# Controlled Firms, Preferences, and Carbon Emissions

**Alexander Dyck**
University of Toronto

**Karl V. Lins**
University of Utah

**Lukas Roth**
University of Alberta

**Mitch Towner**
Arizona State University

**Hannes F. Wagner**
Bocconi University

November 2025

**Abstract**

Controlled firms represent the dominant ownership structure globally, yet their environmental impact relative to widely held firms remains unclear. We test this for 3,769 firms from 35 countries using actual carbon emissions data and a *clean* preference measure built using retrieval-augmented large language models. Overall, controlling owners' preferences affect emissions but are insufficient to address environmental externalities. Controlled firms with low environmental preferences emit 20% more carbon than widely held firms, while those with high environmental preferences have emissions no different than widely held firms. Controlled firms' carbon performance is even worse in settings where marginal emissions abatement costs are high.

*Keywords*: Carbon emissions, family ownership, environmental sustainability, preferences

*JEL Classification*: G32, G34, G54

---

Author contacts: adyck@rotman.utoronto.ca (corresponding author); karl.lins@eccles.utah.edu; lukas.roth@ualberta.ca; mitchtowner@email.arizona.edu; and hannes.wagner@unibocconi.it. We thank Morten Bennedsen, Florencio Lopez de Silanes, Luigi Zingales, Helen Zhang, and seminar participants at University of Arizona, University of Delaware, HEC Montreal, Laval University, McGill, Skema Business School, University of Missouri, University of North Carolina at Chapel Hill, University of Toronto, Waseda University, and Xi'an Jiaotong University, and conference participants at the 2024 ECGI-Baltic Family Firm Institute Conference, the 2025 EFMA Conference, the 2025 IE Madrid Symposium on Financial Markets in the Era of Climate Change, the 2025 Sustainability at Crossroads: The Edinburgh and International Review of Finance Conference, and the 2025 Paris-Dauphine "Ownership, Control and Performance" Conference for helpful comments and suggestions. We are grateful to the Social Sciences and Humanities Research Council of Canada, the BAFFI Centre on Economics, Finance and Regulation, the Michael Lee-Chin Family Institute for Corporate Citizenship, and the Innocenzo Gasparini Institute for Economic Research for financial support. None of the authors has a conflict of interest to declare.

## I. Introduction

Hart and Zingales (2017) ask whether a firm that changed its focus from financial value maximization to shareholder welfare maximization would in fact be more *clean*. For the widely held firm as of today, their answer is no. Even though investors in such a firm may have non-pecuniary preferences for *clean*, "the market for corporate control will push a board who wants to choose *clean* into a choice of *dirty*: we call this an *amoral drift*" (p. 256). However, for the closely controlled firm insulated from takeover pressure the situation is different—its owner can implement personal non-pecuniary preferences for *clean.* As Hart and Zingales (2017) state, if a closely controlled company "has a single shareholder, nobody would suggest that this single shareholder cannot instruct directors to maximize her utility, rather than her financial return." (p. 263).

The likelihood that a controlled firm chooses *clean* depends on whether its owner has *clean* preferences along with additional factors. Two countervailing forces in particular may prevent *cleaner* outcomes. If the marginal costs of becoming *cleaner* are relatively high, environmental preferences would have to be very strong to overcome these costs. Further, all entrenched owners can consume pecuniary private benefits of control by diverting current cash flows to themselves if they wish, reducing cash available for *clean* investment.

Our paper investigates whether non-pecuniary environmental preferences are important for environmental sustainability by assessing actual year-end 2023 Scope 1 (direct) and Scope 2 (indirect) carbon emissions for a sample of 3,769 non-U.S. firms from 35 countries. Aminadav and Papaioannou (2020) show that, outside of the U.S., controlled firms are generally the most common type of firm ownership structure.[1] In our sample, 55% of firms are controlled and 45%

[1] See also La Porta, Lopez-De-Silanes, and Shleifer (1999), among others.

are widely held. We identify three categories of controlled firms: family, government, and other (42%, 7%, and 6% of sample firms, respectively). We conduct baseline tests, as well as tests that consider the strength of environmental preferences and the marginal costs of becoming *clean*, all while controlling for private benefits as well as industry, country, and firm characteristics. Our study is particularly salient to climate change research because global emissions growth now comes primarily from developing countries (Copeland, Shapiro, and Taylor, 2025) where controlled firms are the most common (Lins, 2003).

No database currently exists to measure the environmental preferences of a controlling shareholder. We therefore exploit recent advances in generative AI and use two state-of-the-art large language models (LLMs)—GPT and Perplexity—to construct a novel measure of a controlling shareholder's environmental preferences, at scale. For these tests, we restrict our attention to family-controlled firms. Given their prevalence, they have the potential to materially affect carbon emissions, and they have significant heterogeneity in their environmental preferences. Importantly, the LLM ignores the controlled firm's own environmental performance in its assessment.

We estimate a firm's expected marginal cost of reducing carbon emissions using variation at the country or industry level. At the country level, we split firms into two subsamples based on the median score of the Climate Change Performance Index (CCPI), a climate mitigation performance metric from Germanwatch also used in Bolton and Kacperczyk (2023). The index aggregates country-level regulations, commitments, and actual carbon performance. In high CCPI countries, the government has forced firms to internalize more of their carbon externalities and firms have likely already exhausted low-cost options to improve their carbon performance—spending money to be even cleaner will require very strong environmental preferences. In low

CCPI countries, low-cost options to improve carbon emissions performance likely still exist. Thus, with such relatively low marginal costs of pursuing *clean*, controlling shareholders' preferences should play a larger role.

At the industry level, we split our sample into above- and below-median subsamples based on the industry's percent of Scope 1 (direct) emissions relative to its total Scope 1 and Scope 2 emissions. High Scope 1 industries have emissions that are both largely determined by owners' operating choices and account for a meaningful share of global emissions. Thus, regulators and society are more likely to have held owners accountable in these industries and firms have probably already deployed low-cost abatement opportunities. In contrast, in low Scope 1 industries, direct emissions are relatively small and external pressure has likely been weaker and more low-cost options remain, particularly when owners have pro-environmental preferences.

Our baseline tests that do not incorporate preferences or marginal costs show that no category of controlled firm has lower carbon emissions than the widely held firm. The results range from no difference for the government-controlled firm to marginally and substantially higher emissions for family-controlled and other-controlled firms.

Our second finding is that the environmental preferences of controlling shareholders do indeed matter, but mostly in ways that worsen outcomes. In firms controlled by families with low environmental preferences, carbon emissions are on average about 20% higher—approximately equivalent to the annual carbon emissions of 350 U.S. households for the median sample firm[2]—than those of widely held firms, all else equal. In contrast, emissions are similar to those of widely held firms when firms are controlled by families with high environmental preferences. These

[2] We compute the household equivalence by dividing 20% of the median firm's emissions (83,562 × 0.2 = 16,712 tCO2e; Table 1, Panel A) by the estimated annual carbon footprint of an average U.S. household (48 tCO2e; Center for Sustainable Systems, University of Michigan, 2025).

results suggest that while weak preferences are clearly linked to dirtier outcomes, strong preferences are not sufficient to overcome the pecuniary private benefit drift to remain *dirty* that affects all controlled firms. A broad implication—perhaps counterintuitive—is that allowing shareholder preferences to dictate environmental outcomes can lead to worse, not better, environmental performance.

Our third finding is that the impact of a preference for *clean* on emissions performance depends crucially on the marginal cost of becoming *cleaner*. Where improving carbon efficiency is especially costly (that is, in high CCPI countries and high Scope 1 emissions industries), our tests show that family-controlled firms perform 20-40% worse on both direct and total (direct plus indirect) carbon emissions than widely held firms regardless of their environmental preferences. Therefore, financial incentives to remain *dirty* appear to dominate non-pecuniary preferences for *clean* when abatement costs are high. Where marginal costs to become *cleaner* are lower, we find that family-controlled firms with strong environmental preferences have 35% lower direct carbon emissions than widely held firms, but their total direct and indirect emissions are not different from widely held firms.

Taken together, these findings cast doubt on the hypothesis that moving from financial value maximization to shareholder welfare maximization (Hart and Zingales, 2017) will meaningfully increase the likelihood that firms choose to be *clean*. Controlling shareholder preferences are a lever that can move firms in the direction of better carbon performance, but our evidence suggests preferences are not a particularly strong lever. In most circumstances, controlling shareholders—even those with strong environmental preferences—do not deliver better environmental performance, and those with weak preferences often exacerbate the problem.

All of our analyses use actual emissions data from a single cross-section at year-end 2023. The International Sustainability Standards board, an independent standard-setting body within the IFRS foundation, issued its first detailed sustainability standards in June of 2023. These standards focus exclusively on climate-related disclosures, particularly CO2-equivalent emissions. Countries that use IFRS and adopt the standards were expected to implement them in 2024 or soon after. These new IFRS standards were not a 'shock' to carbon reporting in the strictest sense because they were telegraphed in advance, and not all countries that follow IFRS standards adopted them. Nonetheless, the actual release of these standards arguably represents a 'quasi-exogenous shock,' causing many previously non-reporting firms to begin reporting their carbon emissions. To illustrate the recent improvement in reporting of actual carbon emissions, for our sample of 35 countries, 65% of LSEG firms that meet a minimum size threshold report their emissions in 2022, and this reporting rate increased substantially to 80% in 2023.

We note that a panel data approach, rather than a cross-sectional one, would be inappropriate for our research question for several reasons. First, carbon data from prior years would frequently be missing or would have to be filled in using estimated (imputed) emissions. For example, reporting rates for actual carbon emissions in 2010 were 16% and had increased to only 40% by 2019. With such sparse reporting, inferences from tests using imputed data could be biased if certain ownership types systematically do not disclose their actual carbon emissions because they have worse carbon performance. Regression estimates will then falsely suggest better carbon performance for these firms than is actually the case. Second, imputation is problematic because Aswani, Raghunandan, and Rajgopal (2024) show that "estimated emissions seem to be a nearly deterministic function of size, sales growth, industry, and time" (p. 77). Thus, to our knowledge the imputation process used by commercial data vendors will not capture any independent effect of ownership, and/or preferences of controlling owners on emissions. Finally, a panel data approach would not work well because control structures are remarkably stable over time.[3] Panel estimates with firm fixed effects would thus be identified only from the small number of firms experiencing control changes, likely leading to imprecise or biased estimates. Summarizing, while our cross-sectional design precludes within-firm analysis, the dramatic improvement in actual emissions reporting in 2023 enables a large-scale cross-sectional comparison that is less subject to potential selection biases plaguing earlier periods.

We make several contributions. First, we provide new evidence on the way in which environmental preferences influence corporate sustainability by looking at the preferences of controlling shareholders. This extends prior research that finds outside investors' preferences and social values shape sustainability outcomes (e.g., Hong and Kacperczyk, 2009; Dimson, Karakaş, and Li, 2015; Hart and Zingales, 2017; Dyck, Lins, Roth, and Wagner, 2019; Krueger, Sautner, and Starks, 2020; Shive and Forster, 2020; Pástor, Stambaugh, and Taylor, 2021; Pástor, Stambaugh, and Taylor, 2022; Pedersen, Fitzgibbons, and Pomorski, 2021; Dyck, Lins, Roth, Towner, and Wagner, 2023; Iliev and Roth, 2023; Lins, Roth, Servaes, and Tamayo, 2024; Duchin, Gao, and Xu, 2025). We build on a smaller literature that considers controlling insiders' preferences (e.g., Shive and Forster, 2020) and find that family owners with pro-environmental preferences do not lower firms' carbon emissions on average but do so only in one setting where expected abatement costs are low. Importantly, we find that when family owners lack pro-environmental preferences, their firms produce substantially higher carbon emissions.

Second, we provide new evidence on the relationship between concentrated ownership and carbon emissions using 2023 data when the vast majority of firms report their actual carbon

[3] For example, Franks et al. (2012) track ownership of the 4,000 largest firms in Germany, France, the U.K. and Italy over a decade, and find that family-controlled firms transition to being widely held at an annual rate of 0.5-0.9%.

emissions. We find that controlled firms generally have higher emissions compared to widely held firms. A related paper, Borsuk, Eugster, Klein, and Kowaleski (2024), reports lower carbon emissions for family firms using 2010-2019 data, though their sample relies heavily on imputed emissions (approximately two thirds of observations) and includes primarily U.S. firms.[4] Given our finding that family firms are significantly less likely to report actual emissions even in 2023, selection bias in earlier periods when emissions reporting was sparse may explain these different conclusions.

Our third contribution is a methodological innovation demonstrating that retrieval-augmented LLM's can quantify otherwise unobservable owner characteristics by synthesizing dispersed public information across languages and sources. We construct an index of a controlling family's preference for *clean* using public information about five observable actions: i) the family's personal philanthropy towards environmental causes; ii) the family's public advocacy for environmental issues; iii) the family's participation in environmental NGOs; iv) 'green' investments in the family's personal portfolio outside the firm; and v) the family's support and contributions for environmental policies. Prior work has used text-based and AI methods to extract signals from specific inputs—for example, earnings calls and disclosures (Hassan, Hollander, van Lent, and Tahoun, 2019; de Kok, 2025; Siano, 2025). We broaden the input scope to quantify an otherwise private shareholder attribute and situate our approach within the rapidly evolving AI-in-finance literature (see, for example, the survey by Li, Wang, Ding, and Chen, 2024, and the regulatory perspective in IOSCO, 2025), emerging evaluations of financial-domain retrieval-augmented generation (RAG) systems (Zhao, Singh, Bhathena, Ramos, Joshi, Gadiyaram, and Sharma, 2024; Wang, Tan, Dou, and Wen, 2024; Choi, Kwon, Ha, Choi, Kim, Lee, Sohn; Lopez-

[4] The one test they conduct using actual emissions data is based on a much smaller sample than ours: 1,723 unique firms over a ten-year panel, approximately half of which are U.S. firms.

Lira, 2025). Demonstrating that our RAG-derived measure explains differences in corporate outcomes, we show that otherwise unobservable owner values can be quantified at scale.

## II. Theoretical Considerations

We begin our analysis by postulating that a controlled firm can behave in the way that Hart and Zingales (2017) suggest, acting as if there is only a single shareholder, and directing the firm to pursue the controller's utility maximization irrespective of what other investors may prefer if they had a voice. We make this assumption because a controlled firm is protected from takeover and activist pressures, and its board is effectively entrenched.

If a controlled owner has a strong non-pecuniary preference for *clean,* this should lead their firm to lower emissions all else equal. Two countervailing forces, however, may hamper the implementation of *clean* preferences. The first of these potential countervailing forces is the marginal cost of carbon emissions abatement. A strong preference for *clean* is likely to matter for emissions so long as the marginal costs of becoming *cleaner* are reasonably low. When marginal costs of becoming *cleaner* are relatively high, a controlling owner's environmental preferences would have to be very strong to overcome these costs. It is thus possible that there will be little differentiation in carbon emission outcomes between controlled firms with low and high environmental preferences when expected incremental carbon abatement costs are quite high.

The second countervailing force is the impact of pecuniary private benefits on a firm's likelihood to pursue *clean*. A significant body of literature focuses on how the control of voting power in firms gives controlling shareholders the potential to reward themselves at the expense of all other investors in the firm (e.g., Shleifer and Vishny, 1997). These control rights create financial benefits for controlling shareholders and are significant around the world (e.g., LaPorta et. al., 1999; Lins, 2003; Dyck and Zingales, 2004). If the controlled firm's owner uses their control rights for pecuniary private benefits, this shifts a firm towards being *dirty*—what we call a 'pecuniary private benefit drift.' This is because consuming a firm's current cash flow leaves less available for environmental investments.

Do controlled firm types differ in their expected non-pecuniary private benefits for the controlling owner, and thus the likelihood of overcoming these two countervailing forces? This question of the relative strength of environmental preferences across controlled owners is ultimately an empirical question, but theory offers some guidance.

Family-controlled firms can plausibly have strong environmental preferences and are more likely to act upon them than other types of controlled firms. Families may value reputation and have longer time horizons (e.g., Andersen and Reeb, 2003; Bennedsen and Fan, 2014), both of which can generate high and consistent levels of trust.[5] These long-term assets of the family can be impaired if a firm is perceived to not be *clean* enough, and given that much of the family's wealth is typically concentrated in their own firms, the family is also more sensitive to long-term firm-specific risks such as a sudden clampdown on carbon emissions. These potential incentives may lead families to choose *clean*.

We do not expect government owners to have stronger preferences for *clean* compared to owners of a widely held firm. From an environmental standpoint, if a government controls a firm and believes that *clean* is important, it can enact regulations and force all firms to meet higher standards equally, rather than having only government-controlled firms outperform.

Other-controlled firms in our sample include multiple owners where no single owner is dominant, opaque-controlled firms in which there is a controlling shareholder but the ultimate controlling shareholder cannot be identified, and firms controlled by financial owners (private

[5] For example, a family firm with such trust is better positioned to make implicit contracts with employees and contractors to reward them for making firm-specific investment decisions, thus generating value.

equity, hedge funds, venture capitalists). There are good reasons to expect weaker environmental preferences in such firms. Hart and Zingales (2017) suggest that an owner cares about a *clean* or *dirty* outcome only "if he feels responsible for the action in question" (p. 250). When no owner dominates, no owner is likely to feel the responsibility. When the owner is opaque, there is no reputational benefit from being seen to be *clean*. When an owner is financial-controlled and focused on short-term financial value maximization, there is little likelihood they will invest today to reduce carbon emissions for long-term payoffs.

In summary, this section motivates our tests that control for private benefits, focus on different types of controlled owners, introduce measures of controlled owners' environmental preferences, and assess both high and low expected marginal costs of carbon emissions abatement.

## III. Sample and Summary Statistics

Our starting point is the universe of non-financial publicly traded firms with ESG data coverage by the London Stock Exchange Group (LSEG) as of year-end 2023. LSEG, previously called Refinitiv, is one of several commercial ESG data providers used by both practitioners and academia. We require firms to have non-missing assets and a minimum market capitalization of $100 million. We exclude firms incorporated in the U.S., Russia, and China, and firms from countries where we have less than ten observations.[6] The full sample comprises 3,769 firms from 35 countries. Of these, 3,319 report their emissions as of year-end 2023. Our paper focuses primarily on these 3,319 reporting firms (88% of all sample firms).

[6] We exclude the U.S. because relatively few firms have controlling shareholders. We also exclude Russia and China because political realities make it almost impossible for non-government-affiliated blockholders to establish effective control of firms.

*A. Environmental Performance Metrics*

Our primary emissions metric is actual total CO2-equivalent (CO2e) emissions in 2023. This metric includes all GHG emissions and converts methane and other non-CO2 emissions into carbon equivalent emissions following the Greenhouse Gas Protocol. These carbon emissions are the sum of Scope 1 emissions (direct emissions from firm-owned or controlled sources) and Scope 2 emissions (indirect emissions from the generation of purchased energy). Unlike other ESG metrics, this metric is highly standardized; we compare reported CO2e values across multiple data providers and find virtually identical values.[7]

In our models, the dependent variables are total emissions (sum of Scope 1 and Scope 2) and Scope 1 alone. Both are reported and, in principle, controllable by the owner. Prior research emphasizes Scope 1, arguing that these emissions are easier for owners to manage as they are directly controlled by firms (e.g., Shive and Forster, 2020; Bolton and Kacperczyk, 2023).[8]

As mentioned earlier, until recently there was not widespread disclosure of firms' actual carbon emissions. Reporting has increased recently as a result of a variety of external pressures, including demands from investors, stakeholders, and regulators. We use data from year-end 2023 because it has the highest level of reported actual emissions to date. To illustrate this, Figure 1 plots the percent of firms who report their carbon emissions for all non-financial firms with a minimum market capitalization of $100 million incorporated in one of the 35 countries in our sample in the LSEG universe from 2010 to 2023. While in 2010, only 16% of firms reported

[7] This consistency of CO2e across data providers is in line with the results in Busch, Johnson, Pioch, and Kopp (2018) who report a correlation of approximately 0.99 for this metric across five data providers.
[8] Examples include Shive and Forster (2020), Ilhan, Sautner, and Vilkov (2021), Borsuk et al. (2024), and Bolton and Kacperczyk (2023) We note that as of 2023 there are few firms that report Scope 3 emissions, and we do not include Scope 3 emissions in our analysis. This point is also addressed in Aswani, Raghunandan, and Rajgopal (2024).

emissions, by 2023 80% of firms report them, with a substantial increase of 15% between 2022 and 2023 consistent with the increased pressure from IFRS.

Panel A of Table 1 reports key emission metrics used in our tests. The median firm in our sample emits the equivalent of 83,562 tons of CO2e per year. Median Scope 1 emissions are roughly 28,000 tons, while Scope 2 emissions are roughly 31,000 tons. The large standard deviation in emissions suggests the need to control for the intensity of activity used to generate these emissions, and to control for industry differences—we do both in our tests.

*B. Establishing Controlling Owners*

We identify firms' ownership structures as of the year 2022, using the end of the year prior to the year we use to measure carbon emission performance.[9] We take great efforts to identify controlled firms. We start with commercially available data sources such as Bureau van Dijk's (BvD) Orbis, LSEG, Datastream, and Worldscope, all of which provide data to trace the ownership of firms. We then manually research, categorize, and verify each firm's ultimate ownership with data from a variety of additional sources, including annual reports, internet searches, and country guides. Attempting to categorize ultimate ownership in any other way is insufficient, given the reported findings in Aminadav and Papaioannou (2020) that sources such as BvD have large numbers of misclassifications once a manual check is done.

We construct four categories of ownership: family-controlled, government-controlled, other-controlled, and widely held. We classify a firm as family-controlled if: i) the sum of the shares owned by the family members exceeds those of any other shareholder and is greater than 20%; ii) the sum of family stakes exceeds those of any other shareholder, is greater than 10%, and

[9] Prior papers have assembled information on ownership, but even the more recent ones do not provide hand-collected cross-sections for 2022; for example, family ownership around the world is measured for the year 2002 by Masulis, Pham, and Zein (2011), and up to the year 2012 by Aminadav and Papaioannou (2020).

family members hold the CEO or chair position; or iii) the sum of family stakes exceeds those of any other shareholder, is greater than 10%, and the firm has multiple voting class shares. Government-controlled firms are firms where the largest shareholder is the government and they own at least 20% of the shares.[10] Other-controlled firms are firms with: i) 20% shareholdings by financial owners; ii) 20% shareholdings by multiple owners where no one owner is dominant; or iii) firms in which there is a 20% shareholder, but that owner is opaque. Widely held firms are all remaining firms that are not controlled.

In identifying controlling shareholders, our searches often involve consideration of multiple entities and voting stakes. To illustrate, consider two examples. The first is Pfeiffer Vacuum Technology AG, a small-cap German company specializing in vacuum technology. As of December 2022, it has a single class of common equity, with its largest shareholder, Pangea GmbH, holding a controlling 63% stake. Pangea is an investment vehicle owned by Busch SE, which is wholly owned by Busch GBR, which in turn is entirely owned by members of the Busch family. Through this layered structure, the Busch family exercises indirect control over Pfeiffer Vacuum Technology AG, despite the presence of seemingly separate corporate entities. Another example is Canadian Utilities Limited, a large Canadian electric utility, where we identify Sentgraf Enterprises to be the controlling shareholder based on its voting power (97.3%) rather than its economic stakes (2.5%) We identify the ultimate owner of Sentgraf to be the Southern Family, led by CEO Nancy Southern, who is the daughter of the company's founder, Ron Southern.

Panel A of Table 1 shows summary statistics for the ownership types in our sample. We find that 45% of firms are widely held, 42% are family-controlled, 7% are government-controlled,

[10] Note, we use voting stakes where available, and economic stakes when not. Further, in identifying the largest shareholder we exclude from our consideration those owners that are widely diversified asset managers (e.g. Vanguard) as they are largely passive and unlikely to contest control.

and 6% are other-controlled. This large frequency of controlled firms provides power for empirical tests that aim to assess the impact of ownership structures on environmental performance. Other-controlled firms include 3% that are controlled by financial owners, 2% that have unidentified controlling owner(s), and 1% that have multiple large owners. Our empirical tests do not analyze the sub-categories of other-controlled firms given the small number of such firms in each sub-category.

In Panel B of Table 1, we report, by country, the incidence of the ownership types. There is substantial variation in how common controlled firms are around the world. For example, family ownership is highest in the Philippines and South Korea, where 84% and 83% of firms are family-controlled, respectively, and lowest in Australia, Ireland, Japan, Taiwan, and the U.K., where family firms represent less than 20%. Figure 2 provides a country map of the incidence of family control around the world.

*C. Measuring Environmental Preferences of Controlling Families*

Theoretical interest in the strength of environmental preferences has not yet translated into commercial databases that capture owner preferences. Rather, the strength of environmental preferences of controlled owners is a private characteristic for which no database exists. Since we cannot elicit those preferences directly via a survey or similar mechanism, we rely on the publicly observable data footprint that controlled owners leave across various languages in the public domain.

To that end, we focus specifically on the category of family-controlled firms, where we can identify a specific set of individuals with firm ownership. We proxy for a family's environmental preferences using scores from five different types of activities: i) the family's personal philanthropy towards environmental causes; ii) the family's public advocacy for environmental issues; iii) the family's participation in environmental NGOs; iv) 'green' investments in the family's personal portfolio outside the firm; and v) the family's support and contributions for environmental policies.

Prior research supports the use of indicators of such types of activities. For example, field experiments track donations and show that individuals' donations to environmental causes reflect intrinsic motivations (Alpízar, Carlsson, and Johansson-Stenman, 2008), and in the corporate finance literature researchers measure directors' affiliations with nonprofit organizations and interpret these as signals of prosocial preferences (Masulis and Reza, 2015; Cai, Xu, and Yang, 2021; Kim, Minton, and Williamson, 2025). Other work shows that public advocacy for environmental issues emerges in response to weak regulation and reflects strong environmental preferences among citizens (Daubanes and Rochet, 2019). As a further example, voluntary participation is systematically related to pro-environment attitudes and values (Lowry, 1998), making NGO involvement a credible, observable indicator of underlying environmental commitment.

Tracking multiple components of preferences provides a more comprehensive measure of revealed environmental preferences than focusing on a single component. For example, a family that cared deeply about environmental outcomes might well signal that by doing all of the following: making donations to environmental causes that are reported in the news, by being vocal in advocating personally for pro environmental outcomes that generate coverage, by participating in organizations devoted to environmental improvement that are visible, by making visible investments in green firms, and by political contributions that support pro environmentally policies. Other families may prefer to speak only with money and avoid public engagement, or alternatively only with public engagement and not money.

Manually constructing scores of these preferences measures for 35 countries and across languages is infeasible. A LLM can at low cost consider a wide range of sources in various languages, which is helpful as no single source tracks all five indicators across countries.

To assess a family owner's environmental preferences, we identify the family name of the controlling owner using manual searches. To confirm our manual classification and to assess environmental preferences of the family, we then take advantage of the capabilities of two benchmark-setting LLMs. We now describe our approach in detail and provide additional information about the 'prompts' we use in Appendix B.

We use OpenAI's GPT-4o to identify controlling family names and board members because of its strong performance in parsing corporate ownership structures, and Perplexity's Sonar-pro for preference scoring because its retrieval-augmented architecture provides current citations that enable verification. While other advanced models exist, these represent state-of-the-art capabilities during our data collection from late 2023 to early 2025. Our use of LLMs to score families' environmental preferences proceeds in two sequential stages, executed through the vendors' REST APIs. First, OpenAI's GPT-4o (trained on data through October 2023) receives a structured context block that includes the firm's name, country, and our assessment of family control, and returns the dominant family surname plus up to five family directors. Second, the family identifiers are fed into Perplexity's Sonar-pro, a search-augmented multilingual LLM that retrieves current web content and assigns a score of 0 to 10 on each of the five dimensions described above and an equally weighted sum, with a maximum of 50. The prompt expressly instructs Sonar-pro to ignore the environmental performance of the target firm to avoid tautological inference, and the model records its own confidence level and provides citation-linked sources (capped at 10 sources). We weight all five dimensions equally since we lack theoretical or empirical guidance for differential weighting.

Although this architecture offers broad coverage with fast processing times, it raises potential concerns that we acknowledge and mitigate where possible. First, the open-web RAG approach complicates replicability as the LLM is not restricted to any static dataset. We mitigate this by publishing, in the Internet Appendix, the exact prompts and a Python notebook that reproduces API calls and post-processing steps. Second, LLMs can hallucinate. By separating family identification (GPT-4o) from preference scoring (Sonar-pro) we reduce the risk that errors in one task contaminate the other. Additionally, Sonar-pro's citation-linked output enables ex-post manual verification. Appendix Table A3 provides four examples of families with high environmental preferences from Brazil, Malaysia, the Philippines, and Turkey, to illustrate how the scores are compiled.

Third, although we try to mitigate look-ahead bias by limiting Sonar-pro's web access to items timestamped on or before December 31, 2022, there could be residual leakage. While we cannot fully verify such leakage, it is unlikely to be material, as families' environmental preferences are persistent over time. Fourth, the LLM could base its analysis primarily on the environmental choices of the firm we are analyzing. To mitigate this concern, we explicitly direct the LLM to ignore the target firm in producing its evaluation. Fifth, a generative model can always return an answer even when the underlying evidence is thin. We therefore discard observations in which the model's self-reported confidence falls below 80%.

Together, these design choices yield a transparent environmental preference measure, and—subject to the caveats described—robust to the customary concerns about hallucination, look-ahead bias, and low-information noise. At the same time, we leverage the breadth, multilingual reach, and online search capability of modern LLMs to measure a latent family characteristic across our sample that is otherwise unobservable.

Panel A of Table 1 shows the average family's environmental preference score is 17 out of a maximum of 50, the median is 12. The lowest score we obtain is 1 for several families—the Bangs (Korea), the Marans, Sankeshwars, and Suryavishinis (India), the Freres (Switzerland), the Coutiers and Falcs (France), and the Bijlevads (Thailand), and the maximum is 44 for the Herlins (Finland). We use these scores to construct low and high preference indicators to make sure inferences are based on large differences in preferences, to give weight to all five dimensions of environmental preferences, and for better distributional properties. We classify families with scores of at least 20 as high E family, and those with scores less than 20 as low E family. The LLM cannot reliably assign a score for some families (or has low confidence that it has established the environmental preferences of the family with precision)—we label them as inconclusive E family. These latter families tend to control smaller firms (median assets \$1.4 billion vs. \$1.9 billion for scored families), suggesting data availability constraints.

As a share of the full sample, 20% of firms are classified as low E family, 11% are high E famil*y*, and 11% are inconclusive E family. Since 42% of all firms are family-controlled, these figures imply that within the universe of family firms, almost half exhibit low environmental preferences. The even split between the high and inconclusive preferences underscores a key advantage of our LLM approach—we can flag families for which the public record is too sparse to support a reliable score rather than forcing an arbitrary assignment.

To illustrate Sonar-pro's assessment of families, consider two family firms in our sample. The firm classified as low E family is Korea Zinc Inc, a Korean metals smelter. Its controlling owners are the Chang and Choi families. The environmental preferences of these two families are assessed by Sonar-pro as 7 out of 50, placing them in the third lowest decile among all sample families. Importantly, the LLM explicitly ignores the corporate environmental activities of Korea Zinc in its assessment.

The LLM's reasoning for its assessment is that "the Chang and Choi families, controlling shareholders of Korea Zinc Inc., show limited personal environmental preferences based on available information. There is little evidence of their personal philanthropy, public advocacy, or participation in environmental NGOs. Their focus appears to be primarily on business interests rather than environmental causes. The recent conflicts within the company suggest differing views on green investments and sustainability initiatives, with the Choi faction pushing for more green materials investments while the Chang faction prefers maintaining traditional business models and strong dividends. This indicates some, albeit limited, interest in green investments. Overall, their environmental preferences appear relatively low based on publicly available information."

The firm classified as high E family is Telefonaktiebolaget LM Ericsson, a Swedish network firm. It is controlled by the Wallenberg family. Perplexity assesses the Wallenberg family's environmental preferences at 41 out of 50, placing the family in the third highest decile among all sample firms. The LLM's reasoning is that "the Wallenberg family demonstrates strong environmental preferences across multiple dimensions. They have a long-standing commitment to supporting research and innovation, including significant investments in environmental and climate-related projects through their foundation. The family actively promotes sustainability. Their investment arm, FAM, focuses on innovative and sustainable companies. While direct participation in environmental is less evident, the family's overall approach to long-term, responsible ownership and their emphasis on sustainability in business and research funding indicate a high level of environmental concern."

*D. Measuring Expected Marginal Costs of Improving Carbon Emissions*

We use two approaches to identify the expected marginal cost firms face to improve their carbon emissions, exploiting variation in expected costs across countries and industries.[11] At the country level, we split our sample into two subsamples of countries based on a country-level metric that captures differences in climate protection efforts relative to international standards. In countries with high levels of climate protection efforts it is likely that policies and standards have forced firms to internalize many of the costs of their carbon externalities. Because firms likely have responded accordingly, we conjecture that firms in such countries will have relatively few low-cost options to further improve their carbon emissions performance. In contrast, in the subsample of countries where there has been less emphasis on policies and standards to reduce carbon emissions, firms are likely to have many more low-cost options to further improve their emissions performance.[12]

Specifically, we construct subsamples based on a country's score on the Climate Change Performance Index (CCPI) produced by Germanwatch. The score is based on four categories of climate protection at the country level relative to the strictest international standards: GHG emissions, renewable energy, energy use, and climate policy. The summary CCPI score has a possible range from zero (worst) to 100 (best). We group firms in subsamples based on the sample median score of 60, with all countries below this score identified as low CCPI countries.[13] CCPI scores are highest in the Nordic countries, India, and the Philippines, and lowest in South Korea, Canada, Taiwan, and Malaysia. The CCPI split is particularly useful for our sample, because firms

[11] We note that industry fixed effects capture variation in the expected marginal cost of improved emissions at the industry level. Firm level data in our global sample to capture further variation in expected costs do not exist, and we do not attempt to impute such data given widespread concerns about data imputation discussed earlier.

[12] Evidence in support of this assumption is provided in Chang, Christensen and McKinley (2024). In their setting the environmental problem is gas flaring associated with production. They find substantially greater quantitative reductions in flaring in Africa than other jurisdiction, a setting with much weaker starting rules and expectations.

[13] CCPI scores are not available for Israel, Peru, and Singapore.

from low CCPI countries have 31% higher absolute carbon emissions (significant at the 5% level) than firms from high CCPI countries.[14] An additional attractive feature of the CCPI metric is its low correlation with GDP per capita. For example, Australia, Canada, and Austria are low CCPI countries that have relatively high levels of GDP per capita.

We also conduct robustness tests of this country-level measure by constructing subsamples based on a country's score on just the GHG emissions category (that has a 40% weight in the overall CCPI score). This is based on assessments of countries' GHG emissions per capita, trends in emissions, and current emissions and reduction targets compared to a well-below -2°C compatible pathway.

To capture the difference in expected marginal costs of lowering emissions across industries, we split our sample into two subsamples based on the intensity of direct carbon emissions (Scope 1) in total carbon emissions (sum of Scope 1 and Scope 2) for the seventy-two industries as defined by the Sustainability Accounting Standards Board (SASB) in our sample. We classify an industry as high Scope 1 if at least 51% of an industry's total carbon emissions are Scope 1 emissions. We select this industry split because direct emissions are largely determined by an owner's operating choices and, when proportionally large, regulators and society are likely to hold owners accountable for a firm's emissions because they have control over them. Further, high Scope 1 industries (e.g., Extractives and Minerals Processing) will be in the spotlight and subject to outside pressure as they are some of the biggest contributors to climate change. For these reasons, firms in these industries have probably carefully considered their carbon externalities and exhausted their low-cost carbon abatement opportunities. To illustrate, Table 1 shows high Scope 1 industries have vastly larger total emissions, with average log total CO2e emissions in tons of

[14] The difference in scaled emissions intensity is significant at the one percent level.

12.31 compared to 10.36 for low Scope 1 industries. For low Scope 1 industries, total emissions themselves are relatively small, and direct emissions are even smaller. In these industries, firms are likely to have escaped scrutiny, leaving them with a larger supply of low-cost carbon abatement opportunities available if they want to implement them.

## IV. Results

### *A. Emissions Disclosure and Ownership Type*

As reported in Table 1, 88% of firms disclose their carbon emissions in 2023. With this high level of reporting, any selective-disclosure biases arising from the 12% of non-reporting firms, in which a particular type of controlled owner is less likely to report actual carbon emissions, are likely to be small. Nonetheless, it is instructive to test whether the disclosure of carbon emissions is linked to ownership type using the full sample. We report the results of this test in Table 2.

To isolate the impact of ownership on carbon emissions reporting (and actual carbon emissions in the tables that follow) all regressions include a variety of control variables. For firm controls, we use firm size (log of assets), cash, asset tangibility, leverage, profitability, and dual class shares. We include firm size as prior literature has shown it to be related to ownership structures, and larger firms may be subject to more external pressures. We control for financial slack as Hong, Kubik, and Scheinkman (2012) suggest that this helps explain the adoption of sustainability-oriented policies. To that end, we include cash, asset tangibility, and leverage to capture credit constraints and profitability to capture the impact of performance. We allow for variation across firms in their expected level of private benefits and include an indicator for dual class shares to capture the wedge between control rights and cash flow rights. Given the substantial variation in carbon emissions across countries and industries, we include country and industry (72 SASB industry codes) fixed effects. We cluster standard errors by country.

In Table 2 we find a negative and significant coefficient for family control and government control. This indicates that the frequency of disclosure of carbon emissions is lower for these types of controlled firms relative to widely held firms (the omitted mutually exclusive ownership category). We consider this result when we interpret our findings in later sections. For example, a finding that family-controlled firms had lower emissions than widely held firms would need to be caveated, as emissions of the average family firm if all reported their emissions would likely be higher.[15]

*B. Controlled Firms, Carbon Emissions, and Preferences*

We begin with baseline regressions examining the relation between ownership type and carbon emissions, and then expand this analysis by considering environmental preferences and the marginal costs to improve carbon emissions. In all tests we estimate models using the following baseline specification:

$$Log(Emissions_i) = \alpha + \beta' X_i + \gamma' Y_i + \Lambda + \varepsilon_i , \tag{1}$$

where the dependent variable is either the log of total CO2e emissions or the log of Scope 1 CO2e emissions, scaled by revenue or unscaled, for firm $i$. As independent variables, $X_i$ are ownership structure indicator variables for ownership by family, government, and other opaque, omitting widely held firms as the baseline category, $Y_i$ is a set of firm-level controls, and $\Lambda$ are individual country and industry fixed effects. All right-hand variables are lagged by one year. We use logs

[15] It is likely that selective disclosure bias would have been a more serious problem if we had chosen an unbalanced panel design and incorporated years quite distant from this current point in time.

for our dependent variables to obtain better distributional properties and to reduce the impact of outliers.

We report results using both emissions intensity (scaled emissions) and raw emissions because there is no consensus as to how to appropriately measure emissions. Aswani et al. (2024) argue in favor of emissions intensity as the appropriate metric,[16] and further suggest that revenue-scaled carbon emissions is preferred to asset-scaled emissions given the stronger correlation between emissions and revenue.[17] In regressions with unscaled emissions as the dependent variable, we also control for firms' revenue as emissions are likely to depend heavily on the intensity of their activity which is reflected in sales. We report results both for total Scope 1 and 2 emissions, as these are the focus of the ISSB's sustainability standards, and for Scope 1 emissions alone, as these are directly controlled by owners and have been the primary focus of prior carbon emissions research.[18]

In Table 3 we provide our baseline results. We find that no category of controlled firm delivers statistically significant lower carbon emissions than the widely held firm. In family-controlled firms, where theory suggests the greatest likelihood of strong preferences for *clean,* we find a positive rather than a negative coefficient on family in all specifications, and the coefficient is significant when considering Scope 1 emissions only. These results suggest family firms emit more carbon than widely held firms, and imply that allowing shareholders to pursue welfare

[16] They note that using unscaled emissions 'is analogous to using net income rather than ratios such as return on assets (ROAs) to measure financial performance,' that 'the ratio of emissions to net sales the most commonly used metric in practice', and that it 'better captures a firm's emissions performance by avoiding mechanical correlations with firm size' (p. 78).
[17] Aswani et al. (2024), using a sample of U.S. firms, report a correlation of log Scope 1 emissions and log sales of 0.70 (compared to 0.46 for log assets). Focusing on Scope 2 emissions the correlations are 0.847 for log sales and 0.548 for log assets.
[18] See, for example, Shive and Forster (2020) and Bolton and Kacperczyk (2023), who use scaled and raw Scope 1 emissions.

maximization, as in Hart and Zingales (2017), is unlikely to mitigate unpriced environmental externalities.

For other-controlled firms, we also find a positive coefficient, that is significant when considering Scope 1 and 2 emissions. These controlled firms also emit more carbon than widely held firms, with our priors that these firms lack environmental preferences. Given that such firms represent a small portion of our sample, and are heterogeneous, we hesitate to draw conclusive inferences from these coefficients here and in the rest of our tables. For government-controlled firms, we find an insignificant coefficient consistent with our priors. Given our earlier finding that selective disclosure is a bigger concern for controlled firms, the results that carbon emissions are not better and even higher in controlled firms would be even more pronounced if all firms reported their actual emissions so we could use them in our tests.

Regarding control variables, we find that emissions are greater when firms are larger, when they have more tangible assets, and in specifications looking at absolute emissions, when they have a greater level of activity measured by revenues. Firms have lower emissions when there is more financial slack, with negative coefficients on both cash and profitability. The coefficient estimates on dual class shares are positive, as expected, but insignificant.

In Table 4, we provide our first tests of whether the environmental preferences of controlling shareholders matter, a key component of our analysis. Using the LLM-identified environmental preferences of controlling families, we split family firms into the previously described three groups, firms controlled by families with low environmental preferences (low E family), firms controlled by families with high environmental preferences (high E family), and firms controlled by families with unknown environmental preferences (inconclusive E family).

We find that preferences do indeed matter, but mostly in ways that worsen outcomes. In firms controlled by families with low environmental preferences, carbon emissions are about 20% higher than those of widely held firms, considering all emissions, and are 30% higher when considering Scope 1 emissions. In contrast, emissions are no different than those of widely held firms when firms are either controlled by families with high environmental preferences or when environmental preferences are unknown.

One broad takeaway from Table 4 is that the Hart and Zingales (2017) hypothesis that carbon outcomes can be different if we allow for shareholder utility maximization is true. These results suggest that low environmental preferences are clearly linked to worse carbon outcomes. A preference for *clean* versus *dirty* matters, but it does not give the controlled firm superior carbon performance compared to the widely held firm. Without considering marginal costs of carbon abatement, controlled firms generally deliver worse carbon performance than widely held firms.

*C. Expected Marginal Costs, Preferences, and Carbon Emissions: Country-level Tests*

As described in Section 2, all controlled firms, and particularly family and other controlled firms, face a potential private benefit drift towards *dirty.* Strong environmental preferences are a factor that could shift controlled firms to be *clean.* But the willingness of a controlling owner to act on their environmental preferences will depend on how expensive it is to make their firm *cleaner*. When the costs of becoming *cleaner* are high, preferences must be extremely strong to override the drift towards *dirty*. In this section, we use the CCPI index that captures differences in climate protection efforts relative to international standards at the country level to assess whether expected marginal costs affect the relationship between controlling-owner preferences and carbon emissions performance.

In countries with high levels of climate protection efforts (high CCPI countries), it is likely that policies and standards have forced firms to internalize many of the costs of their carbon externalities, and they will have relatively few low-cost options to further improve their carbon emissions performance. Thus, in high CCPI countries we expect that environmental preferences will have minimal impacts on carbon emissions performance given the high cost of becoming incrementally *cleaner*. Further, we expect no significant differences in carbon emissions performance when comparing owners with different environmental preferences. In contrast, in low CCPI countries there is room for preferences to have an impact, given the lower cost of improving emissions. We expect differences in the impact of relative environmental preferences to be greater in low CCPI countries.

In Table 5, we first present the results for high CCPI countries. In all specifications we find a positive coefficient for family-controlled firms regardless of their preferences. For total emissions (columns 1 and 2), we find that low E families have 23-25% higher emissions than widely held firms, high E families have 18% higher emissions, and Inconclusive E families have 19% higher emissions (statistically insignificant). Further, there is no statistically significant difference between these categories of family preferences. For Scope 1 emissions that are directly controlled by firms' owners (columns 3 and 4) the results are similar with higher coefficient estimates and levels of statistical significance. Low E families have 35-36% higher emissions than widely held firms, high E families have 32% higher emissions, and Inconclusive E families have 28% higher emissions. These results show that in the presence of high marginal costs to improve carbon emissions, environmental preferences of controlling owners, even strong ones, do not move the needle—rather, the outcome is poorer carbon performance than widely held firms.

In columns 5 through 8, we present the results for low CCPI countries. Results are substantially different in the setting where the marginal costs of becoming more *clean* are relatively low. Environmental preferences matter here. In all specifications, a high E family firm emits less carbon on average than a widely held firm. Coefficient estimates suggest 23-25% lower total carbon emissions (33-34% lower Scope 1 emissions). As noted earlier, this finding is subject to the caveat that we have a small but significant carbon reporting selection bias in family firms. If all family firms reported, their emissions would likely be higher than what our coefficients suggest. Interestingly, in this setting the carbon emissions for a low E family firm are not different from those of a widely held firm. The coefficients for inconclusive E families are generally closer to the high E family than the low E family.

*D. Expected Marginal Costs, Preferences, and Carbon Emissions: Industry-level Tests*

In this section, we exploit variation at the industry level in the expected marginal costs firms face when improving environmental performance. In high Scope 1 industries regulators and investors are more likely to have held owners accountable in these industries and firms are more likely to already deploy low-cost abatement opportunities. In contrast, in low Scope 1 industries where direct emissions are a small share of total emissions and the sector's global footprint is smaller, external pressure has likely been weaker. For these reasons, more low-cost options probably remain, particularly when owners have pro-environmental preferences.

In Table 6, we first present the results for high Scope 1 industries. In all specifications, we find a positive coefficient for all types of family-controlled firms. For total emissions (columns 1 and 2), we find that low E families have 29-31% higher emissions than widely held firms, high E families have 29% higher emissions (statistically insignificant), and Inconclusive E families have 41-42% higher emissions. There is no statistically significant difference between these categories of family preferences where marginal costs are expected to be high. For Scope 1 emissions that are directly controlled by firms' owners (columns 3 and 4) the results are even more pronounced, with higher coefficient estimates and statistical significance on all family-controlled coefficients. These results mirror those in Table 5. In the presence of high marginal costs to improve carbon emissions, family firms are *dirtier* than widely held firms even when their owners have strong environmental preferences.

In columns 5 through 8, we present the results for low Scope 1 industries where the marginal costs of becoming more *clean* are low. Again, environmental preferences matter. In all specifications, we find positive but insignificant coefficients for the low E family, again suggesting there is no difference between their carbon performance and that of the widely held firm. In contrast, in all specifications we find a negative coefficient for the high E family firm. Coefficient estimates suggest 15% lower total emissions (statistically insignificant), and 35% lower Scope 1 emissions (statistically significant). The coefficients for Inconclusive E families are similar to those for the high E family.

Taken together, our results show that the willingness of a controlling owner to act on their environmental preferences depends on how expensive it is to make their firm *cleaner*. When the costs of becoming *cleaner* are high, even strong pro-environmental preferences do not override the drift towards *dirty*. Only when the costs of becoming *cleaner* are low do we find that environmental preferences significantly improve carbon performance.

**V. Robustness**

In this section, we provide robustness of our main findings: i) we discuss possible limitations of LLM-based environmental preference scores and how we address them, and ii) we offer additional results in measuring expected marginal costs in reducing carbon emissions.

*A. Environmental Preferences*

A potential concern with using LLM-based environmental preference scores is that the LLM aggregates information from diverse sources in ways that may introduce systematic biases in how it accesses information. For example, the LLM may exhibit language-based biases if training content or web retrieval capabilities are predominantly in English, potentially compromising the quality of assessments for families operating in non-English contexts. The LLM could also disproportionately focus on wealthier countries, wealthier families, or larger firms. For example, wealthier families could attract more (positive) media attention, and the LLM might assign such families a higher score—not because of their stronger environmental preferences.

Some of these concerns have limited validity. To begin, the LLM provider indicates that their model does not focus exclusively on English-language content, and its web retrieval capabilities are not restricted by language. Nevertheless, to mitigate these concerns, we construct an alternative family environmental preference score controlling for language and other possible drivers of our preference measure.

In Panel A of Table 7, we regress environmental preference scores on country, family, and firm attributes. We consider whether English is the native language in the firm's headquarter country, country GDP per capita, the wealth status of the family (using the 2022 Forbes list of billionaires), and firm size. The results show that larger firms exhibit higher preference scores while wealthier countries are, contrary to our concerns, associated with lower scores. The weak relationship between English speaking countries and preference scores suggests adequate multilingual performance, though we cannot rule out subtle biases.

To address concerns about language and other potential determinants of the preference scores we have employed so far, we create alternative, orthogonalized environmental preference scores using the residuals of the regressions of Panel A of Table 7. Using these orthogonalized scores we then, again, sort family firms into low E (negative residuals) and high E (positive residuals) families. Panels B through D employ these orthogonalized measures to show the robustness of our main findings.

Specifically, Panel B of Table 7 replicates the Table 4 regressions when using the alternative, orthogonalized environmental preference scores based on the column 2 estimates from Panel A (results are similar when using column 1 residuals, unreported for brevity). The results confirm our main findings—firms owned by families with stronger environmental preferences have lower carbon emissions and emission intensity for both total emissions and for Scope 1 emissions only. Thus, the negative relation between preferences and emissions persists after stripping out the effects of English language, country income, family wealth, and firm size.

Having established robustness of our main result to orthogonalization, we next verify that the results based on our country-and industry-split tests from Table 5 and 6 remain unchanged. We report these findings in Panels C and D of Table 7. For example, Panel C confirms that in high CCPI countries, where expected marginal costs of improving carbon emissions are high, family firms emit more carbon, regardless of their environmental preferences. As before, family-controlled firms emit less carbon only in those countries where the expected marginal costs of reducing emissions are low (low CCPI countries) and environmental preferences are high. Similarly, in Panel D, when we focus on industry emissions to measure firms expected marginal costs of improving carbon emissions, we confirm our earlier findings.

*B. Alternative Measures of Expected Marginal Costs*

We also test alternative measures of expected marginal carbon abatement costs. The aggregate CCPI score we are using is based on four categories: emissions, renewable energy,

energy use, and climate policy. Not all categories may clearly translate into higher expected marginal costs for firms to improve their carbon performance. To mitigate this concern, we alternatively use only the "i) emissions" category to sort firms into low and high CCPI groups, by country. Table A2 in Appendix A replicates the Table 5 specifications, and the results are substantially similar. Again, family firms have greater emissions in high CCPI emissions countries, regardless of the environmental preferences of the family owner.

## VI. Conclusion

A key takeaway of our paper is that the Hart and Zingales (2017) hypothesis—carbon emissions are different if one allows for shareholder utility maximization—is true. When owners have the freedom to direct firms to satisfy their non-pecuniary preferences, this does influence environmental outcomes. Families having strong environmental preferences translates into meaningful improvements in carbon emissions when the expected marginal cost of reducing emissions is relatively low. But the aggregate effect of allowing for shareholder utility maximization appears to harm rather than help the environment because, in all other scenarios, controlled firms' carbon emissions performance is no better—and often worse—than that of widely held firms. There simply aren't enough families with strong environmental preferences and/or the strength of their preferences are not high enough to overcome either the high marginal cost of further carbon emission reduction or the pecuniary private benefit drift that affects controlled firms.

We interpret these results as evidence that shifting from strict financial value maximization to broader shareholder welfare maximization is unlikely to deliver significant environmental gains without stronger regulatory support. The few exceptions we observe—where family-controlled firms perform better in low-cost contexts—underscore that voluntary improvements tend to arise only under narrow conditions. Taken together, these insights caution against relying solely on controlling shareholders to address negative environmental externalities. Instead, they highlight the need for robust policies and institutions to encourage *cleaner* corporate behavior.

## References


Alpízar, Francisco, Fredrik Carlsson, and Olof Johansson-Stenman, 2008, Anonymity, reciprocity, and conformity: Evidence from voluntary contributions to a national park in Costa Rica, *Journal of Public Economics* 92, 104-1060.

Aminadav, Gur, and Elias Papaioannou, 2020, Corporate control around the world, *Journal of Finance* 75, 1191-1246.

Anderson, Ronald C., and David M. Reeb, 2003, Founding-family ownership and firm performance: evidence from the S&P 500, *Journal of Finance* 58, 1301-1328.

Aswani, Jitendra, Aneesh Raghunandan, and Shiva Rajgopal, 2024, Are carbon emissions associated with stock returns?, *Review of Finance* 28, 75-106.

Bennedsen, Morten, and Joseph PH Fan, 2014, The family business map, *Palgrave Macmillan* 83-108.

Bolton, Patrick, and Marcin Kacperczyk, 2023, Global pricing of carbon-transition risk, *The Journal of Finance* 78, 3677-3754.

Borsuk, Marcin, Nicolas Eugster, Paul-Oliver Klein, and Oskar Kowaleski, 2024, Family firms and carbon emissions, *Journal of Corporate Finance* 89, 102-672.

Busch, Timo, Matthew Johnson, Thomas Pioch, and Matthias Kopp, 2018, Consistency of corporate carbon emission data, *Working Paper*, University of Hamburg Report WWF Deutschland, Hamburg.

Cai, Ye, Jin Xu, and Jun Yang, 2021, Paying by donating: Corporate donations affiliated with independent directors, *Review of Financial Studies* 34, 618-660.

Center for Sustainable Systems, University of Michigan, 2025, Carbon footprint factsheet. *Pub. No*. CSS09-05.

Chang, Samuel, Hans B. Christensen, and Andrew McKinley, 2025, Environmental commitments in the African oil sector: Sustainability or greenwashing?, *Working Paper*, University of Chicago.

Choi, Chanyeol, Jihoon Kwon, Jaeseon Ha, Hojun Choi, Chaewoon Kim, Yongjae Lee, Jy-yong Sohn, and Alejandro Lopez-Lira, 2025, FinDER: Financial dataset for question answering and evaluating retrieval-augmented generation, *arXiv preprint* arXiv:2504.15800.

Copeland, Brian R., Joseph S. Shapiro, and M. Scott Taylor, 2025, Globalization and the environment, *Working Paper*, National Bureau of Economic Research.

Daubanes, Julien, and Jean-Charles Rochet, 2019, The rise of NGO activism, *American Economic Journal: Economic Policy* 11, 183-212.

de Kok, Ties, 2025, ChatGPT for textual analysis? How to use generative LLMs in accounting research, *Management Science*, forthcoming.

Dimson, Elroy, Oğuzhan Karakaş, and Xi Li, 2015, Active ownership, *Review of Financial Studies* 28, 3225-3268.

Dyck, Alexander, Karl V. Lins, Lukas Roth, Mitch Towner, and Hannes F. Wagner, 2023, Renewable governance: good for the environment?, *Journal of Accounting Research* 61, 279-327.

Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes F. Wagner, 2019, Do institutional investors drive corporate social responsibility? International evidence, *Journal of Financial Economics* 131, 693-714.

Dyck, Alexander, and Luigi Zingales, 2004, Private benefits of control: An international comparison, *Journal of Finance* 59, 537-600.

Franks, Julian, Colin Mayer, Paolo Volpin, and Hannes. F. Wagner, 2012, The life cycle of family ownership: International evidence, *Review of Financial Studies* 25, 1675-1712.

Hart, Oliver, and Luigi Zingales, 2017, Companies should maximize shareholder welfare not market value, *Journal of Law* 2, 247-274.

Hassan, Tarek A., Stephan Hollander, Laurence Van Lent, and Ahmed Tahoun, 2019, Firm-level political risk: Measurement and effects, *Quarterly Journal of Economics* 134, 2135-2202.

Hong, Harrison, Jeffrey D. Kubik, and Jose Scheinkman, 2012, Financial constraints on corporate goodness, *Working Paper*, Columbia University.

Hong, Harrison, and Marcin Kacperczyk, 2009, The price of sin: The effects of social norms on markets, *Journal of Financial Economics* 93, 15-36.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2021, Carbon tail risk, *Review of Financial Studies* 34, 1540-1571.

Iliev, Peter, and Lukas Roth, 2023, Director expertise and corporate sustainability, *Review of Finance* 27, 2085-2123.

International Organization of Securities Commissions (IOSCO), 2025, Artificial intelligence in capital markets: Use cases, risks, and challenges, IOSCO report CR/01/2025.

Jha, Manish, Jialin Qian, Michael Weber, and Baozhong Yang, 2024, ChatGPT and corporate policies, *Working Paper*, National Bureau of Economic Research.

Kim, Sehoon, Bernadette A. Minton, Rohan Williamson, 2025, Climate boards: Do natural disaster experiences make directors more prosocial?, *Working Paper*, University of Florida.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067-1111.

La Porta, Rafael, Florencio Lopez-De-Silanes, and Andrei Shleifer, 1999, Corporate ownership around the world, *Journal of Finance* 54, 471-517.

Li, Yinheng, Shaofei Wang, Han Ding, and Hang Chen, 2024, Large language models in finance: A survey, *arXiv preprint* arXiv:2311.10723.

Lins, Karl V., 2003, Equity ownership and firm value in emerging markets, *Journal of Financial and Quantitative Analysis* 38, 159-184.

Lins, Karl V., Lukas Roth, Henri Servaes, and Ane Tamayo, 2024, Sexism, culture, and firm value: evidence from the Harvey Weinstein scandal and the# MeToo movement, *Journal of Accounting Research* 62, 1989-2035.

Lowry, Robert C., 1998, Religion and the demand for membership in environmental citizen groups, *Public Choice* 94, 223-240.

Masulis, Ronald W., and Syed W. Reza, 2015, Agency problems of corporate philanthropy, *Review of Financial Studies* 28, 592-636.

Masulis, Ronald W., Peter Kien Pham, and Jason Zein, 2011, Family business groups around the world: Financing advantages, control motivations, and organizational choices, *Review of Financial Studies* 24, 3556-3600.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550-571.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403-424.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, 2021, Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics* 142, 572-597.

Shive, Sophie, and Margaret Forster, 2020, Corporate governance and pollution externalities of public and private firms, *Review of Financial Studies* 33, 1296-1330.

Shleifer, Andrei, and Robert W. Vishny, 1997, A survey of corporate governance, *The Journal of Finance* 52, 737-783.

Siano, Federico, 2025, The news in earnings announcement disclosures: Capturing word context using LLM methods, *Management Science*, forthcoming.

Wang, Shuting, Jiejun Tan, Zhicheng Dou, and Ji-Rong Wen, 2024, OmniEval: An omnidirectional and automatic RAG evaluation benchmark in financial domain, *arXiv preprint* arXiv:2412.13018.

Zhao, Yiyun, Prateek Singh, Hanoz Bhathena, Bernardo Ramos, Aviral Joshi, Swaroop Gadiyaram, and Saket Sharma, 2024, Optimizing LLM based retrieval augmented generation pipelines in the financial domain, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 6: Industry Track),* 279-294.

**Figure 1**
**Percent of Firms Reporting Carbon Emissions**

This figure reports the percent of firms that report CO2-equivalent emissions from 2010 to 2023 for i) the population of LSEG firms, and ii) our sample of firms. The population of LSEG firms includes all non-financial firms with a minimum market capitalization of $100 million, incorporated in one of our sample countries, and includes between 2,859 (in 2010) and 4,066 firms (in 2023). All data are from LSEG.

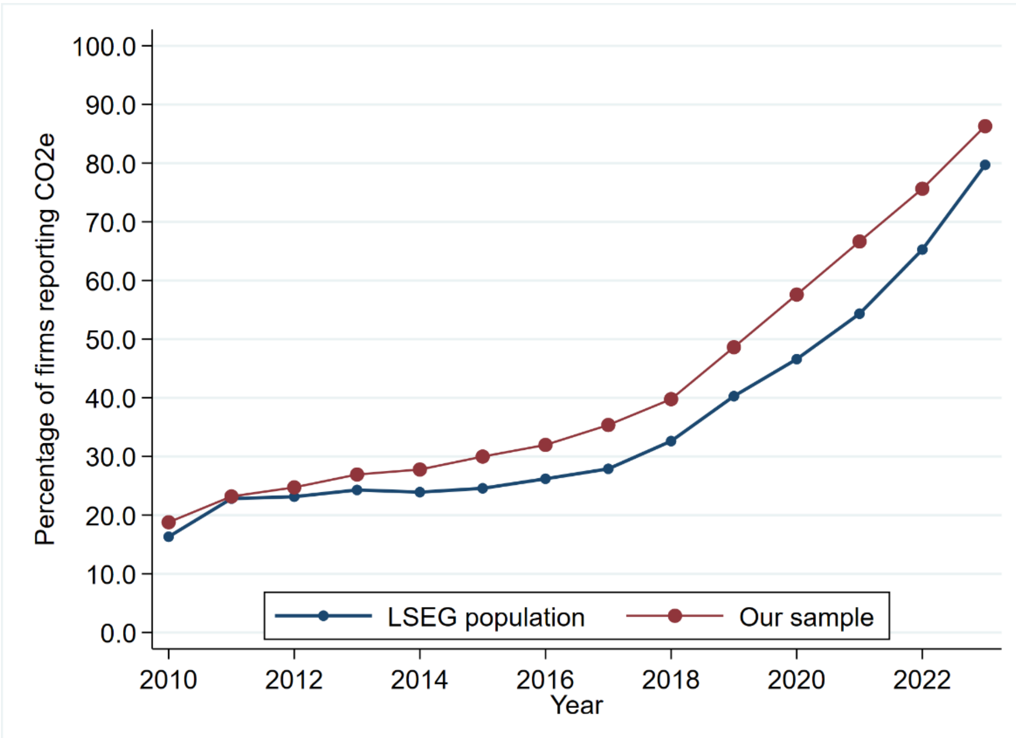

**Figure 2**
**Family Control Around the World**

This figure reports the incidence of family control for the 35 countries in our sample. Family control is manually verified for each firm and defined as follows: we classify a firm as family-controlled if the sum of the shares owned by family members is greater than 20%, family members own at least 10% of the shares and have a position of CEO/Chair, or family members own at least 10% of the shares and the company has multiple voting share classes. We also require that family members own more shares than any other shareholder.

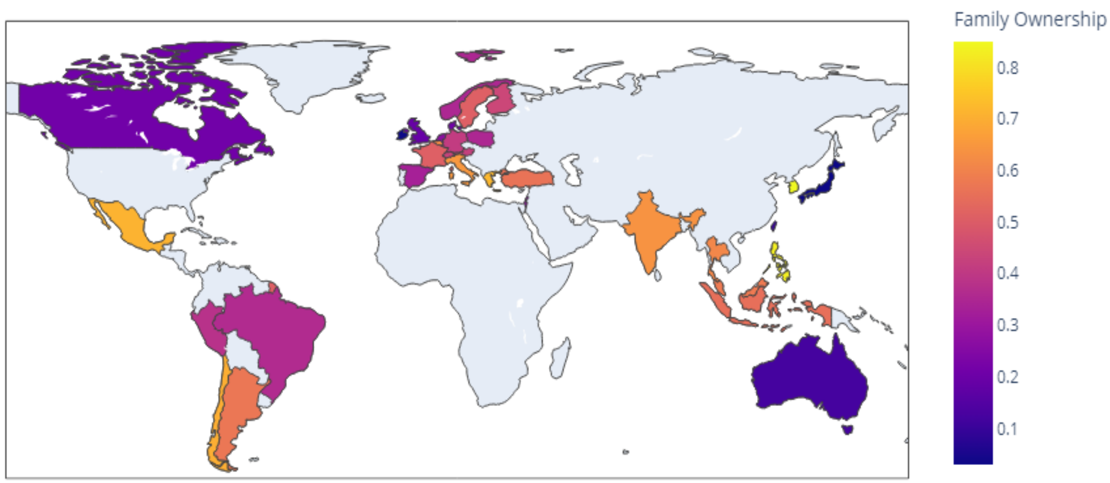

**Table 1**
**Summary Statistics**

This table shows summary statistics. Firms are classified into low and high CCPI groups based on their country's overall Climate Change Performance Index (CCPI) score, with the median score used as the cutoff. Similarly, firms are grouped into low and high Scope 1 industries depending on whether the industry's total Scope 1 emissions account for less (greater) than 51% of the industry's total Scope 1 and 2 CO2-equivalent emissions (based on SASB Industry Classifications). The sample year is 2023. All variables are described in Appendix Table A1.

Panel A: Summary Statistics

| | Mean | Median | SD | N |
|---|---|---|---|---|
| *A. Environmental Performance* | | | | |
| Firm Reports CO2e | 0.88 | 1.00 | 0.32 | 3,769 |
| Scope 1 and 2 Emissions | | | | |
| CO2e | 1,732,000 | 83,562 | 7,477,000 | 3,325 |
| Log (CO2e) | 11.28 | 11.34 | 2.81 | 3,320 |
| Log (CO2e / Revenue) | 3.71 | 3.59 | 2.16 | 3,320 |
| Log (CO2e), Low CCPI Countries | 11.88 | 11.96 | 2.59 | 1,578 |
| Log (CO2e), High CCPI Countries | 10.73 | 10.75 | 2.90 | 1,659 |
| Log (CO2e), Low Scope 1 Industries | 10.36 | 10.50 | 2.38 | 1,622 |
| Log (CO2e), High Scope 1 Industries | 12.16 | 12.31 | 2.92 | 1,698 |
| Scope 1 Emissions | | | | |
| CO2e | 1,485,000 | 26,670 | 7,042,000 | 3,248 |
| Log (CO2e) | 10.21 | 10.23 | 3.32 | 3,205 |
| Log (CO2e / Revenue) | 2.61 | 2.35 | 2.70 | 3,205 |
| *B. Ownership* | | | | |
| Family-controlled | 0.42 | 0.00 | 0.49 | 3,769 |
| Government-controlled | 0.07 | 0.00 | 0.26 | 3,769 |
| Other-controlled | 0.06 | 0.00 | 0.25 | 3,769 |
| Widely Held | 0.45 | 0.00 | 0.50 | 3,769 |
| *C. Family Owners' Environmental Preferences* | | | | |
| Family E Preference | 16.71 | 12.00 | 11.80 | 1,159 |
| Low E Family | 0.20 | 0.00 | 0.40 | 3,769 |
| High E Family | 0.11 | 0.00 | 0.32 | 3,769 |
| Inconclusive E Family | 0.11 | 0.00 | 0.31 | 3,769 |
| *D. Other Firm Characteristics* | | | | |
| Total Assets (in $ million) | 9,551 | 2,331 | 26,393 | 3,769 |
| Log (Total Assets) | 21.62 | 21.57 | 1.64 | 3,769 |
| Log (Revenue) | 7.36 | 7.35 | 1.79 | 3,769 |
| Cash | 0.15 | 0.11 | 0.14 | 3,769 |
| Tangibility | 0.31 | 0.27 | 0.22 | 3,769 |
| Leverage | 0.26 | 0.24 | 0.39 | 3,769 |
| Profitability | 0.04 | 0.04 | 0.18 | 3,769 |
| Dual Class Shares | 0.15 | 0.00 | 0.36 | 3,769 |

Panel B: Summary Statistics by Country

| Country | Ownership | | | | Family Owners' Environmental Preferences | | | CCPI | Average Total Assets (in $ million) | N |
|---|---|---|---|---|---|---|---|---|---|---|
| | Family | Govern-ment | Other | Widely Held | Low | High | Unknown | | | |
| Argentina | 0.67 | 0.07 | 0.07 | 0.20 | 0.60 | 0.07 | 0.00 | 45.4 | 4,109 | 15 |
| Australia | 0.18 | 0.00 | 0.04 | 0.78 | 0.05 | 0.02 | 0.11 | 45.7 | 4,244 | 223 |
| Austria | 0.42 | 0.26 | 0.11 | 0.21 | 0.26 | 0.16 | 0.00 | 58.2 | 7,936 | 19 |
| Belgium | 0.64 | 0.06 | 0.08 | 0.22 | 0.08 | 0.03 | 0.53 | 55.0 | 10,840 | 36 |
| Brazil | 0.42 | 0.07 | 0.15 | 0.37 | 0.11 | 0.06 | 0.25 | 61.7 | 10,847 | 101 |
| Canada | 0.27 | 0.02 | 0.10 | 0.62 | 0.16 | 0.10 | 0.01 | 31.6 | 7,546 | 252 |
| Chile | 0.71 | 0.14 | 0.00 | 0.14 | 0.07 | 0.04 | 0.61 | 68.7 | 8,882 | 28 |
| Denmark | 0.21 | 0.06 | 0.26 | 0.47 | 0.11 | 0.09 | 0.02 | 75.6 | 6,669 | 47 |
| Finland | 0.39 | 0.11 | 0.11 | 0.39 | 0.20 | 0.15 | 0.04 | 61.1 | 4,104 | 54 |
| France | 0.55 | 0.08 | 0.07 | 0.29 | 0.39 | 0.14 | 0.03 | 57.1 | 26,083 | 137 |
| Germany | 0.48 | 0.07 | 0.09 | 0.36 | 0.06 | 0.04 | 0.38 | 65.8 | 17,134 | 174 |
| Greece | 0.68 | 0.26 | 0.00 | 0.05 | 0.11 | 0.53 | 0.05 | 60.3 | 4,917 | 19 |
| India | 0.66 | 0.12 | 0.02 | 0.20 | 0.32 | 0.29 | 0.05 | 70.3 | 3,375 | 459 |
| Indonesia | 0.59 | 0.18 | 0.08 | 0.16 | 0.45 | 0.06 | 0.08 | 57.2 | 4,603 | 51 |
| Ireland | 0.14 | 0.00 | 0.00 | 0.86 | 0.12 | 0.02 | 0.00 | 51.4 | 13,962 | 42 |
| Israel | 0.45 | 0.06 | 0.10 | 0.39 | 0.03 | 0.03 | 0.39 | n/a | 4,264 | 31 |
| Italy | 0.69 | 0.21 | 0.03 | 0.07 | 0.11 | 0.09 | 0.48 | 50.6 | 9,735 | 87 |
| Japan | 0.09 | 0.01 | 0.03 | 0.86 | 0.07 | 0.01 | 0.01 | 42.1 | 17,675 | 413 |
| Luxembourg | 0.50 | 0.00 | 0.08 | 0.42 | 0.04 | 0.13 | 0.33 | 65.1 | 9,033 | 24 |
| Malaysia | 0.65 | 0.17 | 0.06 | 0.13 | 0.46 | 0.17 | 0.03 | 38.6 | 3,117 | 120 |
| Mexico | 0.68 | 0.00 | 0.00 | 0.32 | 0.07 | 0.05 | 0.56 | 55.8 | 7,431 | 57 |
| Netherlands | 0.25 | 0.00 | 0.17 | 0.58 | 0.13 | 0.08 | 0.04 | 70.0 | 17,412 | 53 |
| Norway | 0.38 | 0.09 | 0.13 | 0.40 | 0.16 | 0.15 | 0.07 | 67.5 | 6,603 | 55 |
| Peru | 0.33 | 0.22 | 0.00 | 0.44 | 0.33 | 0.00 | 0.00 | n/a | 2,747 | 18 |
| Philippines | 0.89 | 0.04 | 0.00 | 0.07 | 0.30 | 0.59 | 0.00 | 70.7 | 10,001 | 27 |
| Poland | 0.39 | 0.39 | 0.09 | 0.13 | 0.26 | 0.13 | 0.00 | 44.4 | 8,327 | 23 |
| Singapore | 0.50 | 0.28 | 0.00 | 0.22 | 0.33 | 0.15 | 0.02 | n/a | 8,352 | 54 |
| South Korea | 0.83 | 0.06 | 0.01 | 0.09 | 0.54 | 0.24 | 0.05 | 30.0 | 17,826 | 140 |
| Spain | 0.43 | 0.09 | 0.13 | 0.35 | 0.13 | 0.07 | 0.22 | 63.4 | 16,053 | 54 |
| Sweden | 0.48 | 0.02 | 0.07 | 0.44 | 0.29 | 0.10 | 0.08 | 69.4 | 3,488 | 181 |
| Switzerland | 0.47 | 0.06 | 0.07 | 0.40 | 0.29 | 0.13 | 0.06 | 61.9 | 9,275 | 119 |
| Taiwan | 0.16 | 0.05 | 0.04 | 0.76 | 0.10 | 0.02 | 0.03 | 36.9 | 7,775 | 148 |
| Thailand | 0.64 | 0.17 | 0.02 | 0.17 | 0.40 | 0.20 | 0.05 | 61.4 | 4,872 | 111 |
| Turkey | 0.66 | 0.20 | 0.09 | 0.05 | 0.21 | 0.38 | 0.07 | 43.8 | 7,076 | 56 |
| U.K. | 0.19 | 0.00 | 0.10 | 0.71 | 0.01 | 0.01 | 0.17 | 62.4 | 8,574 | 341 |

**Table 2**
**Controlled Firms and GHG Emissions Disclosure**

This table shows regression estimates of firms' GHG reporting on ownership variables, control variables, and country and industry fixed effects. The dependent variable is Firm Reports CO2e, a dummy variable that equals one if a firm reports CO2-equivalent emissions, and zero otherwise. Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. $^{***}$, $^{**}$, $^{*}$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Firm Reports CO2e |
|---|---|
| Family-controlled | -0.040$^{*}$ |
| | (-1.77) |
| Government-controlled | -0.050$^{*}$ |
| | (-1.73) |
| Other-controlled | 0.017 |
| | (0.82) |
| Log (Total Assets) | 0.001 |
| | (0.16) |
| Log (Revenue) | 0.054$^{***}$ |
| | (6.55) |
| Cash | -0.105$^{**}$ |
| | (-2.10) |
| Tangibility | 0.105$^{**}$ |
| | (2.17) |
| Leverage | 0.005 |
| | (0.59) |
| Profitability | 0.097$^{***}$ |
| | (3.18) |
| Dual Class Shares | 0.031 |
| | (1.55) |
| Country FE | Yes |
| SASB Industry FE | Yes |
| N | 3,769 |
| Adjusted $R^2$ | 0.182 |

**Table 3**
**Controlled Firms and GHG Emissions**

This table shows regression estimates of measures of firms' GHG emissions on ownership variables, control variables, and country and industry fixed effects. The dependent variables are the log of CO2-equivalent emissions (scaled by revenue and raw emissions). Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
|---|---|---|---|---|
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) |
| Family-controlled | 0.128 | 0.126 | 0.179* | 0.173* |
| | (1.60) | (1.64) | (1.71) | (1.70) |
| Government-controlled | -0.037 | -0.042 | -0.095 | -0.102 |
| | (-0.30) | (-0.34) | (-0.61) | (-0.65) |
| Other-controlled | 0.288* | 0.263* | 0.165 | 0.142 |
| | (2.00) | (1.88) | (0.83) | (0.72) |
| Log (Total Assets) | 0.144*** | 0.385*** | 0.215*** | 0.396*** |
| | (7.03) | (5.22) | (7.33) | (4.48) |
| Log (Revenue) | | 0.735*** | | 0.802*** |
| | | (9.42) | | (9.37) |
| Cash | -0.208 | -0.353 | -0.598* | -0.696* |
| | (-0.78) | (-1.38) | (-1.76) | (-2.01) |
| Tangibility | 2.872*** | 2.781*** | 3.055*** | 2.996*** |
| | (7.75) | (7.64) | (7.75) | (7.74) |
| Leverage | -0.026 | -0.015 | -0.159** | -0.150** |
| | (-0.60) | (-0.34) | (-2.54) | (-2.36) |
| Profitability | -1.186*** | -0.769** | -1.466** | -1.182* |
| | (-3.14) | (-2.13) | (-2.20) | (-1.92) |
| Dual Class Shares | 0.039 | 0.050 | 0.088 | 0.098 |
| | (0.34) | (0.43) | (0.61) | (0.70) |
| Country FE | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes |
| N | 3,319 | 3,319 | 3,203 | 3,203 |
| Adjusted $R^2$ | 0.593 | 0.763 | 0.602 | 0.738 |

**Table 4**
**Controlled Firms, GHG Emissions, and Environmental Preferences**

This table shows regression estimates of measures of firms' GHG emissions on family owners' environmental preferences, ownership variables, control variables, and country and industry fixed effects. The dependent variables are the log of CO2-equivalent emissions (scaled by revenue and raw emissions). Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. $^{***}$, $^{**}$, $^{*}$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
|---|---|---|---|---|
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) |
| Low E Family | 0.223$^{**}$ | 0.210$^{**}$ | 0.309$^{**}$ | 0.296$^{**}$ |
| | (2.51) | (2.43) | (2.27) | (2.19) |
| High E Family | 0.043 | 0.044 | 0.005 | 0.003 |
| | (0.43) | (0.47) | (0.04) | (0.02) |
| Inconclusive E Family | 0.061 | 0.072 | 0.141 | 0.145 |
| | (0.61) | (0.73) | (1.13) | (1.18) |
| Government-controlled | -0.037 | -0.043 | -0.103 | -0.110 |
| | (-0.30) | (-0.35) | (-0.66) | (-0.70) |
| Other-controlled | 0.288$^{*}$ | 0.264$^{*}$ | 0.165 | 0.142 |
| | (1.99) | (1.87) | (0.83) | (0.72) |
| Log (Total Assets) | 0.146$^{***}$ | 0.385$^{***}$ | 0.221$^{***}$ | 0.398$^{***}$ |
| | (6.98) | (5.16) | (7.25) | (4.46) |
| Log (Revenue) | | 0.738$^{***}$ | | 0.806$^{***}$ |
| | | (9.40) | | (9.36) |
| Cash | -0.191 | -0.336 | -0.570 | -0.667$^{*}$ |
| | (-0.71) | (-1.29) | (-1.66) | (-1.90) |
| Tangibility | 2.874$^{***}$ | 2.783$^{***}$ | 3.058$^{***}$ | 3.000$^{***}$ |
| | (7.77) | (7.66) | (7.80) | (7.79) |
| Leverage | -0.022 | -0.011 | -0.151$^{**}$ | -0.142$^{**}$ |
| | (-0.51) | (-0.25) | (-2.48) | (-2.30) |
| Profitability | -1.203$^{***}$ | -0.787$^{**}$ | -1.478$^{**}$ | -1.199$^{*}$ |
| | (-3.21) | (-2.18) | (-2.22) | (-1.94) |
| Dual Class Shares | 0.036 | 0.047 | 0.085 | 0.094 |
| | (0.32) | (0.42) | (0.59) | (0.68) |
| Country FE | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes |
| N | 3,319 | 3,319 | 3,203 | 3,203 |
| Adjusted $R^2$ | 0.593 | 0.763 | 0.602 | 0.738 |
| Low vs. High E Family (*p*-value) | (0.034) | (0.048) | (0.038) | (0.046) |

**Table 5**
**Controlled Firms, GHG Emissions, and Expected Marginal Costs: Country-level Splits**

This table shows subsample regression estimates of measures of firms' GHG emissions on ownership variables, family owners' environmental preferences, controls, and country and industry fixed effects. The subsamples are based on a country's score on the Climate Change Performance Index (CCPI), a standardized framework to compare the climate performance of 63 countries and the EU. We construct subsamples using the overall CCPI score, based on four categories: GHG Emissions, Renewable Energy, Energy Use and Climate Policy. The dependent variables are the log of CO2-equivalent emissions (scaled by revenue and raw emissions). Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. $^{***}$, $^{**}$, $^{*}$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | High CCPI | | | | Low CCPI | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 and 2 Emissions | | Scope 1 Emissions | | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low E Family | 0.251$^{**}$ | 0.226$^{**}$ | 0.360$^{**}$ | 0.346$^{**}$ | -0.012 | -0.013 | 0.095 | 0.095 |
| | (2.38) | (2.19) | (2.47) | (2.37) | (-0.11) | (-0.14) | (0.54) | (0.56) |
| High E Family | 0.182$^{*}$ | 0.176$^{*}$ | 0.321$^{***}$ | 0.316$^{***}$ | -0.248$^{**}$ | -0.233$^{*}$ | -0.344$^{**}$ | -0.330$^{**}$ |
| | (1.84) | (1.90) | (3.55) | (3.61) | (-2.26) | (-2.12) | (-2.49) | (-2.37) |
| Inconclusive E Family | 0.186 | 0.193 | 0.277$^{*}$ | 0.277$^{*}$ | -0.315$^{*}$ | -0.319$^{*}$ | -0.187 | -0.189 |
| | (1.60) | (1.69) | (1.80) | (1.81) | (-1.85) | (-1.99) | (-0.88) | (-0.87) |
| Government-controlled | 0.116 | 0.109 | 0.067 | 0.063 | -0.180 | -0.197 | -0.367 | -0.387 |
| | (0.83) | (0.73) | (0.36) | (0.32) | (-1.09) | (-1.24) | (-1.47) | (-1.59) |
| Other-controlled | 0.517$^{***}$ | 0.482$^{***}$ | 0.535$^{***}$ | 0.517$^{***}$ | -0.055 | -0.065 | -0.359$^{*}$ | -0.371$^{**}$ |
| | (3.98) | (3.93) | (3.12) | (3.11) | (-0.35) | (-0.44) | (-2.13) | (-2.19) |
| Log (Total Assets) | 0.185$^{***}$ | 0.421$^{***}$ | 0.233$^{***}$ | 0.327$^{**}$ | 0.089$^{**}$ | 0.377$^{***}$ | 0.229$^{***}$ | 0.487$^{***}$ |
| | (8.99) | (5.05) | (7.33) | (2.71) | (2.83) | (3.02) | (4.01) | (3.82) |
| Log (Revenue) | | 0.736$^{***}$ | | 0.896$^{***}$ | | 0.689$^{***}$ | | 0.723$^{***}$ |
| | | (7.56) | | (7.35) | | (5.98) | | (6.89) |
| Cash | -0.669$^{**}$ | -0.746$^{***}$ | -1.202$^{***}$ | -1.238$^{***}$ | 0.328 | 0.051 | 0.037 | -0.169 |
| | (-2.78) | (-3.23) | (-4.56) | (-4.25) | (0.86) | (0.14) | (0.07) | (-0.31) |
| Tangibility | 3.273$^{***}$ | 3.160$^{***}$ | 3.498$^{***}$ | 3.454$^{***}$ | 2.751$^{***}$ | 2.701$^{***}$ | 2.856$^{***}$ | 2.822$^{***}$ |
| | (6.20) | (6.12) | (5.44) | (5.61) | (5.68) | (5.50) | (5.94) | (5.75) |
| Leverage | 0.024 | 0.038 | -0.097$^{*}$ | -0.091$^{*}$ | -0.318 | -0.379 | -0.711$^{*}$ | -0.747$^{*}$ |
| | (0.68) | (1.18) | (-1.80) | (-1.78) | (-1.09) | (-1.28) | (-1.91) | (-2.00) |
| Profitability | -0.606$^{*}$ | -0.245 | -0.535 | -0.377 | -1.899$^{***}$ | -1.369$^{***}$ | -2.875$^{***}$ | -2.518$^{***}$ |
| | (-1.91) | (-0.66) | (-1.00) | (-0.75) | (-4.18) | (-3.33) | (-3.45) | (-3.25) |
| Dual Class Shares | -0.142 | -0.106 | -0.230 | -0.213 | 0.180 | 0.180 | 0.326$^{***}$ | 0.322$^{**}$ |
| | (-0.52) | (-0.39) | (-1.03) | (-1.00) | (1.56) | (1.44) | (3.09) | (2.89) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,654 | 1,654 | 1,609 | 1,609 | 1,576 | 1,576 | 1,511 | 1,511 |
| Adjusted $R^2$ | 0.624 | 0.782 | 0.584 | 0.737 | 0.580 | 0.743 | 0.639 | 0.747 |
| Low vs. High E Family (*p*-value) | (0.333) | (0.489) | (0.722) | (0.786) | (0.120) | (0.139) | (0.069) | (0.073) |

**Table 6**
**Controlled Firms, GHG Emissions, and Expected Marginal Costs: Industry-level Splits**

This table shows regression estimates of measures of firms' GHG emissions on ownership variables, family owners' environmental preferences, control variables, and country and industry fixed effects for firms in low and high Scope 1 emission industries, respectively. Firms are grouped into low and high Scope 1 industries depending on whether the industry's total Scope 1 emissions account for less (greater) than 51% of the industry's total Scope 1 and 2 CO2-equivalent emissions (based on SASB Industry Classifications). The dependent variables are the log of CO2-equivalent emissions (scaled by revenue and raw emissions). Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. $^{***}$, $^{**}$, $^{*}$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | High Scope 1 Industries | | | | Low Scope 1 Industries | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 and 2 Emissions | | Scope 1 Emissions | | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low E Family | 0.310$^{***}$ | 0.293$^{***}$ | 0.443$^{**}$ | 0.431$^{**}$ | 0.132 | 0.125 | 0.171 | 0.155 |
| | (2.89) | (2.94) | (2.66) | (2.67) | (1.11) | (1.03) | (1.06) | (0.95) |
| High E Family | 0.295 | 0.287 | 0.406$^{*}$ | 0.400$^{*}$ | -0.149 | -0.145 | -0.347$^{**}$ | -0.348$^{**}$ |
| | (1.56) | (1.53) | (1.76) | (1.77) | (-1.38) | (-1.33) | (-2.42) | (-2.40) |
| Inconclusive E Family | 0.420$^{***}$ | 0.409$^{***}$ | 0.541$^{**}$ | 0.533$^{**}$ | -0.293$^{**}$ | -0.275$^{**}$ | -0.280 | -0.262 |
| | (3.27) | (3.42) | (2.66) | (2.65) | (-2.31) | (-2.21) | (-1.64) | (-1.60) |
| Government-controlled | 0.008 | -0.022 | -0.123 | -0.142 | -0.154 | -0.151 | 0.038 | 0.042 |
| | (0.05) | (-0.14) | (-0.58) | (-0.66) | (-0.62) | (-0.63) | (0.17) | (0.20) |
| Other-controlled | 0.276 | 0.233 | 0.209 | 0.179 | 0.274$^{*}$ | 0.266$^{*}$ | 0.124 | 0.113 |
| | (1.29) | (1.17) | (0.80) | (0.70) | (1.82) | (1.80) | (0.57) | (0.52) |
| Log (Total Assets) | 0.193$^{***}$ | 0.508$^{***}$ | 0.273$^{***}$ | 0.453$^{***}$ | 0.090$^{***}$ | 0.238$^{**}$ | 0.164$^{***}$ | 0.346$^{***}$ |
| | (6.43) | (4.61) | (7.08) | (3.95) | (3.07) | (2.10) | (3.64) | (2.89) |
| Log (Revenue) | | 0.661$^{***}$ | | 0.807$^{***}$ | | 0.837$^{***}$ | | 0.800$^{***}$ |
| | | (6.45) | | (7.42) | | (6.85) | | (7.50) |
| Cash | -0.048 | -0.182 | 0.156 | 0.068 | -0.327 | -0.449 | -1.097$^{**}$ | -1.218$^{**}$ |
| | (-0.14) | (-0.63) | (0.40) | (0.16) | (-0.96) | (-1.34) | (-2.43) | (-2.73) |
| Tangibility | 2.875$^{***}$ | 2.774$^{***}$ | 3.434$^{***}$ | 3.381$^{***}$ | 2.771$^{***}$ | 2.719$^{***}$ | 2.685$^{***}$ | 2.635$^{***}$ |
| | (6.37) | (6.27) | (8.15) | (8.22) | (5.31) | (5.32) | (5.09) | (4.91) |
| Leverage | 0.105 | -0.013 | -0.374 | -0.441 | -0.033 | -0.021 | -0.119$^{**}$ | -0.105$^{**}$ |
| | (0.34) | (-0.04) | (-0.93) | (-1.08) | (-0.90) | (-0.58) | (-2.56) | (-2.42) |
| Profitability | -1.580$^{***}$ | -1.169$^{**}$ | -2.260$^{***}$ | -2.007$^{***}$ | -0.960$^{**}$ | -0.681 | -0.982 | -0.696 |
| | (-2.88) | (-2.15) | (-3.13) | (-2.82) | (-2.51) | (-1.65) | (-1.43) | (-1.08) |
| Dual Class Shares | -0.050 | -0.030 | -0.002 | 0.013 | 0.144 | 0.148 | 0.156 | 0.160 |
| | (-0.38) | (-0.23) | (-0.01) | (0.08) | (1.09) | (1.10) | (0.96) | (1.04) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,697 | 1,697 | 1,657 | 1,657 | 1,621 | 1,621 | 1,545 | 1,545 |
| Adjusted $R^2$ | 0.609 | 0.772 | 0.597 | 0.735 | 0.434 | 0.696 | 0.318 | 0.611 |
| Low vs. High E Family (*p*-value) | (0.923) | (0.968) | (0.857) | (0.881) | (0.039) | (0.046) | (0.014) | (0.017) |

**Table 7**
**Orthogonalized Family Owners' Environmental Preferences and GHG Emissions**

This table shows regression estimates of family owner's environmental preferences on country, family and firm characteristics (Panel A), and regression estimates of the residuals from Panel A on measures of GHG emissions (Panels B-D). In Panel A, the dependent variable is the family owners' environmental preferences. In Panels B through D, the dependent variables are the log of CO2-equivalent emissions (scaled by revenue and raw emissions). In Panels B through D, Low (High) E Family, $\varepsilon_{Family\ (2)}$ indicate families with low (high) environmental preferences based on the residuals of column 2 of Panel A. In Panel C, firms are grouped into subsamples based on a country's score on the Climate Change Performance Index (CCPI), a standardized framework to compare the climate performance of 63 countries and the EU. We construct subsamples using the overall CCPI score, based on four categories: GHG Emissions, Renewable Energy, Energy Use and Climate Policy. In Panel D, firms are grouped into low and high Scope 1 industries depending on whether the industry's total Scope 1 emissions account for less (greater) than 51% of the industry's total Scope 1 and 2 CO2-equivalent emissions (based on SASB Industry Classifications). Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. $^{***}$, $^{**}$, $^{*}$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Explaining Family Owners' Environmental Preferences

| | Family Owner's Environmental Preferences ($y_{Family}$) | |
|---|---|---|
| | (1) | (2) |
| English Narrow | 1.367$^{*}$ | 1.370$^{*}$ |
| | (1.89) | (1.94) |
| English Extensive | | 1.436 |
| | | (1.01) |
| Log (GDP/Capita) | -1.688$^{***}$ | -1.319$^{***}$ |
| | (-5.83) | (-3.14) |
| Forbes List | 2.419$^{*}$ | 2.368$^{*}$ |
| | (1.80) | (1.79) |
| Log (Total Assets) | 1.675$^{***}$ | 1.723$^{***}$ |
| | (6.19) | (6.37) |
| Country FE | No | No |
| SASB Industry FE | Yes | Yes |
| N | 1,150 | 1,150 |
| Adjusted $R^2$ | 0.086 | 0.0851 |

Panel B: Family Firm Environmental Preferences and GHG Emissions

| | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
|---|---|---|---|---|
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) |
| Low E Family, $\varepsilon_{Family\ (2)}$ | $0.203^{**}$ | $0.188^{**}$ | $0.316^{**}$ | $0.302^{**}$ |
| | (2.29) | (2.18) | (2.32) | (2.24) |
| High E Family, $\varepsilon_{Family\ (2)}$ | 0.107 | 0.112 | 0.075 | 0.076 |
| | (1.21) | (1.34) | (0.54) | (0.56) |
| Inconclusive E Family | 0.063 | 0.074 | 0.148 | 0.152 |
| | (0.64) | (0.76) | (1.16) | (1.21) |
| Government-controlled | -0.028 | -0.035 | -0.086 | -0.093 |
| | (-0.23) | (-0.28) | (-0.56) | (-0.59) |
| Other-controlled | $0.289^{*}$ | $0.265^{*}$ | 0.171 | 0.149 |
| | (2.01) | (1.90) | (0.86) | (0.75) |
| Log (Total Assets) | $0.143^{***}$ | $0.383^{***}$ | $0.217^{***}$ | $0.394^{***}$ |
| | (6.96) | (5.14) | (7.36) | (4.44) |
| Log (Revenue) | | $0.737^{***}$ | | $0.806^{***}$ |
| | | (9.41) | | (9.37) |
| Cash | -0.200 | -0.346 | $-0.583^{*}$ | $-0.680^{*}$ |
| | (-0.75) | (-1.33) | (-1.69) | (-1.93) |
| Tangibility | $2.874^{***}$ | $2.783^{***}$ | $3.055^{***}$ | $2.997^{***}$ |
| | (7.78) | (7.67) | (7.82) | (7.81) |
| Leverage | -0.025 | -0.014 | $-0.154^{**}$ | $-0.145^{**}$ |
| | (-0.59) | (-0.33) | (-2.52) | (-2.34) |
| Profitability | $-1.200^{***}$ | $-0.783^{**}$ | $-1.474^{**}$ | $-1.195^{*}$ |
| | (-3.19) | (-2.16) | (-2.22) | (-1.94) |
| Dual Class Shares | 0.037 | 0.047 | 0.084 | 0.093 |
| | (0.32) | (0.41) | (0.58) | (0.67) |
| Country FE | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes |
| N | 3,319 | 3,319 | 3,203 | 3,203 |
| Adjusted $R^2$ | 0.593 | 0.763 | 0.602 | 0.738 |
| Low vs. High E Family (*p*-value) | (0.176) | (0.263) | (0.064) | (0.079) |

Panel C: Splits by the Climate Change Performance Index

| | High CCPI | | | | Low CCPI | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 and 2 Emissions | | Scope 1 Emissions | | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low E Family, $\varepsilon_{Family\ (2)}$ | 0.222* | 0.196* | 0.379** | 0.365** | -0.021 | -0.027 | 0.078 | 0.074 |
| | (2.06) | (1.88) | (2.78) | (2.68) | (-0.21) | (-0.29) | (0.45) | (0.45) |
| High E Family, $\varepsilon_{Family\ (2)}$ | 0.240*** | 0.235*** | 0.348*** | 0.343*** | -0.210** | -0.189* | -0.290** | -0.269** |
| | (3.00) | (3.16) | (3.75) | (3.79) | (-2.23) | (-2.01) | (-2.52) | (-2.36) |
| Inconclusive E Family | 0.187 | 0.194 | 0.283* | 0.283* | -0.316* | -0.320* | -0.192 | -0.193 |
| | (1.62) | (1.71) | (1.82) | (1.83) | (-1.85) | (-2.00) | (-0.90) | (-0.89) |
| Government-controlled | 0.124 | 0.117 | 0.077 | 0.073 | -0.178 | -0.194 | -0.366 | -0.386 |
| | (0.89) | (0.78) | (0.41) | (0.38) | (-1.07) | (-1.22) | (-1.46) | (-1.58) |
| Other-controlled | 0.517*** | 0.482*** | 0.540*** | 0.522*** | -0.054 | -0.065 | -0.359* | -0.371** |
| | (4.02) | (3.97) | (3.16) | (3.15) | (-0.35) | (-0.44) | (-2.12) | (-2.18) |
| Log (Total Assets) | 0.182*** | 0.421*** | 0.233*** | 0.326** | 0.086** | 0.374*** | 0.223*** | 0.480*** |
| | (9.12) | (5.07) | (7.43) | (2.70) | (2.79) | (3.01) | (4.04) | (3.80) |
| Log (Revenue) | | 0.734*** | | 0.896*** | | 0.690*** | | 0.724*** |
| | | (7.59) | | (7.35) | | (5.98) | | (6.88) |
| Cash | -0.681** | -0.758*** | -1.206*** | -1.241*** | 0.317 | 0.042 | 0.015 | -0.189 |
| | (-2.82) | (-3.26) | (-4.52) | (-4.23) | (0.84) | (0.11) | (0.03) | (-0.34) |
| Tangibility | 3.270*** | 3.156*** | 3.496*** | 3.451*** | 2.753*** | 2.704*** | 2.856*** | 2.823*** |
| | (6.18) | (6.10) | (5.45) | (5.62) | (5.68) | (5.50) | (5.95) | (5.76) |
| Leverage | 0.021 | 0.035 | -0.098* | -0.091* | -0.324 | -0.384 | -0.716* | -0.752* |
| | (0.61) | (1.11) | (-1.82) | (-1.81) | (-1.11) | (-1.29) | (-1.91) | (-2.01) |
| Profitability | -0.604* | -0.240 | -0.537 | -0.380 | -1.896*** | -1.368*** | -2.862*** | -2.507*** |
| | (-1.89) | (-0.64) | (-1.00) | (-0.76) | (-4.15) | (-3.29) | (-3.44) | (-3.23) |
| Dual Class Shares | -0.144 | -0.107 | -0.230 | -0.213 | 0.183 | 0.184 | 0.333*** | 0.330** |
| | (-0.52) | (-0.40) | (-1.04) | (-1.01) | (1.56) | (1.44) | (3.10) | (2.90) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,654 | 1,654 | 1,609 | 1,609 | 1,576 | 1,576 | 1,511 | 1,511 |
| Adjusted $R^2$ | 0.624 | 0.782 | 0.584 | 0.737 | 0.579 | 0.743 | 0.639 | 0.747 |
| Low vs. High E Family (*p*-value) | (0.908) | (0.805) | (0.182) | (0.213) | (0.783) | (0.821) | (0.042) | (0.049) |

Panel D: Splits by Industry Emissions

| | High Scope 1 Industries | | | | Low Scope 1 Industries | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 and 2 Emissions | | Scope 1 Emissions | | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low E Family, $\varepsilon_{Family\ (2)}$ | 0.311*** | 0.289*** | 0.455*** | 0.442*** | 0.104 | 0.096 | 0.188 | 0.172 |
| | (2.92) | (2.93) | (2.86) | (2.87) | (0.85) | (0.77) | (1.08) | (0.99) |
| High E Family, $\varepsilon_{Family\ (2)}$ | 0.327* | 0.322* | 0.400* | 0.397* | -0.073 | -0.069 | -0.221* | -0.221* |
| | (1.92) | (1.96) | (1.77) | (1.80) | (-0.70) | (-0.64) | (-1.72) | (-1.71) |
| Inconclusive E Family | 0.425*** | 0.413*** | 0.541** | 0.533** | -0.293** | -0.274** | -0.265 | -0.246 |
| | (3.31) | (3.46) | (2.67) | (2.66) | (-2.30) | (-2.20) | (-1.53) | (-1.48) |
| Government-controlled | 0.015 | -0.015 | -0.124 | -0.142 | -0.147 | -0.144 | 0.074 | 0.079 |
| | (0.10) | (-0.10) | (-0.58) | (-0.67) | (-0.59) | (-0.60) | (0.33) | (0.36) |
| Other-controlled | 0.279 | 0.236 | 0.208 | 0.178 | 0.271* | 0.265* | 0.138 | 0.128 |
| | (1.31) | (1.19) | (0.80) | (0.70) | (1.81) | (1.79) | (0.64) | (0.59) |
| Log (Total Assets) | 0.192*** | 0.507*** | 0.273*** | 0.453*** | 0.085*** | 0.235** | 0.157*** | 0.339*** |
| | (6.45) | (4.62) | (7.10) | (3.93) | (2.90) | (2.08) | (3.56) | (2.83) |
| Log (Revenue) | | 0.661*** | | 0.807*** | | 0.836*** | | 0.799*** |
| | | (6.46) | | (7.41) | | (6.85) | | (7.48) |
| Cash | -0.049 | -0.183 | 0.156 | 0.068 | -0.358 | -0.480 | -1.154** | -1.274*** |
| | (-0.14) | (-0.64) | (0.40) | (0.16) | (-1.05) | (-1.43) | (-2.60) | (-2.90) |
| Tangibility | 2.878*** | 2.776*** | 3.435*** | 3.382*** | 2.770*** | 2.718*** | 2.673*** | 2.623*** |
| | (6.36) | (6.26) | (8.11) | (8.18) | (5.33) | (5.32) | (5.12) | (4.94) |
| Leverage | 0.106 | -0.010 | -0.375 | -0.441 | -0.038 | -0.026 | -0.126** | -0.112** |
| | (0.34) | (-0.03) | (-0.92) | (-1.07) | (-1.06) | (-0.73) | (-2.72) | (-2.59) |
| Profitability | -1.575*** | -1.164** | -2.263*** | -2.010*** | -0.964** | -0.682 | -0.984 | -0.699 |
| | (-2.87) | (-2.14) | (-3.14) | (-2.83) | (-2.53) | (-1.65) | (-1.44) | (-1.09) |
| Dual Class Shares | -0.049 | -0.028 | 0.001 | 0.015 | 0.142 | 0.145 | 0.151 | 0.155 |
| | (-0.37) | (-0.21) | (0.01) | (0.09) | (1.07) | (1.08) | (0.94) | (1.01) |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SASB Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,697 | 1,697 | 1,657 | 1,657 | 1,621 | 1,621 | 1,545 | 1,545 |
| Adjusted $R^2$ | 0.609 | 0.772 | 0.597 | 0.735 | 0.433 | 0.695 | 0.316 | 0.610 |
| Low vs. High E Family (*p*-value) | (0.908) | (0.805) | (0.182) | (0.213) | (0.783) | (0.821) | (0.042) | (0.049) |

## Appendix A

### Table A1
### Variable Descriptions and Data Sources

This table reports variable definitions and data sources. Unless otherwise stated, all data are as of fiscal year end 2023

| Variable | Description | Source |
|---|---|---|
| *A. Environmental Performance* | | |
| Firm Reports CO2e | A dummy variable equal to one if a firm reports CO2-equivalent emissions. | LSEG[19] |
| CO2e | Total CO2-equivalent emissions (in tonnes). Depending on the measure, this includes either i) Scope 1 and Scope 2 emissions, or ii) Scope 1 emissions only. CO2-equivalent emissions account for CO2 as well as other greenhouse gases (CH4, N2O, HFCs, PFCs, SF6, NF3) and are calculated in accordance with the Greenhouse Gas Protocol. | LSEG |
| Log (CO2e) | Log of total CO2e. | LSEG |
| Log (CO2e / Revenue) | Log of total CO2e scaled by revenue in millions of $. | LSEG, Worldscope |
| *B. Ownership* | | |
| Family-controlled | A dummy variable equal to one if a firm is classified as controlled by a family (as of December 2022). Control requires that the sum of the shares owned by family members is greater than 20% or that family members own at least 10% of the shares and the company has multiple voting class shares, and the sum is greater than any other shareholder. | Manual classification |
| Government-controlled | A dummy variable equal to one if the largest shareholder of the firm owns at least 20% of the firm and is the government or a sovereign wealth fund (as of December 2022). | Manual classification |
| Other-controlled | A dummy variable equal to one if the largest shareholder owns at least 20% of the firm and is a private equity fund, hedge fund, venture capital fund, other type of blockholder, or if ownership cannot be established (as of December 2022). | Manual classification |
| Widely Held | A dummy variable equal to one if a firm is not classified as Family, Government, or Other Opaque (as of December 2022). | Manual classification |
| *C. Family Owners' Characteristics* | | |
| Family E Preferences | Family owner's environmental preferences are measured with the sum of five LLM generated measures ranking from zero to 50 (each component has a range of 0 to 10). Larger numbers are associated with greater environmental preferences. The five measures are: 1) personal philanthropy and charitable giving towards environmental causes; 2) public statements and advocacy for environmental issues; 3) participation in environmental NGOs; 4) green investments in the family's personal portfolio outside the firm; 5) policy support and political contributions for environmental policies. | GPT, Perplexity |
| Low E Family | A dummy variable equal to one if the sum of the LLM generated family owner's ownership preferences is less than 20, and zero otherwise. | GPT, Perplexity |
| High E Family | A dummy variable equal to one if the sum of the LLM generated family owner's ownership preferences is equal or greater than 20, and zero otherwise. | GPT, Perplexity |

[19] At the time of data extraction, the database was called Refinitiv. Refinitiv was acquired by LSEG in 2021, and rebranding Refinitiv products began in late 2023.

| | | |
|---|---|---|
| Inconclusive E Family | A dummy variable equal to one if the sum of the LLM generated family owner's ownership preferences is unknown, and zero otherwise. | GPT, Perplexity |
| Forbes List | Indicates whether the controlling family appears in Forbes' the World's Billionaires 2022. | Forbes |
| *D. Other Firm Characteristics* | | |
| Total Assets | Total assets in $ million. | Worldscope |
| Revenue | Revenue in $ million. | Worldscope |
| Cash | Cash over total assets. | Worldscope |
| Tangibility | PP&E over total assets. | Worldscope |
| Leverage | Long-term debt over total assets. | Worldscope |
| Profitability | Net income over total assets. | Worldscope |
| Dual Class Shares | A dummy variable that is equal to one if a firm has a dual class share ownership structure, and zero otherwise. | LSEG, Worldscope |
| *E. Country Characteristics* | | |
| CCPI | The Climate Change Performance Index (CCPI) is a standardized framework used to compare the climate performance of 63 countries and the EU. The overall CCPI score is based on four categories: GHG Emissions, Renewable Energy, Energy Use and Climate Policy. | Germanwatch |
| English Narrow | English Narrow indicates native English-speaking countries (Australia, Canada, Ireland, UK). | Wikipedia |
| English Extensive | English Extensive indicates countries with widespread English use (India, Malaysia, the Philippines, Singapore). | Wikipedia |
| Log (GDP/Capita) | Log of GDP per capita in $. | World Bank |

**Table A2**
**Controlled Firms and GHG Emissions: Splits by the GHG Emissions Category of the Climate Change Performance Index**

This table shows subsample regression estimates of measures of firms' GHG emissions on ownership variables, family owners' environmental preferences, control variables, and country and industry fixed effects. The subsamples are based on a country's score on the GHG Emissions Category of the Climate Change Performance Index (CCPI), a standardized framework used to compare the climate performance of 63 countries and the EU. The dependent variables are the log of CO2-equivalent emissions (scaled by revenue and raw emissions). Industry fixed effects are based on SASB Industry Classifications. All variables are described in Appendix Tables A1. The sample year is 2023. Standard errors are clustered at the country level and *t*-statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | High CCPI (GHG Emissions Category) | | | | Low CCPI (GHG Emissions Category) | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 and 2 Emissions | | Scope 1 Emissions | | Scope 1 and 2 Emissions | | Scope 1 Emissions | |
| | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) | Log (CO2e / Revenue) | Log (CO2e) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low E Family | 0.267*** | 0.252*** | 0.449*** | 0.450*** | -0.035 | -0.041 | -0.005 | -0.014 |
| | (3.32) | (3.49) | (6.30) | (7.32) | (-0.22) | (-0.26) | (-0.02) | (-0.05) |
| High E Family | 0.176 | 0.170 | 0.324*** | 0.324*** | -0.241 | -0.218 | -0.382** | -0.360** |
| | (1.72) | (1.75) | (3.69) | (3.95) | (-1.71) | (-1.56) | (-2.72) | (-2.53) |
| Inconclusive E Family | 0.133 | 0.146 | 0.228 | 0.227 | -0.109 | -0.130 | -0.000 | -0.027 |
| | (1.15) | (1.23) | (1.67) | (1.64) | (-0.47) | (-0.58) | (-0.00) | (-0.11) |
| Government-controlled | 0.086 | 0.073 | 0.042 | 0.042 | -0.131 | -0.122 | -0.346 | -0.349 |
| | (0.52) | (0.43) | (0.20) | (0.20) | (-0.81) | (-0.73) | (-1.31) | (-1.30) |
| Other-controlled | 0.410** | 0.386** | 0.370 | 0.371 | 0.098 | 0.071 | -0.132 | -0.170 |
| | (2.53) | (2.50) | (1.68) | (1.74) | (0.42) | (0.33) | (-0.42) | (-0.56) |
| Log (Total Assets) | 0.190*** | 0.369*** | 0.237*** | 0.230 | 0.093** | 0.383*** | 0.242*** | 0.540*** |
| | (10.33) | (3.68) | (8.07) | (1.69) | (2.55) | (3.38) | (3.81) | (4.39) |
| Log (Revenue) | | 0.801*** | | 1.007*** | | 0.684*** | | 0.675*** |
| | | (6.85) | | (7.35) | | (7.05) | | (6.81) |
| Cash | -0.731** | -0.788** | -1.339*** | -1.337*** | 0.045 | -0.282 | 0.045 | -0.236 |
| | (-2.71) | (-2.92) | (-4.15) | (-4.04) | (0.13) | (-0.77) | (0.07) | (-0.36) |
| Tangibility | 3.367*** | 3.277*** | 3.415*** | 3.418*** | 2.503*** | 2.434*** | 2.469*** | 2.411*** |
| | (6.45) | (6.50) | (5.02) | (5.39) | (5.77) | (5.70) | (5.67) | (5.63) |
| Leverage | 0.020 | 0.033 | -0.078 | -0.079 | -0.291 | -0.358 | -0.698* | -0.745* |
| | (0.56) | (1.01) | (-1.46) | (-1.55) | (-0.96) | (-1.19) | (-1.85) | (-2.02) |
| Profitability | -0.724* | -0.418 | -0.249 | -0.261 | -1.717*** | -1.275*** | -2.768*** | -2.466*** |
| | (-1.83) | (-0.87) | (-0.52) | (-0.53) | (-4.23) | (-3.81) | (-3.90) | (-3.70) |
| Dual Class Shares | 0.060 | 0.080 | -0.018 | -0.018 | 0.032 | 0.026 | 0.282* | 0.276* |
| | (0.33) | (0.44) | (-0.10) | (-0.11) | (0.20) | (0.17) | (2.01) | (2.01) |
| SASB Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,587 | 1,587 | 1,537 | 1,537 | 1,500 | 1,500 | 1,441 | 1,441 |
| Adjusted $R^2$ | 0.638 | 0.797 | 0.592 | 0.748 | 0.558 | 0.732 | 0.608 | 0.730 |
| Low vs. High E Family (*p*-value) | (0.154) | (0.210) | (0.140) | (0.146) | (0.278) | (0.343) | (0.237) | (0.276) |

**Table A3**
**Case Studies of Families with High Environmental Preferences**

This table shows examples of families in low-income countries (GPD/capita below the sample median). Family owner's environmental preference is the sum of five AI generated measures ranking from zero to 50 (each component has a range of 0 to 10). Larger numbers are associated with greater environmental preferences. The five measures are: i) personal philanthropy and charitable giving towards environmental causes; ii) public statements and advocacy for environmental issues; iii) participation in environmental NGOs; iv) green investments in the family's personal portfolio outside the firm; and v) policy support and political contributions for environmental policies. Prompts are provided in Appendix B.

**Example A: Ayala Corporation**

| Firm Name | Country | CCPI Split | GDP/ Capita | Family E Preference (0-50) | High E Family | Family Name |
|---|---|---|---|---|---|---|
| Ayala Corporation | Philippines | High | 3,499 | 40 | 1 | Zóbel de Ayala Family |

**LLM Assessment**
The Zóbel de Ayala family demonstrates strong environmental preferences across multiple dimensions. They have shown significant personal philanthropy towards environmental causes through the Ayala Foundation. The family, particularly Jaime Augusto and Fernando, has made numerous public statements advocating for environmental issues and sustainability. They actively participate in environmental NGOs and initiatives. While specific information on their personal 'green' investments is limited, their leadership in renewable energy projects suggests a commitment to environmentally conscious investments. The family has also shown support for environmental policies, particularly in areas of climate change mitigation and adaptation. Overall, the Zóbel de Ayalas exhibit a strong collective commitment to environmental concerns.

**Example 2: Sunway BHD**

| Firm Name | Country | CCPI Split | GDP/ Capita | Family E Preference (0-50) | High E Family | Family Name |
|---|---|---|---|---|---|---|
| Sunway BHD | Malaysia | 0 | 11,972 | 37 | 1 | Cheah Family |

**LLM Assessment**
The Cheah family, particularly Jeffrey Cheah, demonstrates strong environmental preferences through various initiatives. Their personal philanthropy is evident in the Jeffrey Cheah Foundation's support for sustainable education programs. Public advocacy is shown through Jeffrey Cheah's commitment to the UN Sustainable Development Goals. The family participates in environmental NGOs through the establishment of the Jeffrey Sachs Center for Sustainable Development. While specific 'green' investments in their personal portfolio are not explicitly mentioned, their support for sustainability initiatives suggests some level of environmentally conscious investing. The family's policy support is reflected in their alignment with national educational initiatives promoting sustainability. Overall, the Cheah family shows a strong commitment to environmental causes, particularly in education and sustainable development.

**Example 3: Diagnosticos Da America SA**

| Firm Name | Country | CCPI Split | GDP/ Capita | Family E Preference (0-50) | High E Family | Family Name |
|---|---|---|---|---|---|---|
| Diagnosticos Da America SA | Brazil | 1 | 9460 | 33 | 1 | Bueno Family |

**LLM Assessment**
The Bueno family, particularly Pedro Bueno, demonstrates a strong inclination towards environmental concerns. Pedro Bueno's involvement in the "Economic Pact with Nature" and advocacy for a carbon market bill indicate significant public support for environmental issues. The family's philanthropic efforts, while not exclusively environmental, show a commitment to social causes. Their investment in DNA Capital suggests an interest in sustainable healthcare solutions. While direct participation in environmental NGOs is not evident, their support for environmental policies is clear. The family's overall approach reflects a balance between business interests and environmental consciousness, resulting in a moderately high environmental preference score.

**Example 4: Vestel Elektronik Sanayi Ve Ticaret AS**

| Firm Name | Country | CCPI Split | GDP/ Capita | Family E Preference (0-50) | High E Family | Family Name |
|---|---|---|---|---|---|---|
| Vestel Elektronik Sanayi Ve Ticaret AS | Turkey | 0 | 10616 | 36 | 1 | Zorlu Family |

**LLM Assessment**
The Zorlu family demonstrates strong environmental preferences across multiple dimensions. They have implemented significant philanthropic initiatives, such as the Zero Carbon Footprint Forests Project. The family consistently makes public statements advocating for environmental issues and sustainability. They participate in environmental NGOs and support various environmental causes. The family's investment strategy appears to prioritize green investments, particularly in renewable energy. The Zorlus also show support for environmental policies, aligning their business strategies with global sustainability goals. Overall, the family exhibits a robust commitment to environmental concerns, reflected in their actions and statements across various platforms.

**Appendix B**
**Large Language Model Prompts**

## 1. Identifying Controlling Families (OpenAI GPT-4o)

We first identify firms classified as family-controlled and use the LLM to determine the controlling family's name, board members, their gender, and the founder. This is achieved through the prompt below. To validate the LLM's accuracy, we conduct a controlled experiment with Canadian firms by informing the LLM that the firms are family-controlled but withholding any family name data. Across 67 Canadian family firms, the LLM achieved 100% precision in family-name recovery.

We use the following prompt:

> Family Members and Role
>
> You are a financial data expert. You are assessing families that control publicly traded firms. Control is defined as follows. i) the sum of the shares owned by the family members exceeds those of any other shareholder and is greater than 20% OR ii) the sum of family stakes exceeds those of any other shareholder, is greater than 10%, and family members hold the CEO or chair position OR iii) the sum of family stakes exceeds those of any other shareholder, is greater than 10%, and (the firm has multiple voting class shares) OR (the CEO or other board member is a family member).
>
> You are using publicly available data as of December 2022 to make your assessment. For each observation you have several variables, as follows:
> `companyname` - name of the firm
> `familyname` - the name of the family that I have assessed as the one controlling the firm (if available)
> `country`- The country of incorporation of the firm specified in `companyname`
> `dscode` - The Datastream identifier of the firm specified in `companyname`
>
> q1: Assume that each firm is indeed controlled by a family, according to the above given definition of control. Assume also that my assessment of the family name--if available--is correct. Identify the family that in your opinion is most likely the one controlling the firm. Note that the family might represent one or multiple family members. Provide one family name, choosing the most visible one if there are multiple, of the controlling family.
>
> q2: Assess how certain you are about your ability to identify the family in q1 with a posterior confidence score (PCS 0–100).
>
> q3: List up to five members of the controlling family, stating the first name, last name, gender, that meet the condition of having a position on the board of directors in 2022.
>
> q4: Give a summary of the controlling family's involvement in the firm, with historical context, in 80 words. In case you cannot identify the family from q1, give a summary of why you cannot.
>
> In all answers, you are using publicly available data as of December 2022 to make your assessment. Avoid hypothetical or example-based explanations; directly provide insights, conclusions, or statistical trends if applicable. If there is insufficient data and you are not at least 80% sure that you know the answer, reply "NA".
>
> Structure your answer as follows.
> variable q1 as a string (family name(s))
> variable q2 as a number (0 to 100)
> variable q3 as a string (first last (gender), first last (gender), ...)
> variable q4 as a string (80 words)

**2. Assessing Family's Environmental Preferences (Perplexity Sonar-pro)**

The family name identified through GPT is then used as input for Perplexity to assess the family's personal environmental preferences. We leverage the second's search-based LLM capability to provide online references, facilitating our (human) review of the LLM's assessments. The environmental preferences are evaluated across five dimensions on a scale from 0 to 10:

a) Personal philanthropy towards environmental causes.
b) Public statements and advocacy for environmental issues.
c) Participation in environmental NGOs.
d) Green investments in personal portfolios outside the firm.
e) Policy support and political contributions for environmental policies.

The LLM is explicitly instructed to exclude any consideration of the firm's corporate environmental performance. The prompt used for the LLM is customized for each firm, replacing the placeholders [company name], [country], [family name], [family board member names] for each observation.

We use the following prompt:

| Family Preferences (Perplexity API, model sonar-pro) |
| --- |
| Assess the [family name] family's environmental preferences along five dimensions, scoring each dimension on a scale of 0 to 10, where 0 indicates the strongest possible preferences against environmental concerns and 10 are the strongest possible preferences towards environmental concerns. a) Personal philanthropy and charitable giving towards environmental causes b) Public statements and advocacy for environmental issues c) Participation in environmental NGOs d) 'Green' investments in the family's personal portfolio outside the firm e) Policy support and political contributions for environmental policies. f) Provide the sum of these five dimensions as a score between 0 and 50. To avoid confusion, the family is linked to [country] and to [company name] in that country. In case the family name is a frequent name, be especially careful to not confuse the family with another family of the same name. You can use [family board member names] as reference point(s) to help identify the correct family and their preferences, but focus on the entire family and their collective actions. Note that I am interested only in their personal environmental preferences, not in corporate environmental activities of [company name], which the family controls. Note that if you can find evidence of family preferences, but no evidence of environmental preferences, this is consistent with a low or very low score and not a reason to refuse to assign a score. g) Assess how certain you are about your ability to identify the family preferences with a posterior confidence score (PCS 0–100). h) Provide a summary narrative of your assessment, not exceeding 100 words. Begin your answer with the statement: **My answers: a) xx b) xx c) xx d) xx e) xx f) xx, g) xx, g) yyyy, where xx are your numerical scores, yyyy is your summary.. |

### 3. Perplexity API Evaluation Notebook

This notebook processes structured questions about environmental preferences using the Perplexity API. It reads input Excel files, queries the API, and stores the answers along with source citations. It provides a reproducible workflow to evaluate environmental preference indicators using Perplexity's Sonar-pro model. It automates question submission, response parsing, and Excel output generation for further analysis.

#### 3.1. Configuration and Setup

Define file paths, API credentials, and basic configuration constants used in the script.

```
import pandas as pd
import requests
import time
import logging

# Configuration
API_URL = "https://api.perplexity.ai/chat/completions"
API_KEY = "your_api_key_here"  # Replace securely
MODEL_NAME = "sonar-pro"

INPUT_FILES = ["file1", "file2", ...]
INPUT_DIR = "../prep/perplexity/"
OUTPUT_DIR = "../output/perplexity/"

HEADERS = {
    "Authorization": f"Bearer {API_KEY}",
    "Content-Type": "application/json"
}

# Logging setup
logging.basicConfig(level=logging.INFO, format="%(asctime)s - %(message)s")
```

#### 3.2. API Query Function

Defines a reusable function to submit a question to the Perplexity API and retrieve both the answer and any citations.

```
def query_perplexity(question_text):
    payload = {
        "model": MODEL_NAME,
        "messages": [{"role": "user", "content": question_text}]
    }
    try:
        resp = requests.post(API_URL, headers=HEADERS, json=payload)
        resp.raise_for_status()
        data = resp.json()
        answer = data.get("choices", [{}])[0].get("message",
{}).get("content", "No answer found")
        citations = data.get("citations", [])
        return answer, citations
    except requests.exceptions.RequestException as e:
        return f"API request failed: {e}", []
```

### 3.3. File Processing Loop

Iterates over each Excel input file, reads questions, queries the API, and stores responses with source metadata.

```
for file_name in INPUT_FILES:
    input_path = f"{INPUT_DIR}{file_name}.xlsx"
    output_path = f"{OUTPUT_DIR}outputSonar_{file_name}.xlsx"
    logging.info(f"Processing file: {input_path}")

    try:
        df = pd.read_excel(input_path)
    except FileNotFoundError:
        logging.warning(f"File not found: {input_path}. Skipping.")
        continue

    if not {'dscode', 'question'}.issubset(df.columns):
        logging.warning(f"Missing required columns in {file_name}.
Skipping.")
        continue

    results = []
    for idx, row in df.iterrows():
        dscode = row["dscode"]
        question_text = row["question"]

        start = time.time()
        answer, citations = query_perplexity(question_text)
        elapsed = time.time() - start

        logging.info(f"{file_name}: Row {idx+1}/{len(df)} | Code: {dscode} |
Time: {elapsed:.2f}s")

        results.append({
            "dscode": dscode,
            "answer": answer,
            "sources": ", ".join(citations) if citations else "No sources
found"
        })

    pd.DataFrame(results).to_excel(output_path, index=False)
    logging.info(f"Saved results to {output_path}")

logging.info("All files processed.")
```

### 3.4. Next Steps

Review the Excel files saved in the output directory. These include each question, the corresponding response from the model, and citations if returned by the API.