.73	99.69

TABLE A10 (Continued)

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
AUC-ROC	0.7874	0.7448	0.7447	0.7446	0.7598

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A11 Cubic logistic regressions in the S&P 500 index: Training sample.

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−8.026758*** (0.000)	–	–	–	–
BGD^3	0.0000281^{ns} (0.102)	0.0000295* (0.093)	–	−0.000013^{ns} (0.534)	0.0000463* (0.053)
BGD^2	−0.0032324** (0.036)	−0.0033152** (0.036)	–	−0.0005871^{ns} (0.145)	−0.0046244** (0.021)
BGD	0.1247782*** (0.003)	0.123398*** (0.005)	–	0.0237168*** (0.001)	0.1536582*** (0.003)
$BLAU^3$	–	–	−32.09427^{ns} (0.138)	–	–
$BLAU^2$	–	–	20.9132^{ns} (0.262)	–	–
BLAU	–	–	−0.5067059^{ns} (0.920)	–	–
CSRC	0.3434785*** (0.001)	0.2958897*** (0.007)	0.2887594*** (0.009)	0.314786*** (0.004)	0.2996148*** (0.006)
CSRR	0.6760248*** (0.000)	0.6982772*** (0.000)	0.6842352*** (0.000)	0.7041766*** (0.000)	0.7167124*** (0.000)
AUD	0.0182461* (0.083)	0.0234764** (0.037)	0.0235554** (0.036)	0.0211768* (0.059)	0.0240819* (0.053)
BSZ	0.2702589*** (0.000)	0.2624829*** (0.000)	0.2608413*** (0.000)	0.2592617*** (0.000)	0.2289698*** (0.000)
BSK	0.0097637*** (0.000)	0.012159*** (0.000)	0.0119456*** (0.000)	0.0117889*** (0.000)	0.0124784*** (0.000)
BTN	0.0713774*** (0.000)	0.0759902*** (0.000)	0.0758865*** (0.000)	0.0791733*** (0.000)	0.0762542*** (0.000)
NEM	−0.0133812* (0.092)	–	–	–	–
IBM	–	–	–	–	–
DUA	–	–	–	–	–
SEC	0.0115264*** (0.000)	0.0105586*** (0.000)	0.0103936*** (0.000)	0.01027*** (0.000)	0.010932*** (0.000)
CEOC	−0.6730326*** (0.000)	−0.6553859*** (0.000)	−0.6473214*** (0.000)	−0.6059787*** (0.000)	−0.6591562*** (0.000)
BMC	0.1760003*** (0.000)	0.1524908*** (0.000)	0.1526668*** (0.000)	0.148682*** (0.000)	0.287628*** (0.000)
NEC	–	–	–	–	–
ESG	0.0228689*** (0.000)	0.0235416*** (0.000)	0.0241943*** (0.000)	0.0284385*** (0.000)	0.0218964*** (0.000)
CO_2	−0.1576181*** (0.000)	−0.1685325*** (0.000)	−0.1690815*** (0.000)	−0.174267*** (0.000)	−0.1721053*** (0.000)
SIZE	−0.0093264* (0.089)	0.2195785** (0.020)	0.2261227** (0.017)	0.237053** (0.012)	0.1825355* (0.066)
ROA	–	–	–	–	−0.0153552* (0.098)
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–
Number of observations	3604	3572	3572	3572	3572
Hausman test	–	28.83 (0.0110)	11.03 (0.5259)	26.66 (0.0213)	31.89 (0.0067)
Pseudo R^2	0.198	–	–	–	–
McFadden's R^2 (adjust)	0.184	0.234	0.234	0.232	0.239
Nagelkerke R^2	0.318	0.342	0.342	0.340	0.349

(Continues)

TABLE A11 (Continued)

PANEL A. Training sample					
	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Cox & Snell	0.237	0.218	0.219	0.218	0.223
LR χ^2	972.95*** (0.0000)	880.14*** (0.0000)	881.58*** (0.0000)	875.81*** (0.0000)	901.00*** (0.0000)
Wald χ^2	323.60*** (0.0000)	587.85*** (0.0000)	584.94*** (0.0000)	584.50*** (0.0000)	539.30*** (0.0000)
AIC	4017.105	2789.531	2788.092	2793.471	2770.669
BIC	4215.178	2882.244	2880.805	2886.184	2869.563
Mean absolute error	0.3700858	0.5178008	0.5177978	0.5177585	0.5166784
Percent concordant	71.73	44.53	44.53	44.56	44.70
True positives	1632	61	61	61	65
False negatives	421	1992	1992	1992	1988
True negatives	953	1544	1544	1545	1546
False positives	598	7	7	6	5
Sensitivity	79.49	2.97	2.97	2.97	3.17
Specificity	61.44	99.55	99.55	99.61	99.68
AUC-ROC	0.7876	0.7473	0.7479	0.7466	0.7601
PANEL B. 10-folds validation					
I. Mean values of the 10 estimations					
Pseudo R^2	0.198	–	–	–	–
McFadden's R^2 (adjust)	0.183	0.233	0.234	0.232	0.238
Nagelkerke R^2	0.318	0.342	0.343	0.341	0.350
Cox & Snell	0.237	0.219	0.219	0.218	0.223
AIC	3618.295	2511.747	2510.369	2513.302	2494.964
BIC	3811.17	2602.879	2601.502	2606.434	2592.072
Mean absolute error	0.3696753	0.5177045	0.5176998	0.5176672	0.5165940
Percent concordant	71.70	44.56	44.53	44.60	44.68
True positives	1469.1	55.7	54.9	56.0	57.9
False negatives	378.6	1792.0	1792.8	1791.7	1789.8
True negatives	856.4	1389.7	1389.6	1390.6	1391.3
False positives	539.5	6.2	6.3	5.3	4.6
Sensitivity	79.37	3.02	2.97	3.03	3.13
Specificity	61.67	99.56	99.55	99.62	99.67
AUC-ROC	0.7882	0.7476	0.7482	0.7469	0.7603
II. Mean values of the validation					
Mean absolute error	0.3736673	0.5186004	0.5185844	0.5185312	0.5173595
Percent concordant	70.83	44.47	44.45	44.53	44.58
True positives	161.6	5.9	5.8	6.0	6.2
False negatives	43.7	199.4	199.5	199.3	199.1
True negatives	93.8	154.4	154.4	154.5	154.5
False positives	61.6	0.7	0.7	0.6	0.6
Sensitivity	78.34	2.90	2.85	2.94	3.03
Specificity	61.02	99.54	99.54	99.61	99.61
AUC-ROC	0.7787	0.7437	07443	0.7428	0.7566
PANEL C. Prediction in the test sample					
Mean absolute error	0.3734034	0.5059502	0.5059349	0.5059643	0.5044406

TABLE A11 (Continued)

PANEL C. Prediction in the test sample					
Percent concordant	71.94	46.72	46.65	46.65	46.59
True positives	696	46	45	44	43
False negatives	174	824	825	826	827
True negatives	422	680	680	681	681
False positives	262	4	4	3	3
Sensitivity	80.00	5.29	5.17	5.06	4.94
Specificity	61.70	99.42	99.42	99.56	99.56
AUC-ROC	0.7804	0.7370	0.7388	0.7361	0.7582

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

TABLE A12 Cubic logistic regressions in the S&P 500 index: Total sample.

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables	Pool data	Panel data	Blau panel data	Residual panel data	Winsorized panel data
Intercept	−7.254478*** (0.000)	–	–	–	–
BGD^3	0.0000163^{ns} (0.247)	0.0000177^{ns} (0.221)	–	−0.0000186^{ns} (0.279)	0.0000186^{ns} (0.332)
BGD^2	−0.0023488* (0.062)	−0.0025031* (0.053)	–	−0.0007005** (0.035)	−0.0026246* (0.099)
BGD	0.1046917*** (0.002)	0.1088304*** (0.002)	–	0.0251809*** (0.000)	0.1131578*** (0.005)
$BLAU^3$	–	–	−46.60483*** (0.009)	–	–
$BLAU^2$	–	–	33.01114** (0.029)	–	–
BLAU	–	–	−3.293862^{ns} (0.408)	–	–
CSRC	0.3553299*** (0.000)	0.3163295*** (0.001)	0.3137776*** (0.001)	0.3396606*** (0.000)	0.3210325*** (0.001)
CSRR	0.6113577*** (0.000)	0.6389154*** (0.000)	0.6336592*** (0.000)	0.6575372*** (0.000)	0.6635947*** (0.000)
AUD	0.01842** (0.034)	0.0209227** (0.024)	0.0210766** (0.023)	0.0189297** (0.040)	0.0204168* (0.046)
BSZ	0.2442724*** (0.000)	0.2364372*** (0.000)	0.2358885*** (0.000)	0.2332628*** (0.000)	0.1974982*** (0.000)
BSK	0.0085397*** (0.000)	0.0107183*** (0.000)	0.0105816*** (0.000)	0.0104545*** (0.000)	0.0106942*** (0.000)
BTN	0.0618699*** (0.000)	0.0645075*** (0.000)	0.064703*** (0.000)	0.067658*** (0.000)	0.0665358*** (0.000)
NEM	−0.0107861^{ns} (0.104)	–	–	–	–
IBM	–	–	–	–	–
DUA	–	–	–	–	–
SEC	0.0103911*** (0.000)	0.0092262*** (0.000)	0.0091289*** (0.000)	0.0089544*** (0.000)	0.0091807*** (0.000)
CEOC	−0.7537619*** (0.000)	−0.7570751*** (0.000)	−0.7494173*** (0.000)	−0.7073506*** (0.000)	−0.7626775*** (0.000)
BMC	0.208357*** (0.000)	0.1926348*** (0.000)	0.1926594*** (0.000)	0.1869385*** (0.000)	0.342654*** (0.000)
NEC	–	–	–	–	–
ESG	0.0244227*** (0.000)	0.0241954*** (0.000)	0.0245561*** (0.000)	0.028886*** (0.000)	0.0227088*** (0.000)
CO_2	−0.1794752*** (0.000)	−0.1865289*** (0.000)	−0.1876289*** (0.000)	−0.1924729*** (0.000)	−0.1892018*** (0.000)
SIZE	–	0.1362529* (0.084)	0.1406769* (0.074)	0.1529133* (0.051)	0.1012844^{ns} (0.217)
ROA	−0.0073639^{ns} (0.111)	–	–	–	−0.0137651* (0.077)
Sector dummies	Yes	–	–	–	–
Country dummies	Yes	–	–	–	–

(Continues)

TABLE A12 (Continued)

Variables	Model 1 Pool data	Model 2 Panel data	Model 3 Blau panel data	Model 4 Residual panel data	Model 5 Winsorized panel data
Number of observations	5158	5124	5124	5124	5124
Hausman test	–	48.86 (0.0000)	18.80 (0.0934)	47.45 (0.0000)	37.90 (0.0009)
Pseudo R^2	0.194	–	–	–	–
McFadden's R^2 (adjust)	0.184	0.230	0.231	0.229	0.237
Nagelkerke R^2	0.312	0.335	0.336	0.333	0.344
Cox & Snell	0.233	0.214	0.215	0.213	0.220
LR χ^2	1368.75*** (0.0000)	1235.35*** (0.0000)	1240.41*** (0.0000)	1229.54*** (0.0000)	1273.13*** (0.0000)
Wald χ^2	923.20*** (0.0000)	819.99*** (0.0000)	827.59*** (0.0000)	825.61*** (0.0000)	845.01*** (0.0000)
AIC	5753.712	4033.547	4028.485	4039.362	3997.769
BIC	5963.258	4131.673	4126.610	4137.488	4102.436
Mean absolute error	0.3718945	0.5146089	0.5145101	0.5145787	0.5130382
Percent concordant	71.95	45.19	45.15	45.17	45.23
True positives	2324	104	103	102	106
False negatives	599	2819	2820	2821	2817
True negatives	1387	2227	2226	2228	2227
False positives	848	8	9	7	8
Sensitivity	79.51	3.56	3.52	3.49	3.63
Specificity	62.06	99.64	99.60	99.69	99.64
AUC-ROC	0.7877	0.7451	0.7462	0.7443	0.7601

Note: ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better. ns denotes not significant.

APPENDIX B

Results obtained from the two-stage regression modeling of CMPDLM2 (for Euro Stoxx 300) and CMPDLM5 (for S&P 500) with instrumental variables for BGD.

Table B1 lists the variables used as instruments to estimate BGD and define them. The selection of these instruments has been carried out according to prior literature.

Table B2 shows the descriptive statistics of the only continuous instrumental variable (EMGD) and its correlation with BGD. It can be observed that the instrumental variable exhibits a significant positive correlation with the variable instrumentalized.

Table B3 displays the distribution of the percent distribution of the dichotomous instrumental variables (panel I), and the between group differences for the listed companies committed (group 1) and not committed (group 0) to green building, by dichotomous IV for BGD (panel II).

Finally, Table B4 lists the estimation results for CMPDLM2 in the case of the Euro Stoxx 300 and CMPDLM5 when addressing the S&P 500.

TABLE B1 Instrumental variables for BGD.

Abbreviation	Variable	Definition
PBD	Policy board diversity	Dummy variable: 1 if the company reports having a gender diversity policy on its board of directors, 0 otherwise.
EMGD	Executive members gender diversity	Percentage of female executive members
HRP	Human rights policy	Dummy variable: 1 if the company has a policy to ensure the respect of human rights in general, 0 otherwise.
DCS	Day care services	Dummy variable: 1 if the company claims to provide day care services for its employees, 0 otherwise.

TABLE B2 Descriptive statistics of EMGD and Pearson correlation with BGD.

Statistic	Euro Stoxx 300	S&P 500
Mean	11.9835	18.0855
Median	11.1111	17.6471
Standard deviation	12.3204	12.2311
Minimum	0.0000	0.0000
Maximum	50.0000	62.5000
Pearson correlation with BGD	0.3232*** (0.0000)	0.2909*** (0.0000)

TABLE B3 Between group differences for listed companies committed (group 1) and not committed (group 0) to green building, by dichotomous IV for BGD.

Panel I. Percentage distribution in the dichotomous variables						
	Euro Stoxx 300		–	S&P 500		–
Variable	Value 0	Value 1		Value 0	Value 1	
PBD	14.16	85.84		12.35	87.65	
HRP	12.51	87.49		21.29	78.71	
DCS	46.15	53.85		65.64	34.36	
Panel II. Between group differences in the dichotomous variables by board gender diversity						
	Euro Stoxx 300			S&P 500		
Variable	Mean group 1	Mean group 0	Difference (*t*-test)	Mean group 1	Mean group 0	Difference (*t*-test)
PBD	32.1728	24.7666	7.4062*** (0.0000)	25.8929	20.7295	5.1634*** (0.0000)
HRP	32.4892	21.5777	10.9115*** (0.0000)	26.1333	22.0081	4.1252*** (0.0000)
DCS	32.8304	29.1334	3.6970*** (0.0000)	27.6642	23.9854	3.6788*** (0.0000)

Note: Results show that the companies with more accentuated gender policies (higher values in the instrumental variables) have a significantly higher percentage of women on the board of directors.

TABLE B4 IV analysis. Estimation results for CMPDLM2 in Europe and CMPDLM5 in U.S.

	Euro Stoxx 300		S&P 500	
Variable	First-stage IV OLS regression	Second-stage IV CMPDLM2	First-stage IV OLS regression	Second-stage IV CMPDLM5
BGD^3	–	−0.0004593*** (0.000)	–	0.0013209*** (0.000)
BGD^2	–	0.0424762*** (0.000)	–	−0.1084611*** (0.000)
BGD	–	−1.234993*** (0.000)	–	3.122364*** (0.000)
PBD	2.501431*** (0.000)	–	2.81922*** (0.000)	–
EMGD	0.2013515*** (0.000)	–	0.171841*** (0.000)	–
HRP	7.068366*** (0.000)	–	−0.8781701** (0.016)	–
DCS	1.078603** (0.015)	–	0.998911*** (0.001)	–
CSRC	0.0630434^{ns} (0.916)	0.7742093*** (0.000)	0.437105^{ns} (0.210)	0.1554741^{ns} (0.104)
CSRR	5.815639*** (0.000)	3.374981*** (0.000)	1.447566*** (0.000)	0.3140091*** (0.007)
AUD	0.0665229*** (0.000)	−0.0098004*** (0.000)	$−0.0168842^{ns}$ (0.640)	0.0353512*** (0.001)
BSZ	0.2128847*** (0.000)	0.1492724*** (0.000)	−0.2467268*** (0.001)	0.2555206*** (0.000)
BSK	−0.0411532*** (0.000)	−0.0072845** (0.030)	0.0018631^{ns} (0.791)	0.0112589*** (0.000)
BTN	−0.2737959*** (0.000)	0.2227526*** (0.000)	0.0376678^{ns} (0.367)	0.0864591*** (0.000)
NEM	–	–	–	–

(Continues)

TABLE B4 (Continued)

Variable	Euro Stoxx 300 First-stage IV OLS regression	Euro Stoxx 300 Second-stage IV CMPDLM2	S&P 500 First-stage IV OLS regression	S&P 500 Second-stage IV CMPDLM5
IBM	−0.0341917*** (0.000)	0.0160595*** (0.000)	–	–
DUA	–	–	–	–
SEC	−0.0389901*** (0.000)	0.0286034*** (0.000)	0.8849231** (0.035)	0.0082727*** (0.000)
CEOC	4.333752*** (0.000)	−1.064355*** (0.000)	0.8849231** (0.035)	−1.183723*** (0.000)
BMC	–	–	−0.3231018*** (0.008)	0.4155098*** (0.000)
NEC	0.0126741^{ns} (0.135)	0.0105544*** (0.000)	–	–
ESG	–	–	0.1361348*** (0.000)	−0.0123712*** (0.004)
CO_2	−0.2851118*** (0.000)	−0.2906668*** (0.000)	−0.2519846*** (0.000)	−0.1427913*** (0.000)
SIZE	−0.0296328^{ns} (0.769)	0.7677561*** (0.000)	0.2664984*** (0.002)	0.0179453^{ns} (0.831)
ROA	–	–	−0.0018079^{ns} (0.926)	−0.0151923* (0.054)
Constant	15.16706*** (0.000)	–	10.78665** (0.011)	–
Observations	2366	2302	5143	5109
R^2 adjust	0.3084	–	0.1801	–
F-statistic	66.90*** (0.0000)	–	67.43*** (0.0000)	–
Hausman test	–	75.68 (0.0000)	–	27.69 (0.0236)
McFadden's R^2	–	0.251	–	0.274
Nagelkerke R^2	–	0.363	–	0.388
Cox & Snell	–	0.224	–	0.249
LR χ^2	–	583.72*** (0.0000)	–	1461.54*** (0.0000)
Wald χ^2	–	368.40*** (0.0000)	–	875.13*** (0.0000)
AIC	–	1652.876	–	3795.925
BIC	–	1738.999	–	3900.545
Mean absolute error	–	0.4099843	–	0.5070121
Percent concordant	–	57.06	–	46.32
True positives	–	63	–	169
False negatives	–	1002	–	2754
True negatives	–	1287	–	2220
False positives	–	14	–	15
Sensitivity	–	5.92	–	5.78
Specificity	–	98.92	–	99.33
AUC-ROC	–	0.7489	–	0.7707

Note: The results confirm that the percentage of women on the board of directors significantly influences the company's propensity to adopt sustainable buildings, and that this influence is far from being linear. It is worth noting that in when using IV for BGD the cubic term of CMPDLM5 (in U.S.) is significant. ***, ** and * indicate a significance of less than 1%, less than 5% and less than 10%, respectively. AIC and BIC: smaller is better.