Board Ancestral Diversity and Voluntary Greenhouse Gas Emission Disclosure

Johannes A. Barg[1], Wolfgang Drobetz[2], Sadok El Ghoul[3],

Omrane Guedhami[4], Henning Schröder[5]

This draft: May 2022

Abstract

Prior research suggests that the disclosure of greenhouse gas (GHG) emissions—a primary cause of climate change—affects firm valuation. In this paper, we provide new insights into the determinants of the voluntary disclosure of GHG emissions. We show that board ancestral diversity has a positive and statistically significant effect on a firm's scope and quality of voluntary GHG emission disclosure. This effect is robust to controlling for several other dimensions of board diversity as well as to addressing endogeneity and sample selection. Additional analysis suggests that board ancestral diversity has a higher impact on GHG emission disclosure in firms with low institutional ownership and high corporate complexity. We interpret these findings as consistent with the view that board diversity enhances monitoring and advising.

Keywords: greenhouse gas emission disclosure, board of directors, board diversity, ancestry

JEL Classification: G30, G41, M14, M40, Q56

---

[1] Faculty of Business Administration, University of Hamburg, Moorweidenstrasse 18, 20148 Hamburg, Germany.

[2] Faculty of Business Administration, University of Hamburg, Moorweidenstrasse 18, 20148 Hamburg, Germany.

[3] Campus Saint-Jean, University of Alberta, 8406 Rue Marie-Anne-Gaboury (91 Street), Edmonton, AB T6C 4G9, Canada.

[4] Moore School of Business, University of South Carolina, 1014 Greene Street, Columbia, SC 29208, USA.

[5] Faculty of Business Administration, University of Hamburg, Moorweidenstrasse 18, 20148 Hamburg, Germany.

We thank Alexandra Niessen-Rünzi and Stefan Rünzi for helpful comments. Part of this research was completed while Johannes A. Barg was a PhD candidate at the Faculty of Business Administration of the University of Hamburg and a visiting scholar at the Saïd Business School of the University of Oxford. Johannes A. Barg acknowledges financial support from the Übersee-Club Hamburg and the Faculty of Business Administration of the University of Hamburg.

Board Ancestral Diversity and Voluntary Greenhouse Gas Emission Disclosure

This draft: May 2022

Abstract

Prior research suggests that the disclosure of greenhouse gas (GHG) emissions—a primary cause of climate change—affects firm valuation. In this paper, we provide new insights into the determinants of the voluntary disclosure of GHG emissions. We show that board ancestral diversity has a positive and statistically significant effect on a firm's scope and quality of voluntary GHG emission disclosure. This effect is robust to controlling for several other dimensions of board diversity as well as to addressing endogeneity and sample selection. Additional analysis suggests that board ancestral diversity has a higher impact on GHG emission disclosure in firms with low institutional ownership and high corporate complexity. We interpret these findings as consistent with the view that board diversity enhances monitoring and advising.

Keywords: greenhouse gas emission disclosure, board of directors, board diversity, ancestry

JEL Classification: G30, G41, M14, M40, Q56

1 Introduction

In the wake of greater public attention to global warming and climate change, the subject of greenhouse gas (GHG) emissions has become increasingly important, not only for society and politics, but also for the business sector. A growing body of research suggests that firms that are conscious of their impact on the environment, and which are voluntarily transparent about their carbon emissions, can enhance their valuation (Clarkson et al. 2013; Matsumura et al. 2014; Plumlee et al. 2015). This is because voluntary GHG emission disclosure reduces the market penalties that are generally imposed on GHG-emitting firms. The difference in median firm value between voluntarily disclosing and non-disclosing firms can range up to 17% (Matsumura et al. 2014; Liesen et al. 2017; Liu et al. 2017). Stakeholders (including investors, employees, and customers) are increasingly interested in firms' GHG emissions policies when making their investment, employment, and consumption decisions. They naturally wish to benefit from the reductions in information asymmetries and adverse selection costs that result from voluntary GHG emission disclosure.

Despite these benefits, not all firms opt to disclose their GHG emissions voluntarily and publicly (Matsumura et al. 2014; Ben-Amar et al. 2017; Griffin et al. 2017). This study, therefore, shifts the focus from the implications of voluntary disclosure to the determinants of the disclosure decision. Given that the board of directors oversees a firm's discretionary management decisions, such as the strategic decision to voluntarily disclose GHG emissions, we center our analysis on the board. We build on findings that the functioning and effectiveness of a group (or board) is determined not only by its structure and composition, but also by how its members collaborate and jointly make strategic decisions (Hong and Page 2001, 2004; Carter et al. 2003). In particular, our study sheds light on the role of board diversity, assuming that it influences the overall level of both collaboration and decision-making among its members. Board diversity reflects heterogeneity in terms of education, work experience, expertise, gender, ethnicity, and age (Anderson et al. 2011). Greater diversity improves the board's monitoring abilities through better independence, less groupthink, and an enhanced discussion culture (Adams and Ferreira, 2009; Bernile et al. 2018), which increase a board's sensibility for the firm's actions and the likelihood to assess them more critically. We posit that more diverse boards foster a firm's voluntary GHG emission disclosure, as they bring greater resources to problem solving, can better understand the potential benefits, and can better monitor conduct. It is important to note that this support of GHG emission disclosure does not stem from the accumulation of certain *environmental* beliefs, but from the diversity in *general* values, thoughts, and beliefs that results in a generally better ability to identify the risks and benefits for the firm, such as the beneficial role of voluntary GHG emission disclosure.

While interest in board diversity has grown dramatically in recent years, a large literature focuses on the role of gender diversity. Ben-Amar et al. (2017), for example, show that higher board gender diversity increases the probability of voluntary GHG emission disclosure among Canadian firms.[1] However, little is yet known about board diversity in cultural or ancestral backgrounds, although the impact of diversity in such deep-level (attitudinal) attributes tends to increase in working groups over time, while the impact of diversity in surface-level (demographic) attributes decreases. Based on evidence from sociology, social psychology, and organizational behavior, Harrison et al. (1998) argue that although surface-level attributes tend to have an impact on the collaboration of working groups (or boards) in the short run, as they are the first characteristics that directors observe of each other, this impact of diversity diminishes over time when directors get used to them. In contrast, deep-level attributes such as values and beliefs, which are determined by a director's culture or ancestry, develop their impact in the longer run, because these characteristics only become apparent over time and fundamentally shape a person's behavior. Therefore, the diversity in these deep-level attributes should be more persistent.

In light of the long-term nature of fighting climate change, considering diversity in attitude-building director characteristics seems imperative. This is especially true when analyzing environment-related firm outcomes such as voluntary GHG emission disclosure. Given recent evidence that board ancestral diversity is associated with a positive impact on a variety of other firm outcomes (Giannetti and Zhao 2019), we also expect to find a positive impact on voluntary GHG emission disclosure.

To test this relationship, we use two primary data sources. First, we obtain ancestry information from Ancestry.com, a database with aggregated personal information and home countries of immigrants who arrived by ship in New York between 1820 and 1957. Applying the common practice of last name

[1] Unlike our study, Ben-Amar et al. (2017) do not analyze the scope and quality of the voluntary GHG emission disclosure. They focus solely on the binary decision to disclose any GHG emissions voluntarily or not.

matching, we determine the likeliest ancestry of each director in our sample's boards of directors. We then calculate diversity within those boards by using Blau's (1977) measure of heterogeneity. Second, we obtain data on voluntary GHG emission disclosure from the Carbon Disclosure Project (CDP). To increase, facilitate, and harmonize GHG emission disclosure, the CDP annually sends out standardized questionnaires to the portfolio firms of its participating institutional investors. It requests various types of environmental information pertaining to firms' GHG emissions. Due to its standardization, the CDP data enables a comprehensive comparison across different firms. Based on the firm's questionnaire answers, we develop four different measures to proxy for different aspects of voluntary GHG emission disclosure: *disclosure scope*, *disclosure verification*, *integrated disclosure score*, and *CDP score*. This set of variables provides us with two advantages: On the one hand, our own determination of *disclosure scope* and *disclosure verification*, based on the available information of how many of a firm's GHG emission scopes are disclosed or externally verified, circumvents inconsistencies and intertemporal changes within figures that are (opaquely) calculated by different providers of sustainability and/or environmental data (Busch et al., 2020; Berg et al., 2021; Kishan, 2022). On the other hand, additionally using the CDP-provided variables *integrated disclosure score* and *CDP score* enables comparison to other studies that include these ready-to-use variables (Döring et al., 2021).

Our final sample consists of 3,670 firm-year observations for disclosure scope and verification, 3,228 firm-year observations for the integrated disclosure score, and 2,830 firm-year observations for the CDP score for S&P 1500 companies between 2010 and 2017 in the U.S. Using ordered logit models, we find a positive and statistically significant impact of board ancestral diversity on voluntary GHG emission disclosure. This effect holds after controlling for several other dimensions of board diversity and firm characteristics known to affect voluntary GHG emission disclosure.

Endogeneity may obviously be a concern in our analysis. We address the reverse causality problem by running a two-stage least squares (2SLS) instrumental variable regression. We apply two instruments that cover both the supply of and demand for directors. Using ancestral diversity in the county where a firm's headquarters is located (supply) and board ancestral diversity of a firm's peers (demand), we show that our results remain robust. Moreover, sample selection may also be a concern, because firms report their GHG emissions voluntarily only after being asked by the CDP. We therefore use a Heckman correction model, and find that our evidence is not driven by sample selection bias.

In additional tests, we observe a substantially stronger effect of board ancestral diversity on voluntary GHG emission disclosure in firms with a lower percentage of institutional ownership and higher corporate complexity. Interpreting institutional ownership as a proxy for a firm's existing monitoring quality, and corporate complexity as a proxy for a firm's need for strong monitoring, these results indicate that board ancestral diversity plays a more important role in firms with greater potential for improvement, i.e., those with weak monitoring and in special need of stronger monitoring.

This paper contributes to the existing literature in three key ways. First, we provide evidence on an important factor that drives the scope and quality of voluntary GHG emission disclosure. While many prior studies focus on external determinants, such as a firm's institutional ownership (Ilhan et al. 2020; Döring et al. 2021; Kordsachia et al. 2021), this study deepens our understanding of the influence of factors inside the firm, namely, the board of directors. Our analysis of the (deep-level) ancestral diversity within a board provides an explanation that goes beyond (surface-level) gender diversity (Ben-Amar et al. 2017).

Second, we contribute to the growing literature on the impact of ancestry on economic decisions. Focusing on ancestral roots and the transferred values and beliefs, we cover a particularly salient part of individual personality that is inherited even after generations. Unlike other work and life experiences, it is not subject to individual choice (Liu 2016; Pan et al. 2017, 2020; Brochet et al. 2019; Giannetti and Zhao 2019; Bae et al. 2020). We believe this persistence of ancestry better matches the long-term nature of fighting climate change.

Third, we enrich the broader literature on board diversity by introducing board ancestral diversity to the most comprehensive model of board diversity (Harjoto et al. 2015). By controlling for board diversity in gender, race, age, outside directorships, tenure, being appointed to the board before or after the current CEO, and expertise, we show that ancestral diversity covers an aspect of diversity that has not yet been captured by other diversity variables.

2 Literature review and hypothesis development

2.1 Voluntary greenhouse gas emission disclosure

In the absence of mandatory GHG emission disclosure, voluntary disclosure has proven to be immensely informative for the overall public as well as value-relevant for the voluntary disclosing firm itself. As the increased transparency assists stakeholders in evaluating the risks and uncertainties arising from the emission of GHGs, the valuation penalties generally imposed on GHG-emitting firms (Hughes 2000; Clarkson et al. 2004; Chapple et al. 2013; Matsumura et al. 2014; Clarkson et al. 2015; Griffin et al. 2017) are reduced when firms voluntarily disclose their GHG emissions (Matsumura et al. 2014; Plumlee et al. 2015; Liesen et al. 2017; Liu et al. 2017).[2] As per Matsumura et al. (2014), the $16 billion median market value of voluntarily disclosing firms is $2.3 billion (or 17%) higher than that of non-disclosing firms.

Furthermore, the reduction in information asymmetries and adverse selection costs reduces firms' cost of capital (Plumlee et al. 2015; Jung et al. 2018)[3], improves their risk profile (Blacconiere and Patten 1994; Cho et al. 2012), and boosts investor, consumer, and employee interest (Branco and Rodrigues 2006; Dhaliwal et al. 2011). Voluntary disclosing firms send a positive signal to the financial market that they can measure their own GHG emissions effectively, which is perceived as a prerequisite for managing the associated risks in the first place (Al-Tuwaijiri et al. 2004; Matsumura et al. 2014). Moreover, active commitment in this yet unregulated area offers the potential to shape pending regulations to the standards of the voluntary disclosing firms, leading to lower future adoption costs (Ilhan et al. 2020).[4]

[2] For example, firms with high levels of GHG emissions are more likely to attract compliance costs, fines, liabilities, litigation, penalties, and costs to adopt future regulation and mandatory environmental standards (Sharfman and Fernando 2008; Matsumura et al. 2014; Griffin et al. 2017; Bolton and Kacperczyk 2021).

[3] However, we note that Clarkson et al. (2013) test multiple implications of voluntary environmental disclosure, and find no significant impact on a firm's cost of capital.

[4] On the downside, however, voluntary disclosing firms not only face direct costs of compiling, preparing, and disseminating the disclosed information, they also face indirect costs. These can include proprietary costs from potential leakages and revelations of internal business information to competitors and other counterparties (Feltham and Xie 1992; Berger and Hann 2007; Ilhan et al. 2020). The latter may lead to lower innovation incentives, particularly harmful in light of GHG emissions because new technologies must be developed to effectively reduce emissions (Breuer et al. 2020). Voluntary disclosure could further provoke litigation and compliance costs imposed by formerly uninformed competitors, regulators, and public interest groups (Healy and Palepu 2001; Matsumura et al. 2014).

Despite the broad evidence on the economic impact of voluntary GHG emission disclosure, little is known about the drivers of the disclosure decision. We aim to provide further insight beyond the findings in Ilhan et al. (2020), Döring et al. (2021), and Kordsachia et al. (2021) of a positive relation between institutional ownership and voluntary GHG emission disclosure. To that end, the following section sheds light on that corporate organism, whose statutory duty is to make the firm's strategic and reporting decisions: the board of directors.

2.2 Board ancestral diversity

When there is separation of ownership and control in firms, the board of directors plays a central governance role. As described in Fama and Jensen (1983), the board oversees the actions of firm management (control) to ensure it is managed in the best interest of shareholders (ownership). Previous research shows that the actions and efficacy of a board depend on its structure and composition. For example, board characteristics such as size, appointment of independent (external) directors, and industry experience influence various central firm outcomes.[5]

A recent stream of literature recognizes the social dynamics within boards of directors and focuses on the manner in which directors collaborate. Identifying boards as essentially small work groups, and building on the psychology and sociology literature, a major theme emerges: The dynamics and efficacy of a group, or, in our case, a board of directors, is affected by the diversity of its members. The more members with different backgrounds, the higher will be the variety of experience, expertise, incentives, networks, and perspectives (Srinidhi et al. 2011; Upadhyay and Zeng 2014).

Diverse boards have richer discussions and more informed deliberations. Information spillovers and a reduction in groupthink generally lead to consideration of a greater variety of aspects and courses of action. More diverse boards are better able to maintain comprehensive oversight of a firm, which in turn enables them to better understand the firm's operations, challenges, and stakeholder demands. Therefore, such boards can better evaluate performance and management's actions. Board diversity also likely leads to greater personal differences between the board and management. The board may thus be

[5] For a review of the literature on board structure and composition, see Hermalin and Weisbach (2003), Adams et al. (2010), and Drobetz et al. (2018).

more efficient in monitoring because less personal or business ties can improve board independence (Carter et al. 2003; Abbott et al. 2012). Summing up the implications of board diversity, we conclude that board diversity increases a board's sensibility for the firm's actions and the likelihood to evaluate them more critically. However, it is important to emphasize that a board's support of certain corporate action does not originate from the *accumulation of certain beliefs*, but from the *diversity in general values, thoughts, and beliefs,* which results in a generally better ability to identify the risks and benefits for the firm.

Previous literature finds that the enhancements in monitoring from greater board diversity can improve the corporate information environment by, e.g., improving stock price informativeness (Gul et al. 2011) and earnings quality (Srinidhi et al. 2011), or reducing financial restatement likelihood (Abbott et al. 2012) and corporate opacity (Upadhyay and Zeng 2014). Along the same lines, we suggest that board diversity also promotes the disclosure of environmental information like GHG emissions. As elaborated in Section 2.1, GHG emissions impose environmental risks and regulatory uncertainties that are relevant for a firm's overall assessment. Therefore, various stakeholder groups are showing growing preferences for this new type of information to be disclosed.

We posit that more diverse boards of directors should be better able to effectively reach and communicate with various stakeholder groups (D'Acunto et al. 2021), and to understand that the importance of GHG emission disclosure arises from more than ethical or moral imperatives. Therefore, diverse boards may address voluntary disclosure during board meetings and subject managers to more knowledgeable monitoring. Raising awareness of the arguments in favor of voluntary GHG emission disclosure, based on both societal preferences and economic benefits, should make firms more likely to engage in voluntary GHG emission disclosure.

Although board diversity may encompass many facets, the vast majority of empirical studies focus on only a small number of diversity attributes, mostly gender and/or race. Only a few studies have chosen a more holistic view, measuring board diversity on more components (Harjoto et al. 2015; Bernile et al. 2018; An et al. 2021). The current state of research is especially unsatisfying, given that the impact of diversity in surface-level (demographic) attributes decreases in working groups over time, while that in deep-level (attitudinal) attributes increases. Based on the evidence from sociology, social psychology, and organizational behavior, Harrison et al. (1998) argue that, although surface-level attributes tend to have an impact on the collaboration of working groups (or boards) in the short run, because they are the first characteristics that directors observe of each other, this impact of diversity diminishes over time when directors get used to them. In contrast, deep-level attributes such values and beliefs, which are determined by a director's culture or ancestry, develop their impact in the longer run because these characteristics only become apparent over time. Therefore, the diversity in these deep-level attributes is more persistent. In light of the long-term nature of fighting climate change, it seems imperative to particularly consider diversity in attitude-building director characteristics when analyzing environment-related firm outcomes.

One intriguing example of such an attitude-building characteristic is director ancestry. Ancestry transfers values and beliefs that influence and shape attitudes and is inherent even after generations (Guiso et al. 2006). Because ancestry is inherited and not voluntarily developed, it has a low overlap with other surface-level director characteristics. Therefore, ancestral diversity appears promising as a proxy for the deep-level diversity in opinions and values on a board (Giannetti and Zhao 2019; Merkley et al. 2020).

Taken together, more diverse boards are more likely to understand the economic benefits of voluntary GHG emission disclosure. They bring both their own expertise and stakeholder preferences into the boardroom and their discussions with management. In turn, greater board heterogeneity provides more resources for problem solving, strategy formulation, and managerial monitoring, eventually increasing firm competitiveness (Williams and O'Reilly 1998; Hong and Page 2001, 2004; Griffin et al. 2021). By further recognizing that the persistence of ancestral diversity optimally fits the long-term nature of fighting the negative consequences of climate change, we formulate our main hypothesis as:

Hypothesis: *Higher board ancestral diversity improves the scope and quality of voluntary GHG emission disclosure.*

3 Data and methodology

3.1 Greenhouse gas emission disclosure

We obtain information on voluntary GHG emission disclosure from the CDP,[6] an international non-profit organization that aims to improve corporate awareness of carbon and climate change risk by increasing and facilitating corporate GHG emission disclosure. The CDP annually sends out standardized questionnaires to the portfolio firms of its participating institutional investors, requesting environmental information such as actual GHG emissions and their external verification. According to the Greenhouse Gas Protocol (2004), this information is classified into three scopes: Scope 1 includes all direct GHG emissions of the firm; scope 2 incorporates all indirect GHG emissions for the generation of purchased energy; and scope 3 subsumes all other indirect GHG emissions that are produced in association with a firm's business operations (for instance, production of purchased materials, outsourced services, employee business travel, and product use). Although the disclosure and scope of the GHG information provided is voluntary, the CDP reports firm behavior in every case, classifying no answer as an active non-disclosure decision.

Table 1 presents the outcome of the CDP survey for our sample firms for 2010 through 2017. Note that 3,670 questionnaires were initially sent out with a request to disclose GHG emissions (column (1)), but only 2,176 answers were received (column (2)). Among those, 1,780 disclosed at least scope 1 emissions publicly (column (3)), and 1,005 verified at least scope 1 emissions externally (column (4)). The sharp decrease in participation across columns, with only 48.50% of firm-years with publicly disclosed scope 1 emissions (column (3)) and only 27.38% with externally verified scope 1 emissions (column (4)), indicates substantial room for higher participation in voluntary GHG emission disclosure.

Insert Table 1 about here

To account for different aspects of voluntary GHG emission disclosure in our further analyses, we extract four different measures from the CDP data. Our first measure, *disclosure scope*, indicates to

[6] Other recent papers that use data on environmental disclosure from the CDP include Kolk et al. (2008), Matsumura et al. (2014), Clarkson et al. (2015), Ben-Amar et al. (2017), Griffin et al. (2017), Jung et al. (2018), Elijido-Ten and Clarkson (2019), Ilhan et al. (2020), and Döring et al. (2021).

what extent a firm discloses its GHG emissions. It takes the value of 0 if no emissions are disclosed, 1 if only scope 1 is disclosed, 2 if scopes 1 and 2 are disclosed, and 3 if all three scopes are disclosed. In line with Ilhan et al. (2020) and Döring et al. (2021), we construct a second measure, *disclosure verification*, as a proxy of GHG emission disclosure's quality and to account for the extent to which a firm's GHG emission disclosure is externally verified. Again, this ordinal variable takes the value of 0 if no emission disclosure is externally verified, 1 if only scope 1 is externally verified, 2 if scopes 1 and 2 are externally verified, and 3 if all three scopes are externally verified. The construction of *disclosure scope* and *disclosure verification*, based on the transparently available information of how many of a firm's GHG emission scopes are disclosed or externally verified, circumvents apparent inconsistencies and intertemporal changes within measures that are calculated (often opaquely) by different providers of sustainability and /or environmental data (Busch et al., 2020; Berg et al., 2021; Kishan, 2022).

In spite of the benefits of these two variables, we additionally use the CDP-provided variables *CDP score* and *integrated disclosure score* to enable comparison to other studies that include these ready-to-use variables (Döring et al., 2021). CDP score is a composite score that evaluates the information disclosed in CDP's questionnaire and awards points for availability and comprehensiveness of specific information. Building on the residual total number of points, firms are ranked by the CDP and receive a score from A (best) to D (worst), which we translate for computational reasons to numerical value of 4 (best) to 0 (worst).

Despite its active promotion by the CDP as well as its good comparability and wide recognition within the academic literature, we notice that the CDP score also considers some performance-related questions that go beyond the pure disclosure of emission information. Therefore, we additionally include CDP's now-ceased *integrated disclosure score*, which concentrates on the assessment of the detailedness and comprehensiveness of the disclosure.[7] In line with the CDP score, we transform the integrated disclosure score's scale from 0 (worst) to 100 (best) into a score with a numerical value of 1 to 4 based on empirical quartiles. Firms with an original disclosure score of 0 also receive a score of 0

[7] Although the CDP reported data for its integrated disclosure score only until 2015, we observe a high correlation of this score with our other three variables: disclosure scope, disclosure verification, and CDP score. We predict the missing values of 2016 and 2017 based on a first-stage OLS regression of disclosure scope, disclosure verification, and CDP score on the integrated disclosure score during the years of available data.

after the transformation. For both the CDP score and the integrated disclosure score, we assign non-disclosing firms to the lowest-scoring category.

3.2 Board ancestral diversity

To obtain a measure of ancestral diversity among the members of a given board, we start our sample construction with annual data on board compositions from ISS (formerly RiskMetrics). ISS provides detailed board data for Standard & Poor's (S&P) 1500 companies that includes directors' names, age, board function, employment status, ethnicity, expertise, gender, independency status, and outside directorships.

Next, we add the directors' ancestries from Ancestry.com. This database provides information on the country of origin of immigrants that arrived via ship at New York between 1820 and 1957. We aggregate this information to the level of last names, and match the most common ancestry of each last name to the directors' last names of our ISS sample (Liu 2016; Pan et al. 2017, 2020; Giannetti and Zhao 2019; Bae et al. 2020; Merkley et al. 2020).

Table 2 describes the distribution of the top 20 ancestries in our sample. Similar to earlier studies, directors with ancestral connections to the United Kingdom constitute the highest proportion (about 38.36% of our sample). The next most populous are directors with ancestries in Germany (14.12%), re-immigrating U.S. Americans (13.70%), Ireland (8.39%), and Italy (5.50%).

Insert Table 2 about here

After establishing the ancestry of each board member, we calculate the ancestral diversity within a specific board in a given year using Blau's (1977, p. 78) widely used measure of heterogeneity:

$$board\ ancestral\ diversity = 1 - \sum_{a \in A} P_a^2, \tag{1}$$

where P_a is the percentage of a board's directors with ancestry a, and A is the entirety of all ancestries present on the board. This index is a measure of the probability that two randomly selected directors from the same board do not have the same ancestry.[8] In particular, it takes values between 0 (lower diversity) and 1 (higher diversity). As a robustness test, we also explore the effect of an alternative measure of diversity (see Section 6.2).

3.3 Controls

We include several control variables that may affect our results. Detailed definitions of all variables are provided in Appendix Table A1. First, to avoid our results being driven by other diversity effects within the board, we follow Harjoto et al. (2015), and incorporate additional board diversity measures based on ISS board data. These include board diversity in gender, race, age, outside directorships, tenure, being appointed to the board before or after the current CEO, and expertise. For each dimension, we repeat Blau's (1977) measure of heterogeneity as described in equation (1), and standardize the results within industry-years between 0 and 1. The sum of these seven standardized diversity measures is our overall diversity control, labelled *div*.[9]

Second, we control for other board characteristics that may influence board decisions. As is common in the literature, based on ISS board data, these include average age and tenure of directors, board size, CEO-chairman duality, whether the CEO is the only company insider on the board of directors, and percentage of independent directors. To limit complexity, we summarize the information content of these variables in one aggregate variable, *board factor*. It is the first component of a principal component analysis on the aforementioned board variables.[10]

Finally, we also include a set of standard firm controls. To ensure comparability with related research on GHG emission disclosure (Döring et al. 2021), these variables include firm size, payout ratio, leverage, profitability, capex, and book-to-market ratio. All firm controls are calculated using fundamental data from Compustat.

---

[8] Although this interpretation relies on either an infinite sample size or sampling with replacement, Blau's (1977) index has proven useful in a variety of empirical studies on board diversity (Campbell and Mínguez-Vera 2008; Miller and del Carmen Triana 2009; Bear et al. 2010; Tuggle et al. 2010; Harjoto et al. 2015; Ben-Amar et al. 2017; Giannetti and Zhao 2019).

[9] Our baseline results remain qualitatively unchanged when we include these additional diversity measures independently to our regression.

[10] Our baseline results remain qualitatively unchanged when we include these additional board measures independently to our regression.

3.4 Summary statistics

For inclusion in our subsequent analysis, we require that all firm-year observations in the CDP database have non-missing data for explanatory and control variables. Following common practice in the literature, we exclude firms in the finance industry (those with security industrial classification (SIC) codes between 6000 and 6999), because this industry tends to be heavily regulated. All continuous variables are corrected for outliers by winsorizing at the 1% and 99% levels.

Due to varying data availability, our final datasets consist of 3,670 firm-year observations for disclosure scope and verification, 3,228 for the integrated disclosure score, and 2,830 for the CDP score between 2010 and 2017 in the U.S. Table 3 presents the respective summary statistics in detail. Correlations between our dependent variables and main explanatory variables are in Table 4.

Insert Tables 3 and 4 about here

3.5 Research design

Given the ordinal structure of our dependent variables, we use an ordered logit model to estimate the coefficients of the following baseline regression equation:

$$disclosure_{i,t} = \alpha + \beta_1 \cdot board\ ancestral\ diversity_{i,t} + \sum_{c \in C} \beta_c \cdot control_{c,i,t} + \iota_i + \tau_t + \varepsilon_{i,t} \quad (2)$$

where *i* and *t* index firms and years, respectively. *Disclosure* is disclosure scope, disclosure verification, integrated disclosure score, or CDP score; *board ancestral diversity* is as defined in Section 3.2; and *control* denotes control *c* out of the entirety of controls *C* from Section 3.3. Industry fixed effect ι_i and year fixed effect τ_t control for constant unobserved industry characteristics and temporal shocks. The regression constant α and the error term $\varepsilon_{i,t}$ complete our model.

Although using non-linear ordered logit models accounts for the ordinal structure of our data, we acknowledge two important differences in comparison to the linear regression models commonly used in empirical finance research. First, although they have the right sign and significance level, the coefficients of non-linear regression models cannot be interpreted as the marginal effect that a one-unit increase in the explanatory variable would have on the dependent variable (Beck et al. 2006). Therefore, we cannot directly compare the magnitudes of our coefficient estimates across subsamples. However, to enable comparability and interpretation, we introduce an additional panel to our main regression tables that reports the elasticities of our model. Strictly speaking, we present the percentage changes that a 1% increase in board ancestral diversity has on the probability that an average firm will have a certain disclosure scope, disclosure verification, integrated disclosure score, or CDP score.[11]

Second, while it is common practice in empirical research to use interactions of the explanatory variable with a moderating variable to examine how the effect of the explanatory variable on the dependent variable is affected by the moderating variable, this practice may result in a misleading coefficient for ordered logit models. In this context, Norton et al. (2004, p. 154) find that "the marginal effect of a change in both interacted variables is not equal to the marginal effect of changing just the interaction term. More surprisingly, the sign may be different for different observations." Therefore, to analyze heterogeneities in the effect of board ancestral diversity on voluntary GHG emission disclosure, we introduce sample split tests as an alternative.

4 Results

4.1 Baseline results

Table 5 presents the results of our baseline regression. As indicated in Panel B, board ancestral diversity has a positive and statistically significant effect on all four GHG emission disclosure variables. Independent of whether voluntary GHG emission disclosure is measured by disclosure scope, disclosure verification, integrated disclosure score, or CDP score, higher board ancestral diversity improves a firm's voluntary GHG emission disclosure. The simultaneously positive and statistically significant coefficient estimates of both board ancestral diversity and the aggregation of other board diversity variables supports the notion that diversity in general matters for voluntary GHG emission disclosure. It also suggests that board ancestral diversity covers a dimension of diversity not captured by other previously used diversity measures.

[11] As is common for determining elasticities, we define the average firm at the mean of the model's independent variables.

Insert Table 5 about here

Further insight into the interpretation of the described effects is in Panel A of Table 5. It shows how a 1% increase in board ancestral diversity changes the average firm's probability of having a certain GHG emission disclosure level. In line with our argument that board ancestral diversity enhances voluntary GHG emission disclosure, we see a decrease in the probability of having the lowest GHG emission disclosure levels. At the same time, the probability of having higher GHG disclosure levels increases.

At the upper end of the disclosure scale, we find that the average firm's probability of having the highest disclosure scope, disclosure verification, integrated disclosure score, or CDP score increases disproportionately by 1.32%, 1.43%, 1.43%, or 1.36%, respectively, in response to a 1% change in board ancestral diversity. Alternatively, we may express this in terms of standard deviation changes. A one-standard-deviation increase in board ancestral diversity would yield analogous increases in the average firm's probability of having the highest disclosure scope, disclosure verification, integrated disclosure score, or CDP score of 21.92%, 23.76%, 23.76%, and 22.60%, respectively.[12]

In summary, we conclude that our hypothesis is confirmed. Higher board ancestral diversity improves the scope and quality of voluntary GHG emission disclosure. We also find support for the more general notion that board heterogeneity brings various backgrounds, experiences, and skills to the boardroom that improve managerial monitoring. In contrast, we find no evidence for the alternative view that the costs from heterogeneity due to, for example, greater communication and coordination (or free-riding) problems from a group of board members with dissimilar backgrounds may protract the decision-making process (O'Reilly et al. 1989).

[12] The corresponding figures for our board diversity (as opposed to board ancestral diversity) variable are 27.01%, 23.31%, 33.02%, and 31.36%. Recognizing that the board diversity variable is a composite board diversity index that captures seven different diversity dimensions (see Table A1 in the Appendix), the effect of board ancestral diversity on voluntary GHG emission disclosure can be considered economically large in both absolute and relative terms, i.e., even when compared to the impact of all other diversity dimensions taken together.

4.2 Instrumental variable regression

Our baseline results indicate a positive and statistically significant relation between board ancestral diversity and voluntary GHG emission disclosure for all four dependent variables. However, endogeneity may be a concern in our analysis and affect the interpretation of the causal relation. One common source of endogeneity is omitted variables correlated with both board ancestral diversity and GHG emission disclosure. These may bias our coefficient estimates. However, given our inclusion of industry and time fixed effects, as well as our large set of control variables that account for a greater variety of firm characteristics from the literature, we assume that our model does not suffer from omitted variable bias. Nevertheless, to alleviate any remaining concerns, we conduct robustness tests in Section 6.1, and show that our results continue to hold when including additional variables.

Another potential source of endogeneity is reverse causality. Our results seem to provide evidence that higher board ancestral diversity drives improved voluntary GHG emission disclosure. However, one could also argue that firms with higher voluntary GHG emission disclosure attract more directors with diverse ancestral backgrounds (or even choose to create more diverse boards to satisfy internal and external political demands). In the latter case, we would also observe a positive relation in our regression. To alleviate this concern, we complement our baseline results with a 2SLS instrumental variable regression. Because the supply of and demand for certain directors essentially shapes the composition of a board, and board composition in turn determines the ancestral diversity, we instrument our main independent variable by two instruments: One covers the impact of director supply; the other covers the impact of director demand.

On the supply side, we use the ancestral diversity of the county in which a firm's headquarters is located as the instrument for board ancestral diversity (Anderson et al. 2011; Giannetti and Zhao 2019). This approach is based on the idea that firms recruit a high proportion of their directors from their local environment (Knyazeva et al. 2013; Alam et al. 2014; Giannetti et al. 2015). Therefore, the local labor market reflects the supply of directors, and the composition of the board should reflect the composition of the local population. For our analysis, this suggests that a board's ancestral diversity should be positively correlated with that of the people. Therefore, similar to Giannetti and Zhao (2019), we base our calculation of *county ancestral diversity* on the 2000 U.S. Census Integrated Public Use

Microdata Series (IPUMS) database from the University of Minnesota (Ruggles et al. 2021). In this database, 74% of the 2000 U.S. census respondents gave specific answers about their ancestral roots. Aggregating the IPUMS information at the county level, we obtain the county-level ancestral diversity in line with our diversity measure at the board level from applying Blau's (1977) index of heterogeneity (see Equation (1)) to each county.

On the demand side, we use average board ancestral diversity among firms of the same peer group (excluding the focal firm) as an instrument for board ancestral diversity (*peers' board ancestral diversity*). A peer group consists of all firms that belong to the same size tercile (small/medium/large) and operating industry (2-digit SIC codes) as the focal firm. In line with Carter et al. (2017) and Bernile et al. (2018), this instrument works on the intuition that firms are prone to peer effects when it comes to board appointments, and will adjust their own boards to match those of their peers. Accordingly, firms also adjust their board ancestral diversity to reflect that of their competitors.

To meet the requirements for a 2SLS instrumental variable regression, our instruments need to satisfy the *exclusion restriction* as well as the *relevance condition*. The exclusion restriction demands both instruments to not have a direct effect on voluntary GHG emission disclosure. Given that a firm's voluntary emission disclosure is usually neither determined by the personal characteristics of local individuals unconnected to the firm nor by the personal characteristics of individual directors in peer firms, our instruments seem to be appropriate choices that do not violate the exclusion restriction.[13] The correlation coefficients in columns (1), (3), (5), and (7) of Table 6 (see bottom of table) show that the two instruments are positively and statistically significantly related to board ancestral diversity, thereby fulfilling of the relevance condition. Furthermore, the Kleibergen–Paap rk Wald F statistics are well above both Staiger and Stock's (1997) rule of thumb (F statistic > 10) and Stock and Yogo's (2005)

[13] We are aware that a potential danger of our supply side instrument could be that the ancestral diversity of the county in which a firm's headquarters is located may not only impact the composition of the group of directors but also of the group of local retail investors and the group of people that are working in local media. The impact of the two latter groups should, however, be limited in our case. On the one hand, the impact of retail investors in corporate strategic decisions making is low in comparison to the more sophisticated group of institutional investors, who usually diversify their portfolio beyond local regions. On the other hand, building on Kölbel et al. (2017), we do not find in untabulated analyses that the local media coverage of corporate misconduct in relation to GHG emissions has any impact on the respective firm's voluntary GHG emission disclosure.

critical value (F statistic > 19.93, given their strictest specification of a 5% significance level and a maximum Wald test size distortion of 10%).[14] Therefore, we conclude the instruments are not weak. Because our concerns of under- and overidentification are alleviated by the statistically significant Kleibergen–Paap rk LM statistics and the statistically insignificant Hansen J statistics, we assume that our instrumental variable regressions are well defined, and that the chosen instruments are appropriate.

The instruments' coefficient estimates in the first-stage regression, the OLS regression of the instruments on board ancestral diversity, are positive and statistically significant. The second-stage regression, which uses the predictions of the first-stage regression, confirms the positive and statistically significant coefficient estimates of our baseline regressions. These results suggest that higher board ancestral diversity drives improved voluntary GHG emission disclosure.

Insert Table 6 about here

4.3 Heckman selection correction

Since the inclusion of a firm in our sample is not random, but rather dependent on the CDP's decision to send out its questionnaire, concerns about selection bias may arise. To address these concerns, we conduct a Heckman (1979) selection correction based on all firms for which we have non-missing data to compute the regressions' diversity, board, and firm controls. After defining a dummy variable (*CDP sample*) that is equal to 1 if a firm is contacted by the CDP in a given year, and 0 otherwise, we estimate a first-stage probit model that regresses all our previously used control variables and fixed effects on the CDP sample dummy. Based on the predictions of this first-stage regression, we calculate the inverse Mills ratio (*lambda*) and include this variable as a control for selection bias in our second-stage ordered logit regression on the CDP score.

Lennox et al. (2012) emphasize that the first-stage regression of the Heckman (1979) selection correction needs at least one exclusion restriction to effectively control for selection bias. Therefore,

[14] The Kleibergen–Paap rk Wald F statistic of 17.48 in the case of the integrated disclosure score is still above Stock and Yogo's (2005) second strictest critical value (F statistic > 11.59). This threshold indicates that at a 5% significance level the maximum Wald test size distortion is still only 15%.

we include two further variables in our first stage that will not affect the dependent variables of the second stage, but affects that of the first stage. For the first exclusion restriction, we build on Matsumura et al. (2014) and Bose et al. (2020), and use the percentage of firms in the same industry that are contacted by the CDP (*industry fraction covered by CDP*). This variable seems to be appropriate because when, in a given industry, a higher proportion of firms is contacted for the questionnaire, the CDP allocates more time and resources to the analysis of this industry. It is then more likely that the CDP discovers additional firms in that industry and the likelihood of any firm in that industry being included in the next CDP sample increases.

Our second exclusion restriction is similar to that of Griffin et al. (2017). It is a dummy variable that equals 1 if a firm received the CDP questionnaire in the year prior to a given year, and 0 otherwise (*inclusion in previous year's CDP sample*). The rationale here is that once a firm has entered the CDP database, it is highly likely that it is contacted again the following year.

Both variables would not meet the requirements for an exclusion restriction within a Heckman (1979) selection correction if they did not only affect the probability to be selected by the CDP, but also the extent to which a firm voluntarily discloses and externally verifies its GHG emissions. Previous literature on voluntary disclosure suggests that once a firm starts to disclose voluntarily, it will continue to do so because investors and other stakeholders expect that voluntary disclosure becomes a routine decision (Stanny, 2013; Matsumura et al., 2014). At the same time, however, managers try to avoid setting disclosure precedents that will be difficult to maintain in the future (Graham et al., 2005). Therefore, although they continue to disclose, managers will chose a manageable level of voluntary disclosure. In our context here, these arguments suggest that the scope of disclosure and external verification of GHG emissions remain an individual firm decision, which is separate from the participation decision and not determined by the mere repeated interaction with the CDP.

Column (1) of Table 7 presents the results of the first stage, and columns (2)–(5) those of the second stage of the Heckman (1979) selection correction. The coefficient estimates of the first-stage probit regression on the CDP sample dummy indicate that both our exclusion restrictions influence the likelihood of being included in the CDP sample positively and statistically significantly. The results of our second-stage ordered logit regression on disclosure scope, disclosure verification, integrated disclosure score, and CDP score are qualitatively similar to those of our main regression. Combined with the insignificant coefficient of the newly introduced variable *lambda*, these findings suggest that selection bias is not a concern in our analyses.

Insert Table 7 about here
----

5 Heterogeneity across firms

Having already established the positive impact of board ancestral diversity on voluntary GHG emission disclosure, this section aims to highlight differences in the cross-section of firms. Given that a board's ancestral diversity affects its monitoring abilities, we focus on heterogeneity with respect to managerial monitoring. We analyze both the current state of monitoring proxied for by institutional ownership, and the current need for monitoring proxied for by corporate complexity. This two-sided analysis allows us to consider both the current supply of and demand for monitoring.

Because monitoring enhances the effect of board ancestral diversity, we expect it to have a more pronounced effect on the voluntary disclosure of GHG emissions for firms with weak monitoring than for those with strong monitoring because those firms generally have less room for improvement. Similarly, the improvements in monitoring through higher board ancestral diversity should be more pronounced in firms that are in greater need of stronger monitoring, as they are expected to be more susceptible to changes.

5.1 Institutional ownership

We begin our analysis of firm heterogeneity with a view of the already prevalent quality of monitoring within firms. To proxy for this current state of monitoring, we use the common perception that institutional investors are the most sophisticated participants in the financial market (Hand 1990; Walther 1997; Bushee 1998; Bartov et al. 2000; Jiambalov et al. 2002). As such, they typically implement the most efficient corporate governance through monitoring and intervention (Shleifer and Vishny 1986).

We obtain firms' *total institutional ownership* based on institutional investors' equity holdings of common stock from the Thomson Reuters Financial (F-13) database. This variable is the percentage of common shares owned by institutional owners. Firms with values equal to or above the median ("high" subsamples) are expected to have stronger monitoring standards; those below ("low" subsamples) are expected to have weaker monitoring standards.

Panel A of Table 8 shows the results of the ordered logit regressions separately for the "high" and "low" subsamples. Subpanel A3 presents the coefficient estimates of the regressions. Across all measures of voluntary GHG emission disclosure, we observe a positive and highly significant effect of board ancestral diversity on GHG emission disclosure for the subsample with low total institutional ownership. In contrast, the effect is consistently insignificant for the subsample with high total institutional ownership. Subpanel A1 reports (similar to our baseline results) that, for the low institutional ownership sample, changes in the average firm's probability of achieving the highest disclosure scope, disclosure verification, integrated disclosure score, and CDP score grow disproportionally when board ancestral diversity rises by 1%. For our most prominent measure, CDP score, this effect is 2.11%. To put this in perspective, consider Subpanel A2, which compares differences in the average firm's probability of having the highest CDP score. When board ancestral diversity increases by 1%, this results in a 331.97% higher effect for firms with low institutional ownership than for those with high institutional ownership.[15]

Recognizing that institutional investors are not homogeneous, however, we run additional analyses on those that are arguably the best monitors: long-term and independent institutional investors. Long-term investors are able to spread out the costs and benefits of monitoring over a longer period, which confers a competitive advantage (Chen et al. 2007; Gaspar et al. 2005). Moreover, institutional investors with long investment horizons have incentives to build relationships with portfolio firms' management, to engage in higher-quality research, and to collect more detailed firm information (Attig et al. 2012).

[15] Observing that some of the estimates in the "high" subgroups are statistically insignificant, and therefore not necessarily different from 0, we consider these estimates rather conservative.

We also note that monitoring by more independent institutional investors should be more effective, as they are unlikely to be biased by personal or business ties to the portfolio firm. We would expect them to prioritize the investment relationship itself (Chen et al. 2007). Therefore, the positive effect of board ancestral diversity on voluntary GHG emission disclosure should be more pronounced in firms with only a small percentage of long-term institutional ownership, and those with a low percentage of independent institutional ownership.

Insert Table 8 about here

We define *long-term institutional ownership* for each sample firm as the percentage of common shares owned by long-term institutional owners. We classify owners as long-term if they have a churn rate (see Gaspar et al. 2005) below the sample's median churn rate. *Independent institutional ownership* is defined as the percentage of common shares owned by independent institutional owners. They are classified as independent if they are mutual funds, investment advisors, or public pension funds (Bushee 1998; Chen et al. 2007). As for *total institutional ownership*, firms with values equal to or above the respective median ("high" subsamples) are expected to have stronger monitoring standards; those with values below the median ("low" subsamples) are expected to have weaker monitoring standards.

Panels B and C of Table 8 present the results of the ordered logit regressions for each subgroup of institutional ownership characteristics on all four of our GHG emission disclosure variables. As predicted, Subpanels B3 and C3 show that board ancestral diversity has a consistently positive and statistically significant impact on voluntary GHG emission disclosure only for those subgroups that have poor external monitoring (those with low long-term institutional ownership (columns (2), (4), (6), and (8) in Panel B) and low independent institutional ownership (columns (2), (4), (6), and (8) in Panel C)).

Again, Subpanels B1 and C1 show the impact is substantial. For example, for an average firm, a 1% increase in board ancestral diversity raises the probability of having the highest CDP score by 2.11% in the low long-term institutional ownership subsample, and by 1.76% in the low independent institutional ownership subsample. As shown in Subpanels B2 and C2, this effect is 134.04% higher than the effect on high long-term institutional ownership firms, and 59.08% higher than the effect on high independent institutional ownership firms.

In summary, the dynamics of board ancestral diversity and GHG emission disclosure, contingent on different monitoring qualities, are attributable to different levels of total, long-term, and independent institutional ownership. We conclude that the positive effect of board ancestral diversity on GHG emission disclosure is more pronounced among firms with low external monitoring, and thus lower overall monitoring.

5.2 Corporate complexity

This section moves our focus to firms' specific monitoring needs. We argue that firms with complex operational and informational environments have a particular need for strong and efficient monitoring to limit the moral hazard and information asymmetries arising from limited oversight (Bushman et al. 2004). We thus use firms' corporate complexity as a measure of monitoring needs.

Beyond managerial monitoring, boards provide top managers with advice and counsel to promote shareholder interests. Fama (1980) notes that managers can turn to their boards for insight and advice to deal with the breadth and depth of operational complexity. Coles et al. (2008) document that complex firms tend to benefit from the advice of larger and more independent boards, while Anderson et al. (2011) show that operationally complex firms maintain more heterogeneous boards. Therefore, our measures of firm complexity can also be interpreted as managers' need for board advice.

Following Coles et al. (2008, 2020), we denote *structural complexity* as the first component of a principal component analysis on firm size, leverage, and number of segments. We define firm size and leverage as before, and number of segments is the number of business segments from the Compustat segment file.[16] We classify firms with values equal to or above the median as firms with high complexity, and thus stronger needs for efficient monitoring ("high" subsamples). Those with values

[16] In contrast to Coles et al. (2008, 2020), we define firm size as the natural logarithm of total assets to ensure consistency with our previous definitions and analyses. However, using Coles et al.'s (2008, 2020) definition of firm size as the natural logarithm of sales does not qualitatively change our results.

below the median are considered firms with less complexity, and thus weaker needs for efficient monitoring ("low" subsamples).

Panel A of Table 9 shows the results of the ordered logit regressions on disclosure scope, disclosure verification, integrated disclosure score, and CDP score separately for both the "high" and "low" subsamples. As indicated in Subpanel A3, the regression coefficients on board ancestral diversity are consistently positive and statistically significant for the "high" subsamples. According to Subpanel A1, a 1% increase in board ancestral diversity increases the average firm's probability of having the highest disclosure scope, disclosure verification, integrated disclosure score, and CDP score disproportionately by 2.03%, 2.24%, 2.30%, and 2.47%, respectively. In relation to the results for the "low" subsamples, Subpanel A2 shows the effects are 53.39% to 77.36% lower for firms with comparably lower complexity and lower monitoring needs.

However, besides determining corporate complexity based on firm characteristics like firm size, leverage, and number of segments, Bushee et al. (2018) suggest it can also be determined by the linguistic complexity of its disclosures. This follows the reasoning that more complex business models and technologies are more difficult to describe, and thus the descriptive text becomes linguistically more complex.

To test how board ancestral diversity affects voluntary GHG emission disclosure across firms with various levels of *linguistic complexity*, we use Bushee et al.'s (2018) "Fog index" of the conference call parts in which a firm presents information about its business. The Fog index, which is a function of the number of words per sentence and the percentage of complex words, approximates how many years of formal education are necessary to comprehend the company presentation on a first reading/listening. As before, we classify firms with a Fog index equal to or above the median as firms with higher complexity and stronger needs for monitoring ("high" subsamples). Those below the median are considered firms with lower complexity and weaker needs for monitoring ("low" subsamples).

Panel B of Table 9 shows the results of the ordered logit regressions of board ancestral diversity on each of our dependent variables separately for firms with high and low linguistic complexity. As before, the coefficient estimate on board ancestral diversity is consistently positive and strongly statistically significant for the "high" subsamples (see Subpanel B3). To illustrate the effect, Subpanel

B1 shows that, for our most prominent measure, the CDP score, a 1% increase in board ancestral diversity increases the average firm's probability of having the highest score by 1.47%.

Finally, Subpanel B2 shows that the impact of board ancestral diversity on having the highest disclosure scope, disclosure verification, integrated disclosure score, or CDP score is substantially lower among firms with lower complexity. Compared to firms with higher complexity, the effects are 31.49% to 73.32% lower in the case of a 1% increase in board ancestral diversity.

Insert Table 9 about here

To sum up our heterogeneity analyses with respect to corporate complexity, we find that the beneficial effect of board ancestral diversity on voluntary GHG emission disclosure is more pronounced among firms with higher corporate complexity. The results hold irrespective of the choice of the proxy for corporate complexity. Our finding highlights that the monitoring enhancing effect of board ancestral diversity is more effective at influencing voluntary GHG emission disclosure in more complex firms that need more monitoring and advising.

6 Robustness tests

We note that our analyses provide conclusive evidence of the positive impact of board ancestral diversity on voluntary GHG emission disclosure. We consider multiple measures of GHG emission disclosure and alleviate concerns about endogeneity through both demand- and supply-based instruments. We also address questions about selection biases through a Heckman (1979) selection correction. However, in the next section, we conduct a series of additional tests to further assess the robustness of our results.

6.1 Additional controls

To address concerns about omitted variables, we add an additional set of control variables to our baseline regression. Detailed information on all additional variables is given in Appendix Table A1.

Panel A of Table 10 incorporates factors that directly refer to the components of voluntary environmental disclosure, i.e., a firm's general disclosure practices and its environmental performance. Following Stanny (2013) and Matsumura et al. (2014), we also control in columns (1) to (4) for whether a firm is subject to the Mandatory Reporting of Greenhouse Gases rule of the U.S. Environmental Protection Agency (*EPA*, 2009), and whether it has therefore already mandatory obligations to report certain GHG information. This could lower the incentives or efforts for firms to provide additional voluntary disclosures of GHG emissions to the CDP. In columns (5) to (8), we control for the *general voluntary disclosure level*, measured by the amount of information that is provided on a firm's website (Boulland et al., 2021). The underlying rationale is that one could assume that firms, which generally disclose more information voluntarily, also tend to disclose more GHG emissions voluntarily. Finally, although there is not yet any agreement on the direction, we acknowledge in columns (9) to (12) for various empirical studies that have found an effect of environmental performance on the willingness to disclose GHG emissions (Al-Tuwaijri et al. 2004; Cho and Patten 2007; Clarkson et al. 2008; Hummel and Schlick 2016). We control for this effect by adding Dyck et al.'s (2019) environmental score (based on data from Thomson Reuters ESG) as a measure of *environmental performance*.

Panel B of Table 10 extends the set of additional controls by also including variables in relation to a firm's corporate governance quality, which in turn may also impact the voluntary GHG emission disclosure. While already controlling for a broad range of board characteristics, we further complement our analysis by considering the impact of foreign (Miletkov et al. 2017) and multi-board directors (Iliev and Roth 2021) on board decisions. Further, we include independence of the audit committee, because this is most likely to be the committee that develops the proposals about a firm's accounting and disclosure policies. Specifically, we add percentage of foreign directors (*board foreignness*), percentage of directors with more than one board mandate (*board distraction*), and percentage of independent directors in the audit committee (*audit committee independence*) as additional controls. We also control for the impact of ownership in the context of CSR activities such as GHG emission disclosure (Masulis et al. 2011; El Ghoul et al. 2016; Dyck et al. 2019; Gloßner 2019; Christensen et al. 2021). To this end, we include *total institutional ownership* (as used in the heterogeneity analysis) and dummy variables that indicate whether a firm has a family or block owner who holds more than 25% of its shares (*family ownership dummy* and *block ownership dummy*).

Both panels of Table 10 show that the inclusion of these additional control variables does not change the direction of board ancestral diversity's impact on disclosure scope, disclosure verification, integrated disclosure score, or CDP score. We continue to observe a significant improvement in voluntary GHG emission disclosure with increases in board ancestral diversity.

Insert Table 10 about here

6.2 Alternative diversity variable

Blau's (1977) index of heterogeneity, which we use as our measure of board ancestral diversity in all regression specifications above, could, in some cases, fail to account for cultural similarities across countries.[17] Therefore, we rerun our analysis using an alternative measure that incorporates differences in ancestral cultures (Giannetti and Zhao 2019; Merkley et al. 2020). To obtain this measure, we follow Giannetti and Zhao (2019), and provide each director with the levels of Hofstede's power distance (PDI), individualism (IDV), and uncertainty avoidance (UAI) belonging to their respective ancestry. We then calculate the pairwise cultural distance between any two directors on a board using the standardized Euclidean distance:

$$pairwise\ cultural\ distance_{i,j} = \sqrt{\sum_{d \in D} \frac{\left(I_{d,i} - I_{d,j}\right)^2}{V_d}}, \tag{4}$$

where $I_{d,i}$ and $I_{d,j}$ are director *i*'s and *j*'s scores on cultural dimension *d*, and V_d is variance in cultural dimension *d*. *D* pools the cultural dimensions power distance, individualism, and uncertainty avoidance.

[17] Using Blau's (1977) index of heterogeneity may suggest that a political border between two ancestral countries is sufficient to ensure two distinct ancestries that transfer different values and beliefs and lead to different impacts on the board's directors. However, this does not take into account cases where systems of values may be shared across borders, especially with neighboring countries like, e.g., Germany and Austria, or the U.K. and Ireland. It is therefore possible that we may observe cases with high values of board ancestral diversity, despite also observing a narrower range of thoughts, beliefs, and values.

We subsequently determine overall *board cultural distance* as the average of all pairwise cultural distances within a board.

Rerunning the ordered logit regressions on each of our measures for voluntary GHG emission disclosure with this new diversity measure results in the coefficient estimates presented in columns (1)–(4) of Table 11. The coefficient estimates of board cultural distance are still positive and statistically significant for all four dependent variables. This implies that our hypothesis of GHG emission disclosure enhancement through higher board ancestral diversity continues to hold when we emphasize the cultural differences between directors' ancestries.

Insert Table 11 about here

6.3 Alternative dependent variable

Thus far we use ordinal variables to underline the extent of voluntary GHG emissions disclosure. To enable comparison with other studies that concentrate on, for example, the pure decision of whether to voluntarily disclose GHG emissions (Matsumura et al. 2014; Ben-Amar et al. 2017; among others), we define additional dummy variables that equal 0 for firms in the lowest category of each GHG emission disclosure variable (i.e., those with no or very bad scope and quality of GHG emission disclosure), and 1 otherwise. The results of the logit regression of board ancestral diversity on this new dummy variable are in columns (5)–(8) of Table 10. For each of our emission disclosure proxies, the coefficient estimate of board ancestral diversity is positive and statistically significant. This indicates that higher board ancestral diversity significantly increases the probability of achieving a level of voluntary GHG emission disclosure better than the worst. This finding continues to support our main argument of improved voluntary GHG emission disclosure through higher board ancestral diversity.

7 Conclusion

In this paper, we find a positive and statistically significant relationship between board ancestral diversity and firms' voluntary GHG emission disclosure. This finding remains robust after addressing endogeneity and sample selection. Additional heterogeneity analysis reveals a higher impact of board ancestral diversity on voluntary GHG emission disclosure for firms with lower institutional ownership and higher corporate complexity. This indicates that board ancestral diversity is more effective in firms with stronger monitoring and advising needs.

Our results are consistent with theories suggesting that board diversity improves monitoring because it reflects variety of experiences, values, skills, and perspectives (Adams and Ferreira, 2009; Bernile et al. 2018). By documenting a positive relationship between board ancestral diversity and voluntary GHG emission disclosure, we contribute to exploring one mechanism that may foster the desirable improvement of environmental disclosure. Our paper offers new evidence in favor of more diversity in corporate boards. Translating our results to the corporate world, we corroborate managerial statements like those of Alphabet Inc.'s CEO Sundar Pichai: "A diverse mix of voices leads to better discussions, decisions, and outcomes for everyone."

References

Abbott, L.J., S. Parker, and T.J. Presley, 2012, Female board presence and the likelihood of financial restatement, *Accounting Horizons* 26(4), 607-629.

Adams, R. B., and D. Ferreira, 2009, Women in the boardroom and their impact on governance and performance, *Journal of Financial Economics* 94(2), 291-309.

Adams, R.B., B.E. Hermalin, and M.S. Weisbach, 2010, The role of boards of directors in corporate governance: A conceptual framework and survey, *Journal of Economic Literature* 48(1), 58-107.

Al-Tuwaijiri, S.A., T.E. Christensen, and K.E. Hughes II, 2004, The relations among environmental disclosure, environmental performance, and economic performance: A simultaneous equations approach, *Accounting, Organizations and Society* 29(5-6), 447-471.

Alam, Z.S., M.A. Chen, C.S. Ciccotello, and H.E. Ryan, Jr., 2014, Does the location of directors matter? Information acquisition and board decisions, *Journal of Financial and Quantitative Analysis* 49(1), 131-164.

An, H., C.R. Chen, Q. Wu, and T. Zhang, 2021, Corporate innovation: Do diverse boards help?, *Journal of Financial and Quantitative Analysis* 56(1), 155-182.

Anderson, R.C., D.M. Reeb, A. Upadhyay, and W. Zhao, 2011, The economics of director heterogeneity, *Financial Management* 40(1), 5-38.

Attig, N., S. Cleary, S. El Ghoul, and O. Guedhami, 2012, Institutional investment horizons and the cost of equity capital, *Financial Management* 42(2), 441-477.

Bae, K.-H., S. El Ghoul, Z.(J.) Gong, and O. Guedhami, 2020, In CEO we trust: Negative effects of trust between the board and the CEO, Working Paper.

Bartov, E., S. Radhakrishnan, and I. Krinsky, 2000, Investor sophistication and patterns in stock returns after earnings announcements, *The Accounting Review* 75(1), 43-63.

Bear, S., N. Rahman, and C. Post, 2010, The impact of board diversity and gender composition on corporate social responsibility and firm reputation, *Journal of Business Ethics* 97, 207-221.

Beck, T., A. Demirgüç-Kunt, and R. Levine, 2006, Bank supervision and corruption in lending, *Journal of Monetary Economics* 53(8), 2131-2163.

Ben-Amar, W., M. Chang, and P. McIlkenny, 2017, Board gender diversity and corporate response to sustainability initiatives: Evidence from the Carbon Disclosure Project, *Journal of Business Ethics* 142, 369-383.

Berg, F., K. Fabisik, and Z. Sautner, 2021, Is history repeating itself? The (un)predictable past of ESG ratings, ECGI Finance Working Paper 708.

Berger, P.G., and R.N. Hann, 2007, Segment profitability and the proprietary and agency costs of disclosure, *Accounting Review* 82(4), 869-906.

Bernile, G., V. Bhagwat, and S. Yonker, 2018, Board diversity, firm risk, and corporate policies, *Journal of Financial Economics* 127(3), 588-612.

Blacconiere, W.G., and D.M. Patten, 1994, Environmental disclosures, regulatory costs, and changes in firm value, *Journal of Accounting and Economics* 18(3), 357-377.

Blau, P.M., 1977, *Inequality and heterogeneity*, The Free Press, New York.

Bolton, P., and M. Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142(2), 517-549.

Bose, S., A. Saha, and I. Abeysekera, 2020, The value relevance of corporate social responsibility expenditure: Evidence from regulatory decisions, *Abacus* 56(4), 455-494.

Boulland, R., T. Bourveau, and M. Breuer, 2021, Corporate websites: A new measure of voluntary disclosure, SSRN Working Paper 3816623.

Branco, M.C., and L.L. Rodrigues, 2006, Corporate social responsibility and resource-based perspectives, *Journal of Business Ethics* 69, 111-132.

Breuer, M., C. Leuz, and S. Vanhaverbeke, 2020, Reporting regulation and corporate innovation, NBER Working Paper 26291.

Brochet, F., G.S. Miller, P. Naranjo, and G. Yu, 2019, Managers' cultural background and disclosure attributes, *The Accounting Review* 94(3), 57-86.

Busch, T., M. Johnson, and T. Pioch, 2020, Corporate carbon performance data: Quo vadis?, *Journal of Industrial Ecology* 26(1), 350-363.

Bushee, B.J., 1998, The influence of institutional investors on myopic R&D investment behavior, *Accounting Review* 73(3), 305-333.

Bushee, B.J., I.D. Gow, and D.J. Taylor, 2018, Linguistic complexity in firm disclosures: Obfuscation or information?, *Journal of Accounting Research* 56(1), 85-121.

Bushman, R., Q. Chen, E. Engel, and A. Smith, 2004, Financial accounting information, organizational complexity and corporate governance systems, *Journal of Accounting and Economics* 37(2), 167-201.

Campbell, K., and A. Mínguez-Vera, 2008, Gender diversity in the boardroom and firm financial performance, *Journal of Business Ethics* 83, 435-451.

Carter, D.A., B.J. Simkins, and W.G. Simpson, 2003, Corporate governance, board diversity, and firm value, *Financial Review* 38(1), 33-53.

Carter, M.E., F. Franco, and M. Gine, 2017, Executive gender pay gaps: The roles of female risk aversion and board representation, *Contemporary Accounting Research* 34(2), 1232-1264.

Chapple, L., P.M. Clarkson, and D.L. Gold, 2013, The cost of carbon: Capital market effects of the proposed emission trading scheme (ETS), *Abacus* 49(1), 1-33.

Chen, X., J. Harford, and K. Li, 2007, Monitoring: Which institutions matter?, *Journal of Financial Economics* 86(2), 279-305.

Cho, C.H., M. Freedman, and D.M. Patten, 2012, Corporate disclosure of environmental capital expenditures, *Accounting, Auditing, and Accountability Journal* 25(3), 486-507.

Cho, C.H., and D.M. Patten, 2007, The role of environmental disclosures as tools of legitimacy: A research note, *Accounting, Organizations and Society* 32(7-8), 639-647.

Christensen, H.B., L. Hail, and C. Leuz, 2021, Mandatory CSR and sustainability reporting: Economic analysis and literature review, *Review of Accounting Studies* 26, 1176-1248.

Clarkson, P.M., X. Fang, Y. Li, and G. Richardson, 2013, The relevance of environmental disclosures: Are such disclosures incrementally informative?, *Journal of Accounting and Public Policy* 32(5), 410-431.

Clarkson, P.M., Y. Li, M. Pinnuck, and G.D. Richardson, 2015, The valuation relevance of greenhouse gas emissions under the European Union Carbon Emissions Trading Scheme, *European Accounting Review* 24(3), 551-580.

Clarkson, P.M., Y. Li, and G.D. Richardson, 2004, The market valuation of environmental capital expenditures by pulp and paper companies, *The Accounting Review* 79(2), 329-353.

Clarkson, P.M., Y. Li, G.D. Richardson, and F.P. Vasvari, 2008, Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis, *Accounting, Organizations and Society* 33(4-5), 303-327.

Coles, J.L., N.D. Daniel, F. Durani, and L. Naveen, 2020, Director connections and board advising, Working Paper, SSRN 2002250.

Coles, J.L., N.D. Daniel, and L. Naveen, 2008, Boards: Does one size fit all?, *Journal of Financial Economics* 87(2), 329-356.

D'Acunto, F., A. Fuster, and M. Weber, 2021, Diverse policy committees can reach underrepresented groups, Working paper, Becker Friedman Institute, SSRN 3901975.

Dhaliwal, D.S., O.Z. Li, A. Tsang, and Y.G. Yang, 2011, Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting, *The Accounting Review* 86(1), 59-100.

Döring, S., W. Drobetz, S. El Ghoul, O. Guedhami, and H. Schröder, 2021, Institutional investor legal origins and corporate GHG emissions disclosure quality, Working Paper, Universität Hamburg, SSRN 3725355.

Drobetz, W., F. von Meyerinck, D. Oesch, and M. Schmid, 2018, Industry expert directors, *Journal of Banking & Finance* 92, 195-215.

Dyck, A., K.V. Lins, L. Roth, and H.F. Wagner, 2019, Do institutional investors drive corporate social responsibility? International evidence, *Journal of Financial Economics* 131(3), 693-714.

El Ghoul, S., O. Guedhami, H. Wang, and C.C.Y. Kwok, 2016, Family control and corporate social responsibility, *Journal of Banking & Finance* 73, 131-146.

Elijido-Ten, E.O., and P. Clarkson, 2019, Going beyond climate change risk management: Insights from the world's largest most sustainable corporations, *Journal of Business Ethics* 157, 1067-1089.

Fama, E.F., 1980, Agency problems and the theory of the firm, *Journal of Political Economy* 88(2), 288-307.

Fama, E.F., and M.C. Jensen, 1983, Separation of ownership and control, *Journal of Law and Economics* 26(2), 301-325.

Feltham, G.A., and J.Z. Xie, 1992, Voluntary financial disclosure in an entry game with continua of types, *Contemporary Accounting Research* 9(1), 46-80.

Gaspar, J.-M., M. Massa, and P. Matos, 2005, Shareholder investment horizons and the market for corporate control, *Journal of Financial Economics* 76(1), 135-165.

Giannetti, M., G. Liao, and X. Yu, 2015, The brain gain of corporate boards: Evidence from China, *Journal of Finance* 70(4), 1629-1682.

Giannetti, M., and M. Zhao, 2019, Board ancestral diversity and firm-performance volatility, *Journal of Financial and Quantitative Analysis* 54(3), 1117-1155.

Gloßner, S., 2019, Investor horizons, long-term blockholders, and corporate social responsibility, *Journal of Banking & Finance* 103, 78-97.

Graham J.R., C.R. Harvey, and S. Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40(3), 3-73.

Greenhouse Gas Protocol, 2004, *A corporate accounting and reporting standard*, World Business Council for Sustainable Development, Conches-Geneva, Switzerland, and World Resources Institute, Washington, DC.

Griffin, D., K. Li, and T. Xu, 2021, Board gender diversity and corporate innovation: International evidence, *Journal of Financial and Quantitative Analysis* 56(1), 123-154.

Griffin, P.A., D.H. Lont, and E.Y. Sun, 2017, The relevance to investors of greenhouse gas emission disclosures, *Contemporary Accounting Research* 34(2), 1265-1297.

Guiso, L., P. Sapienza, and L. Zingales, 2006, Does culture affect economic outcomes?, *Journal of Economic Perspectives* 20(2), 23-48.

Gul, F.A., B. Srinidhi, and A.C. Ng, 2011, Does board gender diversity improve the informativeness of stock prices?, *Journal of Accounting and Economics* 51(3), 314-338.

Hand, J.R.M., 1990, A test of the extended functional fixation hypothesis, *The Accounting Review* 65(4), 740-763.

Harjoto, M., I. Laksmana, and R. Lee, 2015, Board diversity and corporate social responsibility, *Journal of Business Ethics* 132, 641-660.

Harrison, D.A., K.H. Price, and M.P. Bell, 1998, Beyond relational demography: Time and the effects of surface- and deep-level diversity on work group cohesion, *Academy of Management Journal* 41(1), 96-107.

Healy, P.M., and K.G. Palepu, 2001, Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature, *Journal of Accounting and Economics* 31(1-3), 405-440.

Heckman, J.J., 1979, Sample selection bias as a specification error, *Econometrica* 47(1), 153-161.

Hermalin, B.E., and M.S. Weisbach, 2003, Boards of directors as an endogenously determined institution: A survey of the economic literature, *Federal Reserve Bank of New York Economic Policy Review* 9(1), 7-26.

Hong, L., and S.E. Page, 2001, Problem solving by heterogeneous agents, *Journal of Economic Theory* 97(1), 123-163.

Hong, L., and S.E. Page, 2004, Groups of diverse problem solvers can outperform groups of high-ability problem solvers, *Proceedings of the National Academy of Sciences of the United States of America* 101(46), 16385-16389.

Hughes, K.E., 2000, The value relevance of nonfinancial measures of air pollution in the electric utility industry, *The Accounting Review* 75(2), 209-228.

Hummel, K., and C. Schlick, 2016, The relationship between sustainability performance and sustainability disclosure – Reconciling voluntary disclosure theory and legitimacy theory, *Journal of Accounting and Public Policy* 35(5), 455-476.

Ilhan, E., P. Krueger, Z. Sautner, and L.T. Starks, 2020, Climate risk disclosure and institutional investors, Working Paper No. 661/2020, European Corporate Governance Institute.

Iliev, P., and L. Roth, 2021, Do directors drive corporate sustainability?, Working Paper, SSRN 3575501.

Jiambalov, J., S. Rajgopal, and M. Venkatachalam, 2002, Institutional ownership and the extent to which stock prices reflect future earnings, *Contemporary Accounting Research* 19(1), 117-145.

Jung, J., K. Herbohn, and P. Clarkson, 2018, Carbon risk, Carbon risk awareness and the cost of debt financing, *Journal of Business Ethics* 150, 1151-1171.

Kishan, S., 2022, Corporate greenhouse gas data doesn't always add up, Bloomberg, accessed on 27 April 2022: https://www.bloomberg.com/news/newsletters/2022-01-12/corporate-greenhouse-gas-data-doesn-t-always-add-up.

Knyazeva, A., D. Knyazeva, and R.W. Masulis, 2013, The supply of corporate directors and board independence, *Review of Financial Studies* 26(6), 1561-1605.

Kölbel, J.F., T: Busch, and L.M. Jancso, 2017, How media coverage of corporate social irresponsibility increases financial risk, *Strategic Management Journal* 38(11), 2266-2284.

Kolk, A., D. Levy, and J. Pinske, 2008, Corporate responses in an emerging climate regime: The institutionalization and commensuration of carbon disclosure, *European Accounting Review* 17(4), 719-745.

Kordsachia, O., M. Focke, and P. Velte, 2021, Do sustainable institutional investors contribute to firms' environmental performance? Empirical evidence from Europe, *Review of Managerial Science*, forthcoming.

Lennox, C.S., J.R. Francis, and Z. Wang, 2012, Selection models in accounting research, *The Accounting Review* 87(2), 589-616.

Liesen, A., F. Figge, A. Hoepner, and D.M. Patten, 2017, Climate change and asset prices: Are corporate carbon disclosure and performance priced appropriately?, *Journal of Business Finance & Accounting* 44(1), 35-62.

Liu, X., 2016, Corruption culture and corporate misconduct, *Journal of Financial Economics* 122(2), 307-327.

Liu, Y., X. Zhou, J.H. Yang, and A.G.F. Hoepner, 2017, Corporate carbon emissions and financial performance: Does carbon disclosure mediate the relationship in the UK?, Working Paper, SSRN 2941123.

Masulis, R.W., P.K. Pham, and J. Zein, 2011, Family business groups around the world: Financing advantages, control motivations, and organizational choices, *Review of Financial Studies* 24(11), 3556-3600.

Matsumura, E.M., R. Prakash, and S.C. Vera-Muñoz, 2014, Firm-value effects of carbon emissions and carbon disclosures, *The Accounting Review* 89(2), 695-724.

Merkley, K., R. Michaely, and J. Pacelli, 2020, Cultural diversity on Wall Street: Evidence from consensus earnings forecasts, *Journal of Accounting and Economics* 70(1), 101330.

Miletkov, M., A. Poulsen, and M.B. Wintoki, 2017, Foreign independent directors and the quality of legal institutions. *Journal of International Business Studies* 48, 267-292.

Miller, T., and M. del Carmen Triana, 2009, Demographic diversity in the boardroom: Mediators of the board diversity-firm performance relationship. *Journal of Management Studies* 46(5), 755-786.

Norton, E.C., H. Wang, and C. Ai, 2004, Computing interaction effects and standard errors in logit and probit models, *Stata Journal* 4(2), 154-167.

O'Reilly, C.A., III, D.F. Caldwell, and W.P. Barnett, 1989, Work group demography, social integration, and turnover, *Administrative Science Quarterly* 34(1), 21-37.

Pan, Y., S. Siegel, and T.Y. Wang, 2017, Corporate risk culture, *Journal of Financial and Quantitative Analysis* 52(6), 2327-2367.

Pan, Y., S. Siegel, and T.Y. Wang, 2020, The cultural origin of CEOs' attitudes toward uncertainty: Evidence from corporate acquisitions, *Review of Financial Studies* 33(7), 2977-3030.

Plumlee, M., D. Brown, R.M. Hayes, and R.S. Marshall, 2015, Voluntary environmental disclosure quality and firm value: Further evidence, *Journal of Accounting and Public Policy* 34(4), 336-361.

Ruggles, S., S. Flood, S. Foster, R. Goeken, J. Pacas, M. Schouweiler, and M. Sobek, 2021, IPUMS USA: Version 11.0, Minneapolis, MN, https://doi.org/10.18128/D010.V11.0.

Sharfman, M.P., and C.S. Fernando, 2008, Environmental risk management and the cost of capital, *Strategic Management Journal* 29(6), 569-592.

Shleifer, A., and R.W. Vishny, 1986, Large shareholders and corporate control, *Journal of Political Economy* 94(3), 461-488.

Srinidhi, B., F.A. Gul, and J. Tsui, 2011, Female directors and earnings quality, *Contemporary Accounting Research* 28(5), 1610-1644.

Staiger, D., and J.H. Stock, 1997, Instrumental variables regression with weak instruments, *Econometrica* 65(3), 557-586.

Stanny, E., 2013, Voluntary disclosures of emissions by US firms, *Business Strategy and the Environment* 22, 145-158.

Stock, J.H., and M. Yogo, 2005, Testing for weak instruments in linear IV regression, in D.W.K. Andrews and J.H. Stock, Eds.: *Identification and inference for econometric models*, Cambridge University Press, Cambridge, UK.

Tuggle, C.S., K. Schnatterly, and R.A. Johnson, 2010, Attention patterns in the boardroom: How board composition and processes affect discussion of entrepreneurial issues, *Academy of Management Journal* 53(3), 550-571.

U.S. Environmental Protection Agency, 2009, Mandatory reporting of greenhouse gases; Final rule, *Federal Register,* 74 FR 56259.

Upadhyay, A., and H. Zeng, 2014, Gender and ethnic diversity on boards and corporate information environment, *Journal of Business Research* 67(11), 2456-2463.

Walther, B.R., 1997, Investor sophistication and market earnings expectations, *Journal of Accounting Research* 35(2), 157-179.

Williams, K.Y., and C.A. O'Reilly, III, 1998, Demography and diversity in organizations: A review of 40 years of research, *Research in Organizational Behavior* 20, 77-140.

Appendix Table A1: Definitions of variables

Variable	Definition	Source
GHG emission disclosure		
CDP dummy	Dummy variable that equals 1 if a firm's CDP score is higher than the worst score E, and 0 otherwise.	Authors' calculations based on CDP data
CDP sample	Dummy variable that equals 1 if a firm was asked by the CDP to answer its questionnaire in a given year, and 0 otherwise.	Authors' calculations based on CDP data
CDP score	GHG disclosure and performance score provided by the CDP. The score is based on companies' answers to the CDP questionnaire and is translated to numerical values from 0 (worst, E) to 4 (best, A).	CDP data
Disclosure scope	Ordinal value that describes the highest scope of GHG emission disclosure. The variable ranges from 0 (no disclosure) to 3 (disclosure of Scope 1, 2, and 3).	Authors' calculations based on CDP data
Disclosure scope dummy	Dummy variable that equals 1 if a firm's disclosure scope is 1, 2, or 3, and 0 otherwise.	Authors' calculations based on CDP data
Disclosure verification	Ordinal value that describes the highest scope for which the GHG emission has been externally verified. The variable ranges from 0 (no external verification) to 3 (external verification of Scopes 1, 2, and 3).	Authors' calculations based on CDP data
Disclosure verification dummy	Dummy variable that equals 1 if a firm's disclosure verification is 1, 2, or 3, and 0 otherwise.	Authors' calculations based on CDP data
Inclusion in previous years' CDP sample	Dummy variable that equals 1 if a firm was asked by the CDP to answer its questionnaire in the year previous to a given year, and 0 otherwise.	Authors' calculations based on CDP data
Industry fraction covered by CDP	Percentage of firms that are contacted by the CDP to answer its questionnaire in a given year and industry (2-digit SIC code).	Authors' calculations based on CDP data and Compustat
Integrated disclosure dummy	Dummy variable that equals 1 if a firm's integrated disclosure score is higher than the worst score 0, and 0 otherwise.	Authors' calculations based on CDP data
Integrated disclosure score	Disclosure score provided by the CDP that ranks firms based on the quality and completeness of their disclosure on a scale of 0 to 100. For comparability with the CDP score, it is transformed to a scale of 0 (worst) to 4 (best), where 0 describes non-disclosing firms and 1–4 the quartiles of the original disclosure score.	Authors' calculations based on CDP data
Board diversity		
Board ancestral diversity	Index of ancestral diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i\in I} P_i$, where I is the number of ancestry groups and P_i is the proportion of directors in group i.	Authors' calculations based on ISS Director Data and Ancestry.com
Board diversity	Composite board diversity index that is the sum of age, appointment, expertise, gender, outside directorship, race, and tenure diversity.	Authors' calculations based on ISS Director Data
Age diversity	Index of age diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i\in I} P_i$, where I is the number of age groups (<40, 40–49, 50–59, 60–69, >70), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data
Appointment diversity	Index of appointment diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i\in I} P_i$, where I is the number of appointment groups in relation to the CEO appointment (appointed to the board before the CEO, appointed to the board after the CEO), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data
Expertise diversity	Index of expertise diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i\in I} P_i$, where I is the number of expertise groups (financial, consulting, legal, management, other), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data
Gender diversity	Index of gender diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i\in I} P_i$, where I is the number of gender groups (male, female), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data

Outside directorship diversity	Index of outside directorship diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i \in I} P_i$, where I is the number of outside directorship groups (0, 1, 2, 3, >4 outside directorships), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data
Race diversity	Index of race diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i \in I} P_i$, where I is the number of race groups (African-American, Asian, Caucasian, Hispanic, Indian, Middle-Eastern, Native American), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data
Tenure diversity	Index of tenure diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i \in I} P_i$, where I is the number of tenure groups (<3, 3–6, 6–9, 9–12, 12–15 and >15 years), and P_i is the proportion of directors in group i. The index is standardized between 0 and 1.	Authors' calculations based on ISS Director Data
County ancestral diversity	Index of ancestral diversity based on Blau's (1977) index of heterogeneity, i.e., $1-\sum_{i \in I} P_i$, where I is the number of ancestry groups, and P_i is the proportion of county population in group i.	Authors' calculations based on IPUMS 2000 US Consensus Data
Cultural distance	Average cultural distance within the board of directors, measured as the average of board members' pairwise Euclidean distances between their ancestries' levels of power distance, individualism, and uncertainty avoidance.	Author's calculations based on ISS Director Data, Ancestry.com, and Hofstede's cultural dimensions
Peers' board ancestral diversity	Average board ancestral diversity among firms of the same peer group (excluding the focal firm). Firms belong to one peer group if they belong to the same size tercile (small/medium/large) in their operating industry (given by 2-digit SIC code).	Authors' calculations based on ISS Director Data, Ancestry.com, and Compustat
Board characteristics		
Board factor	First factor of the principal component analysis on the board characteristics average age, average tenure, board independence, board size, CEO insider dummy, and chair/CEO duality dummy.	Authors' calculations based on ISS Director Data
Average age	Average age of board members.	Authors' calculations based on ISS Director Data
Average tenure	Average tenure of board members.	Authors' calculations based on ISS Director Data
Board independence	Percentage of independent directors on the board.	Authors' calculations based on ISS Director Data
Board size	Number of board directors.	Authors' calculations based on ISS Director Data
CEO insider dummy	Dummy variable that equals 1 if the CEO is the only company insider on the board of directors, and 0 otherwise.	Authors' calculations based on ISS Director Data
Chair/CEO duality dummy	Dummy variable that equals 1 if the CEO is also the chair of the board of directors, and 0 otherwise.	Authors' calculations based on ISS Director Data
Firm characteristics		
Book-to-market ratio	Ratio of the difference between total assets and total liabilities to the market value of equity.	Authors' calculations based on Compustat
Capex	Ratio of capital expenditures to total assets.	Authors' calculations based on Compustat
Firm size	Natural logarithm of 1 plus total assets.	Authors' calculations based on Compustat
Leverage	Ratio of long- and short-term debt to total assets.	Authors' calculations based on Compustat
Payout ratio	Ratio of common and preferred dividends to net income.	Authors' calculations based on Compustat
Profitability	Ratio of operating income before depreciation to total assets.	Authors' calculations based on Compustat
Additional firm variables		
Audit committee independence	Percentage of independent directors on the audit committee.	Authors' calculations based on ISS Director Data

Board distraction	Percentage of directors with more than one board mandate.	Authors' calculations based on ISS Director Data
Board foreignness	Percentage of foreign directors.	Authors' calculations based on BoardEx
Block ownership dummy	Dummy variable that equals 1 if there is a non-family block ownership of more than 25% in a given firm, and 0 otherwise.	Authors' calculations based on Osiris
Environmental performance	Dyck et al.'s (2019) environmental score based on data from Thomson Reuters ESG.	Authors' calculations based on Thomson Reuters ESG data
EPA	Dummy variable that takes the value of 1 if a firm is subject to the EPA's GHG Mandatory Reporting Rule, and 0 otherwise. Following Stanny (2013) and Matsumura et al. (2014), a firm is subject to this rule if its NAICS is listed in the EPA's publication in the U.S. Federal Register.	Authors' calculations based on Compustat
Family ownership dummy	Dummy variable that takes the value of 1 if an individual family has a block ownership of more than 25% in a given firm, and 0 otherwise.	Authors' calculations based on Osiris
General voluntary disclosure level	Natural logarithm of 1 plus the average size of a firm's website (in bytes) per year.	Data provided on Romain Boulland's GitHub repository (https://github.com/r-boulland/corporate-website-disclosure)
Independent institutional ownership	Percentage of independent institutional owners, where independent institutional owners are classified in line with Bushee (1998) and Chen et al. (2007) as investment companies, independent investment advisors, and public pension funds.	Authors' calculations based on Thomson Reuters 13-F data
Linguistic complexity	Fog index of the firm's presentation during conference calls according to Bushee et al. (2018).	Data provided on Daniel J. Taylor's website (https://danieltayloranalytics.com/data/)
Long-term institutional ownership	Percentage of common shares owned by long-term institutional owners, where long-term institutional owners are categorized as institutional investors if their churn rate is below the median, where the churn rate is defined according to Gaspar et al. (2005).	Authors' calculations based on Thomson Reuters 13-F data
Structural complexity	First factor of the principal component analysis on firm size, leverage, and number of business segments according to Coles et al. (2008).	Authors' calculations based on Compustat
Total institutional ownership	Percentage of common shares owned by institutional owners.	Authors' calculations based on Thomson Reuters 13-F data

Table 1: Sample distribution by year

This table presents the number of U.S. firms in our sample that were asked by the Carbon Disclosure Project (CDP) to complete their questionnaire between 2010 and 2017 (column (1)). Column (2) shows the number that replied. Columns (3) and (4) show how many firms disclose at least their scope 1 emissions publicly, and how many verify at least scope 1 emissions externally.

Year	(1) Firms contacted by CDP	(2) Firms that replied	(3) Firms that disclosed at least scope 1 emissions publicly	(4) Firms that verified at least scope 1 emissions externally
2010	368	254	196	65
2011	377	253	201	104
2012	520	267	221	131
2013	577	285	229	135
2014	570	293	235	141
2015	443	290	234	146
2016	404	262	224	138
2017	411	272	240	145
Total	3,670	2,176	1,780	1,005

Table 2: Directors' top 20 ancestral origins

This table presents the 20 most common ancestral origins of our sample's 6,387 directors.

Origin	Frequency	Percentage
United Kingdom	2450	38.36
Germany	902	14.12
United States	875	13.70
Ireland	536	8.39
Italy	351	5.50
Israel	286	4.48
Scandinavia	204	3.19
Spain	123	1.93
France	119	1.86
China	88	1.38
Netherlands	66	1.03
Greece	48	0.75
Poland	46	0.72
Czechoslovakia	37	0.58
India	36	0.56
Hungary	28	0.44
Portugal	27	0.42
Russia	26	0.41
Japan	22	0.34
Syria	22	0.34
Others	95	1.51
Total	6387	100.00

Table 3: Descriptive statistics

This table reports the frequency as well as the mean, minimum, 25th percentile, median, 75th percentile and maximum values of each variable used in our models. It also shows the respective standard deviations. Detailed variable descriptions are in Table A1.

	N	Mean	Min.	P25	Median	P75	Max.	SD
GHG emission reporting								
Disclosure scope	3670	1.320	0	0	0	3	3	1.400
Disclosure verification	3670	0.630	0	0	0	1	3	1.100
Integrated disclosure score	3228	1.293	0	0	1	3	4	1.460
CDP score	2830	1.210	0	0	0	2	4	1.415
Board diversity								
Board ancestral diversity	3670	0.694	0.278	0.640	0.720	0.778	0.860	0.115
County ancestral diversity	2884	0.874	0.652	0.851	0.885	0.922	0.944	0.061
Peers' board ancestral diversity	3661	0.693	0.519	0.663	0.698	0.729	0.799	0.051
Cultural distance	3668	1.892	0.393	1.382	1.848	2.336	3.664	0.691
Board diversity	3670	4.102	2.064	3.554	4.123	4.650	6.000	0.820
Board characteristics								
Board factor	3670	0.007	-3.572	-0.715	0.279	0.961	1.858	1.230
Firm characteristics								
Firm size	3670	9.189	6.630	8.329	9.040	10.006	12.491	1.228
Payout ratio	3670	0.330	-1.526	0.000	0.267	0.497	3.418	0.541
Leverage	3670	0.277	0.000	0.162	0.268	0.373	0.786	0.165
Profitability	3670	0.150	-0.021	0.098	0.139	0.187	0.376	0.073
Capex	3670	0.051	0.004	0.020	0.036	0.066	0.256	0.047
Book-to-market ratio	3670	0.405	-0.096	0.203	0.341	0.552	1.528	0.290

Table 4: Correlation table

This table presents the pairwise correlation of the dependent variables with the diversity measures used in our analyses. Correlation coefficients larger than 0.5 are high-lighted in bold. Detailed variable descriptions are in Table A1. * indicates significance at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Disclosure scope	1.000								
(2) Disclosure verification	**0.646***	1.000							
(3) Integrated disclosure score	**0.862***	**0.774***	1.000						
(4) CDP score	**0.848***	**0.784***	**0.931***	1.000					
(5) Board ancestral diversity	0.158*	0.109*	0.136*	0.130*	1.000				
(6) County ancestral diversity	0.079*	0.071*	0.095*	0.098*	0.156*	1.000			
(7) Peers' board ancestral diversity	0.161*	0.127*	0.151*	0.164*	0.376*	0.149*	1.000		
(8) Cultural distance	0.126*	0.072*	0.100*	0.099*	**0.651***	0.205*	0.262*	1.000	
(9) Board diversity	0.231*	0.178*	0.253*	0.258*	0.148*	-0.022	0.086*	0.112*	1.000

Table 5: Board ancestral diversity and GHG emission disclosure

This table presents the estimation results for an ordered logit regression of board ancestral diversity and other control variables on disclosure scope, disclosure verification, integrated disclosure score, and CDP score. Detailed variable descriptions are in Table A1. Panel A reports the magnitude of the effect of a 1% increase in ancestral diversity. Columns (1) and (2) give the percentage changes in the probability that an average firm discloses/verifies its GHG emission for no, one, two, or three scopes, and columns (3) and (4) give the percentage changes in the probability that an average firm has an integrated disclosure/CDP score of 0, 1, 2, 3, or 4. Panel B presents the regressions' coefficient estimates. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	Disclosure scope	Disclosure verification	Integrated disclosure score	CDP score
Panel A: Magnitude of the effects				
0	-0.522***	-0.135***	-0.594***	-0.420***
	(0.001)	(0.007)	(0.001)	(0.006)
1	0.594***	1.249**	0.596***	0.704***
	(0.005)	(0.012)	(0.007)	(0.009)
2	0.828***	1.342**	1.056***	1.023***
	(0.002)	(0.011)	(0.002)	(0.007)
3	1.323***	1.434**	1.300***	1.263***
	(0.001)	(0.010)	(0.002)	(0.007)
4			1.434***	1.364***
			(0.002)	(0.006)
Panel B: Regression estimates				
Board ancestral diversity	2.323***	2.127**	2.127***	1.995***
	(0.001)	(0.011)	(0.002)	(0.006)
Board diversity	0.401***	0.293**	0.415***	0.387***
	(0.000)	(0.022)	(0.001)	(0.004)
Board factor	0.169***	0.164**	0.137**	0.132**
	(0.008)	(0.022)	(0.039)	(0.041)
Firm size	0.783***	0.882***	0.877***	0.954***
	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.136	0.135	0.235**	0.209**
	(0.210)	(0.158)	(0.020)	(0.045)
Leverage	-0.610	0.117	-0.652	-0.789
	(0.293)	(0.843)	(0.161)	(0.106)
Profitability	0.148	0.800	1.212	1.266
	(0.908)	(0.534)	(0.300)	(0.348)
Capex	-2.858	-0.219	-3.373	-1.859
	(0.160)	(0.927)	(0.100)	(0.398)
Book-to-market ratio	-0.537	-0.162	-0.544	-0.425
	(0.120)	(0.695)	(0.112)	(0.304)
N	3670	3670	3228	2830
pseudo R^2	0.213	0.206	0.197	0.208
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Table 6: Instrumental variable regression

This table presents the estimation results for ordered logit IV regressions on disclosure scope, disclosure verification, integrated disclosure score, and CDP score. County ancestral diversity and ancestral diversity of peer firms instrument board ancestral diversity, and columns (1), (3), (5), and (7) show the respective first stages of the IV regressions. Detailed variable descriptions are in Table A1. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage	(5) First stage	(6) Second stage	(7) First stage	(8) Second stage
Dependent variable:	Board ancestral diversity	Disclosure scope	Board ancestral diversity	Disclosure verification	Board ancestral diversity	Integrated disclosure score	Board ancestral diversity	CDP score
County ancestral diversity	0.216**		0.216**		0.187**		0.175*	
	(0.019)		(0.019)		(0.039)		(0.071)	
Peers' board ancestral diversity	0.643***		0.643***		0.617***		0.654***	
	(0.000)		(0.000)		(0.001)		(0.001)	
$\widehat{\text{Board ancestral diversity}}$		7.711**		13.484***		9.834***		12.298***
		(0.019)		(0.001)		(0.007)		(0.000)
Board diversity	0.018***	0.315**	0.018***	0.075	0.018***	0.251	0.019**	0.185
	(0.008)	(0.021)	(0.008)	(0.636)	(0.009)	(0.108)	(0.014)	(0.243)
Board factor	0.003	0.123*	0.003	0.082	0.001	0.121	0.001	0.134*
	(0.439)	(0.092)	(0.439)	(0.335)	(0.741)	(0.110)	(0.843)	(0.081)
Firm size	-0.002	0.783***	-0.002	0.796***	-0.000	0.831***	-0.000	0.906***
	(0.686)	(0.000)	(0.686)	(0.000)	(0.912)	(0.000)	(0.910)	(0.000)
Payout ratio	-0.001	0.153	-0.001	0.170*	-0.002	0.230*	-0.000	0.200
	(0.710)	(0.230)	(0.710)	(0.097)	(0.561)	(0.085)	(0.936)	(0.146)
Leverage	0.032	-0.612	0.032	0.006	0.025	-0.457	0.029	-0.748
	(0.235)	(0.369)	(0.235)	(0.993)	(0.295)	(0.417)	(0.271)	(0.225)
Profitability	0.156**	-0.714	0.156**	-1.019	0.167**	0.009	0.156*	-0.272
	(0.039)	(0.647)	(0.039)	(0.504)	(0.032)	(0.995)	(0.055)	(0.865)
Capex	-0.182	-3.250	-0.182	1.276	-0.164	-3.189	-0.154	-1.508
	(0.115)	(0.222)	(0.115)	(0.664)	(0.170)	(0.216)	(0.228)	(0.574)
Book-to-market ratio	0.039**	-0.737*	0.039**	-0.718	0.044**	-0.808*	0.043*	-0.957**
	(0.037)	(0.070)	(0.037)	(0.141)	(0.031)	(0.053)	(0.052)	(0.047)
N	2874	2874	2874	2874	2530	2530	2214	2214
R^2	0.190		0.190		0.181		0.199	
adj. R^2	0.170		0.170		0.159		0.174	
pseudo R^2		0.207		0.196		0.189		0.203
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Correlation of instrument	0.156 / 0.376		0.156 / 0.376		0.147 / 0.368		0.151 / 0.384	
	(0.000) / (0.000)		(0.000) / (0.000)		(0.000) / (0.000)		(0.000) / (0.000)	
Kleibergen–Paap rk LM statistic	6.331		6.331		5.847		5.534	
	(0.042)		(0.042)		(0.054)		(0.063)	
Kleibergen–Paap rk Wald F statistic	23.684		23.684		17.481		20.229	
	(0.001)		(0.001)		(0.002)		(0.002)	
Hansen J statistic	1.283		1.316		1.717		1.192	
	(0.257)		(0.251)		(0.190)		(0.275)	

Table 7: Heckman selection correction

This table presents the results of a Heckman selection correction. Column (1) presents the coefficient estimates of the first-stage probit regression of board ancestral diversity and all previously used control variables and fixed effects on a dummy variable (CDP sample) that equals 1 if a firm is contacted by the CDP in a given year, and 0 otherwise. To ensure an effective control for selection bias, the industry percentage covered by CDP and the inclusion in the previous year's CDP sample are included as additional explanatory variables (exclusion restriction). Columns (2)–(5) present the coefficient estimates of the second-stage ordered logit regression of board ancestral diversity and other control variables on disclosure scope, disclosure verification, integrated disclosure score, and CDP score, where the inverse Mills ratio (lambda) is included as a control for selection bias. Detailed variable descriptions are in Table A1. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	First stage	Second stage			
Dependent variable:	CDP sample	Disclosure scope	Disclosure verification	Integrated disclosure score	CDP score
Industry fraction covered by CDP	5.265***				
	(0.000)				
Inclusion in previous years' CDP sample	3.019***				
	(0.000)				
Board ancestral diversity	-0.158	2.385***	2.055**	2.075***	1.852**
	(0.534)	(0.001)	(0.014)	(0.003)	(0.014)
Board diversity	0.042	0.371***	0.276**	0.385***	0.392***
	(0.452)	(0.003)	(0.038)	(0.002)	(0.003)
Board factor	-0.024	0.170**	0.189**	0.150**	0.135**
	(0.566)	(0.012)	(0.017)	(0.029)	(0.045)
Firm size	0.964***	0.755***	0.865***	0.809***	0.865***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	-0.062	0.163	0.168*	0.243**	0.204*
	(0.350)	(0.154)	(0.079)	(0.022)	(0.052)
Leverage	-0.793*	-0.605	-0.035	-0.685	-0.719
	(0.067)	(0.307)	(0.956)	(0.154)	(0.143)
Profitability	3.233***	-0.162	1.118	0.894	0.896
	(0.000)	(0.917)	(0.478)	(0.503)	(0.543)
Capex	1.166	-4.003*	-1.055	-4.111*	-3.153
	(0.374)	(0.062)	(0.683)	(0.067)	(0.181)
Book-to-market ratio	-0.572***	-0.666*	-0.131	-0.569	-0.459
	(0.000)	(0.095)	(0.787)	(0.166)	(0.313)
Lambda		-0.208	-0.598	-0.691	-0.631
		(0.680)	(0.309)	(0.394)	(0.417)
N	6751	3067	3067	2707	2613
pseudo R^2	0.809	0.222	0.205	0.201	0.204
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Table 8: Heterogeneity across firms regarding institutional ownership

For various subsamples, this table presents the estimation results for an ordered logit regression of board ancestral diversity and other control variables on disclosure scope, disclosure verification, integrated disclosure score, and CDP score. Detailed variable descriptions are in Table A1. Panel A splits the sample along the median value of total institutional ownership, Panel B along the median value of long-term institutional ownership, and Panel C along the median value of independent institutional ownership. In all panels, firm-year observations are categorized as "low" if their value is below the respective median value, and "high" if their value is equal to or above the median value. The first subpanel of each panel reports the magnitude of the effect of a 1% increase in board ancestral diversity. It shows the percentage changes in the probability that an average firm has a disclosure scope, disclosure verification, integrated disclosure score, or CDP score of 0, 1, 2, 3, or 4. Each second subpanel shows the percentage differences in the magnitude of the first subpanel's effect for the highest category of disclosure scope, disclosure verification, integrated disclosure score, or CDP score. The third subpanels present the regressions' coefficient estimates. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Disclosure scope		Disclosure verification		Integrated disclosure score		CDP score	
Panel A: Sample split by median total institutional ownership								
Institutional ownership:	High	Low	High	Low	High	Low	High	Low
Subpanel A1: Magnitude of the effects								
0	-0.089	-1.346***	-0.007	-0.374***	-0.078	-1.390***	-0.030	-1.197***
	(0.294)	(0.000)	(0.708)	(0.006)	(0.217)	(0.000)	(0.534)	(0.000)
1	0.538	-0.139	0.325	1.764***	0.715	0.032	0.444	0.143
	(0.297)	(0.366)	(0.710)	(0.006)	(0.232)	(0.860)	(0.532)	(0.281)
2	0.580	0.423**	0.330	2.035***	0.781	1.025***	0.468	0.982***
	(0.296)	(0.013)	(0.709)	(0.005)	(0.229)	(0.000)	(0.533)	(0.001)
3	0.665	1.703***	0.334	2.293***	0.808	1.669***	0.483	1.750***
	(0.295)	(0.000)	(0.710)	(0.004)	(0.230)	(0.000)	(0.533)	(0.000)
4					0.820	2.065***	0.488	2.108***
					(0.231)	(0.000)	(0.532)	(0.000)
Subpanel A2: Percentage differences in magnitude of the effect for the highest score								
Δ	156.09%		586.53%		151.83%		331.97%	
Subpanel A3: Regression estimates								
Board ancestral diversity	1.026	3.582***	0.485	3.451***	1.191	3.149***	0.708	3.125***
	(0.295)	(0.000)	(0.710)	(0.004)	(0.231)	(0.000)	(0.532)	(0.000)
Board diversity	0.450***	0.361***	0.419**	0.266**	0.501***	0.314**	0.450**	0.344***
	(0.002)	(0.009)	(0.049)	(0.028)	(0.002)	(0.012)	(0.012)	(0.006)
Board factor	0.051	0.288***	0.218*	0.118	0.078	0.190**	0.039	0.197**
	(0.638)	(0.001)	(0.078)	(0.192)	(0.421)	(0.036)	(0.706)	(0.024)
Firm size	0.870***	0.732***	0.878***	0.861***	1.045***	0.774***	1.085***	0.857***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.291*	0.028	0.201	0.107	0.497***	0.045	0.440***	0.037
	(0.053)	(0.838)	(0.308)	(0.422)	(0.000)	(0.736)	(0.000)	(0.786)
Leverage	-1.518*	0.103	-0.187	0.479	-1.694**	0.320	-1.493**	0.137
	(0.081)	(0.880)	(0.833)	(0.559)	(0.034)	(0.615)	(0.044)	(0.846)
Profitability	-0.407	0.738	-0.418	1.226	1.058	1.734	0.724	1.947
	(0.794)	(0.725)	(0.828)	(0.488)	(0.519)	(0.319)	(0.697)	(0.320)
Capex	-0.847	-4.509	0.778	-1.907	-1.055	-6.321*	-0.562	-4.295
	(0.702)	(0.185)	(0.774)	(0.604)	(0.632)	(0.066)	(0.813)	(0.262)
Book-to-market ratio	-0.759*	-0.018	-0.545	0.311	-0.998**	0.030	-0.914*	0.238
	(0.081)	(0.974)	(0.295)	(0.580)	(0.047)	(0.957)	(0.099)	(0.732)
N	1809	1810	1809	1810	1581	1599	1429	1355
pseudo R2	0.211	0.220	0.201	0.212	0.210	0.189	0.212	0.197
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Disclosure scope		Disclosure verification		Integrated disclosure score		CDP score	

Panel B: Sample split by median long-term institutional ownership

Long-term institutional ownership:	High	Low	High	Low	High	Low	High	Low
Subpanel B1: Magnitude of the effects								
0	-0.297	-0.738***	-0.080	-0.122*	-0.337	-0.878***	-0.195	-0.620***
	(0.989)	(0.000)	(0.998)	(0.070)	(0.999)	(0.000)	(0.199)	(0.000)
1	0.595	0.697***	1.204	1.352*	0.677	0.623***	0.601	1.139***
	(0.990)	(0.009)	(0.978)	(0.064)	(0.999)	(0.005)	(0.205)	(0.001)
2	0.723	1.073***	1.257	1.442*	0.934	1.339***	0.756	1.618***
	(0.983)	(0.001)	(0.966)	(0.064)	(0.996)	(0.000)	(0.204)	(0.000)
3	1.008	1.758***	1.310	1.525*	1.078	1.669***	0.862	1.970***
	(0.942)	(0.000)	(0.934)	(0.062)	(0.995)	(0.001)	(0.202)	(0.000)
4					1.158	1.831***	0.902	2.111***
					(0.975)	(0.001)	(0.200)	(0.000)
Subpanel B2: Percentage differences in magnitude of the effect for the highest score								
Δ	74.40%		16.41%		58.12%		134.04%	
Subpanel B3: Regression estimates								
Board ancestral diversity	1.691*	3.063***	1.921*	2.249*	1.704*	2.706***	1.310	3.077***
	(0.082)	(0.000)	(0.083)	(0.062)	(0.057)	(0.001)	(0.200)	(0.000)
Board diversity	0.229*	0.531***	0.238	0.284**	0.312**	0.498***	0.296**	0.510***
	(0.097)	(0.000)	(0.122)	(0.039)	(0.013)	(0.000)	(0.033)	(0.001)
Board factor	0.141	0.211***	0.263***	0.072	0.148	0.133*	0.099	0.164**
	(0.121)	(0.001)	(0.004)	(0.342)	(0.103)	(0.057)	(0.266)	(0.015)
Firm size	0.822***	0.814***	0.924***	0.893***	0.931***	0.879***	0.955***	1.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.212	0.089	0.059	0.178	0.333*	0.146	0.300	0.137
	(0.298)	(0.417)	(0.762)	(0.210)	(0.089)	(0.202)	(0.143)	(0.195)
Leverage	-0.919	-0.375	0.185	0.216	-0.832	-0.395	-0.875	-0.630
	(0.208)	(0.601)	(0.820)	(0.795)	(0.167)	(0.505)	(0.172)	(0.423)
Profitability	0.218	0.029	0.704	0.761	1.696	0.413	1.568	0.879
	(0.885)	(0.986)	(0.712)	(0.656)	(0.269)	(0.770)	(0.327)	(0.620)
Capex	-1.881	-4.895	2.593	-4.481	-1.066	-5.806*	-0.127	-5.881*
	(0.436)	(0.137)	(0.370)	(0.167)	(0.673)	(0.055)	(0.964)	(0.097)
Book-to-market ratio	-0.708*	-0.299	-0.371	-0.108	-0.792*	-0.374	-0.653	-0.288
	(0.070)	(0.530)	(0.489)	(0.825)	(0.057)	(0.443)	(0.161)	(0.651)
N	1809	1810	1809	1810	1586	1594	1524	1260
pseudo R2	0.212	0.247	0.226	0.224	0.199	0.219	0.194	0.255
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Dependent variable:	(1) Disclosure scope	(2)	(3) Disclosure verification	(4)	(5) Integrated disclosure score	(6)	(7) CDP score	(8)
Panel C: Sample split by median independent institutional ownership								
Independent institutional ownership:	High	Low	High	Low	High	Low	High	Low
Subpanel C1: Magnitude of the effects								
0	-0.146*	-1.009***	-0.013	-0.424**	-0.190**	-1.170***	-0.115	-0.998***
	(0.055)	(0.001)	(0.138)	(0.019)	(0.039)	(0.001)	(0.151)	(0.002)
1	1.003*	0.015	1.336	1.125**	1.038**	0.025	0.936	0.103
	(0.060)	(0.906)	(0.174)	(0.018)	(0.038)	(0.859)	(0.147)	(0.410)
2	1.080*	0.417***	1.345	1.422**	1.201**	0.828***	1.030	0.784***
	(0.059)	(0.008)	(0.173)	(0.017)	(0.037)	(0.001)	(0.147)	(0.004)
3	1.219*	1.373***	1.354	1.717**	1.263**	1.393***	1.086	1.444***
	(0.057)	(0.001)	(0.173)	(0.016)	(0.037)	(0.001)	(0.147)	(0.002)
4					1.290**	1.760***	1.107	1.761***
					(0.037)	(0.001)	(0.146)	(0.002)
Subpanel C2: Percentage differences in magnitude of the effect for the highest score								
Δ	12.63%		26.81%		36.43%		59.08%	
Subpanel C3: Regression estimates								
Board ancestral diversity	1.865*	2.840***	1.966	2.644**	1.884**	2.683***	1.613	2.609***
	(0.057)	(0.001)	(0.173)	(0.015)	(0.037)	(0.001)	(0.146)	(0.002)
Board diversity	0.342**	0.463***	0.297	0.346***	0.388**	0.433***	0.362**	0.442***
	(0.026)	(0.001)	(0.169)	(0.003)	(0.013)	(0.000)	(0.042)	(0.001)
Board factor	0.017	0.322***	0.188	0.156*	0.057	0.208**	0.029	0.205**
	(0.851)	(0.000)	(0.106)	(0.067)	(0.496)	(0.013)	(0.733)	(0.016)
Firm size	0.791***	0.750***	0.845***	0.787***	0.980***	0.742***	1.041***	0.810***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.158	0.150	0.180	0.122	0.376***	0.163	0.331***	0.139
	(0.268)	(0.184)	(0.236)	(0.331)	(0.002)	(0.133)	(0.009)	(0.164)
Leverage	-1.759**	0.439	0.112	0.208	-1.729***	0.296	-1.784**	0.038
	(0.022)	(0.514)	(0.890)	(0.779)	(0.010)	(0.648)	(0.012)	(0.954)
Profitability	-1.169	0.968	-1.295	1.170	0.182	1.591	-0.244	1.699
	(0.419)	(0.599)	(0.483)	(0.465)	(0.915)	(0.340)	(0.898)	(0.361)
Capex	-3.035	-2.183	-0.011	-0.937	-2.866	-4.487	-1.987	-2.358
	(0.178)	(0.506)	(0.997)	(0.776)	(0.248)	(0.183)	(0.464)	(0.475)
Book-to-market ratio	-0.235	-0.426	0.180	-0.106	-0.527	-0.229	-0.483	-0.056
	(0.546)	(0.372)	(0.641)	(0.844)	(0.188)	(0.639)	(0.296)	(0.924)
N	1810	1809	1810	1809	1576	1604	1397	1387
pseudo R2	0.200	0.230	0.194	0.199	0.201	0.185	0.202	0.194
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 9: Heterogeneity across firms regarding corporate complexity

For various subsamples, this table presents the estimation results for an ordered logit regression of board ancestral diversity and other control variables on disclosure scope, disclosure verification, integrated disclosure score, and CDP score. Panel A splits the sample along the median value of a complexity (advice) measure, which is similar to Coles et al. (2008, 2020) defined as the factor score based on the number of business segments, the natural log of total assets (as a proxy of firm size), and leverage. Panel B splits the sample along the median value of the complexity measure of Bushee et al. (2018), which is defined as the average annual Fog index (i.e. readability) of the company presentation during conference calls. In all panels, firm-year observations are categorized as "low" if their value is below the respective median value, and "high" if their value is equal to or above the median value. The first subpanel of each panel reports the magnitude of the effect of a 1% increase in ancestral diversity. It shows the percentage changes in the probability that an average firm has a disclosure scope, disclosure verification, integrated disclosure score, or CDP score of 0, 1, 2, 3, or 4. Each second subpanel shows the percentage differences in the magnitude of the first subpanel's effect for the highest category of disclosure scope, disclosure verification, integrated disclosure score, or CDP score. The third subpanels present the regressions' coefficient estimates. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Disclosure scope		Disclosure verification		Integrated disclosure score		CDP score	
Panel A: Sample split by median structural complexity as defined by Coles et al. (2008, 2020)								
Structural complexity:	High	Low	High	Low	High	Low	High	Low
Subpanel A1: Magnitude of the effects								
0	-1.020***	-0.029	-0.208**	-0.001	-1.228***	-0.050	-0.981***	-0.016
	(0.000)	(0.347)	(0.010)	(0.987)	(0.000)	(0.221)	(0.001)	(0.516)
1	0.580**	0.604	1.955**	1.043	0.586**	0.857	0.951***	0.535
	(0.021)	(0.344)	(0.023)	(0.266)	(0.026)	(0.197)	(0.005)	(0.509)
2	1.069***	0.619	2.104**	1.044	1.537***	0.900	1.695***	0.548
	(0.001)	(0.344)	(0.021)	(0.264)	(0.000)	(0.198)	(0.001)	(0.510)
3	2.032***	0.646	2.240**	1.044	2.026***	0.915	2.228***	0.556
	(0.000)	(0.344)	(0.020)	(0.264)	(0.000)	(0.198)	(0.001)	(0.510)
4					2.303***	0.921	2.465***	0.558
					(0.001)	(0.198)	(0.001)	(0.509)
Subpanel A2: Percentage differences in magnitude of the effect for the highest score								
Δ	-68.21%		-53.39%		-60.01%		-77.36%	
Subpanel A3: Regression estimates								
Board ancestral diversity	3.679***	0.957	3.301**	1.516	3.444***	1.335	3.613***	0.810
	(0.000)	(0.344)	(0.020)	(0.264)	(0.001)	(0.198)	(0.001)	(0.509)
Board diversity	0.257	0.418**	0.305**	0.262	0.347**	0.534**	0.378**	0.473*
	(0.108)	(0.031)	(0.023)	(0.301)	(0.012)	(0.010)	(0.011)	(0.058)
Board factor	0.235**	0.001	0.034	0.221*	0.093	0.096	0.017	0.102
	(0.013)	(0.991)	(0.732)	(0.077)	(0.400)	(0.290)	(0.864)	(0.404)
Firm size	0.814***	0.900***	0.817***	0.988***	0.815***	1.193***	0.865***	1.315***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.109	0.148	0.080	0.335	0.211	0.430**	0.234	0.359
	(0.626)	(0.493)	(0.512)	(0.158)	(0.213)	(0.014)	(0.280)	(0.110)
Leverage	-1.444*	-0.154	-1.258	0.362	-1.394*	-0.872	-1.779**	-0.636
	(0.086)	(0.889)	(0.177)	(0.809)	(0.099)	(0.405)	(0.023)	(0.595)
Profitability	0.309	-0.440	-0.386	1.188	0.013	1.198	-0.010	0.294
	(0.875)	(0.816)	(0.839)	(0.645)	(0.993)	(0.569)	(0.995)	(0.896)
Capex	-5.916*	0.239	0.333	-0.942	-2.754	-2.150	-0.465	-1.395
	(0.070)	(0.933)	(0.914)	(0.876)	(0.424)	(0.541)	(0.885)	(0.751)
Book-to-market ratio	-1.182**	0.154	-0.612	0.329	-1.100*	-0.472	-1.156*	-0.669
	(0.029)	(0.776)	(0.301)	(0.684)	(0.057)	(0.375)	(0.098)	(0.281)
N	1487	1487	1487	1487	1332	1258	1156	1093
pseudo R2	0.224	0.211	0.197	0.238	0.186	0.231	0.196	0.239
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Disclosure scope		Disclosure verification		Integrated disclosure score		CDP score	

Panel B: Sample split by median linguistic complexity as measured by Bushee et al. (2018)

Linguistic complexity:	High	Low	High	Low	High	Low	High	Low
Subpanel B1: Magnitude of the effects								
0	-0.532***	-0.352**	-0.119***	-0.046	-0.512***	-0.522**	-0.329**	-0.292*
	(0.001)	(0.015)	(0.000)	(0.902)	(0.006)	(0.032)	(0.043)	(0.098)
1	1.242***	0.667**	2.627***	0.679	0.942***	0.419**	0.954*	0.484
	(0.002)	(0.018)	(0.001)	(0.438)	(0.010)	(0.045)	(0.050)	(0.117)
2	1.494***	0.855**	2.713***	0.712	1.343***	0.851**	1.204**	0.724
	(0.001)	(0.016)	(0.000)	(0.346)	(0.006)	(0.030)	(0.048)	(0.107)
3	1.986***	1.188**	2.789***	0.744	1.550***	1.048**	1.392**	0.878
	(0.001)	(0.014)	(0.000)	(0.293)	(0.007)	(0.025)	(0.047)	(0.104)
4					1.661***	1.138**	1.471**	0.930
					(0.007)	(0.024)	(0.046)	(0.104)
Subpanel B2: Percentage differences in magnitude of the effect for the highest score								
Δ	-40.18%		-73.32%		-31.49%		-36.78%	
Subpanel B3: Regression estimates								
Board ancestral diversity	3.270***	1.946**	4.074***	1.089	2.442***	1.676**	2.143**	1.354
	(0.001)	(0.014)	(0.000)	(0.290)	(0.007)	(0.024)	(0.046)	(0.104)
Board diversity	0.405***	0.413***	0.167	0.380***	0.288**	0.538***	0.268*	0.495***
	(0.006)	(0.005)	(0.282)	(0.007)	(0.041)	(0.000)	(0.092)	(0.001)
Board factor	0.191*	0.125	0.245*	0.099	0.179*	0.079	0.140	0.132*
	(0.075)	(0.155)	(0.084)	(0.259)	(0.093)	(0.303)	(0.153)	(0.071)
Firm size	0.804***	0.930***	0.891***	1.020***	0.904***	1.003***	0.974***	1.131***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.187	0.129	0.107	0.185	0.212*	0.214	0.149	0.200*
	(0.240)	(0.283)	(0.512)	(0.102)	(0.065)	(0.216)	(0.272)	(0.095)
Leverage	-1.435*	0.371	-1.535	1.303	-0.965	-0.183	-1.146	-0.304
	(0.084)	(0.595)	(0.114)	(0.139)	(0.160)	(0.763)	(0.135)	(0.648)
Profitability	-1.446	-0.305	0.001	0.890	-1.183	1.773	-1.939	2.834
	(0.351)	(0.859)	(0.999)	(0.681)	(0.459)	(0.254)	(0.268)	(0.145)
Capex	-4.148	-1.858	-0.428	-0.090	-3.216	-2.959	-2.295	-0.442
	(0.110)	(0.542)	(0.902)	(0.977)	(0.239)	(0.338)	(0.411)	(0.903)
Book-to-market ratio	-0.524	-0.574	0.008	-0.131	-0.488	-0.673	-0.344	-0.387
	(0.255)	(0.313)	(0.987)	(0.858)	(0.239)	(0.204)	(0.462)	(0.556)
N	1752	1752	1752	1752	1531	1551	1366	1335
pseudo R2	0.230	0.269	0.233	0.249	0.201	0.238	0.209	0.254
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: Additional controls

This table presents the estimation results for various robustness tests. To avoid bias from omitted variables, we add in columns (1)-(4) of Panel A a dummy that indicates a firm's subject to the EPA's Mandatory Reporting of Greenhouse Gases rule, in columns (5)-(8) a firm's general voluntary disclosure level, and in columns (9)-(12) a firms environmental performance. Furthermore, Panel B includes additional board characteristics in columns (1)–(4), and additional ownership characteristics in columns (5)–(8) to our baseline ordered logit regressions of board ancestral diversity and other control variables on disclosure scope, disclosure verification, integrated disclosure score, and CDP score. Detailed variable descriptions are in Table A1. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	(1) Disclosure scope	(2) Disclosure verification	(3) Integrated disclosure score	(4) CDP score	(5) Disclosure scope	(6) Disclosure verification	(7) Integrated disclosure score	(8) CDP score	(9) Disclosure scope	(10) Disclosure verification	(11) Integrated disclosure score	(12) CDP score
Panel A: Additional controls with regard to disclosure and environmental performance												
Board ancestral diversity	2.322***	2.148**	2.124***	1.986***	1.604**	1.529*	1.442*	1.348*	2.187***	1.754*	1.766***	1.362*
	(0.001)	(0.010)	(0.002)	(0.007)	(0.031)	(0.080)	(0.053)	(0.087)	(0.002)	(0.056)	(0.007)	(0.072)
Board diversity	0.402***	0.298**	0.416***	0.388***	0.356***	0.250*	0.360***	0.327**	0.206*	0.177	0.231*	0.182*
	(0.000)	(0.021)	(0.001)	(0.004)	(0.003)	(0.065)	(0.008)	(0.024)	(0.085)	(0.233)	(0.059)	(0.096)
Board factor	0.174***	0.171**	0.139**	0.135**	0.121*	0.105	0.078	0.075	0.117	0.094	0.059	0.043
	(0.007)	(0.019)	(0.037)	(0.039)	(0.081)	(0.174)	(0.281)	(0.299)	(0.150)	(0.258)	(0.427)	(0.545)
Firm size	0.784***	0.884***	0.878***	0.955***	0.848***	0.928***	0.936***	1.001***	0.339***	0.446***	0.384***	0.419***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
Payout ratio	0.137	0.133	0.235**	0.207**	0.151	0.127	0.240**	0.243**	0.148	0.133	0.264**	0.183
	(0.211)	(0.160)	(0.020)	(0.047)	(0.220)	(0.261)	(0.043)	(0.040)	(0.294)	(0.363)	(0.027)	(0.213)
Leverage	-0.630	0.067	-0.658	-0.802	-0.988	0.035	-0.929*	-1.083*	-0.176	0.545	-0.036	-0.376
	(0.282)	(0.910)	(0.159)	(0.101)	(0.144)	(0.958)	(0.084)	(0.058)	(0.783)	(0.398)	(0.943)	(0.444)
Profitability	0.086	0.706	1.185	1.227	0.486	1.013	1.564	1.493	-1.270	-0.005	-1.036	-1.522
	(0.946)	(0.587)	(0.313)	(0.364)	(0.733)	(0.501)	(0.239)	(0.341)	(0.363)	(0.997)	(0.401)	(0.256)
Capex	-2.461	0.318	-3.206	-1.547	-4.111**	-0.116	-3.363	-2.149	-1.382	1.207	-1.956	-0.827
	(0.229)	(0.893)	(0.119)	(0.488)	(0.043)	(0.963)	(0.125)	(0.384)	(0.560)	(0.576)	(0.331)	(0.684)
Book-to-market ratio	-0.538	-0.167	-0.545	-0.425	-0.546	-0.252	-0.563	-0.548	-0.262	0.379	-0.243	-0.123
	(0.122)	(0.688)	(0.113)	(0.306)	(0.122)	(0.565)	(0.133)	(0.234)	(0.518)	(0.391)	(0.486)	(0.771)
EPA	-0.311	-0.510	-0.118	-0.212								
	(0.408)	(0.317)	(0.733)	(0.604)								
General voluntary disclosure level					0.097**	0.100*	0.127***	0.130***				
					(0.012)	(0.052)	(0.000)	(0.000)				
Environmental performance									0.030***	0.026***	0.029***	0.033***
									(0.000)	(0.000)	(0.000)	(0.000)
N	3670	3670	3228	2830	3123	3123	2743	2413	3234	3234	2863	2509
pseudo R2	0.213	0.207	0.198	0.208	0.231	0.225	0.211	0.222	0.318	0.274	0.270	0.296
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Dependent variable:	(1) Disclosure scope	(2) Disclosure verification	(3) Integrated disclosure score	(4) CDP score	(5) Disclosure scope	(6) Disclosure verification	(7) Integrated disclosure score	(8) CDP score
Panel B: Additional controls with regard to the board of directors and ownership								
Board ancestral diversity	2.130***	1.786**	1.813**	1.560**	2.174***	1.891**	2.156***	1.846**
	(0.004)	(0.049)	(0.015)	(0.037)	(0.002)	(0.027)	(0.002)	(0.011)
Board diversity	0.388***	0.281*	0.470***	0.456***	0.372***	0.288**	0.418***	0.390**
	(0.003)	(0.098)	(0.000)	(0.000)	(0.003)	(0.045)	(0.005)	(0.012)
Board factor	0.126*	0.135	0.118	0.130*	0.198***	0.191**	0.171**	0.178**
	(0.076)	(0.106)	(0.110)	(0.060)	(0.005)	(0.022)	(0.018)	(0.012)
Firm size	0.758***	0.863***	0.862***	0.963***	0.727***	0.842***	0.836***	0.896***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.098	0.065	0.228**	0.219*	0.236*	0.134	0.372***	0.349***
	(0.415)	(0.547)	(0.026)	(0.053)	(0.092)	(0.305)	(0.004)	(0.009)
Leverage	-1.172**	0.211	-0.903*	-1.032*	-0.602	0.325	-0.621	-0.627
	(0.039)	(0.715)	(0.081)	(0.075)	(0.322)	(0.571)	(0.236)	(0.238)
Profitability	-0.459	0.705	1.042	1.336	0.159	0.803	1.486	1.562
	(0.730)	(0.600)	(0.399)	(0.386)	(0.905)	(0.539)	(0.235)	(0.275)
Capex	-1.612	-0.487	-4.043*	-1.819	-1.987	0.140	-2.970	-1.404
	(0.459)	(0.861)	(0.065)	(0.508)	(0.341)	(0.954)	(0.173)	(0.535)
Book-to-market ratio	-0.608*	-0.216	-0.706**	-0.500	-0.287	0.032	-0.293	-0.120
	(0.096)	(0.623)	(0.033)	(0.253)	(0.433)	(0.942)	(0.404)	(0.777)
Board foreignness	0.704	1.021	1.349**	1.425**				
	(0.283)	(0.135)	(0.023)	(0.044)				
Board distraction	1.027***	0.800**	0.621	0.591				
	(0.009)	(0.044)	(0.124)	(0.191)				
Audit committee independency	1.715	-2.221	-0.889	-0.817				
	(0.201)	(0.328)	(0.521)	(0.652)				
Total institutional ownership					-1.269*	-0.985	-0.830	-1.138
					(0.050)	(0.190)	(0.193)	(0.100)
Family ownership dummy					-0.225	-0.375	-0.176	-0.077
					(0.617)	(0.330)	(0.667)	(0.849)
Block ownership dummy					-0.283	-0.051	0.024	0.079
					(0.502)	(0.892)	(0.931)	(0.795)
N	2806	2806	2430	2037	3142	3142	2742	2362
pseudo R2	0.215	0.203	0.206	0.218	0.211	0.206	0.203	0.212
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 11: Alternative specifications

This table presents the estimation results for various robustness test. Columns (1)–(4) present coefficient estimates of ordered logit regressions on disclosure scope, disclosure verification, integrated disclosure score, and CDP score, where the explanatory diversity variable board ancestral diversity is substituted for by board cultural distance. Columns (5)–(8) report the outcomes of a logit regression of board ancestral diversity and other control variables on a disclosure scope dummy, disclosure verification dummy, integrated disclosure dummy, and CDP dummy. Detailed variable descriptions are in Table A1. Standard errors are clustered at the firm and year level. p-values are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	(1) Disclosure scope	(2) Disclosure verification	(3) Integrated disclosure score	(4) CDP score	(5) Disclosure scope dummy	(6) Disclosure verification dummy	(7) Integrated disclosure score dummy	(8) CDP score dummy
Board ancestral diversity					2.424***	1.957**	2.508***	2.449***
					(0.001)	(0.021)	(0.001)	(0.001)
Board cultural distance	0.394***	0.218*	0.274**	0.237*				
	(0.002)	(0.063)	(0.024)	(0.092)				
Board diversity	0.392***	0.299**	0.416***	0.390***	0.497***	0.350**	0.589***	0.550***
	(0.001)	(0.021)	(0.001)	(0.005)	(0.000)	(0.021)	(0.000)	(0.000)
Board factor	0.171***	0.162**	0.138**	0.132**	0.186***	0.180**	0.183**	0.174**
	(0.006)	(0.024)	(0.037)	(0.042)	(0.004)	(0.017)	(0.021)	(0.024)
Firm size	0.806***	0.887***	0.887***	0.957***	0.859***	1.027***	1.164***	1.183***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout ratio	0.136	0.131	0.233**	0.211**	0.136	0.158	0.324**	0.342**
	(0.221)	(0.152)	(0.020)	(0.042)	(0.226)	(0.144)	(0.031)	(0.029)
Leverage	-0.527	0.182	-0.598	-0.746	-0.939*	0.151	-0.761	-0.920
	(0.357)	(0.754)	(0.203)	(0.131)	(0.082)	(0.799)	(0.210)	(0.139)
Profitability	0.229	0.929	1.353	1.398	0.018	0.918	2.741	1.921
	(0.857)	(0.473)	(0.251)	(0.306)	(0.990)	(0.514)	(0.119)	(0.293)
Capex	-2.247	-0.069	-2.894	-1.537	-4.125**	0.065	-6.419**	-4.648*
	(0.276)	(0.977)	(0.171)	(0.490)	(0.034)	(0.979)	(0.011)	(0.076)
Book-to-market ratio	-0.503	-0.121	-0.484	-0.369	-0.488	-0.129	-0.520	-0.530
	(0.139)	(0.765)	(0.152)	(0.363)	(0.160)	(0.739)	(0.150)	(0.191)
N	3668	3668	3226	2828	3498	3446	3052	2670
pseudo R2	0.213	0.204	0.196	0.206	0.277	0.283	0.361	0.367
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES