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Does genetic diversity on corporate boards lead to improved environmental performance?

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ABSTRACT

We study the effects of boards' genetic diversity on corporate environmental performance. Using a multidimensional information set for 3690 US firms during the period from 2005 to 2019, and three different measures of genetic diversity, we find that, pursuant to the diversity theory, which posits that diversity improves the quality of management decisions and business ethics, genetic diversity leads to improved environmental performance. We also find that genetic diversity improves carbon and governance performance, and ESG disclosure. Particularly, a one percentage point increase in boards' genetic diversity will increase the carbon performance, measured by the inverse of the carbon emissions to total assets ratio, and environmental performance by 3.54% and 5.57%, respectively. Our results remain robust to different model specifications, while also controlling for endogeneity. In terms of policy implications, results suggest that the key to tackling climate challenges is to promote boards' genetic diversity.

1. Introduction

Can boards' genetic diversity improve corporate environmental performance? Over the last years, we have witnessed a rising interest in mitigating and offsetting environmental degradation and climate change. Businesses in the US have come under scrutiny by regulators and must shrink their carbon footprint and eventually show their ethical principles. Therefore, it is not surprising that environmental and carbon performance has become a key corporate goal of firms, and has been enshrined in firms' overarching business strategy. Both the literature on climate finance and boards' diversity literature have grown in recent years (Ashraf and Galor, 2013a,b; Delis et al., 2017; Bolton and Kacperczyk, 2021). Yet, we have little knowledge on the role of boards' genetic diversity in firms' environmental performance (Liang and Renneboog, 2017; Giannetti and Zhao, 2019). In this study, we argue that boards' diversity, with a particular focus on genetic diversity, might be a key impetus to promoting corporate environmental and carbon performance.

As early as Hambrick and Mason (1984), researchers have highlighted that environmental performance is influenced by the legal, ethical and social environment, as well as various governance characteristics, mirroring boards' diversity. There are different types of boards' diversity, such as race, age, origin, culture, gender, and genetic. Irrespective of the type of diversity, a diverse board dictates corporate policies, drives corporate governance mechanisms, and provides both a means and an end to corporate social responsibility (Girardone et al., 2021). In this context, legislative bodies and regulatory agencies have taken the stewardship

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of ensuring that board and workforce diversity becomes commonplace in the corporate sector.[1] According to DiMaggio and Powell (1983), such initiatives can be regarded as coercive isomorphism, a key tenet of organisational change, according to which sustainable development pressures are induced by governments, as well as national and supranational regulatory agencies. In anticipation of such legislative and regulatory changes, board-diversity pledges were made by large multinational companies (e.g., Bank of America Merrill Lynch, Meta, and Alphabet, among others),[2] which succumbed to the pressure orchestrated by large institutional investors,[3] and exerted by their stakeholders. While anecdotal evidence displays concerted efforts and a trend towards greater workplace and board diversity over time and across companies, industries, and states, there is no firm empirical evidence as to whether such a trend is conducive to improved environmental performance, or more generally, the environmental, social and governance (ESG) performance.

In our study, we focus on genetic diversity-related measure of board heterogeneity; henceforth, (boards') genetic diversity or board heterogeneity. On the one hand, the general *theory of diversity* of Nehring and Puppe (2002) attaches special emphasis on biodiversity. This is also related to the *gene-culture co-evolution theory*, which focuses on the evolutionary success of homo sapiens (Gintis, 2011), and indicates that boards' genetic diversity provides a rich source of information that captures differences in deep-rooted social, psychological, ethical, and behavioural characteristics shaped over thousands of years. Following this logic, Nehring and Puppe (2002) and Docquier et al. (2014) show that boards' diversity is associated with new, smarter ideas that translate into superior business solutions in response to the fast-changing business environment and competitive pressures within the industry. Similarly, Girardone et al. (2021) demonstrates that board's diversity can promote innovation and productivity at the firm level. On the other hand, the *theory of conflict* of Pelled et al. (1999) represents an antagonistic theoretical stand, which envisages a negative relation between corporate carbon/environmental performance and boards' diversity. Although the theoretical support of a positive relationship between genetic diversity and corporate environmental (carbon) performance is evidently strong, it is ultimately an empirical question as to which direction this relationship goes. Informed by this body of research, our study seeks to demystify a missing link by examining whether boards' genetic diversity is conducive to improved environmental performance while controlling for a plethora of issues, such as model functional form, measurement of key variables, endogeneity, and different sub-samples. We postulate that genetic diversity can influence a decision-making process at a firm level, which in turn enhances environmental performance. A more heterogeneous board would provide diverse and innovative management solutions to climate change, in contrast to a homogeneous board.

This paper measures boards' genetic diversity in line with Ashraf and Galor (2013a,b). Our genetic diversity score is a number, measured with the data from the HGDP-CEPH Human Genome Diversity Cell Line Panel, and the framework of Ramachandran et al. (2005). As in Delis et al. (2017), we calculate the standard deviation by firm-year of genetic diversity across the country-specific values assigned to each board member of a firm in our data-set. Each director's genetic diversity score is linked to the country of nationality of that director. This is by no means an easy task as there are 53 ethnic groups, which are not only historically native to their current geographical location but have also been isolated from genetic flows from other ethnic groups. Population geneticists typically measure the extent of diversity in genetic material across individuals within a given population (such as an ethnic group) using the so-called expected heterozygosity measure. Specifically, the expected heterozygosity measure for a given population is constructed by geneticists using sample data on allelic frequencies, i.e., the frequency with which a "gene variant" or allele occurs in the population sample. Given allelic frequencies for a particular gene or DNA locus, it is possible to compute a gene-specific heterozygosity statistic (i.e., the probability that two randomly selected individuals differ with respect to a given gene), which when averaged over multiple genes or DNA loci yields the overall expected heterozygosity for the relevant population. As a robustness check, we alternately use the average country-level genetic score instead of its standard deviation.

To quantify a firm's environmental performance, we use two different variables. First, the environmental performance is measured by means of the Thomson Reuters environmental pillar, which consists of three categories: emissions' reduction, product innovation, and resource reduction. Our second variable measures greenhouse gas emissions (carbon footprint), since these emissions are at the heart of the climate-change debate.

Fig. 1 further motives our discussion as it illustrates the variability in both genetic diversity and environmental (carbon) performance, measured by corporate environmental performance (CEP) and corporate carbon performance relative to total assets (CCPA) across US states. This variability across states might reveal some hidden associations between the key variables. For example, firms located in the Southeast region and parts of the Northwest region appear to have higher genetic diversity scores and relatively higher environmental and carbon performance compared to firms located in the central states. However, note that not all states follow the same pattern (e.g., QR). Fig. 1 provides some general support to our premise that higher genetic diversity on the firms' board of directors is conducive to a superior corporate carbon/environmental performance.

[1] Whilst the US federal government has limited instruments to influence corporate environmental behaviour, (Please see https://news.bloomberglaw.com/bloomberg-law-analysis/analysis-mandated-board-diversity-takes-center-stage-in-2021.) some of the US states have adopted regulations that aim to attain improved corporate environmental, social and governance performance. For instance, on 30/09/2020, the Assembly Bill 979 (AB 979) was enacted in California, which requires minimum representation by minority individuals on corporate boards. (Please see https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201920200AB979). Similar legislation has been enacted in other 12 US states.

[2] Please see https://hbr.org/2016/07/why-diversity-programs-fail.

[3] The demand for larger workplace diversity metrics and disclosures is spearheaded by large institutional investors. For instance, BlackRock recognise that diversity is multifaceted and mandates boards. Therefore, "in identifying potential candidates, boards should take into consideration the full breadth of diversity, including personal factors, such as gender, ethnicity, race, and age, as well as professional characteristics…". For further details, please see https://www.blackrock.com/corporate/literature/fact-sheet/blk-responsible-investment-guidelines-us.pdf.

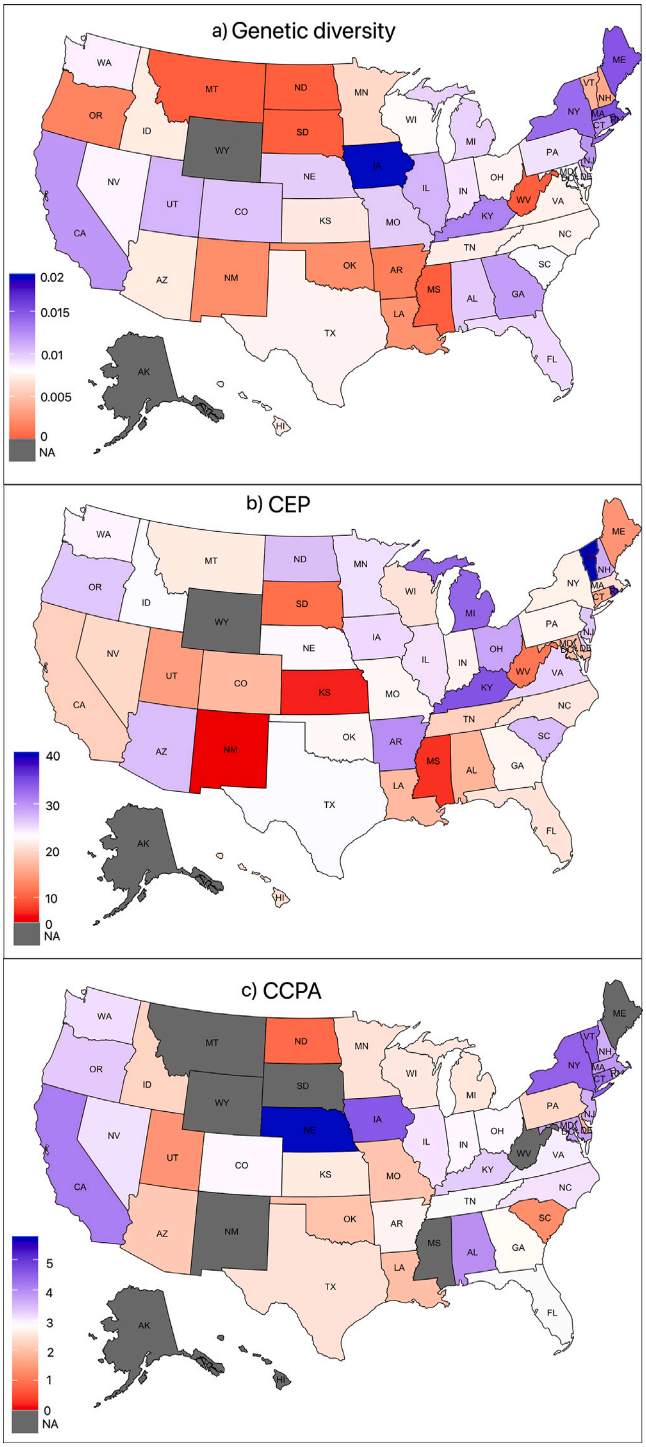

Fig. 1. Genetic diversity, environmental performance, and carbon performance per US state. Notes: The maps display the mean values of genetic diversity, CEP and CCPA per state. States with less than 2 firms are excluded (See Table A5). The grey area indicates the unavailability of observations per state. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

We employ two empirical approaches to investigate how boards' genetic diversity influences environmental (carbon) performance. First, linear panel data models allow exploiting the continuous nature of our data set, which leads to more informative statistical inference. In our linear models, the quantity of greenhouse gas emissions is used as a continuous measure of corporate carbon performance. We employ OLS and 2SLS to estimate these models. Specifically, the 2SLS estimation method entails two instrumental variables to estimate boards' genetic diversity – the migratory distance and ultraviolet exposure – which are arguably exogenous to environmental (carbon) performance (Delis et al., 2017). Second, we employ discrete response (i.e., probit and logit) models. On the one hand, these models enable us to assess how the probability that a firm is categorised as quartile-m environmental performer or discloser changes when genetic diversity increases by one percentage point. On the other hand, unlike in linear models with constant partial slope, in discrete response models, a change in the probability that the firm is quartile-m environmental performer or discloser responds non-linearly when genetic diversity rises by one percentage point. Responses of firms are categorical and are ranked or ordered from lower to higher categories. These discrete response models are estimated by means of the maximum likelihood estimation (MLE) method.

Our sample comprises 3690 US firms over the period from 2005 to 2019, though as part of the robustness analysis, we expand our sample to the global level. The main results indicate that genetic diversity improves corporate ESG performance and disclosures. Importantly, this enhancement mainly stems from the environmental pillar, which validates our main expectation. Further decomposing the corporate environmental performance provides compelling evidence that the carbon performance is where we observe the main improvement due to genetic diversity. As a part of our comprehensive robustness analysis, we employ a World sample to investigate whether results are country-specific, and we separate between high and low profitability and gender diversity firms. Thereafter, we consider two alternative genetic diversity measures. First, we calculate the average (or country-level) genetic diversity score across all members of the board. Second, we opt for an alternative genetic diversity measure (i.e., genetic fractionalisation and boards' average genetic score), informed by Giannetti and Zhao (2019). Overall, our main finding remains unaltered, implying that genetic diversity can improve firms' carbon and environmental performance and therefore mitigate the crisis of climate change.

Research into the impact of genetic diversity on the economy, business, and financial markets is still in an embryonic stage. Delis et al. (2017) study the effects of genetic diversity on economic growth and firm performance, whereas (Giannetti and Zhao, 2019; Becker et al., 2020) examine its implications on risk aversion and volatility. In general, genetic diversity is found to boost growth and improve firm performance. Our research contribution is mainly empirical. Particularly, we seek to enhance our understanding of boards' genetic diversity in at least three ways. First, we are the first to evaluate how the board members' genetic diversity influences corporate ESG performance. Second, we delve deeper into the response of the environmental performance pillar by exploiting the relationship between corporate carbon performance and boards' genetic diversity, which so far has escaped academic scrutiny. Moreover, it is worth noting that corporate ESG disclosures in the US were voluntary until 2021. Arguably, such disclosures were determined by corporate policies and were driven by stakeholders' demands. Thus, our third contribution is to ascertain if greater corporate transparency regarding ESG performance (with special emphasis on the environmental pillar) is attained by firms that are governed by more heterogeneous boards.

The rest of the paper is structured as follows. Section 2 outlines the theoretical framework of the study. Section 3 describes the data, sample selection, and variables of the study. Section 4 pins down the empirical methodology and reports the main results. Section 5 presents several robustness checks. Finally, Section 6 concludes.

2. Theoretical identification

The importance of economic and social diversity has been emphasised for some time (Ely et al., 2012). For example, demographic, human, and social diversity leads to (i) economic competitive advantage (Ely et al., 2012; Williams and O'Reilly III, 1998), (ii) corporate innovations (Bernile et al., 2018; Griffin et al., 2021), (iii) diversified M&As (Fang et al., 2018), (iv) different type of knowledge and opportunities (Williams and O'Reilly III, 1998), (v) higher levels of economic development (Eagle et al., 2010), and (vi) strategic change of a company (Triana et al., 2014). In addition, studies show that organisational diversity is instrumental in (a) creating firm value (Fang et al., 2018), (b) lowering firm risk through more robust corporate policy choices (Bernile et al., 2018), and (c) increasing investment returns (Gompers et al., 2016). In this light, it is surprising that 91% of US companies hire American CEOs, despite only 4.4% of the world population being American (Yonker, 2017), which places a restraint on board diversity.

Recent studies of economic growth theory emphasise the importance of genetic diversity (Ashraf and Galor, 2013a,b; Delis et al., 2017). Becker et al. (2020) uncover evidence of the implication of this measure on the inter-societal differences in economic preference, particularly risk aversion and trust. Genetic diversity can also drive financial market size (Cardella et al., 2018). Delis et al. (2017) exploit panel variation across firms listed in the stock market in North America and the United Kingdom to show that adding members to a firm's board of directors from countries of origin with differing levels of genetic diversity increases its corporate performance. The findings of Delis et al. (2017) contribute to the literature strands of corporate governance, management, and financial economics, and shed light on the significance of genetic diversity for the effectiveness of the board's decision-making process. Their contribution is founded on the premise that interpersonal differences in cultural, psychological, and other characteristics, embedded in genetic diversity, cannot be captured by alternative measures of diversity. Therefore, understanding the value of boards' genetic diversity in achieving a range of corporate objectives, in addition to financial performance, is of utmost importance.

We build on the above literature to argue that the normative prescription of a single objective (i.e., profit maximisation) is inconsistent with the operating and strategic principles of modern firms (Obloj and Sengul, 2020). Indeed, companies are compelled to set out multiple corporate objectives, including those that address corporate environmental (and carbon) performance. Within this strand of research, firms with more diverse boards, and separation between chair and CEO roles, show higher levels of sustainability. Differentiation of board members' cognitive diversity can bring new perspectives and views that enhance the quality of company operations and corporate reporting. Therefore, the level of interpersonal diversity within the group of top management can crystallise into a governance mechanism that can reduce the economic incentives for misreporting or under-reporting environmental and financial information. Moreover, the board's diversity is a valuable corporate resource, since it enhances problem-solving skills and improves the decision-making processes of the company across multiple objectives, including environmental (and carbon) performance.

The link between diversity and decision-making at a group level, i.e., in a firm's board, has been investigated by Forbes and Milliken (1999) and Burgess and Tharenou (2002). The diversity theory postulates that the decision-making process of a group is greatly assisted by the variability in personal perspectives and behaviours of a diverse group vis-à-vis a non-diverse group (Singh and Vinnicombe, 2004). The diversity theory finds that diversity in groups improves decision-making because groups show variability in underlying demographic traits of their members, as well as in perspectives and opinions that would simplify complex decisions (Forbes and Milliken, 1999). If variability is absent in groups, i.e., boards, this would come at the cost of variability in critical thinking, and it would lead to a collective group thinking that would not support disagreement among group members (Janis, 1982) and thereby would lead to herding in decision making.

Following this literature, the theorisation of our analysis derives from the diversity theory of Nehring and Puppe (2002) that considers diversity functions based on biodiversity. The authors argue that biodiversity assists a problem-solving management culture within a firm and promotes innovation and productivity (Nehring and Puppe, 2002; Docquier et al., 2014). Moreover, in firms with more diverse boards, corporate innovation practices are encouraged (Griffin et al., 2021). This is because more diverse boards are more creative than more homogeneous boards (Østergaard et al., 2011). They can bring different knowledge and perspectives to problem-solving (Dezsö and Ross, 2012). Firms with more diverse boards, and separation between chair and CEO roles, show higher levels of corporate sustainability. In addition, firms with higher board gender diversity are less often sued for environmental infringements (Liu, 2018). Along similar lines, Adams and Ferreira (2009) and Boone et al. (2019) demonstrate that boards with higher gender and nationality diversity achieve higher standards of corporate responsibility as well as financial outcomes. Also, an increase in board gender diversity leads to a significant reduction in bank-specific credit risk (Kinateder et al., 2021), financial and operating risk of firms in developing countries (Mohsni et al., 2021). In a similar vein, board tenure diversity is associated with lower firm risk (Ji et al., 2021). Moreover, Atif et al. (2021) shows that higher boards' gender diversity can increase renewable energy consumption in the US as female directors improve environmental performance. In a related study, Zhang et al. (2021) find that firms with a stronger female presence on board tend to use more renewable energy.

In this paper, we investigate whether genetic diversity, which is a crucial diversity characteristic, would affect firm decisions making with regard to environmental (and carbon) performance. Also, in consonance with the positive relationship between diversity and environmental performance, the gene-culture co-evolution theory underscores the importance of culture and complex social organisation to the evolutionary success of Homo sapiens (Gintis, 2011). According to this theory, since culture is both constrained and promoted by the human genome, human cognitive, affective, and moral capacities are the product of evolutionary dynamics involving the interaction of genes and culture. This co-evolutionary process has endowed society with preferences that go beyond the self-regarding concerns emphasised in traditional economic and biological theories, and with a social epistemology that facilitates the sharing of intentionality across minds. This theory is applicable to global challenges, such as environmental degradation and climate change, which cannot be solved by self-regarded decision-makers. Gintis (2011) asserts that this theory can explain the salience of such other-regarding values as a taste for cooperation, fairness, and retribution, as well as the capacity to empathise, to name just a few. In the gene-culture co-evolution theory, a genetically diverse firm should be able to better deal with social dilemmas such as acting against climate change. The positive relation between board genetic diversity and the environmental performance of a firm is also advocated by the agency theory. This theory posits that the separation of ownership and control of a firm translates into an agency relationship subject to principal and agent conflict (Jensen and Meckling, 1976) and different risk appetites (Eisenhardt, 1989). Board members have a fiduciary duty to shareholders to run the firm in their interests. To effectively monitor the managers on behalf of the shareholders, the board needs to be endowed with an appropriate mix of experience, expertise, and qualifications (Bear et al., 2010). Pursuant to the agency theory, board gender diversity can be regarded as an effective tool for monitoring firm managers. For instance, a genetically diverse board can be better positioned to monitor how the firm adheres to its environmental strategy and implements environmental policy.

Building on the above discussion, we examine the underlying relationship between genetic diversity and environmental performance. If the agency, diversity, and gene-culture co-evolution theories are valid, our expectation is that higher genetic diversity would be associated with enhanced environmental performance.

As part of our research problem, we additionally examine whether genetic diversity might improve corporate social responsibility. Diversity theory could also underpin corporate social responsibility; that is, both social and governance activities. Therefore, genetic diversity might influence overall corporate ESG performance, its underlying components (environmental, social, and governance pillars), sub-components of the environmental pillar, such as research and development (R&D), energy efficiency (EnergyE), as well as individual elements of corporate carbon performance (e.g., Scope 1, Scope 2 and Scope 3). For a similar reason, genetic diversity might also impact ESG disclosure (e.g., Kim and Starks, 2016; Dyck et al., 2020). In this regard, Hambrick and Mason (1984) propose the upper echelons theory according to which board members would analyse their roles and decisions derived from their own personal perspectives. Board members differ in experiences, values, personalities, and, importantly for this study, their genetics. Following from Cannella et al. (2009) on strategic leadership, understanding what drives corporate social responsibility preferences of firms requires examining the underlying diversity across board members for those firms.

It should be noted that, even though genetic diversity might boost environmental performance, an opposite sign should not be surprising. This is because genetically diverse boards need to overcome several challenges. First, firms have limited resources, and thus managers should decide on the best allocation of such resources according to their preferences. For example, a genetically diverse board might pay more attention to financial performance and less to environmental performance. In general, diversity can lead to intra-group (Pelled, 1996) and inter-group (Arbatlı et al., 2020) conflicts. An astounding finding in Arbatlı et al. (2020) is that population diversity, determined predominantly during the exodus of humans from Africa tens of thousands of years ago, has been paramount to civil conflicts, which manifest in the prevalence of mistrust, the divergence in preferences for public goods and re-distributive policies, as well as in a higher degree of ethnic, linguistic, and religious fractionalisation and polarisation. To further polarise the debate on the diversity-conflict nexus within this body of research, Pelled et al. (1999) exploit the mediating role of conflict on the complex relationship between diversity and performance. They distinguish between 'good' and 'bad' conflicts, and they find that functional background diversity drives intra-group task ('good') conflict, whereas race and tenure (age) diversity increase (decrease) the prevalence of intra-group emotional ('bad') conflict. Pelled et al. (1999) demonstrate that task conflict enhances performance whereas emotional conflict tends to diminish it. So, as long as disparities in functional background and age are conducive to superior environmental performance, firms' managers have the incentive to ensure that the board structure is optimised in terms of such disparities. However, if the members of the board are also diverse in terms of race and tenure, then the net effect on the company's environmental performance might depend on the balance of the two opposing forces. More crucially, if in a board with functional, cultural, or genetic disparities mistrust becomes commonplace, this can translate into increased turnover rates for group members (Pelled, 1996; Wagner et al., 1984; Alesina and La Ferrara, 2000). It is also worth noting that diversity can hinder effective communication among the members of the board (Lazear, 1999; Nehring and Puppe, 2002). Thus, the negative relation between genetic diversity and environmental performance is founded on the theory of conflict.

3. Data

We employ four main data sources. First, firms' corporate governance characteristics are from BoardEx. Second, firms' financial characteristics are from Thomson Reuters' Worldscope, and Datastream. Third, environmental characteristics are from REFINITIV. Fourth, genetic diversity scores are from Ashraf and Galor (2013b). We additionally gathered data from various other sources, such as Worldwide Governance Indicators, World bank Indicators, Hofstede's database,[4] Kaufmann et al. (2011), and POLITI V, to construct some of the control variables. Our initial world sample enumerates 112,542 firm-year observations; however, we are interested in the US sample, which includes 65,259 observations. Then, we merge financial and environmental with board data, and our final sample drops to 19,551 observations, consisting of 3690 US firms. [In the Online Appendix (see Table A2), the sample selection process is thoroughly explained.] Our geographical choice is based on the fact the US ratified the Paris Agreement in 2016, one year before withdrawing from it, only to re-join it in 2021. Therefore, it is interesting to examine whether and, if so, how this alteration in the US political stance in relation to climate change shapes the green corporate governance of US firms. Moreover, the US has the largest stock market in the world attracting large international investors, which also justifies our focus on the US. To this end, we download all available CEO information from BoardEx from 2005, the starting point of environmental and GHG data availability, to 2019. During this period, we find 664,208 year-director observations, whose firms reported environmental and financial data. As shown in Fig. 2, only 6.43% of these directors are non-Americans, while the rest are mainly coming from the UK and Canada. In Tables A3, A4, and A5 in the Online Appendix, we show the composition of our sample according to industry, year, and state, respectively. Our unbalanced sample spans 36 industries and 50 US states. Descriptive statistics show that the smallest number of firms (679) included in our sample is in 2009, during the Global Financial Crisis, whereas the largest number of firms was recorded in 2019.

3.1. Measuring corporate carbon and environmental performance

We use the total volume of greenhouse gas (GHG) emissions (or CO2 emissions equivalent) of firms to measure corporate carbon performance. Total CO2 emissions equivalent can be decomposed into direct emissions (Scope 1), which represent the emissions owned or operated directly by the company (e.g., combustion of fuel), indirect emissions (Scope 2), which are related to the electricity consumption, and Scope 3, which quantifies emissions from activities not owned or controlled by the reporting firm. The term "equivalent" is related to other GHG emissions. For example, apart from carbon dioxide (CO2), which has the largest proportion of GHG emissions (82%) (EPA, 2019),[5] we also consider other gases such as Methane (CH4), Nitrous Oxide (N2O), and Chlorofluorocarbons (CFCs). Corporate carbon performance (CCPA) is our first dependent variable. In line with previous studies (Tzouvanas et al., 2020a; Hsu et al., 2021), the CCPA is calculated as the negative of the log-ratio of GHG to total assets of a firm in a given year:

$$CCPA_{i,t} = -ln\left(\frac{GHG_{i,t}}{Total\ Assets_{i,t}}\right) \tag{1}$$

An increase in $CCPA_{i,t}$ shows an improvement in corporate carbon performance per value unit of assets.

Our second dependent variable, which has also been used by previous studies (Avramov et al., 2022; Hsu et al., 2021), is the natural logarithm of corporate environmental performance score (CEP), produced by REFINITIV, and it is scaled in 3 different ways.

[4] See more details about the Hofstede's scores in: Hefstede insights. Country comparison. https://www.hofstede-insights.com/country-comparison/.

[5] See more details about the Environmental Protection Agency (EPA) in the link below: https://www.epa.gov/newsroom/epa-year-review-2019.

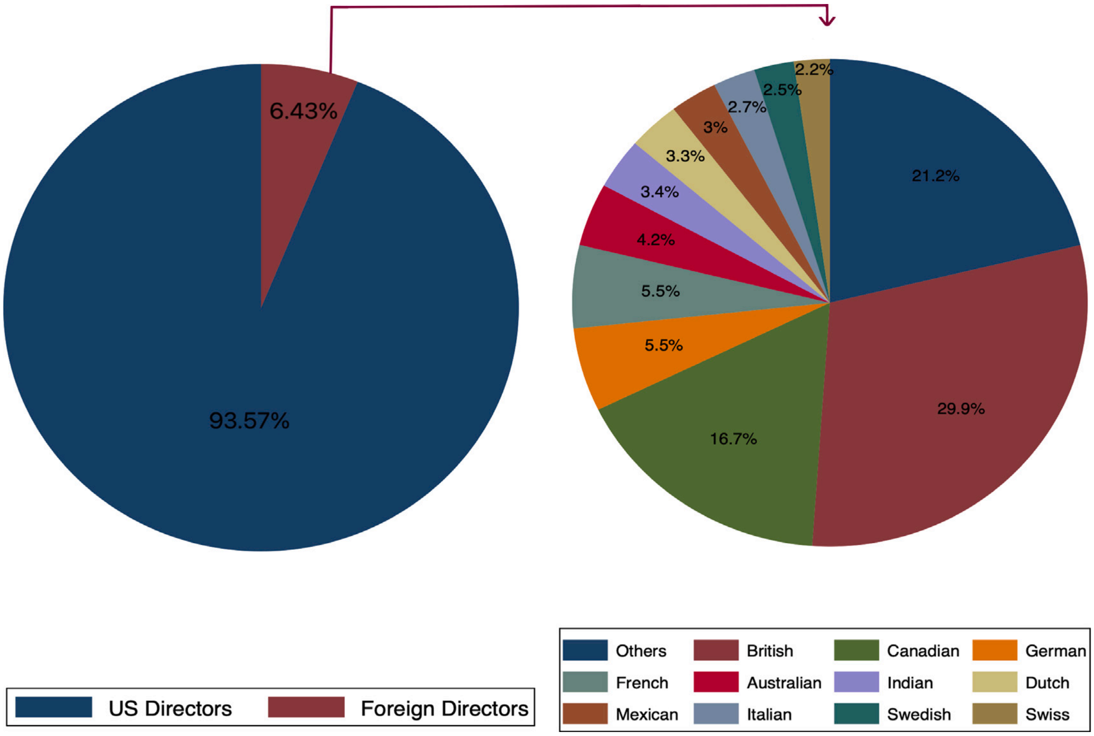

Fig. 2. Directors' nationality. Notes: Our sample enumerates 664,208 directors from 2005 to 2019 in 3690 US firms. 93.57% of them are Americans and 6.43% foreigners. The majority of the foreign directors are British (29.9%), followed by Canadians, Germans, French, Australians, Indians, Dutch, Mexicans, Italians, Swedish and Swiss. The remaining 21.2% of foreign directors are from 73 different nationalities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The score takes on values from 0 to 100, where higher values indicate higher environmental performance. The score is also reported as a categorical variable with 4 categories (or quartiles), D, C, B and A. It is further subdivided into 12 subcategories (or grades), –D, D, +D, −C, C, +C, −B, B, +B, –A, A, +A. –D comprises firms with an "extremely low" CEP, and +A comprises firms with an "extremely high" CEP. Over 10,000 firms are covered in this scoring scheme. Our sample includes 3690 firms with available scores. CEP contains scores that are based on three main categories, (i) emissions, (ii) innovations, and (iii) resource use. The first category consists of GHG emissions, including total waste, biodiversity reduction, and environmental management system policy. The second category evaluates environmental product innovation and green capital expenditures. The third category considers total water wasted, the total energy used, sustainable packaging of products, and environmental supply chain management. The weights and scores are assigned based on two criteria: transparency and industry median. Transparency is based on a binary answer to the question "Do they disclose?" (YES or NO). The industry median criterion indicates how firms performed relative to the industry where they operate. Then, the firms are ranked relative to their peers.[6] Weights are calculated based on data availability. Variables with sufficient disclosure are used as a proxy to measure the industry's weights. For instance, if GHG emissions is the only variable with available data across the industry, it will be assigned a weight of 100%. Thus, in our example in footnote 6, the CEP for this firm would be based solely on GHG emissions and will be given by 92.5, or grade +A (i.e., based on the 12-group scoring), or quartile A (i.e., based in the 4-group scoring). (For further details, please see Appendix C of ESG scores from REFINITIV, which contains detailed scores for each industry.) Fig. 3 displays the average pollution (GHG/TA) of firms with and without genetic diversity. We do the same for firms according to the CEP score, which is also normalised as provided by REFINITIV. Although this figure is simple and does not include, for example, standard errors, it appears to suggest that firms that have no genetic diversity in their boards have higher levels of pollution vis à vis firms with genetic diversity boards.

[6] Consider an example pertaining to the GHG emissions scoring. The first question is "Do they disclose GHG emissions?" If YES, then the firm scores 1; if NO the firm scores 0. The next question is "How much?" Assume that 25 firms operate in an industry, 20 of which disclose GHG and 5 do not disclose it. Also, suppose that out of those 20 firms a firm is ranked second in terms of GHG emissions (negative polarity data point; the lower volume of GHG emissions the better). The GHG score for this firm is:

$$SCORE = \frac{\#\ Firms\ with\ WORSE\ GHG\ emissions + \frac{\#\ Firms\ with\ SAME\ GHG\ emissions}{2}}{\#\ Firms\ that\ DISCLOSE\ GHG\ emissions} = \frac{18 + \frac{1}{2}}{20} = 0.925$$

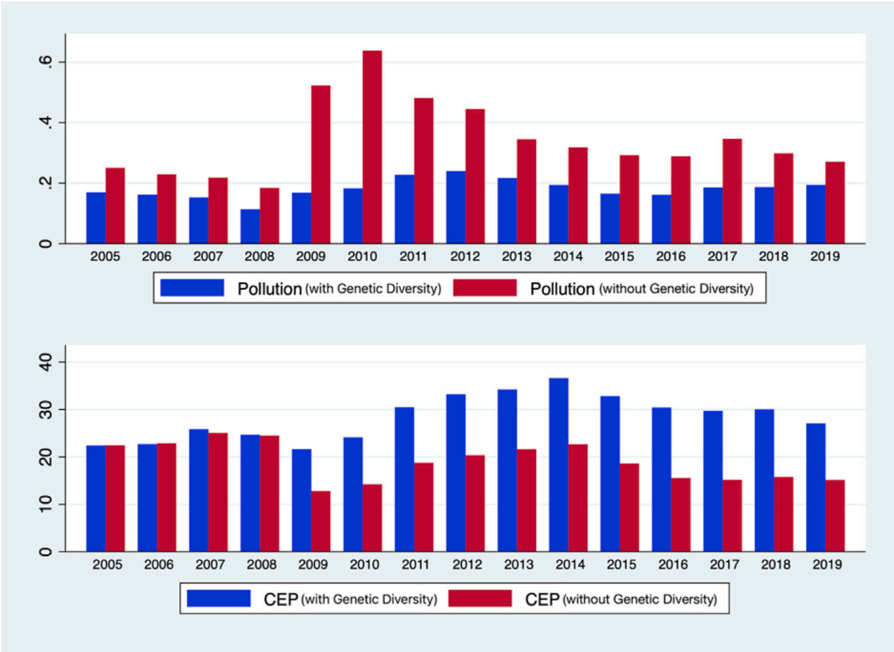

Fig. 3. Pollution and CEP by year. Notes: Pollution is (GHG/TA) and CEP is the environmental performance index from Thomson Reuters. Blue and red bars show firms with genetic diversity and without genetic diversity, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Genetic diversity

Ashraf and Galor (2013a,b) employ an index of a country's specific genetic diversity score based on data from the HGDP-CEPH Human Genome Diversity Cell Line Panel and the framework of Ramachandran et al. (2005).[7] Following Delis et al. (2017), the genetic diversity-related measure of board heterogeneity is calculated as the standard deviation by firm-year of genetic diversity scores across the country-specific values assigned to each board member in our dataset. More formally, we consider the following measure:

$$GENETICD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - m)^2}, \tag{2}$$

where GENETICD is the standard deviation of the genetic diversity score d attached to the N board directors of each firm. Each director's genetic diversity score is linked to the country of nationality of that director (i), and m is the mean score of each board. The Human Genome Diversity Cell Line Panel that was assembled by the Human Genome Diversity Project-Centre d'Étude du Polymorphisme Humain (HGDP-CEPH) can be used to trace the origins of data on genetic diversity. This panel provides reliable and consistent data for genetic diversity among indigenous populations of 53 ethnic groups across the world. Research in anthropology shows the presence of 53 ethnic groups, which are historically native to their current geographical location and have also been isolated from genetic flows from other ethnic groups. Population geneticists employ the so-called expected heterozygosity index to estimate the genetic diversity across individuals within a given population, i.e., an ethnic group. The expected heterozygosity

[7] It is worth mentioning that Ashraf and Galor (2013b) received criticism from D'Alpoim Guedes et al. (2013) and from other scholars on several grounds. These critical reviews referred to as 'misconceptions' are summarised and addressed in Ashraf et al. (2019). The first criticism is that the population data employed in the analysis of development outcomes in the pre-colonial period in Ashraf and Galor (2013b) is imperfectly measured. However, in the response of Ashraf et al. (2019), it is argued that the historical analysis performed in Ashraf and Galor (2013a) accounts for the possibility that the data on population density before the year 1500 could be afflicted by measurement errors. The second criticism is that expected heterozygosity in neutral genetic markers is not representative of the diversity in functional (phenotypic) markers and, hence, cannot influence behavioural and social interactions. In response to this criticism, it is asserted in Ashraf et al. (2019) that, since the migratory distance from Africa influences diversity in neutral genetic markers, as well as diversity in typically, expressed morphological and cognitive traits, the methodology used in Ashraf and Galor (2013b), based upon predicted (as opposed to observed) diversity, is suitably designed to gauge the influence of interpersonal population diversity on behavioural and social outcomes. The third criticism is that the presence of a productivity-maximising level of diversity could translate into disturbing policy prescriptions (e.g., the forcible movement or "engineering" of populations, designed to achieve an "optimal" diversity level). In their answer to this criticism, Ashraf et al. (2019) maintain that: (i) the most productive nations tend to be more diverse, and (ii) pluralism-oriented education policy can mitigate the cost of diversity and thus can further strengthen the importance of diversity for economic prosperity.

measure for a given ethnic group is estimated using data about the frequency with which a "gene variant" occurs in the ethnic group. Using the gene variant frequency data, a gene-specific heterozygosity measure is estimated that shows the probability that two randomly selected individuals are different in terms of gene. In some detail, consider a single gene or locus l with k observed variants or alleles in the population and let p_i denote the frequency of the ith allele. Then, the expected heterozygosity of the population with respect to locus l, H^l_{exp}, is:

$$H^l_{exp} = 1 - \sum_{i=1}^{k} p_i^2$$

Given allelic frequencies for each of m different genes or loci, the average across these loci then yields an aggregate expected heterozygosity measure of overall genetic diversity, H_{exp}, as:

$$H_{exp} = 1 - \frac{1}{m} \sum_{l=1}^{m} \sum_{i=1}^{k_l} p_i^2,$$

where k_l is the number of observed variants in locus l.

3.3. Control variables

Informed by previous literature, we control for a list of variables that are expected to explain the CCPA/CEP of firms. Our information set comprises three different groups of control variables: financial, governance, and other diversity variables. Starting with the financial variables, we include variables that capture firms' actual size, risk, profitability, and liquidity. The size of the firm (SIZE) can be an important determinant of CCPA/CEP, as literature has shown that large firms are subject to more external pressure (Dyck et al., 2020). Inefficiency (INEF) measures the extent to which firms can effectively comply with new climate policies. Intangible assets (INTA) can be thought of as a proxy of the firm's CCPA/CEP investments. Cash to sales ratio (CASHSALES) indicates that the more cash held within the firm, the lower the environmental expenditures. Leverage (LEV) captures the riskiness of the firms, as it has been found that riskier firms undertake more environmental projects (Tzouvanas et al., 2020b), Tobin's Q (TOBINS) is a proxy for profitability, as highly profitable firms have financial resources to invest in new technologies. Finally, liquidity (CURRATIO), captures the availability of assets to be invested. This set of variables is commonly incorporated into environmental performance regressions as shown by prior literature (Kim and Starks, 2016; Liu, 2018; Dyck et al., 2020). The second set of control variables, related to the governance characteristics, are informed by Kim and Starks (2016), Delis et al. (2017), Liu (2018) and Dyck et al. (2020). This is because corporate governance is responsible for the level of environmental engagement. Such characteristics include the board size (BOARDSIZE), foreign director indicator (FOREIGN), the share of female CEOs on the board (GENDERD), independent past roles (INDEPAST), independent directors on the audit committee (INDEAUDIT), independent directors on the ESG committee (INDEPESG), the average age of the board (AGE), time in role (TIMER), director network (NETWORK), an indicator if the CEO is also a member of board dummy (CHAIRMAN), and share of non-executive directors on the board (NEDD). These variables capture the experience of the board in dealing with various socio-economic problems, the different committees to allocate tasks, as well as the dispersion in opinions to bring new ideas. Finally, to ensure that the effect of genetic diversity is unrelated to influences of other diversity dimensions, to reduce the omitted variable bias, as well as the remaining heterogeneity of the country of the origin of the directors, we also control for the diversity in terms of rule of law (RULED), democracy (DEMD), culture (CULTD), and development (DEVD). These variables denote the conceptions of what is desirable in society, and they represent systems of values and beliefs that support specific decision-making within the firms (Pan et al., 2017; Shi and Veenstra, 2020). The diversity variables are computed similarly to the genetic diversity score. Finally, we control for year, industry, and state-specific effects that are very likely to affect the level of environmental and carbon performance (for further details, see Section 4.1). We report in Table 1 the descriptive statistics of the variables of the study. Please also see Table A1 (Online Appendix) for more detailed definitions and sources of our variables.

4. Emprical results

In this section, we describe the research design that we employ to examine the relationship between carbon performance (environmental performance) and genetic diversity. Our research design aims to exploit the panel and ordinal nature of our data-set. For this reason, our rigorous empirical methodology comprises multiple linear and nonlinear (logit and probit) regression models. These models are estimated by means of three different estimation methods. The linear models are estimated by means of panel ordinary least squares (OLS) and panel two-stage least squares (2SLS) to control for endogeneity, though we also use lagged variables to eliminate the presence of a bias driven by reverse causality. The nonlinear (logit and probit) models are estimated by means of the maximum likelihood estimation method. In addition, as ESG variables might feature overlapping information contents, we consider different ESG components. For this reason, we test the genetic diversity effects on corporate social and governance performance as well as sub-components of environmental performance such as Energy efficiency, R&D, Scope 1, Scope 2, and Scope 3 emissions.

Table 1
Descriptive statistics.

Variable	N	Mean	p25	Median	p75	SD	Min	Max	Skew	Kurt
GENETICD	19,551	0.0102	0	0	0.0135	0.0182	0	0.1018	1.5176	3.9502
CCPA	5,197	3.2064	1.6413	3.1434	4.5397	2.1927	−2.3386	16.0702	0.4286	3.5322
CEP	19,515	22.1656	0	9.3	39.8500	26.7099	0	98.55	1.0089	2.7406
SIZE	19,276	15.2743	14.2190	15.2422	16.3366	1.7249	7.3479	21.7128	0.1256	3.5536
INEF	16,497	0.4907	0.3016	0.5123	0.6883	0.3579	−0.0841	30.3771	37.5043	3019.966
INTA	18,958	11.5078	10.9021	12.9380	14.4269	4.7725	0	19.5521	−1.5447	4.3768
CASHSALES	19,029	2.5541	2.1258	2.7408	3.3051	1.0777	−4.6052	9.3124	−1.042	4.2832
LEV	19,266	0.0986	0.0185	0.0587	0.1205	2.8222	−220.2293	218.3592	0.4924	3982.9151
TOBINSQ	19,232	0.3977	0.1928	0.3577	0.5686	0.2535	−0.1167	0.9946	0.4734	2.2456
CURRATIO	15,510	2.6331	1.2000	1.7700	2.7500	4.9166	0.0702	415.0231	43.0289	3286.064
BOARDSIZE	19,540	9.7525	8	10	11	2.4969	1	36	1.0771	8.6481
FOREIGN	19,551	0.0822	0	0	0	0.2747	0	1	3.0411	10.2482
GENDERD	19,551	0.1324	0	0.1111	0.2000	0.1604	0	1	2.0240	9.9853
INDEPAST	19,551	0.0119	0	0	0	0.0577	0	1	9.0614	121.9917
INDEAUDIT	19,551	0.2153	0	0.2	0.3333	0.2067	0	1	1.3689	5.7642
AGE	19,551	62.5766	59.6670	62.875	65.7142	5.4096	34	90	−0.3205	4.8982
TIMER	19,551	4.2651	2.5	4	5.7500	2.5441	0	17	0.8285	4.0347
NETWORK	19,551	1.2863	0.5	1	1.7500	1.5796	0	49	10.9792	244.0334
CHAIRMAN	19,551	0.442	0	0	1	0.4966	0	1	0.2337	1.0546
NEDD	19,551	0.1392	0	0.1111	0.2000	0.1645	0	1	2.3400	11.4621
INDEPESG	19,551	0.472	0	0	1	0.4992	0	1	0.1121	1.0125
RULED	19,551	0.0723	0	0	0.0326	0.203	0	2.3428	3.8153	19.5128
DEMD	19,551	0.1715	0	0	0	0.591	0	7.0711	5.4556	38.9243
CULTD	19,551	0.1674	0	0	0.0862	0.3868	0	3.6233	2.6951	10.2349
DEVD	19,551	0.0218	0	0	0.0165	0.055	0	1.0108	4.8401	40.2895
MDIST	19,551	18.1282	18.2057	18.8892	18.8892	1.8251	2.8687	25.8977	−3.6988	21.0215
ULTRAD	19,551	129.1688	131.5942	131.5942	131.5942	12.2674	42.9775	265.1124	−0.3654	24.818
CGP	19,545	46.2619	28.1300	46.1400	64.2500	22.5073	0.1632	98.5404	0.0308	2.0717
CSP	19,515	40.7244	25.5700	37.2600	53.5500	19.8717	0.6512	97.8433	0.5965	2.6982
CESG	19,551	36.3029	23.5600	33.3700	46.5900	16.9335	0	92.5343	0.6633	2.9209
SCOPE1	4,438	4.5214	−7.4690	−6.1609	−5.0925	2.9727	−2.3386	16.4613	0.2921	2.6846
SCOPE2	4,252	4.2535	−4.1480	−3.0870	−2.1865	1.8041	−1.7788	14.7075	0.6462	3.9521
SCOPE3	2,487	4.6929	2.1802	4.5291	6.4279	2.9485	−5.9351	14.8705	−0.2027	2.7124
ENERGYE	3,793	1.1846	3.0107	4.0707	5.2034	2.1363	−6.886	13.2493	0.3931	3.9334
R&D	7,892	3.2306	2.6015	5.0503	6.7241	1.4745	10.5598	0.95615	0.5512	3.4395
CESGD	19,551	2.0107	1	2	2	0.8115	1	4	0.4782	2.7194
CCD	19,551	0.2658	0	0	1	0.4417	0	1	1.0602	2.1244
MEANGEN	19,551	0.637	0.6317	0.6317	0.6343	0.014	0.5981	0.7522	3.9393	22.4951
FRAC	19,551	0.1324	0	0	0.2099	0.2297	0	1	1.8549	5.8339

Notes: This table presents the descriptive statistics of our unbalanced panel data set over the period from 2005 to 2019 for a total of 3690 companies: number of observations ("N"), mean ("Mean"), median ("Median"), standard deviation ("SD"), minimum ("Min"), maximum ("Max"), skewness ("Skew"), and kurtosis ("Kurt"). Descriptive statistics are organised in columns, and variables are organised in rows. The computational details and measurements of the variables are outlined in Table A1.

4.1. The impact of genetic diversity on corporate environmental performance

In terms of identification of the impact of genetic diversity on environmental and carbon performance, we opt for a panel data model that considers heterogeneity across industries and states and over time. Eq. (3) outlines the model below:

$$\begin{aligned} Y_{i,t} = \alpha_0 + \alpha_1 GENETICD_{i,t} + \alpha_2' \mathbf{FINANCIAL_{i,t}} + \alpha_3' \mathbf{GOVERNANCE_{i,t}} + \\ \alpha_4' \mathbf{DIVERSITY_{i,t}} + \alpha_5' \mathbf{YEAR_t} + \alpha_6' \mathbf{INDUSTRY_j} + \alpha_7' \mathbf{STATE_k} + u_{i,t}, \end{aligned} \tag{3}$$

In Eq. (3), the dependent variable, $Y_{i,t}$, measures either corporate carbon performance, $CCPA_{i,t}$, or environmental performance, $CEP_{i,t}$, for firm i at time (year) t, where $i = 1, 2, \ldots, N$, $t = 2005, 2006, \ldots, 2019$, and $u_{i,t}$ is the random disturbance term. The key explanatory variable, $GENETICD_{i,t}$, is the genetic diversity score. Next, we include a set of $\mathbf{FINANCIAL_{i,t}}$ (firm size, inefficiency, cash to sales ratio, leverage, Tobin's Q, and liquidity), $\mathbf{GOVERNANCE_{i,t}}$ (board size, foreign directors, share of female CEOs, independent past roles, independent directors on the audit committee, independent directors on the ESG committee, age of the board, time in role, director network, chairman dummy and share of non-executive directors), and other diversity variables ($\mathbf{DIVERSITY_{i,t}}$) (rule of law, democracy, culture, and development diversity). We also control for a year, industry, and state fixed effects; thus, the intercept α_0 is referred to the base year (2005), base industry (Aerospace & Defence), and base state (Alaska).[8] The use of year-fixed effects allows us to account for an unobserved time variation in the data that is not already captured by the time-varying

[8] Naturally, we also attempted to account for firm fixed effects. However, boards' genetic diversity (GENETICD), our main explanatory variable, shows little variation within firms (around 80% of our firms in the sample feature time invariant GENETICD). When firm fixed effects are accounted for, GENETICD drops due to a near-perfect collinearity. Therefore, panel data models, which include board genetic diversity, albeit not firm fixed effects, are preferred. This is because such models account for the observed cross-sectional heterogeneity that is ex-post driven by boards' genetic diversity.

covariates. The use of year-fixed effects receives support from Fig. 3, which shows that average corporate pollution levels and environmental standards show a significant variation over time. The industry fixed effects are theoretically motivated. In this regard, pursuant to institutional theory, organisations operating in the same industry and facing similar institutional pressures converge on institutional norms in terms of sustainable development through coercive, mimetic, and normative processes (DiMaggio and Powell, 1983; Escobar and Vredenburg, 2011). Specifically, normative isomorphism predicates that product certifications, as well as professional accreditations, conventions, and standards evolve into organisational norms at the industry level (DiMaggio and Powell, 1983). Further, the use of state-fixed effects allows us to control the interstate variation in ESG legislation, regulation, reporting, and standards, as well as diversity disclosures. We use the panel OLS estimation method to estimate Eq. (3). The estimated coefficient standard errors are robust to autocorrelation and heteroscedasticity.

Table 2 presents the estimated panel data model, outlined in Eq. (3). We follow a specific-to-general modelling approach. In Model 1 (Column 1) of Table 2, the dependent variable is corporate carbon performance relative to total assets (CCPA), whereas the array of explanatory variables encompasses genetic diversity and key firm-specific control variables (i.e., size, Tobin's Q, etc.). Then, Models 2 and 3 expand the list of covariates by incorporating characteristics of board members (gender diversity, age, etc.), as well as country-specific variables (i.e., rule of law, etc.). Further, Models 4–6 entail the same arrays of covariates as Models 1–3, except that the dependent variable is now an index of corporate environmental performance (CEP). Before considering the effect of our key explanatory variable, genetic diversity (GENETICD), it is worth noting that the control variables' effects have anticipated signs. For example, the effect of size is either positive or insignificant, indicating that larger firms have more resources to improve their environmental performance. There is some variability regarding the effects of inefficiency, intangibility, liquidity, and board size on CCPA vis à vis CEP. For instance, INEF and BOARDSIZE decrease CCPA, but increase CEP, while the opposite is true for INTA and CURRATIO. In addition, an increase in cash flows is associated with a decrease in both CCPA and CEP, as keeping more cash within the firm indicates that less resources become available for environmental projects. Similarly, according to the trade-off view, high TOBINSQ deducts investments from environmental projects. Finally, it is important to underline that gender diversity appears to have a positive and significant impact on CCPA and CEP, which accords with previous studies that examine the role of diversity (e.g., Kim and Starks, 2016; Liu, 2018).

The main result of our analysis across all models shows that genetic diversity improves corporate environmental performance. In particular, the effect of genetic diversity on corporate carbon performance (corporate environmental performance) is estimated between 3.182 (4.835) and 3.961 (5.419) respectively. Since Eq. (3) represents a linear model for the variable $CCPA_{i,t} = -ln(\frac{GHG_{i,t}}{Total\ \ Assets_{i,t}})$, albeit a semi-logarithmic model for the variable $(\frac{GHG_{i,t}}{Total Assets_{i,t}})^{-1}$, caution should be exercised when interpreting the coefficient estimates. For example, as reported in Column 3, a one percentage point increase in the board's genetic diversity will increase the corporate carbon performance, measured as the inverse of the greenhouse gas emissions to total assets ratio, $(\frac{GHG_{i,t}}{Total Assets_{i,t}})^{-1}$, by $(e^{3.476\times0.01} - 1)\times 100\% = 3.54\%$. Turning to Columns 4–6 of Table 2, it is worth noting that the dependent variable is measured as the natural logarithm of the corporate environmental performance score. Therefore, a one percentage point rise in the genetic diversity score translates into a $(e^{5.419\times0.01} - 1)\times 100\% = 5.57\%$ rise in the corporate environmental performance score. Overall, in Columns 1–6, the coefficient estimates are sizeable in magnitude and always significant. These findings are in line with diversity theory, that is, a higher diversity is conducive to improved environmental performance. To the best of our knowledge, this is the first time that the role of genetic diversity in improving carbon and environmental performance is evidenced.[9]

It should be recognised that panel data models, in which all the variables enter contemporaneously, may not provide an accurate representation of the underlying relationship between corporate carbon performance (corporate environmental performance) and genetic diversity for several reasons. First, the contemporaneous relationship might be suffering from an endogeneity/reverse causality bias. Second, changes in genetic diversity might not materialise within the same period due to, e.g., decision lags. Considering that dynamic models can provide a more accurate representation of the relationship between genetic diversity and environmental performance, we estimate panel data models where our main explanatory variables are lagged by one period. Again, we follow a specific-to-general modelling approach. Qualitatively similar results obtain, which are summarised in Table 3. Concretely, we find that increases in genetic diversity are conducive to improved environmental performance in the model specification with lagged explanatory variables.

4.2. The impact of genetic diversity on social and governance performance

Corporate environmental performance is just one pillar of the ESG score. However, ESG also comprises the governance and social pillars. Thus, we ask if a firm that performs well in environmental activities can perform equally well in social and governance activities. If the diversity theory holds, GENETICD might influence the social and governance performance of a firm, as well as the composite ESG index. Our data gathers information about the total corporate ESG performance indicator (CESGP) of the firm that is divided into three components: corporate environmental performance (CEP), corporate social performance (CSP), and corporate governance performance (CGP). We also subdivide the environmental pillar into energy efficiency (ENERGYE) and research and development (R&D), and sub-components of CCPA (Scope 1, Scope 2, and Scope 3). We test whether those components and sub-components significantly respond to changes in genetic diversity. In Table 4, we report the estimated regression models for the CESGP components, as well as for the sub-components of CEP and CCPA. In Column 1, the total CESGP significantly responds to

[9] We also estimated an alternative model by using Year × Industry, Year × State and Industry × State fixed effects to capture any unobserved heterogeneity. Results are similar to Table 2 and can be found in the Online Appendix, Table A10.

Table 2
The impact of genetic diversity on corporate environmental performance.

	CCPA			CEP		
	(1)	(2)	(3)	(4)	(5)	(6)
GENETICD	3.961***	3.182**	3.476**	4.985***	4.835***	5.419***
	(1.203)	(1.286)	(1.638)	(0.606)	(0.652)	(0.820)
SIZE	0.004	0.026	0.026	0.617***	0.561***	0.562***
	(0.019)	(0.022)	(0.022)	(0.009)	(0.011)	(0.011)
INEF	−2.079***	−2.067***	−2.055***	0.282***	0.280***	0.279***
	(0.137)	(0.136)	(0.136)	(0.032)	(0.032)	(0.032)
INTA	0.054***	0.055***	0.055***	−0.011***	−0.012***	−0.013***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
CASHSALES	−0.369***	−0.362***	−0.361***	−0.031**	−0.026**	−0.026**
	(0.037)	(0.037)	(0.037)	(0.012)	(0.012)	(0.012)
LEV	0.009	0.008	0.008	0.000	−0.001	−0.001
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
TOBINSQ	−1.525***	−1.514***	−1.521***	−0.662***	−0.613***	−0.615***
	(0.146)	(0.146)	(0.146)	(0.066)	(0.066)	(0.066)
CURRATIO	0.096***	0.090***	0.092***	−0.025***	−0.022***	−0.022***
	(0.020)	(0.020)	(0.020)	(0.004)	(0.004)	(0.004)
BOARDSIZE		−0.036***	−0.037***		0.058***	0.058***
		(0.012)	(0.012)		(0.006)	(0.006)
FOREIGN		0.149**	0.158**		−0.007	−0.001
		(0.073)	(0.073)		(0.042)	(0.042)
GENDERD		0.614***	0.619***		0.364***	0.364***
		(0.176)	(0.177)		(0.072)	(0.072)
INDEPAST		0.002	−0.016		0.106	0.112
		(0.489)	(0.489)		(0.185)	(0.186)
INDEAUDIT		−0.255**	−0.253**		0.060	0.061
		(0.126)	(0.126)		(0.054)	(0.054)
AGE		−0.010*	−0.010*		0.004*	0.004*
		(0.005)	(0.005)		(0.002)	(0.002)
TIMER		−0.018	−0.018		0.014***	0.014***
		(0.012)	(0.012)		(0.005)	(0.005)
NETWORK		−0.011	−0.011		0.011	0.011
		(0.019)	(0.019)		(0.008)	(0.008)
CHAIRMAN		−0.056	−0.055		0.022	0.022
		(0.049)	(0.049)		(0.026)	(0.026)
NEDD		−0.144	−0.134		0.027	0.024
		(0.184)	(0.185)		(0.081)	(0.081)
INDEPESG		−0.013	−0.013		0.027	0.028
		(0.044)	(0.044)		(0.022)	(0.023)
RULED			−0.084			−0.041
			(0.148)			(0.084)
DEMD			−0.049			0.032
			(0.044)			(0.025)
CULTD			−0.009			−0.006
			(0.087)			(0.045)
DEVD			0.575			−0.482*
			(0.473)			(0.286)
CONS	2.307***	2.899***	2.817***	−4.974***	−5.045***	−5.006***
	(0.872)	(0.918)	(0.920)	(0.776)	(0.783)	(0.784)
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
STATE	YES	YES	YES	YES	YES	YES
N	4544	4544	4544	14,924	14,924	14,924
R2	0.474	0.479	0.480	0.416	0.422	0.422

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3). Genetic diversity ("GENETICD") is our key explanatory variable, calculated as the standard deviation of country-level board directors' genetic scores (Delis et al., 2017). In Columns 1–3, the dependent variable is corporate carbon performance relative to total assets ("CCPA"). In Columns 4–6, the dependent variable is corporate environmental performance, measured as an index number ("CEP"). The calculations of CCPA and CEP are provided in Table A1. In Columns 1 and 4, we control for company-level accounting ratios and financial variables. In Columns 2 and 5, our set of control variables consists of accounting ratios/financial variables as well as corporate governance variables. In Columns 3 and 6, we additionally control for country-level diversity variables: diversity in rule of law ("RULED"), diversity in democracy ("DEMD"), cultural diversity ("CULTD"), diversity in the development level ("DEVD"). The sample period runs from 2005 to 2019. The cross-section comprises a total of 3690 companies, with a varying number of companies each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

Table 3
Linear regressions with lagged explanatory variables.

	CCPA			CEP		
	(1)	(2)	(3)	(4)	(5)	(6)
$GENETICD_{t-1}$	4.222***	3.974***	4.504***	5.569***	5.149***	5.800***
	(1.264)	(1.353)	(1.719)	(0.684)	(0.738)	(0.927)
$SIZE_{t-1}$	−0.023	0.010	0.012	0.594***	0.535***	0.537***
	(0.021)	(0.024)	(0.024)	(0.011)	(0.012)	(0.012)
$INEF_{t-1}$	−2.040***	−2.034***	−2.032***	0.751***	0.762***	0.760***
	(0.146)	(0.145)	(0.145)	(0.064)	(0.064)	(0.064)
$INTA_{t-1}$	0.046***	0.047***	0.048***	−0.013***	−0.015***	−0.015***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
$CASHSALES_{t-1}$	−0.327***	−0.323***	−0.324***	0.017	0.026*	0.025*
	(0.039)	(0.039)	(0.039)	(0.015)	(0.015)	(0.015)
LEV_{t-1}	0.030**	0.030**	0.030**	0.001	0.0003	0.0003
	(0.015)	(0.015)	(0.015)	(0.004)	(0.004)	(0.004)
$TOBINS_{t-1}$	−1.463***	−1.463***	−1.472***	−0.744***	−0.699***	−0.701***
	(0.157)	(0.157)	(0.157)	(0.077)	(0.077)	(0.077)
$CURRATIO_{t-1}$	0.063***	0.056***	0.057***	−0.025***	−0.022***	−0.022***
	(0.020)	(0.020)	(0.020)	(0.005)	(0.005)	(0.005)
$BOARDSIZE_{t-1}$		−0.045***	−0.045***		0.057***	0.057***
		(0.012)	(0.012)		(0.007)	(0.007)
$FOREIGN_{t-1}$		0.094	0.103		0.032	0.036
		(0.076)	(0.076)		(0.047)	(0.047)
$GENDERD_{t-1}$		0.599***	0.605***		0.438***	0.436***
		(0.193)	(0.193)		(0.085)	(0.085)
$INDEPAST_{t-1}$		−0.361	−0.388		0.114	0.120
		(0.545)	(0.545)		(0.228)	(0.228)
$INDEAUDIT_{t-1}$		−0.359***	−0.350**		0.078	0.078
		(0.136)	(0.136)		(0.063)	(0.063)
AGE_{t-1}		−0.009	−0.009		0.004	0.004
		(0.006)	(0.006)		(0.003)	(0.003)
$TIMER_{t-1}$		−0.022*	−0.022*		0.010	0.009
		(0.013)	(0.013)		(0.006)	(0.006)
$NETWORK_{t-1}$		−0.010	−0.009		0.029***	0.029***
		(0.020)	(0.020)		(0.009)	(0.009)
$CHAIRMAN_{t-1}$		−0.085*	−0.080		0.028	0.029
		(0.051)	(0.052)		(0.029)	(0.029)
$NEDD_{t-1}$		−0.100	−0.111		0.051	0.046
		(0.205)	(0.206)		(0.096)	(0.096)
$INDEPESG_{t-1}$		−0.021	−0.021		0.033	0.033
		(0.046)	(0.046)		(0.025)	(0.025)
$RULED_{t-1}$			−0.275*			−0.046
			(0.165)			(0.098)
$DEMD_{t-1}$			0.013			0.038
			(0.047)			(0.028)
$CULTD_{t-1}$			0.021			−0.018
			(0.095)			(0.053)
$DEVD_{t-1}$			0.313			−0.407
			(0.493)			(0.314)
CONS	2.702***	3.209***	3.170***	−4.771***	−4.759***	−4.755***
	(1.025)	(1.071)	(1.071)	(0.937)	(0.944)	(0.944)
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
STATE	YES	YES	YES	YES	YES	YES
N	4010	4010	4010	11,746	11,746	11,746
R2	0.493	0.499	0.499	0.409	0.416	0.416

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3). All the explanatory variables are lagged by one year. Genetic diversity ("GENETICD") is our key explanatory variable, calculated as the standard deviation of country-level board directors' genetic scores (Delis et al., 2017). In Columns 1–3, the dependent variable is corporate carbon performance relative to total assets ("CCPA"). In Columns 4–6, the dependent variable is corporate environmental performance, measured as an index number ("CEP"). The calculations of CCPA and CEP are provided in Table 1. In Columns 1 and 4, we control for company-level accounting ratios and financial variables. In Columns 2 and 5, our set of control variables consists of accounting ratios/financial variables as well as corporate governance variables. In Columns 3 and 6 we additionally control for country-level diversity variables: diversity in rule of law ("RULED"), diversity in democracy ("DEMD"), cultural diversity ("CULTD"), diversity in the development level ("DEVD"). The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

Table 4
Linear regressions with different dependent variables.

	CESGP	ESG Components		CEP Components		CCPA Components		
	(1)	CSP	CGP	ENERGYE	R&D	SCOPE1	SCOPE2	SCOPE3
		(2)	(3)	(4)	(5)	(6)	(7)	(8)
GENETICD	0.629**	−0.126	1.199***	3.000	1.041	8.769***	6.291***	0.400
	(0.262)	(0.293)	(0.359)	(2.018)	(0.799)	(2.425)	(1.624)	(4.522)
SIZE	0.134***	0.169***	0.105***	−0.074***	−0.163***	−0.029	0.086***	−0.103*
	(0.003)	(0.004)	(0.005)	(0.026)	(0.011)	(0.032)	(0.022)	(0.059)
INEF	0.018*	−0.021*	0.059***	−1.643***	−0.365***	−2.397***	−2.702***	−1.134***
	(0.010)	(0.012)	(0.014)	(0.172)	(0.026)	(0.199)	(0.135)	(0.351)
INTA	0.001	0.001	−0.004***	0.061***	0.001	0.083***	0.018***	0.056***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.004)	(0.009)	(0.006)	(0.018)
CASHSALES	−0.034***	−0.065***	−0.013**	−0.426***	−0.235***	−0.540***	−0.224***	0.008
	(0.004)	(0.004)	(0.005)	(0.045)	(0.013)	(0.054)	(0.037)	(0.094)
LEV	−0.001	0.000	−0.000	0.021	0.003	0.007	−0.002	0.128**
	(0.001)	(0.001)	(0.002)	(0.016)	(0.004)	(0.008)	(0.005)	(0.051)
TOBINSQ	−0.280***	−0.415***	−0.144***	−1.296***	−2.146***	−2.297***	0.008	−0.277
	(0.021)	(0.024)	(0.029)	(0.184)	(0.079)	(0.216)	(0.147)	(0.406)
CURRATIO	−0.009***	−0.007***	−0.007***	0.041*	−0.019***	0.192***	−0.022	0.178***
	(0.001)	(0.002)	(0.002)	(0.024)	(0.004)	(0.030)	(0.020)	(0.051)
BOARDSIZE	0.028***	0.026***	0.012***	−0.013	0.001	−0.063***	−0.025**	−0.033
	(0.002)	(0.002)	(0.003)	(0.015)	(0.007)	(0.017)	(0.012)	(0.031)
FOREIGN	−0.017	−0.005	−0.040**	0.025	−0.030	0.192*	−0.025	0.043
	(0.014)	(0.015)	(0.019)	(0.090)	(0.042)	(0.106)	(0.071)	(0.189)
GENDERD	0.200***	0.074***	0.380***	0.716***	0.337***	0.973***	0.219	0.653
	(0.023)	(0.026)	(0.032)	(0.213)	(0.075)	(0.262)	(0.177)	(0.477)
INDEPAST	0.258***	0.263***	0.305***	0.976	0.363**	1.199*	0.920*	5.690***
	(0.059)	(0.066)	(0.081)	(0.603)	(0.177)	(0.717)	(0.475)	(1.219)
INDEAUDIT	0.006	0.035*	−0.029	−0.005	−0.008	−0.653***	−0.044	−0.167
	(0.017)	(0.019)	(0.024)	(0.155)	(0.056)	(0.191)	(0.128)	(0.341)
AGE	0.001	−0.001	0.003**	0.013**	−0.012***	0.011	−0.008	0.009
	(0.001)	(0.001)	(0.001)	(0.007)	(0.002)	(0.008)	(0.005)	(0.015)
TIMER	0.015***	−0.001	0.038***	−0.019	0.032***	−0.047***	0.016	0.056
	(0.002)	(0.002)	(0.002)	(0.015)	(0.006)	(0.018)	(0.012)	(0.035)
NETWORK	−0.004*	−0.003	−0.015***	−0.020	0.034***	−0.043	−0.032*	−0.152***
	(0.002)	(0.003)	(0.003)	(0.023)	(0.009)	(0.028)	(0.019)	(0.059)
CHAIRMAN	−0.017**	0.015	−0.058***	−0.040	0.095***	−0.170**	0.006	0.237*
	(0.008)	(0.009)	(0.012)	(0.061)	(0.028)	(0.071)	(0.049)	(0.129)
NEDD	−0.060**	−0.070**	−0.091**	0.192	−0.093	0.124	−0.257	−0.718
	(0.026)	(0.029)	(0.036)	(0.224)	(0.084)	(0.270)	(0.185)	(0.510)
INDEPESG	0.044***	0.041***	0.068***	−0.106*	−0.074***	−0.130**	−0.032	−0.107
	(0.007)	(0.008)	(0.010)	(0.055)	(0.024)	(0.065)	(0.044)	(0.119)
RULED	−0.039	−0.046	−0.007	−0.334*	−0.150*	−0.315	−0.056	−0.888**
	(0.027)	(0.030)	(0.037)	(0.191)	(0.088)	(0.222)	(0.148)	(0.386)
DEMD	−0.002	−0.009	−0.011	0.016	0.084***	−0.050	−0.001	0.152
	(0.008)	(0.009)	(0.011)	(0.053)	(0.025)	(0.065)	(0.043)	(0.120)
CULTD	0.025*	0.050***	−0.026	0.136	0.074*	0.055	−0.123	0.635***
	(0.015)	(0.016)	(0.020)	(0.110)	(0.045)	(0.125)	(0.084)	(0.222)
DEVD	0.114	0.198*	0.116	0.063	0.257	0.638	0.666	−0.922
	(0.092)	(0.102)	(0.125)	(0.588)	(0.288)	(0.699)	(0.464)	(1.196)
CONS	1.864***	1.383***	2.795***	−6.245***	1.031***	2.347*	8.160***	5.255***
	(0.251)	(0.279)	(0.343)	(1.025)	(0.302)	(1.284)	(0.854)	(1.821)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES	YES	YES
STATE	YES	YES	YES	YES	YES	YES	YES	YES
N	14,937	14,922	14,937	3279	7591	3859	3662	2060
R2	0.312	0.290	0.225	0.380	0.570	0.511	0.349	0.273

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3). Genetic diversity (“GENETICD”) is our key explanatory variable, calculated as the standard deviation of country-level board directors’ genetic scores (Delis et al., 2017). In all model specifications, a comprehensive set of control variables is employed, which consists of accounting ratios/financial variables, corporate governance variables, and diversity variables. In Column 1, the dependent variable is corporate composite environmental, social, and governance (“CESGP”). In Column 2, the dependent variable is corporate social performance (“CSP”). In Column 3, the dependent variable is corporate governance performance (“CGP”). In columns, 4–5 the dependent variable are components of CEP, energy efficiency (ENERGY), and research and development (R&D). In Columns 6–8, the dependent variables are three components of corporate carbon performance, SCOPE1 (direct emissions), SCOPE2 (indirect emissions), and SCOPE3 (indirect emissions). The corporate carbon performance components are described in Table A1. The sample period runs from 2005 to 2019. The cross-section comprises a total of 3690 companies, with a varying number of companies each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

GENETICD. The corporate governance performance (Column 3) is positively associated with genetic diversity, while the response of the corporate social performance (Column 2) is negative, albeit insignificant. In other words, genetic diversity appears to improve corporate governance, which is related to the quality of managerial decisions, but it does not influence the firm's social performance, which is related to improving employees' rights, safety implications of a product, and community engagement. This result is in line with the upper echelons theory as managerial diversity shapes important corporate and managerial decisions (Hambrick and Mason, 1984); it shows that higher genetic diversity on the board can improve corporate responsibility. In addition, in Columns 4 and 5, ENERGYE and R&D are not influenced by genetic diversity. This implies that higher levels of CEP are mainly attained by reducing the company's greenhouse gas emissions. Indeed, in Columns 6 and 7, the Scope 1 and Scope 2 emissions are associated with genetic diversity, while the Scope 3 emissions are not. Taken together, our results show that emissions managed directly by the firm are affected by the board's genetic diversity. In turn, corporate carbon performance appears to be the key driver of the relationship between genetic diversity and CEP.

4.3. The impact of genetic diversity on corporate environmental performance: Two-stage least squares estimation (2SLS)

To control for endogeneity in Eq. (3), we opt for a panel 2SLS estimation. Endogeneity could arise from numerous sources. For example, foreign directors might be attracted by higher environmental performance, in which case CEP could drive variations in foreign membership on the board. Also, an unanticipated change in a 'third' variable, captured by the random disturbance term, can drive both corporate environmental performance and genetic diversity, which can result in biased coefficient estimates.

The objective is to instrument GENETICD with exogenous variables, which can drive GENETICD, albeit not CCPA or CEP. The estimation of this panel data model proceeds in two stages. In the first stage, following Ashraf and Galor (2013b), GENETICD is regressed on migratory distance (MDIST) and ultraviolet exposure as instruments (Eq. (4)). These two instruments are unlikely to affect corporate carbon performance, but they can be thought of as drivers of genetic diversity. MDIST is proxied by the human mobility index. The same instrument was used by Delis et al. (2017). The mobility index captures the average distance from Addis Ababa to the HGDP ethnic groups. The index accounts for natural impediments to human mobility, including weather and topographical conditions, while it contains information on the time cost of travelling under such conditions. It naturally satisfies the exclusion restriction criteria as MDIST is an important factor, which determines our genes. Similarly, according to the biology literature, ultraviolet exposure (UVEXP) is demonstrated to affect our skin, and cause mutation to our genes (Ashraf and Galor, 2013b). In the second stage, the forecast of GENETICD from Eq. (4) is used as an explanatory variable in Eq. (5). The first-stage equation is as follows:

$$GENETICD_{i,t} = \beta_0 + \beta_1 MDIST_{i,t} + \beta_2 UVEXP_{i,t} + \Xi' \mathbf{X_{i,t}} + e_{i,t}, \tag{4}$$

where $\mathbf{X_{i,t}}$ is a vector of control variables.

The second-stage regression resembles Eq. (3), which is outlined as follows:

$$\begin{aligned} Y_{i,t} = \alpha_0 + \alpha_1 \widehat{GENETICD}_{i,t} + \alpha_2' \mathbf{FINANCIAL_{i,t}} + \alpha_3' \mathbf{GOVERNANCE_{i,t}} + \\ \alpha_4' \mathbf{DIVERSITY_{i,t}} + \alpha_5' \mathbf{YEAR_t} + \alpha_6' \mathbf{INDUSTRY_j} + \alpha_7' \mathbf{STATE_k} + u_{i,t}, \end{aligned} \tag{5}$$

where $\widehat{GENETICD}_{i,t}$ is the forecast value from Eq. (4). In a similar vein to Eq. (3), the panel two-stage least squares estimator of the coefficient standard errors is robust to the presence of autocorrelation and heteroscedasticity. The Hansen J test of over-identified restrictions is also reported to determine that the two exogenous variables are valid instruments.

Table 5 presents the coefficient estimates of the panel data model, outlined in Eq. (5). As in the previous section, a one percent change in genetic diversity instigates a positive and significant effect on CCPA and CEP. Specifically, the estimated effect ranges from 3.718 to 6.429 if the dependent variable is CCPA, and from 1.934 to 3.100 for CEP. Specifically, a one percentage point rise in the board's genetic diversity will boost the corporate carbon performance score by $(e^{6.429\times0.01}-1)\times100\% = 6.64\%$ (see Column 3). Further, an unexpected positive change in genetic diversity is conducive to a positive and significant (at the significance level of 10%) effect on the corporate environmental performance score, estimated at $(e^{3.100\times0.01} - 1) \times 100\% = 3.15\%$ (see Column 6). All in all, treating for possible endogeneity does not alter the main result of our analysis, according to which genetic diversity improves environmental performance. As an additional robustness test, we construct two alternative measures of corporate carbon performance. The first measure is the negative logarithm of the firm's greenhouse gas emissions to total sales ratio (CCPS). The second measure is computed in a similar way, except that the industry's average greenhouse gas emissions, in which the firm operates, are set as a benchmark of carbon performance, in lieu of total assets or sales (CCPI). Results remain unaltered and are reported in Table A6 in the Online Appendix of the study.

4.4. The impact of genetic diversity on corporate environmental performance: Discrete response models

In addition to the semi-logarithmic models, considered in the previous subsection, which can be estimated with the OLS or 2SLS estimation methods, we also consider ordered discrete response models (i.e., logit and probit). The use of ordered discrete response models is motivated by two reasons. First, unlike linear (or semi-logarithmic) models, which allow us to evaluate the determinants of continuous changes in the dependent variable, ordered discrete response models enable us to assess how the probability that a firm is categorised as quartile (or grade)-m environmental performer changes when genetic diversity increases by one percentage point. Second, while in linear models, the partial slope estimate is constant, in ordered discrete response models – where the underlying

Table 5
2SLS estimates of linear regressions.

	CCPA			CEP		
	(1)	(2)	(3)	(4)	(5)	(6)
GENETICD	3.718**	3.975**	6.429***	1.934*	2.149*	3.100*
	(1.581)	(1.649)	(2.209)	(1.117)	(1.183)	(1.631)
SIZE	0.004	0.015	0.017	0.579***	0.544***	0.545***
	(0.021)	(0.022)	(0.022)	(0.011)	(0.012)	(0.012)
INEF	−1.398***	−1.387***	−1.367***	0.149***	0.146***	0.145***
	(0.128)	(0.128)	(0.129)	(0.033)	(0.033)	(0.033)
INTA	0.076***	0.076***	0.076***	−0.010***	−0.012***	−0.011***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
CASHSALES	−0.131***	−0.134***	−0.133***	−0.011	−0.009	−0.009
	(0.026)	(0.026)	(0.026)	(0.013)	(0.013)	(0.013)
LEV	0.003	0.003	0.003	−0.003	−0.003	−0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
TOBINSQ	−1.165***	−1.170***	−1.168***	−0.420***	−0.402***	−0.402***
	(0.116)	(0.116)	(0.116)	(0.069)	(0.069)	(0.069)
CURRATIO	0.123***	0.121***	0.122***	−0.016***	−0.015***	−0.014***
	(0.016)	(0.016)	(0.016)	(0.004)	(0.004)	(0.004)
BOARDSIZE		−0.019**	−0.019**		0.038***	0.038***
		(0.008)	(0.008)		(0.006)	(0.006)
FOREIGN		0.029	0.031		0.014	0.020
		(0.038)	(0.038)		(0.034)	(0.033)
GENDERD		0.284*	0.294*		0.166*	0.165*
		(0.155)	(0.155)		(0.085)	(0.085)
INDEPAST		0.866**	0.785*		0.122	0.117
		(0.424)	(0.427)		(0.211)	(0.211)
INDEAUDIT		−0.106	−0.110		0.030	0.030
		(0.076)	(0.076)		(0.048)	(0.048)
AGE		0.005	0.004		0.000	0.000
		(0.006)	(0.006)		(0.003)	(0.003)
TIMER		0.009	0.009		0.020***	0.020***
		(0.011)	(0.011)		(0.006)	(0.006)
NETWORK		0.007	0.007		−0.004	−0.004
		(0.015)	(0.015)		(0.009)	(0.009)
CHAIRMAN		−0.004	−0.005		0.047*	0.047*
		(0.037)	(0.037)		(0.028)	(0.028)
NEDD		−0.146	−0.155		0.039	0.035
		(0.164)	(0.164)		(0.093)	(0.093)
INDEPESG		−0.015	−0.016		−0.019	−0.020
		(0.034)	(0.034)		(0.024)	(0.024)
RULED			0.186*			0.007
			(0.101)			(0.079)
DEMD			−0.030			0.049*
			(0.035)			(0.026)
CULTD			−0.181**			−0.116**
			(0.080)			(0.058)
DEVD			0.099			−0.150
			(0.261)			(0.238)
CONS	0.884	0.612	0.545	−4.829***	−4.754***	−4.739***
	(1.495)	(1.527)	(1.529)	(1.168)	(1.174)	(1.175)
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
STATE	YES	YES	YES	YES	YES	YES
HANSEN P	0.6491	0.4816	0.9568	0.5467	0.6456	0.6312
N	4544	4544	4544	14,924	14,922	14,922
R2	0.451	0.453	0.452	0.404	0.410	0.410

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (5). Genetic diversity ("GENETICD") is our key explanatory variable, calculated as the standard deviation of country-level board directors' genetic scores (Delis et al., 2017). In Columns 1–3, the dependent variable is corporate environmental performance ("CEP"). In Columns 4–6, the dependent variable is corporate carbon performance ("CCPA"). The calculations of the variables are provided in Table A1. In Columns 1, and 4, we control for company-level accounting ratios and financial variables. In Columns 2 and 5, our set of control variables consists of both accounting ratios/financial variables and corporate governance variables. In Columns 3 and 6, we additionally control for country-level diversity variables: diversity in rule of law ("RULED"), diversity in democracy ("DEMD"), cultural diversity ("CULTD"), diversity in the development level ("DEVD"). The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the Two Stage Least Squares (2SLS) estimation method. Insignificant Hansen test indicates that the over-identified restrictions are valid. MDIST and ULTRAD are used as instruments in the first stage. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

probability density function is either logistic or normal – the change in this probability responds non-linearly to a one percentage point change in the genetic diversity score. As discussed in Section 3.1, the corporate environmental performance score is also reported as a categorical variable. Based on this score, firms are classified into four quartiles (A, B, C, and D), which can be further subdivided into twelve subcategories or grades. The dependent variable in a discrete response model is the probability of outcome m; i.e., the probability that firm i in year t is classified as quartile-m (or grade-m) environmental performer. In an ordered discrete response model, the probability of outcome m, which is confined between two unknown cut points (or threshold parameters), κ_{m-1} and κ_m, is given by:

$$\begin{aligned} P(Y_{i,t}=m) = P(\kappa_{m-1} &< \alpha_1 GENETICD_{i,t} + \alpha_2' \mathbf{FINANCIAL_{i,t}} + \alpha_3' \mathbf{GOVERNANCE_{i,t}} \\ &+ \alpha_4' \mathbf{DIVERSITY_{i,t}} + \alpha_5' \mathbf{YEAR_t} + \alpha_6' \mathbf{INDUSTRY_j} + \alpha_7' \mathbf{STATE_k} + u_{i,t} < \kappa_m), \end{aligned} \tag{6}$$

where $Y_{i,t}$ is corporate environmental performance of firm i at time t, $P(Y_{i,t}=m)$ is the probability that firm i at time t is categorised as quartile-m (or grade-m) environmental performer. Eq. (6) can be written in terms of the cumulative distribution function, $G()$, which represents either a logistic or standard normal distribution function (see Eq. (7)):

$$P(Y_{i,t}=m) = P(\kappa_{m-1} < \mathbf{\Pi' X_{i,t}} + u_{i,t} < \kappa_m) = G(\kappa_m - \mathbf{\Pi' X_{i,t}}) - G(\kappa_{m-1} - \mathbf{\Pi' X_{i,t}}) \tag{7}$$

In an ordered logit model, the cumulative distribution function $G(\kappa_m - \mathbf{\Pi' X_{i,t}})$ is given by $\frac{1}{1+e^{-(\kappa_m - \mathbf{\Pi' X_{i,t}})}}$, whereas in an ordered probit model, it is given by $\Phi(\kappa_m - \mathbf{\Pi' X_{i,t}}) = \int_{-\infty}^{\kappa_m - \mathbf{\Pi' X_{i,t}}} \phi(v)\,dv$, where $\Phi()$ ($\phi()$) is the cumulative distribution function (probability density function) of a standard normal distribution. $\mathbf{\Pi}$ is the vector of regression coefficients without a constant, $\mathbf{X_{i,t}}$ is the vector of explanatory variables (including genetic diversity) for firm i at time t. More generally, if genetic diversity increases by one percentage point, $dGENETICD_{i,t} = 0.01$, the probability of outcome m changes according to Eq. (8):

$$\frac{\partial P(Y_{i,t}=m)}{\partial GENETICD_{i,t}} = -0.01\alpha_1[g(\kappa_m - \mathbf{\Pi' X_{i,t}}) - g(\kappa_{m-1} - \mathbf{\Pi' X_{i,t}})] \tag{8}$$

At the first cut point, $\frac{\partial P(Y_{i,t}=1)}{\partial GENETICD_{i,t}} = -0.01\alpha_1 g(\kappa_1 - \mathbf{\Pi' X_{i,t}})$, which is negative if $\alpha_1 > 0$. At the last cut point, $\frac{\partial P(Y_{i,t}=M)}{\partial GENETICD_{i,t}} = 0.01\alpha_1 g(\kappa_{M-1} - \mathbf{\Pi' X_{i,t}})$, which is positive if $\alpha_1 > 0$. However, $\frac{\partial P(Y_{i,t}=m)}{\partial GENETICD_{i,t}}$, where $m = 2, \ldots, M-1$, could be of either sign. Unlike in the linear panel data model, specified in Eq. (3), the marginal effect of genetic diversity on the probability of outcome m is not constant, but rather depends on the probability density function (either logistic or normal), and the function arguments $\kappa_{m-1} - \mathbf{\Pi' X_{i,t}}$ or $\kappa_m - \mathbf{\Pi' X_{i,t}}$.

An advantage of the ordered logit model is that it allows us to calculate the odds ratio of being classified in a higher quartile (or grade) in terms of environmental performance. For instance, when genetic diversity increases by one percentage point, the resulting change in the log odds ratio of being in a category higher than m in terms of environmental performance (versus being in a lower or equal category than m) can be computed as $\log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.01)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.01)}) - \log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.00)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.00)}) = 0.01\alpha_1$. Thus, when the genetic diversity score rises by one percentage point, the odds ratio increases $e^{0.01\alpha_1}$ times. Further, the coefficient in the ordered probit model $0.01\alpha_1$ indicates the change in the z-value of $Y_{i,t}$ when genetic diversity increases by one percentage point.

Table 6 presents the coefficient estimates of the ordered logit (Columns 1–3) and probit (Columns 4–6) models for 4 environmental performance quartiles.[10] The estimated models indicate a positive and significant relationship between genetic diversity and the probability that firm i at time t can be classified as quartile-m environmental performer. The results are in line with our estimated semi-logarithmic models (see Tables 2–5) and scrutinised in Sections 4.1 and 4.3, which are supportive of theory of diversity. In particular, if genetic diversity increases by one percentage point, the log odds ratio of being in a category higher than m in terms of environmental performance (versus being in a lower or equal category than m) increases by $\log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.01)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.01)}) - \log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.00)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.00)}) = 0.01\alpha_1 = 0.01 \times 8.907 = 0.08907$ (see Column 3 of Table 6), and the odds ratio increases $e^{0.08907} = 1.0932$ times or by 9.32%. Further, the estimated ordered probit model indicates that the z-score of $Y_{i,t}$ rises by 0.05041 when genetic diversity goes up by one percentage point (see Column 6 of Table 6). Thus, the estimated ordered logit and probit models lend support to the theory of diversity.[11]

4.5. The impact of genetic diversity on disclosure of ESG

We also study the impact of boards' genetic diversity on disclosure of ESG, which is motivated by the agency theory (Jensen and Meckling, 1976; Eisenhardt, 1989) and the upper echelons theory (Hambrick and Mason, 1984). An important implication of agency theory is that the board of directors has a delegated authority to alleviate the agency conflict and hence reduce information

[10] Table A7 in the Online Appendix summarises the estimated discrete response models for 12 subcategories (grades). The estimated ordered logit and probit models show qualitatively similar results.

[11] It is worth noting that ordered discrete response models can encounter endogeneity issues, following our discussion in Section 4.3. To this end, we employ the instrumental variables ordered probit model to account for the possible presence of endogeneity. The results are summarised in Table A8 (see Online Appendix) for both 4 categories (Columns 1–3) and 12 subcategories (Columns 4–6). We find that a one percentage point rise in genetic diversity leads to an increase in the z-score of $Y_{i,t}$ by 0.02133 (Column 3) and 0.01158 (Column 6) when the corporate environmental performance score features 4 and 12 categories, respectively.

Table 6
Ordered probit and logit models with 4 CEP groups.

	OLOGIT			OPROBIT		
	(1)	(2)	(3)	(4)	(5)	(6)
GENETICD	7.508***	7.335***	8.907***	4.587***	4.376***	5.041***
	(1.037)	(1.131)	(1.434)	(0.599)	(0.653)	(0.823)
SIZE	1.141***	1.035***	1.040***	0.645***	0.585***	0.588***
	(0.019)	(0.020)	(0.020)	(0.010)	(0.011)	(0.011)
INEF	0.657***	0.645***	0.645***	0.326***	0.325***	0.325***
	(0.088)	(0.088)	(0.088)	(0.047)	(0.048)	(0.048)
INTA	−0.006	−0.009	−0.009*	−0.002	−0.004	−0.004
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
CASHSALES	−0.129***	−0.116***	−0.117***	−0.074***	−0.070***	−0.070***
	(0.021)	(0.022)	(0.022)	(0.012)	(0.012)	(0.012)
LEV	−0.002	−0.003	−0.003	−0.000	−0.001	−0.001
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
TOBINSQ	−1.787***	−1.676***	−1.676***	−0.964***	−0.907***	−0.907***
	(0.117)	(0.118)	(0.118)	(0.066)	(0.067)	(0.067)
CURRATIO	−0.113***	−0.099***	−0.098***	−0.060***	−0.052***	−0.052***
	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.008)
BOARDSIZE		0.121***	0.122***		0.067***	0.067***
		(0.010)	(0.010)		(0.006)	(0.006)
FOREIGN		−0.030	−0.020		−0.000	0.003
		(0.071)	(0.072)		(0.041)	(0.042)
GENDERD		0.346**	0.346**		0.202**	0.201**
		(0.138)	(0.138)		(0.079)	(0.079)
INDEPAST		−0.291	−0.297		−0.219	−0.217
		(0.394)	(0.395)		(0.228)	(0.229)
INDEAUDIT		0.084	0.088		0.049	0.051
		(0.105)	(0.105)		(0.060)	(0.060)
AGE		−0.002	−0.002		−0.002	−0.002
		(0.004)	(0.004)		(0.002)	(0.002)
TIMER		0.053***	0.053***		0.031***	0.031***
		(0.010)	(0.010)		(0.006)	(0.006)
NETWORK		0.022*	0.023*		0.012	0.013*
		(0.013)	(0.013)		(0.008)	(0.008)
CHAIRMAN		0.108**	0.111**		0.059**	0.061**
		(0.044)	(0.044)		(0.026)	(0.026)
NEDD		−0.120	−0.143		−0.048	−0.060
		(0.153)	(0.153)		(0.087)	(0.087)
INDEPESG		0.016	0.014		0.007	0.006
		(0.039)	(0.039)		(0.022)	(0.022)
RULED			−0.135			−0.055
			(0.140)			(0.080)
DEMD			0.122***			0.073***
			(0.042)			(0.024)
CULTD			−0.092			−0.043
			(0.078)			(0.045)
DEVD			−0.762			−0.481*
			(0.470)			(0.270)
CUT1	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
N	14,938	14,936	14,936	14,938	14,936	14,936
R2	0.238	0.245	0.245	0.237	0.244	0.244
P	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table summarises the coefficient estimates of the ordered probit and logit models, outlined in Eq. (3). The dependent variable is corporate environmental performance ("CEP"). The description of CEP is provided in Table 1. Genetic diversity ("GENETICD") is our key explanatory variable, calculated as the standard deviation of country-level board directors' genetic scores (Delis et al., 2017). In Columns 1–3, estimates of the ordered probit model are summarised. In Columns 4–6, estimates of the ordered logit model are summarised. In Columns 1 and 4, we control for company-level accounting ratios and financial variables. In Columns 2 and 5, our set of control variables consists of accounting rations/financial variables as well as corporate governance variables. In Columns 3 and 6, we additionally control for country-level diversity variables: diversity in rule of law ("RULED"), diversity in democracy ("DEMD"), cultural diversity ("CULTD"), diversity in the development level ("DEVD"). The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the maximum likelihood (ML) estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

asymmetries between the firm's managers and the shareholders. One such tool to monitor the alignment between managers' and shareholders' interests consists of disclosing environmental and social information. We argue that a genetically diverse board can bring new perspectives and views, and problem-solving skills, which can enhance the quality of the firm's accounting information and ESG reporting standards. Therefore, the level of interpersonal diversity within the top management echelon translates into a governance mechanism that can reduce the economic incentives for disclosing misleading financial information. At the US federal level, ESG reporting was not mandatory until 2021. However, on 17/06/2021, the US House of Representatives passed the so-called "H.R. 1187 – the ESG Disclosure Simplification Act of 2021" that would envisage new ESG disclosure requirements on publicly traded companies. Specifically, publicly traded companies would need to disclose their commitments to ensuring that ESG metrics are reflected in their operations, activities, and supply chains.[12] This means that within our sample period, which runs from 2005 to 2019, ESG reporting was voluntary, hence, driven by corporate ESG policies, as well as boards' endeavours to communicate ESG metrics to institutional investors, who deem such information fundamental to the firm's core business and one of the key drivers of investment returns. Institutional investors are increasingly more concerned about the availability of ESG reporting (e.g., Krueger et al., 2021). We opt for ordered discrete response (logit and probit) models to explore the association between genetic diversity and the disclosure of ESG. In some detail, ESG disclosure, sourced by REFINITIV, takes values on ordinal scale from A to D. We assign the value of 4 to category A (very high ESG disclosure) and the value of 1 to category D (very low ESG disclosure). We also examine what drives corporate carbon disclosure, which takes on the value of 1 if the firm reports its greenhouse gas emissions in a given year and takes on the value of 0 otherwise. In an ordered discrete response model, the probability of an outcome m is given by Eqs. (6) and (7). In these equations, $Y_{i,t}$ is either ESG or corporate carbon disclosure by firm i at time t, and $P(Y_{i,t} = m)$ is the probability that firm i at time t is in category m in terms of ESG disclosure. For corporate carbon disclosure, $Y_{i,t} = 1$ ($Y_{i,t} = 0$) means that firm i at time t discloses (does not disclose) greenhouse gas emissions. If genetic diversity increases by one percentage point, $dGENETICD_{i,t} = 0.01$, the probability of outcome m changes in accordance with Eq. (8). Also, the log odds ratio of being in a category higher than m (versus being in a lower or equal category than m) responds according to $\log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.01)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.01)})-\log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.00)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.00)}) = 0.01\alpha_1$. Thus, the odds ratio increases $e^{0.01\alpha_1}$ times. The coefficient of the ordered probit model $0.01\alpha_1$ indicates the change in the z-value of $Y_{i,t}$ when genetic diversity increases by one percentage point.

Table 7 presents the coefficient estimates of the ordered logit (probit) and simple logit (probit) models. The dependent variables are corporate ESG disclosure (CESGD) and corporate carbon disclosure (CCD). The estimated models show a positive and significant relationship between genetic diversity and CESGD (CDD). Our results are in line with our previous estimations, as a genetically diverse board can be thought of as a channel, through which information of corporate environmental performance is transmitted to market participants in a reliable and transparent way. These findings indicate that higher genetic diversity can improve information disclosure, with special emphasis on green corporate governance, in line with the agency theory (Jensen and Meckling, 1976), and the upper echelons theory (Hambrick and Mason, 1984). In particular, if genetic diversity increases by one percentage point, the log odds ratio of being in a category higher than m in terms of corporate ESG disclosure (versus being in a category lower or equal to m) increases by $\log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.01)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.01)}) - \log(\frac{P(Y_{i,t}>m|GENETICD_{i,t}=0.00)}{P(Y_{i,t}\leq m|GENETICD_{i,t}=0.00)}) = 0.01\alpha_1 = 0.01 \times 3.831 = 0.03831$, and the odds ratio increases $e^{0.03831} = 1.03905$ times or 3.905% (Column 1). Further, the estimated ordered probit model indicates that the z-score of $Y_{i,t}$ rises by 0.02187 when genetic diversity goes up by one percentage point (Column 2). Turning to the response of corporate carbon disclosure, if genetic diversity increases by one percentage point, the log of odds ratio of disclosing carbon emissions versus non-disclosing is given by $\log(\frac{p_1^{GENETICD=0.01}}{p_0^{GENETICD=0.01}}) - \log(\frac{p_1^{GENETICD=0.00}}{p_0^{GENETICD=0.00}}) = 0.01\alpha_1 = 0.01 \times 5.618 = 0.05618$, and the odds ratio increases $e^{0.05618} = 1.0578$ times or by 5.78% (see Column 3). Also, when genetic diversity rises by one percentage point the z-score increases by 0.03352 (see Column 4).

5. Robustness analysis

In this section, we analyse the robustness of our results. First, in Section 5.1, we examine whether our results are specific to the US sample. To this end, we estimate our panel data models on a larger world sample, which incorporates other countries. We further ask if our results remain intact when financial firms are excluded, which must comply with a different regulatory framework than non-financial firms. Second, in Section 5.2, we split our sample into high and low profitability firms. Results show that high profitability firms are more likely to engage in environmental projects. Our third robustness check seeks to ascertain if the baseline results are not driven by gender diversity. Section 5.3 scrutinises the results. Accordingly, we divide our sample into two subsamples that comprise firms with high and low gender diversity on the board. This robustness exercise indicates no material change to our qualitative results. In Section 5.4, we consider an alternative genetic diversity measure, calculated as the average genetic diversity score across the board's directors. Our fifth robustness check on Section 5.5 considers yet another genetic diversity measure based on Herfindahl index. Finally in Section 5.6, we use the two-stage Heckman selection model to correct for a selection bias. Our main findings are confirmed afresh.

[12] Please see https://www.congress.gov/117/bills/hr1187/BILLS-117hr1187rfs.pdf.

Table 7
Impact of genetic diversity on disclosures.

	Corporate ESG disclosure		Corporate carbon disclosure	
	Ordered logit	Ordered probit	Logit	Probit
	(1)	(2)	(3)	(4)
GENETICD	3.831***	2.187***	5.618***	3.352***
	(1.251)	(0.711)	(1.779)	(1.008)
SIZE	0.791***	0.456***	1.134***	0.647***
	(0.018)	(0.010)	(0.028)	(0.015)
INEF	0.039	0.029	0.167***	0.104***
	(0.068)	(0.036)	(0.059)	(0.040)
INTA	0.001	0.000	−0.031***	−0.018***
	(0.005)	(0.003)	(0.006)	(0.004)
CASHSALES	−0.205***	−0.115***	−0.049*	−0.037**
	(0.020)	(0.012)	(0.029)	(0.017)
LEV	0.001	0.000	−0.003	−0.002
	(0.006)	(0.003)	(0.005)	(0.003)
TOBINSQ	−1.715***	−0.963***	−1.569***	−0.923***
	(0.108)	(0.061)	(0.147)	(0.083)
CURRATIO	−0.045***	−0.024***	−0.098***	−0.055***
	(0.010)	(0.006)	(0.017)	(0.010)
BOARDSIZE	0.116***	0.067***	0.100***	0.055***
	(0.010)	(0.005)	(0.014)	(0.008)
FOREIGN	−0.044	−0.027	−0.022	−0.008
	(0.066)	(0.037)	(0.090)	(0.052)
GENDERD	0.816***	0.452***	0.799***	0.479***
	(0.111)	(0.063)	(0.162)	(0.092)
INDEPAST	1.191***	0.691***	−0.019	0.067
	(0.249)	(0.144)	(0.445)	(0.247)
INDEAUDIT	−0.001	0.000	−0.034	−0.014
	(0.083)	(0.047)	(0.129)	(0.073)
AGE	0.003	0.001	−0.015***	−0.009***
	(0.004)	(0.002)	(0.006)	(0.003)
TIMER	0.054***	0.031***	0.037***	0.021***
	(0.008)	(0.005)	(0.012)	(0.007)
NETWORK	−0.017	−0.008	−0.013	−0.007
	(0.012)	(0.007)	(0.017)	(0.009)
CHAIRMAN	0.012	0.009	0.075	0.043
	(0.040)	(0.023)	(0.056)	(0.032)
NEDD	−0.369***	−0.213***	−0.403**	−0.183
	(0.128)	(0.073)	(0.202)	(0.113)
INDEPESG	0.148***	0.090***	0.045	0.020
	(0.035)	(0.020)	(0.048)	(0.027)
RULED	−0.144	−0.061	−0.553***	−0.312***
	(0.149)	(0.081)	(0.176)	(0.100)
DEMD	0.018	0.011	0.193***	0.104***
	(0.041)	(0.023)	(0.051)	(0.029)
CULTD	0.099	0.057	0.000	0.009
	(0.073)	(0.041)	(0.092)	(0.053)
DEVD	0.282	0.098	0.874	0.490
	(0.512)	(0.275)	(0.613)	(0.345)
CONS			−17.945***	−10.134***
			(0.902)	(0.499)
YEAR	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES
N	14,937	14,937	14,865	14,865
R2	0.180	0.182	0.344	0.343
P	0.000	0.000	0.000	0.000

Notes: This table summarises the coefficient estimates of the ordered probit and logit models. The dependent variables are corporate ESG disclosure (CESGD) and corporate carbon disclosure (CCD). The description of CESGD and CCD are provided in Table A1. Genetic diversity (“GENETICD”) is our key explanatory variable, calculated as the standard deviation of country-level board directors’ genetic scores (Delis et al., 2017). In Column 1, estimates of the ordered logit model are summarised. In Column 2, estimates of the ordered probit model are summarised. In Column 3, estimates of the logit model are summarised. In Column 4, estimates of the probit model are summarised. In Columns 1 and 2, the dependent variable is CESGD, and in Columns 3 and 4 the dependent variable is CCD. We consider a set of control variables consists of accounting rations/financial variables as well as corporate governance variables. We additionally control for country-level diversity variables: diversity in rule of law (“RULED”), diversity in democracy (“DEMD”), cultural diversity (“CULTD”), diversity in the development level (“DEVD”). The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the maximum likelihood (ML) estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

5.1. The impact of genetic diversity on corporate environmental performance: alternative samples

We continue our analysis by considering three variations to our sample: (a) a US sample excluding the financial firms, (b) a full world sample, and (c) a world sample excluding US firms. Table 8 presents the coefficient estimates of the model, outlined in Eq. (3), excluding financials (Columns 1–2), considering the whole world sample (Columns 3–4) and using the world sample without the US firms (Columns 5–6). In the first two columns, we exclude banks, investment, insurance, real estate, and private equity firms (see Table A3 in the Online Appendix), because these firms have naturally more diverse boards and lower impact on the environmental performance. We obtain a positive and significant genetic diversity effect on corporate environmental performance. Concretely, genetic diversity improves both environmental and carbon performance scores. Thus, we can argue that financial firms do not drive our main findings. Next, in Columns 3–6, we use the full world sample to test whether our baseline results hold across different countries. This sample comprises more than 6000 firms from 50 countries, where over 50% of firms are based in the US (Table A9 in the Online Appendix). Notably, we observe that the US strongly drives the results, as the world sample without the US (Columns 5 and 6) yields insignificant results. This finding is of paramount importance as it illustrates that US firms with genetic diversity on their boards can improve their environmental performance. Also, the fact that results for the world sample excluding US firms show no statistical significance insinuates that genetic diversity mostly benefits environmental performance in the US.

5.2. The impact of genetic diversity on corporate environmental performance: Controlling for profitability

In this subsection, we control for firms with low vs. high profitability. Table 9 presents the coefficient estimates of the panel data model, outlined in Eq. (3), for high and low levels of corporate profitability. The results are supportive of the financial slack argument that firms with available financial resources are more likely to invest in environmental projects. These results are also in line with our previous estimations. Thus, there is evidence that firms with higher financial performance would benefit from a more genetically diverse board. It could be the case that once a certain threshold of profitability is reached, genetically diversified boards are more likely to invest in environmental performance projects (this could imply underlying non-linearities). On the contrary, a genetically diversified board of a low-profitability firm cannot afford a heightened carbon performance, while still can improve their overall environmental performance. The Wald test, which tests for the difference in the coefficient estimates between low and high-profitability firms, indicates that this difference is significant (at 1%) for CCPA. In terms of CEP, in Column 4, we report a larger GENETICD coefficient estimate compared to Column 3; however, the difference is insignificant. Taken together, the findings indicate that the effect of a change in genetic diversity on environmental performance is conditional on profitability levels. Specifically, a genetically diverse board of a more profitable firm is likely to perform ‘greener’ than its lower profitability counterpart. It is not surprising that the availability of financial resources (such as reinvested profits) is positively associated with the implementation of environmental projects by a genetically diverse board.

5.3. The impact of genetic diversity on corporate environmental performance: Controlling for gender diversity

Prior research shows that high female representation on the board is conducive to both environmental and financial performance (Kim and Starks, 2016; Liu, 2018; Saeed et al., 2021).[13] To control for gender diversity, we employ our panel data model, outlined in Eq. (3), for high versus low levels of gender diversity. Table 10 presents the coefficient estimates. Interestingly, genetic diversity improves the environmental performance of firms that feature higher gender diversity. Thus, our results show that gender diversity can amplify the effect of genetic diversity on environmental performance, in line with diversity theory. This result can be of utmost importance for both companies and policymakers. Human resource policies could be geared towards a larger proportion of women in a genetically diverse board of directors. In terms of policy-making, quotas could be considered for women’s representation, as well as requirements to disclose ethnic diversity on the board of directors. Importantly, genetic diversity should be considered as a diversity factor in the firm’s sustainability reports.

5.4. The impact of boards’ average genetic score on corporate environmental performance

Arguably, GENETICD is the genetic diversity-related measure of board heterogeneity or the variation in boards’ genetic diversity. Therefore, higher genetic diversity values portray a relatively larger variation in board members’ genetic diversity scores. However, if all board members are from the same country, then GENETICD would yield a value of 0. Suppose there are two companies; the board of one company consists of directors from a country with a low genetic diversity score, while the board of another company comprises directors from a country with a high genetic diversity score. Our genetic diversity score would assign a score of zero to boards composed of individuals who are all from a high genetic diversity country, similarly to boards composed of individuals who are all from a low genetic diversity country. However, using the country-level average genetic diversity score allows helps us avoid such a misapprehension. Therefore, we additionally ask if the country-level diversity on the board (rather than its variation) can translate into improved carbon and environmental performance. The country-level diversity score is calculated as the firm-year average genetic diversity score as follows:

$$MEANGEN = \frac{1}{N}\sum_{i=1}^{N} d_i \tag{9}$$

[13] We also tested the effect of gender diversity in different sub-samples based on other institutional characteristics such as % foreign directors, the average age of directors, and culture. However, results reveal no discernible pattern among the estimation outputs.

Table 8
The impact of GENETICD using sub-samples.

	US EX-FINANCIALS		WORLD		WORLD EX-US	
	CCPA	CEP	CCPA	CEP	CCPA	CEP
	(1)	(2)	(3)	(4)	(5)	(6)
GENETICD	3.822**	5.501***	2.252***	1.454***	1.094	−0.290
	(1.659)	(0.828)	(0.713)	(0.448)	(0.769)	(0.474)
SIZE	0.025	0.567***	0.019	0.469***	0.068***	0.360***
	(0.023)	(0.011)	(0.013)	(0.007)	(0.016)	(0.009)
INEF	−2.116***	0.233***	−0.080***	−0.0001*	−0.022	−0.0001*
	(0.142)	(0.033)	(0.023)	(0.0001)	(0.022)	(0.0001)
INTA	0.051***	−0.012***	0.038***	−0.001	0.011**	0.006*
	(0.006)	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)
CASHSALES	−0.350***	−0.023*	−0.038**	−0.027***	−0.045**	−0.021**
	(0.038)	(0.013)	(0.018)	(0.008)	(0.021)	(0.010)
LEV	0.008	−0.002	0.011*	−0.002	0.001	−0.018**
	(0.006)	(0.003)	(0.005)	(0.003)	(0.013)	(0.009)
TOBINSQ	−1.513***	−0.603***	−0.886***	−0.386***	−0.532***	−0.288***
	(0.152)	(0.068)	(0.082)	(0.044)	(0.097)	(0.055)
CURRATIO	0.095***	−0.023***	0.146***	−0.029***	0.138***	−0.033***
	(0.021)	(0.004)	(0.012)	(0.003)	(0.015)	(0.004)
BOARDSIZE	−0.034***	0.057***	−0.012**	0.034***	0.001	0.026***
	(0.012)	(0.006)	(0.005)	(0.003)	(0.006)	(0.003)
FOREIGN	0.151**	0.002	−0.019	−0.044**	−0.059*	−0.067***
	(0.074)	(0.043)	(0.031)	(0.020)	(0.032)	(0.020)
GENDERD	0.584***	0.397***	−0.079	0.346***	−0.203***	0.291***
	(0.181)	(0.076)	(0.056)	(0.036)	(0.057)	(0.036)
INDEPAST	0.085	0.179	−0.412***	−0.097	−0.494***	−0.257***
	(0.495)	(0.189)	(0.133)	(0.080)	(0.133)	(0.076)
INDEAUDIT	−0.261**	0.055	−0.078	−0.003	−0.027	−0.003
	(0.131)	(0.056)	(0.052)	(0.030)	(0.054)	(0.032)
AGE	−0.008	0.003	−0.012***	0.003**	−0.013***	0.004***
	(0.006)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
TIMER	−0.017	0.012**	−0.013**	0.009***	−0.011*	0.004
	(0.013)	(0.005)	(0.005)	(0.003)	(0.006)	(0.003)
NETWORK	−0.008	0.009	−0.022***	−0.004	−0.018***	0.002
	(0.020)	(0.008)	(0.007)	(0.004)	(0.007)	(0.004)
CHAIRMAN	−0.032	0.020	0.021	0.015	0.210***	−0.114***
	(0.051)	(0.027)	(0.035)	(0.019)	(0.052)	(0.030)
NEDD	−0.183	0.017	−0.171***	−0.034	−0.344***	0.094**
	(0.199)	(0.085)	(0.064)	(0.039)	(0.068)	(0.039)
INDEPESG	−0.029	0.042*	−0.122***	0.029*	−0.316***	0.077***
	(0.045)	(0.023)	(0.032)	(0.017)	(0.045)	(0.027)
RULED	−0.069	−0.067	−0.161**	−0.011	−0.172**	−0.001
	(0.150)	(0.085)	(0.071)	(0.046)	(0.077)	(0.048)
DEMD	−0.041	0.036	−0.032	0.010	−0.035	−0.007
	(0.045)	(0.025)	(0.021)	(0.013)	(0.023)	(0.014)
CULTD	−0.009	0.004	0.074**	0.036	0.096**	0.064**
	(0.088)	(0.046)	(0.038)	(0.025)	(0.040)	(0.026)
DEVD	0.363	−0.474	−0.256	−0.365***	−0.466**	−0.159
	(0.480)	(0.289)	(0.193)	(0.133)	(0.201)	(0.130)
CONS	2.827***	−5.025***	7.570***	−7.414***	6.900***	−6.224***
	(0.933)	(0.782)	(0.574)	(0.342)	(0.583)	(0.319)
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
STATE/ COUNTRY	YES	YES	YES	YES	YES	YES
N	4302	13,916	13,136	28,492	8588	13,557
R2	0.477	0.430	0.601	0.436	0.679	0.438

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3), excluding financials (Columns 1 and 2), for the world sample (Columns 3 and 4) and exclude the US sample (Columns 5 and 6). Genetic diversity (“GENETICD”) is our key explanatory variable, calculated as the standard deviation of country-level board directors’ genetic scores (Delis et al., 2017). In Columns 1 and 3, the dependent variable is corporate carbon performance relative to total assets (“CCPA”). In Columns 2 and 4, the dependent variable is corporate environmental performance (“CEP”). The descriptions of CCAP and CEP are provided in Table 1. In all model specifications, a comprehensive set of control variables is employed, which consists of accounting ratios/financial variables, corporate governance variables, and diversity variables. The sample period runs from 2005 to 2019. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

Table 9
Firms with High vs. Low profitability.

	CCPA		CEP	
	LOW	HIGH	LOW	HIGH
	(1)	(2)	(3)	(4)
GENETICD	−3.676*	7.342***	4.178***	6.260***
	(2.060)	(2.535)	(1.136)	(1.180)
SIZE	−0.045*	0.021	0.543***	0.562***
	(0.025)	(0.037)	(0.015)	(0.015)
INEF	−2.770***	−0.902***	0.163***	0.693***
	(0.160)	(0.220)	(0.036)	(0.082)
INTA	0.074***	0.048***	−0.011**	−0.029***
	(0.009)	(0.008)	(0.005)	(0.004)
CASHSALES	−0.256***	−0.334***	0.041**	−0.077***
	(0.054)	(0.051)	(0.018)	(0.020)
LEV	−0.010	0.011*	−0.003	−0.000
	(0.034)	(0.006)	(0.018)	(0.003)
CURRATIO	0.031	0.139**	−0.009*	−0.047***
	(0.022)	(0.054)	(0.005)	(0.014)
BOARDSIZE	−0.036**	−0.031*	0.075***	0.055***
	(0.015)	(0.018)	(0.009)	(0.008)
FOREIGN	0.061	0.187*	−0.004	0.024
	(0.090)	(0.112)	(0.060)	(0.060)
GENDERD	0.061	0.950***	0.231**	0.393***
	(0.226)	(0.265)	(0.100)	(0.105)
INDEPAST	−0.694	0.604	0.367	−0.247
	(0.573)	(0.831)	(0.227)	(0.322)
INDEAUDIT	0.151	−0.490***	0.054	0.090
	(0.160)	(0.186)	(0.074)	(0.079)
AGE	0.011	−0.031***	0.001	0.006*
	(0.007)	(0.008)	(0.003)	(0.003)
TIMER	−0.041**	−0.018	0.024***	−0.007
	(0.016)	(0.018)	(0.008)	(0.007)
NETWORK	0.053*	−0.044*	−0.011	0.029***
	(0.028)	(0.026)	(0.011)	(0.010)
CHAIRMAN	−0.273***	0.149**	0.015	0.030
	(0.061)	(0.075)	(0.038)	(0.036)
NEDD	0.120	−0.528*	0.038	−0.005
	(0.237)	(0.275)	(0.113)	(0.117)
INDEPESG	0.032	−0.044	0.018	0.037
	(0.054)	(0.068)	(0.032)	(0.032)
RULED	−0.258	0.006	0.135	−0.102
	(0.195)	(0.223)	(0.121)	(0.117)
DEMD	0.027	−0.120	0.009	0.049
	(0.053)	(0.074)	(0.033)	(0.038)
CULTD	0.236**	−0.145	0.020	−0.049
	(0.112)	(0.133)	(0.063)	(0.066)
DEVD	0.839	−0.187	−0.838**	−0.029
	(0.554)	(0.780)	(0.398)	(0.409)
CONS	5.063***	2.331**	−7.039***	−4.729***
	(0.763)	(1.098)	(0.402)	(0.796)
WALD TEST	27.95***		1.73	
YEAR	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES
STATE	YES	YES	YES	YES
N	2273	2275	7462	7460
R2	0.472	0.486	0.454	0.386

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3), for high and low levels of corporate profitability. Genetic diversity ("GENETICD") is our key explanatory variable, calculated as the standard deviation of country-level board directors' genetic scores (Delis et al., 2017). In Columns 1 and 2, the dependent variable is corporate carbon performance relative to total assets ("CCPA"). In Columns 3 and 4, the dependent variable is corporate environmental performance ("CEP"). The descriptions of CCAP and CEP are provided in Table A1. In all model specifications, a comprehensive set of control variables is employed, which consists of accounting ratios/financial variables, corporate governance variables, and diversity variables. The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses. The Wald test statistic is used to test if the estimates are significantly different for high and low levels of corporate profitability.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

Table 10
Linear regressions for firms with High vs. low gender diversity.

	CCPA		CEP	
	LOW (1)	HIGH (2)	LOW (3)	HIGH (4)
GENETICD	1.497	3.864**	3.628***	6.411***
	(3.138)	(1.863)	(1.193)	(1.133)
SIZE	−0.073*	0.061**	0.506***	0.538***
	(0.041)	(0.025)	(0.015)	(0.014)
INEF	−1.979***	−1.684***	0.175***	0.455***
	(0.248)	(0.144)	(0.038)	(0.064)
INTA	0.075***	0.043***	−0.013***	−0.008*
	(0.010)	(0.007)	(0.004)	(0.004)
CASHSALES	−0.015***	−0.001***	−0.022	0.051***
	(0.004)	(0.0001)	(0.017)	(0.018)
LEV	0.005	0.037**	−0.004	0.022**
	(0.006)	(0.018)	(0.004)	(0.010)
TOBINSQ	−1.741***	−0.508***	−0.583***	−0.566***
	(0.243)	(0.176)	(0.092)	(0.096)
CURRATIO	0.060*	0.078***	0.071***	0.042***
	(0.035)	(0.025)	(0.009)	(0.008)
BOARDSIZE	−0.051**	−0.042***	−0.010	0.007
	(0.022)	(0.013)	(0.064)	(0.056)
FOREIGN	0.046	0.192**	0.068	0.407
	(0.146)	(0.080)	(0.242)	(0.289)
INDEPAST	4.145***	−2.970***	0.177**	−0.156*
	(0.884)	(0.586)	(0.069)	(0.088)
INDEAUDIT	−0.161	−0.218	0.004	0.006
	(0.189)	(0.167)	(0.003)	(0.004)
AGE	−0.031***	0.016*	0.011	0.016**
	(0.007)	(0.009)	(0.008)	(0.008)
TIMER	−0.038*	−0.014	0.071***	0.042***
	(0.022)	(0.015)	(0.009)	(0.008)
NETWORK	−0.066**	0.086***	0.001	0.022*
	(0.026)	(0.032)	(0.010)	(0.012)
CHAIRMAN	−0.096	−0.030	−0.143***	0.133***
	(0.090)	(0.059)	(0.042)	(0.035)
NEDD	−0.300	0.378	0.389***	−0.607***
	(0.253)	(0.328)	(0.100)	(0.157)
INDEPESG	0.175**	−0.095*	−0.038	0.062**
	(0.081)	(0.051)	(0.034)	(0.030)
RULED	0.429	−0.239	0.022	−0.044
	(0.326)	(0.160)	(0.125)	(0.113)
DEMD	0.059	−0.092*	0.005	0.057*
	(0.081)	(0.052)	(0.037)	(0.033)
CULTD	−0.230	0.011	0.055	−0.052
	(0.182)	(0.097)	(0.068)	(0.062)
DEVD	0.188	0.527	−1.018**	−0.062
	(0.995)	(0.506)	(0.449)	(0.366)
CONS	5.976***	−0.932	−4.327***	−5.294***
	(1.689)	(1.084)	(1.347)	(0.956)
WALD TEST	0.50		2.99*	
YEAR	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES
STATE	YES	YES	YES	YES
N	1713	2835	7525	7397
R2	0.485	0.564	0.410	0.446

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3), for high and low levels of gender diversity. Genetic diversity ("GENETICD") is our key explanatory variable, calculated as the standard deviation of country-level board directors' genetic scores (Delis et al., 2017). In Columns 1 and 2, the dependent variable is corporate carbon performance relative to total assets ("CCPA"). In Columns 3 and 4, the dependent variable is corporate environmental performance ("CEP"). The descriptions of CCAP and CEP are provided in Table A1. In all model specifications, a comprehensive set of control variables is employed, which consists of accounting ratios/financial variables, corporate governance variables, and diversity variables. The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses. The Wald test statistic is used to test if the estimates are significantly different for high and low gender diversity.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

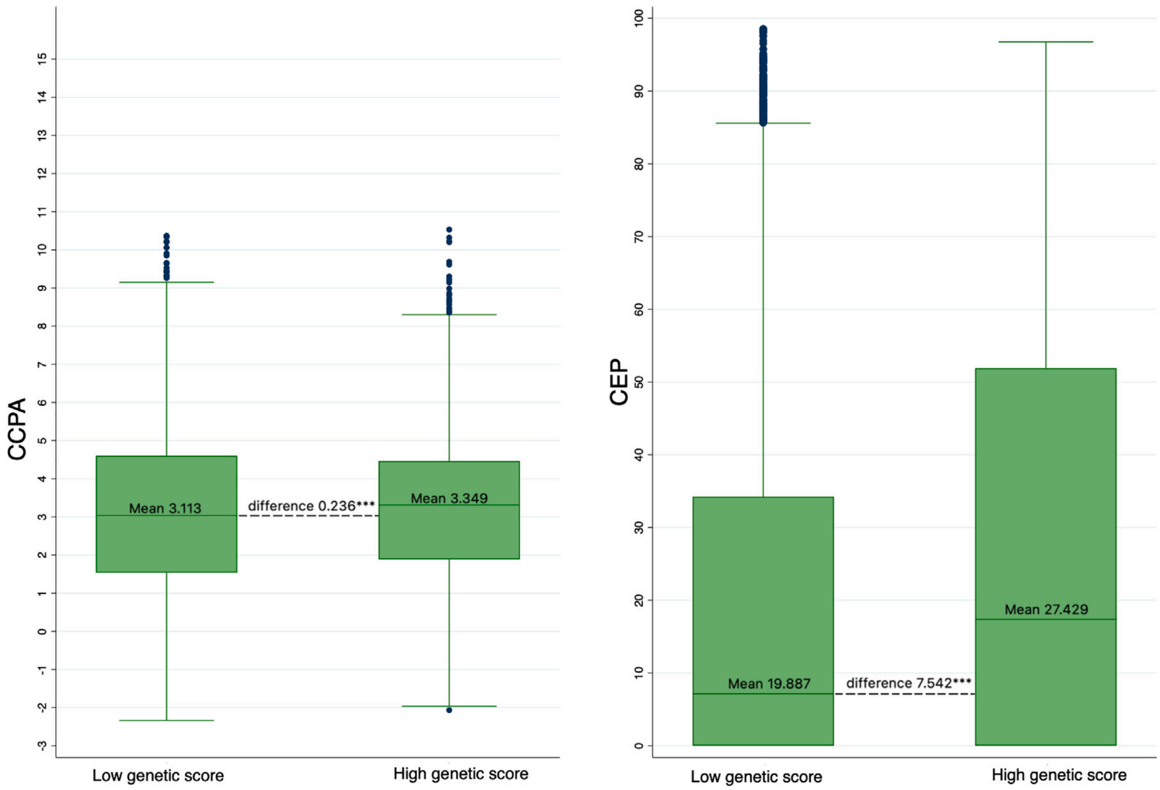

Fig. 4. CCPA and CEP by genetic group. Notes: Low diversity score indicates boards below the average genetic score level (i.e lower than the median < 0.6716), while High diversity score indicates boards above the average genetic score level (i.e > 0.6716). T-test shows that there are statistical differences between the two groups for both CCPA and CEP at 1% level.

Fig. 4 illustrates that boards with relatively high genetic scores are more likely to experience a higher CCPA and CEP performance than boards with low genetic diversity scores. We distinguish between 'low' and 'high' genetic boards based on the sample's median value which is estimated at 0.6716. Higher genetic diversity boards score on average 0.236 (7.542) CCPA (CEP) more than lower genetic diversity boards; moreover, the estimated difference is statistically significant.

We now move to statistically test the relationship between the country-level genetic score and CCPA (CEP). Table 11 demonstrates that the average genetic diversity score on a board (MEANGEN) is positively associated with both CCPA and CEP. A one percentage point increase in MEANGEN improves CCPA (CEP) by $(e^{7.079\times0.01} - 1) \times 100\% = 7.34\%$ (2.36%). Therefore, an increase in the country-level diversity on a board leads to improved environmental performance.

5.5. The impact of genetic fractionalisation on corporate environmental performance

We opt for an alternative measure of genetic diversity, which is calculated based on the directors' ancestral origins, in line with Giannetti and Zhao (2019). We define genetic fractionalisaction (FRAC) as the probability that two randomly selected directors have different nationality, using the Herfindahl-based index:

$$FRAC_{i,t} = 1 - \sum_{f=1}^{F} s^2_{f,i,t} \tag{10}$$

where $s_{f,i,t}$ is the share of board members of ancestry f among all board members of firm i at time t. While (Giannetti and Zhao, 2019) scrutinise last names of directors to find the ancestral origins utilising information from *Ancestry.com.*, we use their actual nationality as it has been provided in BoardEX database. An advantage of the genetic fractionalisation measure is that it is not driven by genetic diversity scores (based on data from the HGDP-CEPH Human Genome Diversity Cell Line Panel), used to calculate our main measure.

Table 12 shows that genetic fractionalisation (FRAC) appears to be positively related to both CCPA and CEP. A one percentage point increase in FRAC translates into an improved corporate carbon performance (corporate environmental performance) by $(e^{0.317\times0.01} - 1)\times 100\% = 0.318\%$ (0.279%). Qualitatively, these results are in line with the previous estimations, in which the genetic diversity measured was used. Overall, our research findings are robust to various measures of genetic diversity/fractionalisation; in particular, they are not sensitive to measurement error.

Table 11
The impact of mean genetic score on corporate environmental performance.

	CCPA			CEP		
	(1)	(2)	(3)	(4)	(5)	(6)
MEANGEN	8.301***	6.783***	7.079***	3.163***	3.229***	2.336**
	(1.831)	(1.962)	(2.140)	(0.814)	(0.899)	(0.958)
SIZE	0.009	0.030	0.029	0.623***	0.564***	0.562***
	(0.019)	(0.022)	(0.022)	(0.009)	(0.011)	(0.011)
INEF	−2.096***	−2.080***	−2.068***	0.282***	0.280***	0.280***
	(0.137)	(0.136)	(0.136)	(0.033)	(0.032)	(0.032)
INTA	0.054***	0.055***	0.055***	−0.010***	−0.012***	−0.012***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
CASHSALES	−0.373***	−0.366***	−0.365***	−0.034***	−0.028**	−0.027**
	(0.037)	(0.037)	(0.037)	(0.012)	(0.012)	(0.012)
LEV	0.009	0.008	0.008	0.000	−0.000	−0.000
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
TOBINSQ	−1.529***	−1.513***	−1.522***	−0.681***	−0.629***	−0.623***
	(0.145)	(0.146)	(0.146)	(0.066)	(0.066)	(0.066)
CURRATIO	0.098***	0.093***	0.094***	−0.025***	−0.022***	−0.022***
	(0.020)	(0.020)	(0.020)	(0.004)	(0.004)	(0.004)
BOARDSIZE		−0.035***	−0.036***		0.059***	0.058***
		(0.012)	(0.012)		(0.006)	(0.006)
FOREIGN		0.120	0.126*		0.041	0.021
		(0.073)	(0.074)		(0.043)	(0.044)
GENDERD		0.608***	0.613***		0.373***	0.371***
		(0.176)	(0.176)		(0.073)	(0.073)
INDEPAST		0.040	0.022		0.135	0.128
		(0.487)	(0.488)		(0.186)	(0.186)
INDEAUDIT		−0.252**	−0.251**		0.065	0.064
		(0.126)	(0.126)		(0.054)	(0.054)
AGE		−0.010*	−0.009*		0.004	0.004
		(0.005)	(0.005)		(0.002)	(0.002)
TIMER		−0.017	−0.016		0.015***	0.015***
		(0.012)	(0.012)		(0.005)	(0.005)
NETWORK		−0.011	−0.011		0.012	0.011
		(0.019)	(0.019)		(0.008)	(0.008)
CHAIRMAN		−0.044	−0.044		0.032	0.029
		(0.049)	(0.049)		(0.026)	(0.026)
NEDD		−0.200	−0.189		−0.011	−0.004
		(0.185)	(0.185)		(0.081)	(0.082)
INDEPESG		−0.009	−0.009		0.039*	0.038*
		(0.043)	(0.043)		(0.022)	(0.023)
RULED			−0.063			−0.047
			(0.148)			(0.084)
DEMD			−0.066			0.023
			(0.044)			(0.025)
CULTD			0.011			0.097**
			(0.080)			(0.042)
DEVD			0.613			−0.176
			(0.464)			(0.282)
CONS	−3.004**	−1.462	−1.734	−7.046***	−7.129***	−6.512***
	(1.448)	(1.557)	(1.657)	(0.932)	(0.973)	(0.997)
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
STATE	YES	YES	YES	YES	YES	YES
N	4544	4544	4544	14,914	14,912	14,912
R2	0.475	0.480	0.481	0.414	0.420	0.420

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3). Instead of Genetic diversity, firms' average genetic score ("MEANGEN") is our key explanatory variable. In Columns 1–3, the dependent variable is corporate carbon performance relative to total assets ("CCPA"). In Columns 4–6, the dependent variable is corporate environmental performance, measured as an index number ("CEP"). The calculations of CCPA and CEP are provided in Table A1. In Columns 1 and 4, we control for company-level accounting ratios and financial variables. In Columns 2 and 5, our set of control variables consists of accounting ratios/financial variables as well as corporate governance variables. In Columns 3 and 6, we additionally control for country-level diversity variables: diversity in rule of law ("RULED"), diversity in democracy ("DEMD"), cultural diversity ("CULTD"), diversity in the development level ("DEVD"). The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

Table 12
The impact of genetic fractionalisation on corporate environmental performance.

	CCPA			CEP		
	(1)	(2)	(3)	(4)	(5)	(6)
FRAC	0.406***	0.279**	0.317**	0.262***	0.298***	0.279***
	(0.100)	(0.115)	(0.145)	(0.049)	(0.059)	(0.073)
SIZE	0.005	0.027	0.026	0.621***	0.562***	0.562***
	(0.019)	(0.022)	(0.022)	(0.009)	(0.011)	(0.011)
INEF	−2.083***	−2.067***	−2.055***	0.284***	0.282***	0.281***
	(0.136)	(0.136)	(0.136)	(0.032)	(0.032)	(0.032)
INTA	0.053***	0.054***	0.055***	−0.011***	−0.012***	−0.012***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
CASHSALES	−0.371***	−0.363***	−0.362***	−0.033***	−0.028**	−0.028**
	(0.037)	(0.037)	(0.037)	(0.012)	(0.012)	(0.012)
LEV	0.008	0.008	0.008	0.000	−0.000	−0.000
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
TOBINSQ	−1.540***	−1.527***	−1.538***	−0.681***	−0.629***	−0.629***
	(0.145)	(0.146)	(0.146)	(0.066)	(0.066)	(0.066)
CURRATIO	0.097***	0.091***	0.093***	−0.025***	−0.022***	−0.022***
	(0.020)	(0.020)	(0.020)	(0.004)	(0.004)	(0.004)
BOARDSIZE		−0.035***	−0.036***		0.059***	0.059***
		(0.012)	(0.012)		(0.006)	(0.006)
FOREIGN		0.118	0.121		−0.022	−0.024
		(0.078)	(0.078)		(0.047)	(0.047)
GENDERD		0.594***	0.597***		0.373***	0.373***
		(0.177)	(0.177)		(0.073)	(0.073)
INDEPAST		0.008	−0.019		0.103	0.105
		(0.489)	(0.489)		(0.186)	(0.186)
INDEAUDIT		−0.246*	−0.241*		0.066	0.066
		(0.126)	(0.126)		(0.054)	(0.054)
AGE		−0.010*	−0.010*		0.004*	0.004*
		(0.005)	(0.005)		(0.002)	(0.002)
TIMER		−0.017	−0.016		0.016***	0.015***
		(0.012)	(0.012)		(0.005)	(0.005)
NETWORK		−0.012	−0.012		0.011	0.011
		(0.019)	(0.019)		(0.008)	(0.008)
CHAIRMAN		−0.047	−0.045		0.032	0.032
		(0.049)	(0.049)		(0.026)	(0.026)
NEDD		−0.163	−0.157		0.006	0.003
		(0.184)	(0.185)		(0.081)	(0.081)
INDEPESG		−0.009	−0.009		0.033	0.034
		(0.044)	(0.044)		(0.022)	(0.023)
RULED			−0.136			−0.078
			(0.148)			(0.084)
DEMD			−0.051			0.024
			(0.044)			(0.025)
CULTD			0.014			0.071
			(0.082)			(0.043)
DEVD			0.568			−0.365
			(0.473)			(0.288)
CONS	2.237**	2.824***	2.730***	−5.070***	−5.141***	−5.087***
	(0.871)	(0.919)	(0.921)	(0.777)	(0.784)	(0.785)
YEAR	YES	YES	YES	YES	YES	YES
INDUSTRY	YES	YES	YES	YES	YES	YES
STATE	YES	YES	YES	YES	YES	YES
N	4544	4544	4544	14,924	14,924	14,924
R2	0.475	0.479	0.480	0.414	0.421	0.421

Notes: This table summarises the coefficient estimates of the linear panel data model, outlined in Eq. (3). Instead of Genetic diversity, fractionalisation (“FRAC”) is our key explanatory variable, which is defined as the probability of two randomly selected directors to have different nationality. In Columns 1–3, the dependent variable is corporate carbon performance relative to total assets (“CCPA”). In Columns 4–6, the dependent variable is corporate environmental performance, measured as an index number (“CEP”). The calculations of CCPA and CEP are provided in Table A1. In Columns 1 and 4, we control for company-level accounting ratios and financial variables. In Columns 2 and 5, our set of control variables consists of accounting ratios/financial variables as well as corporate governance variables. In Columns 3 and 6, we additionally control for country-level diversity variables: diversity in rule of law (“RULED”), diversity in democracy (“DEMD”), cultural diversity (“CULTD”), diversity in the development level (“DEVD”). The sample period runs from 2005 to 2019. The cross section comprises a total of 3690 companies, with a varying number of companies in each year. The model is estimated by means of the OLS estimation method. Robust standard errors are indicated in round parentheses.

*Denote the 10% levels of significance.

**Denote the 5% levels of significance.

***Denote the 1% levels of significance.

5.6. Two-stage heckman selection model

It is worth noting that when corporate carbon performance is used as the dependent variable, the sample selection bias may arise due to the potential self-selection by firms included in the sample. To understand the nature of the problem, we recall that CCPA comprises GHG emissions. From a behavioural perspective, a firm may have a greater incentive to disclose information about GHG emissions reduction to communicate improved environmental performance. On the contrary, firms might try to hide information about GHG emission surges, as this worsens firms' environmental performance. To correct for this self-selection bias, we first estimate the selection equation for the sub-sample of firms that disclose information about CEP. Second, we estimate the outcome equation, which is corrected for the self-selection bias. Further details about the two-stage Heckman selection model are available in the Online Appendix (Page 11). Findings are summarised in the Online Appendix, Table A11. They show that CCPA is correlated with the non-selection hazard, with a positive and significant coefficient of correlation. This indicates the presence of the self-selection bias. Importantly, when the self-selection bias is corrected for, the effect of genetic diversity on CCPA remains positive and significant.

6. Conclusion

This paper sheds light on whether boards' genetic diversity can impact on environmental and carbon performance of US firms. We measure genetic diversity in three different ways; (i) as the standard deviation of board directors' genetic diversity scores (Delis et al., 2017) (the genetic diversity-related measure of board heterogeneity), (ii) as the average of board directors' genetic diversity scores, and (iii) as a measure of genetic fractionalisation (Giannetti and Zhao, 2019). We present comprehensive evidence that boards' genetic diversity can significantly improve corporate environmental and carbon performance. There is some variability across results, though our main finding of the positive contribution of genetic diversity to environmental performance stands across various identifications and estimation methods.

Overall, our findings are in line with previous empirical studies and theories (agency, diversity, gene-culture co-evolution, and upper-echelons theories). For example, previous research (Nehring and Puppe, 2002; Docquier et al., 2014) shows that organisations benefit from social diversity within the board in terms of higher innovation and productivity. We significantly complement previous studies and emphasise the importance of genetic diversity to deal with climate change. Our results show that, in line with diversity theory, genetic diversity can enhance corporate environmental performance. Similarly, a genetically diverse board improves corporate carbon performance. Moreover, we find that corporate transparency in terms of ESG performance is positively associated with boards' genetic diversity. Furthermore, we document that the relationship between genetic diversity and environmental performance is more prominent for firms based in the US than firms located in other countries. This finding indicates that US firms should increase genetic diversity within the corporate boards. We reveal that boards should seek diversification not only in terms of gender, race, and nationality but also in terms of genetics. Clearly, our research shows that genetic diversity on corporate boards can improve environmental performance, while controlling for various variables and methodologies.

Future research could dig deeper into the theoretical potential channels through which a more diverse board influences the firm's environmental disclosures and performance. In this regard, Dyck et al. (2019) show that institutional investor activism is instrumental in stronger firm-level environmental and social performance across the globe. Further, Buchanan et al. (2018) find that the effect of corporate social responsibility (CSR) on firm value varies with the level of influential institutional investment. The authors show that the overall CSR effect is a result of the relative dominance of two effects: conflict resolution and the overinvestment effect. An interesting research question would seek to evaluate the nature and the direction of the relationship between corporate environmental performance and diversity in the board of directors. Another promising research direction would be to examine the robustness of our results by using different genetic data. For example, Cook (2015) focuses on a heterozygosity measure, which is responsible for infectious pathogens.

In terms of economic policy, we postulate that the key to tackling climate challenges is to promote genetic diversity on a firm's board. It is positive to observe that recent policy initiatives in the US (see California AB 979 Act) actively promote diversity on boards. Alas, there is further progress on this front to be achieved. Lastly, we should underline that promoting genetic diversity (i.e., people with different nationalities) reduces inequalities within companies, which is in line with the tenth Sustainable Development Goal. Firms should promote inclusion of all, irrespective of ethnicity, nationality, and origin, and thus they can reduce inequalities and also improve environmental performance.

CRediT authorship contribution statement

Renatas Kizys: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Emmanuel C. Mamatzakis:** Conceptualization, Formal analysis, Investigation, Supervision, Validation, Writing – original draft, Writing – review & editing. **Panagiotis Tzouvanas:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Investigation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.intfin.2023.101756.

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