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Controlled Firms, Preferences, and Carbon Emissions

Finance Working Paper N° 983/2024
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Abstract

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Keywords: Carbon emissions, Family ownership, Environmental sustainability, Preferences
JEL Classifications: G32, G34, G54

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I. Introduction

If a firm changed its focus from financial value maximization to shareholder welfare maximization would it be more *clean*? Hart and Zingales (2017) assess this and conclude that, for the widely held firm as of today, the answer is no. While 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, their answer is different. As they 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. 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 controlled firms are *cleaner* by assessing the actual carbon emissions of 3,769 non-U.S. firms from 35 countries. In this global sample, controlled firms are generally the most common type of firm ownership structure.[1] In our sample, 54% of firms are controlled and 46% are widely held. We identify three categories of controlled firms: family, government, and other (42%, 7%, and 6% of sample firms, respectively).

No database currently exists to measure the environmental preferences of a controlling shareholder. A contribution of our paper is to demonstrate that generative AI can be used to construct such a measure of the environmental preferences of a controlling shareholder, at scale.

[1] See Aminadav and Papaioannou (2020) and La Porta, Lopez-De-Silanes, and Shleifer (1999), among others.

We measure these preferences for family-controlled firms, given their prevalence. We construct an index for *clean* using five actions observable by AI: 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.

To measure expected marginal costs of reducing carbon emissions we would ideally obtain detailed information on all carbon-reducing projects available to a firm. Because such firm-level data do not exist and cannot be feasibly imputed, we measure marginal abatement costs at the country and industry levels, which we acknowledge has limitations. At the country level, we split firms into two subsamples based on a climate performance index that assesses each country's climate protection efforts relative to international standards. Where climate performance is weak, low-cost options to improve carbon emissions likely still exist. At the industry level, we split firms into two subsamples based on the importance of direct (Scope 1) emissions as a fraction of total industry emissions. We are most interested in direct emissions, as they can be more easily managed by a controlling owner and will likely have drawn greater regulator or social scrutiny, but also need to take account an industry's total emissions. If direct emissions are relatively unimportant, outside pressures to reduce emissions will be muted, and low-cost options to improve emissions likely remain.

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 baseline tests 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 25% higher—approximately equivalent to the annual carbon emissions of 437 U.S. households for the median sample firm[2]—than those of widely held firms, all else equal. In contrast, carbon emissions are similar to those of widely held firms when firms are controlled by families with high environmental preferences. These results indicate 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.

We also provide suggestive evidence that the impact of a preference for *clean* depends on the marginal cost of becoming *cleaner*. Where improving carbon efficiency is arguably more costly (that is, in high CCPI countries and high Scope 1 emissions industries), our tests show that family-controlled firms have about 20-50% higher carbon emissions than widely held firms regardless of their environmental preferences. Where carbon efficiency improvements are arguably less costly, we find that family-controlled firms with strong environmental preferences have 10-24% lower carbon emissions than 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

[2] We compute the household equivalence by dividing 25% of the median firm's emissions (83,950 × 0.25 = 20,988 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).

evidence suggests preferences are not a particularly strong lever. In most circumstances, controlling shareholders—even those with strong environmental preferences—do not deliver better carbon performance, and those with weak preferences often exacerbate the problem.

Our analyses use actual emissions rather than imputed data to avoid a selective disclosure bias problem. If certain ownership types systematically do not disclose their actual emissions because they have worse emissions, regression estimates that use imputed data will falsely suggest better carbon performance for these ownership types than is actually the case (i.e., selection bias).

Actual carbon emissions have been infrequently reported until recently. For example, emission reporting rates in 2010 are just 18% for LSEG firms from our 35 sample countries that meet a minimum size threshold. We study the years 2023 and 2024 when emission reporting jumps, with disclosure rates of 81% in 2023 and 86% in 2024. This increased disclosure stems in part from the International Sustainability Standards Board, an independent standard-setting body within the IFRS foundation, issuing its first detailed standards in June of 2023, focusing exclusively on climate-related disclosures, particularly CO2-equivalent emissions. Countries that use IFRS and adopt the standards were expected to disclose CO2-equivalent emissions 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.

Our paper makes 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. When family owners lack pro-environmental preferences, their firms produce substantially higher carbon emissions. This result extends earlier findings that 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).

Second, we provide new evidence on the relationship between concentrated ownership and carbon emissions using data from 2023 and 2024 when the vast majority of firms report their actual carbon emissions. We find that controlled firms generally have higher emissions compared to widely held firms. A related paper, Borsuk, Eugster, Klein, and Kowalewski (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 U.S. firms. Potential selective disclosure bias in samples from this period could explain their different conclusions.[3]

Our third contribution is a methodological innovation demonstrating that retrieval-augmented LLMs can quantify otherwise unobservable owner characteristics by synthesizing dispersed public information across languages and sources. 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). Our approach is situated 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,

[3] 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. In 2010 15% of U.S. firms that meet our sample selection criteria disclose their emissions. By 2024, this had only increased to 48% (vs. 86% for non-U.S. firms).

Kwon, Ha, Choi, Kim, Lee, Sohn, Lopez-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., La Porta 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., Anderson and Reeb, 2003; Bennedsen and Fan, 2014), both of which can generate high and consistent levels of trust.[4] 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

[4] 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.

controlling shareholder cannot be identified, and firms controlled by financial owners (private 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

A. Sample Design

Our sample is a two-year cross-section of non-U.S. firms in the years 2023 and 2024. In these years there is extensive reporting of actual carbon emissions due to the IFRS carbon reporting mandate. To illustrate, Figure 1 plots the percentage of non-financial firms with a minimum market capitalization of $100 million from the 35 countries in our sample that report actual carbon emissions from 2010 to 2024. There is a substantial 12 percentage point increase in carbon emission reporting between 2022 and 2023, consistent with the increased pressure from IFRS. In 2023, 81% of firms report emissions and in 2024, 86% report. In contrast, in 2010 only 18% of firms reported emissions.

We note that the use of data from earlier years would be inappropriate for our research question due to a concern that, with voluntary disclosure, firms with excessive carbon emissions

will be less likely to report. In earlier years, with actual emissions data sparse, researchers would have to make extensive use of estimated (imputed) emissions to maximize sample size. However, 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. Imputation is also 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). By using simple parameters, the commercial data vendor imputation process would not capture any independent effect of ownership and/or preferences of controlling owners on emissions.[5]

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.

B. Sample Construction

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 2023. We also include year 2024 data for these same firms if such data is available. 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 and exclude firms from countries where we have less than ten observations. We exclude firms incorporated in Russia and China because political realities make it almost impossible for non-government-affiliated

[5] We note that even if it were feasible to construct a long time series of carbon emissions for controlled firms, the resulting panel estimates would be imprecise or biased. This is because control structures are remarkably stable over time (see, e.g. Franks et al., 2012, who report that family-controlled firms transition to being widely held at an annual rate of 0.5-0.9%) and estimates with firm fixed effects would be identified only from the small number of firms experiencing control changes.

blockholders to establish effective control of firms. We exclude firms from the U.S. because these firms were not subject to the IFRS 'shock' to reporting actual carbon emissions and their relatively low reporting frequency makes them unsuitable to use given the sample selection bias issues discussed earlier.

Our full sample comprises 7,232 observations from 3,769 firms across 35 countries. Carbon emissions tests use a subsample of 6,434 firm-year observations for which firms report actual emissions data in 2023 or 2024.

C. Environmental Performance Metrics

Our primary emissions metric is actual total CO2-equivalent (CO2e) emissions. 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.[6]

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).

Panel A of Table 1 reports key emission metrics used in our tests. The median firm in our sample emits an average of 83,950 tons of CO2e per year over the 2023 and 2024 reporting years. Median Scope 1 emissions are roughly 26,000 tons, while Scope 2 emissions are roughly 30,000

[6] We compare reported CO2e values across multiple data providers and find virtually identical values. 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.

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. The pooled sample helps to address any concerns about unusual reporting of either emissions or revenues in a specific year.

D. Establishing Controlling Owners

We identify firms' ownership structures as of the year-end 2022, the year prior to measuring carbon emission performance.[7] 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 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

[7] 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).

own at least 20% of the shares.[8] 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 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 46% of firms are widely held, 42% are family-controlled, 7% are government-controlled, and 6% are other-controlled. This large frequency of controlled firms provides power for empirical tests 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

[8] 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.

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 89% 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.

E. Measuring Environmental Preferences of Controlling Families

The strength of environmental preferences of controlled owners is a private characteristic for which no commercial 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) corporate finance

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 11. 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 above 11 (i.e., above the median) as high E family, and those with scores at or below 11 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, 15% of firms are classified as low E family, 15% are high E famil*y*, and 11% are inconclusive E family.

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 LLMs 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 LLMs 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."

F. Measuring Expected Marginal Costs of Improving Carbon Emissions

We use two approaches to identify the expected marginal abatement costs firms face to improve their carbon emissions, exploiting variation in expected costs at the country level and at the industry level. We note at the outset that the results of these tests should be viewed as suggestive, given that it is impossible to construct marginal abatement cost estimates at the firm level for all of the firms in our sample.

At the country level, we form two subsamples based on a country's Climate Change Performance Index (CCPI) score. The CCPI, produced by Germanwatch, assesses each country's performance in four categories, capturing differences in climate protection efforts relative to international standards. The index is based on GHG Emissions (40% of the overall ranking), Renewable Energy (20%), Energy Use (20%) and Climate Policy (20%). Around 80% of the CCPI score is based on quantitative data from the International Energy Agency (IEA), PRIMAP, the Food and Agriculture Organization, and the national GHG inventories submitted to the United Nations Framework Convention on Climate Change.[9] Twenty percent of the CCPI is based on

[9] According to Germanwatch, "the CCPI quantitative categories are each defined by four indicators: Current Level, Past Trend, Well-Below-2°C Compatibility of the Current Level, and Well-Below-2°C Compatibility of the Countries' 2030 Target." It assesses "the extent to which each country is taking appropriate action in the areas of Emissions, Renewable energy and Energy use in order to achieve the climate goals set in Paris."

qualitative indicators of National Climate Policy and International Climate Policy assessed annually with a comprehensive questionnaire from over 450 climate and energy policy experts from the evaluated countries.

The CCPI is a comprehensive measure capturing the effects of policies that penalize emissions, such as tax policy, as well as proactive incentives for emission abatement. Low CCPI countries have less emphasis on policies and standards to reduce carbon emissions. Firms in these countries likely have more low-cost options to further improve their emissions performance. The CCPI has been used extensively in prior carbon emission research (see, for example, Bolton and Kacperczyk, 2023, and Eskildsen, Ibert, Jensen, and Pedersen, 2025).

A country's 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.[10] CCPI scores are highest in Denmark, and lowest in South Korea. The CCPI metric has a 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.[11]

To help to validate the CCPI as a carbon abatement cost measure, we assess its correlation with two prominent, but narrower, country-level metrics the OECD uses to gauge the relative costs of improving carbon emissions across countries. First, the OECD (2025) calculates and uses effective carbon rates as a summary statistic to measure the extent to which governments have used the tax system to incentivize firms in their country to consider their carbon emissions. The Effective Carbon Rates statistic "summarizes the price signals from ETSs (emission trading systems), carbon taxes and fuel excise taxes, and is expressed in EUR/tCO2e." This is available at

[10] CCPI scores are not available for Israel, Peru, and Singapore.
[11] 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.

the country level and for a subset of industries they define as 'energy use sectors' (i.e., industries that account for the greatest energy use).

In our sample of countries, the effective carbon rates range from 0.5 to 151 Euros/ tCO2e in 2023.[12] Consistent with the contention that high CCPI countries have high marginal costs of abatement, there is a positive and significant correlation between effective carbon rates and CCPI scores of 0.43. In high CCPI countries the median (mean) effective carbon rate is 89.7 (77.2) and it is 26.0 (41.6) in low CCPI countries.[13] We next build cross-country variation by looking only at a country's energy use sectors. We find a similar positive and significant correlation between the CCPI and effective carbon rates in all 'energy use sectors' (0.43), and in two of the most important energy use sectors 'industry' (0.43) and 'road transportation' (0.36).[14]

Environmental patenting also relates to carbon abatement costs, albeit less directly. The idea here is that firms are more likely to patent environmentally efficient technologies if a country provides greater incentives to reduce emissions. The OECD also provides country level statistics on patenting, and we focus on environmental patents as a percentage of all technical patents (thus accounting for a country's overall patenting propensity).[15] This environmental patenting metric ranges from 4.2% to 22.3% in our sample of countries. We find a positive and statistically significant correlation between this measure and CCPI scores of 0.21. The median (mean)

[12] These rates capture how "Countries deploy taxes on energy use, carbon taxes and greenhouse gas emissions trading systems in view of policy objectives related to climate change, public revenue raising, energy affordability and cost of living, energy security and competitiveness." OECD reports data for 33 out of 35 countries in our sample.

[13] These coefficients are statistically different with p-values of 0.026 (0.023). We further note that results are similar using an alternative OECD metric of net effective carbon tax rates, which in addition takes into account fossil fuel. By this metric, the median (mean) net effective carbon rate is 89.1 (71.4) in high CCPI countries and the median (mean) net effective carbon rate in low CCPI countries is 26.0 (34.5). These differences are also statistically significant.

[14] The OECD defines energy-use sectors as industry, road transportation, electricity, buildings, agriculture and fisheries and off-road transportation.

[15] This data comes from the OECD, STI Micro-data lab: Intellectual Property Data bases that is available via the OECD Data Explorer (accessed April 16, 2026).

percentage of environmental patents is greater in high CCPI than low CCPI countries, however this difference is not significantly different.

Next, we identify marginal emission abatement costs using variation in expected costs across industries. Regulators and society are likely to hold owners accountable for a firm's emissions and will pay attention to both total emissions and direct emissions. We conjecture, however, that they will be particularly interested in a firm's direct emissions as these are largely determined by an owner's operating choices. In industries with a high proportion of direct emissions, firms will arguably have exhausted their low-cost carbon abatement opportunities.

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.[16] We classify an industry as high Scope 1 if at least 51% of an industry's total carbon emissions are Scope 1 emissions. High Scope 1 industries have vastly larger total emissions, with average log total CO2e emissions in tons of 12.14 compared to 10.38 for low Scope 1 industries (see Table 1). 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, 89% of firm-year observations that meet our sample selection criteria disclose their carbon emissions. With this high level of reporting, any selective-disclosure

[16] We also examine industry splits based solely on direct emissions, irrespective of total emissions. As described in the next section, the pattern of results is similar.

biases are likely to be small. To validate this conjecture, we test whether the disclosure of carbon emissions is linked to ownership type using the full sample 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 firm size (log of assets), cash, asset tangibility, leverage, profitability, and dual class shares as control variables. 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. Hong, Kubik, and Scheinkman (2012) suggest that financial slack helps explain the adoption of sustainability-oriented policies. We thus include cash, asset tangibility, and leverage to capture credit constraints and profitability to capture the impact of performance. We control for expected private benefits of control using 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 along with year fixed effects. We cluster standard errors by country.

In Table 2 we find a negative coefficient for family control and government control, but both are insignificant. Thus, in our sample period there is no evidence of selection bias related to ownership type.

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 expected marginal costs to improve carbon emissions. In all tests we estimate models using the following baseline specification:

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

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 Λ are individual country, industry, and year fixed effects. All right-hand variables are lagged by one year. We use logs 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,[17] and further suggest that revenue-scaled carbon emissions is preferred to asset-scaled emissions given the stronger correlation between emissions and revenue.[18] When unscaled emissions are the dependent variable, we also control for firms' revenue as emissions likely depend heavily on the intensity of firm 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.[19]

In Table 3 we provide our baseline results. We find that no category of controlled firm delivers statistically significantly *lower* carbon emissions than the widely held firm. In family-controlled firms, where theory suggests the greatest likelihood of strong preferences for *clean,* we

[17] 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).

[18] 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.

[19] See, for example, Shive and Forster (2020) and Bolton and Kacperczyk (2023), who use scaled and raw Scope 1 emissions.

find the opposite. There is a positive and significant coefficient on family in all specifications. These results suggest family firms emit more carbon than widely held firms, and imply that allowing shareholders to pursue welfare 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.

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 22-24% higher than those of widely held firms, considering all emissions, and are about 30% higher when

considering Scope 1 emissions.[20] 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 II, 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 should 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*. As noted above, the results of these tests should be viewed as suggestive, given that we cannot construct marginal abatement cost estimates at the firm level. 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 high CCPI countries, we expect that environmental preferences will have minimal impacts on carbon emissions performance given the high cost of becoming incrementally *cleaner*.

[20] All economic magnitudes are calculated as exp(coefficient)-1*100%.

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 columns 1 through 4. In all specifications we find a positive (albeit not always significant) coefficient for family-controlled firms regardless of their environmental preferences. The coefficient estimates for both scaled and raw emissions are very similar for both low and high environmental preference families and there is never a statistically significant difference between these categories of family preferences. These results suggest 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 higher carbon emissions than widely held firms.

In columns 5 through 8, we present the results for low CCPI countries. Results are different in this subsample of firms with lower expected marginal carbon abatement costs. The evidence suggests that environmental preferences matter in this setting as there are negative coefficients for high E families and positive coefficients for low E families across all specifications. The negative high E family coefficients are significantly different than those for widely held firms in all four models. In terms of magnitude, the coefficients imply that high E families have 13% lower total emissions and 21% lower Scope 1 emissions than widely held firms. Further, the difference between high E and low E families is statistically significant in all four of these low-CCPI models.

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

In this section, we split firms into two industry subsamples based on the importance of direct (Scope 1) emissions as a fraction of total industry emissions. If direct emissions are relatively

unimportant, regulator/stakeholder pressures to reduce emissions will be muted, and low-cost options to improve emissions likely remain.

In Table 6, for all specifications focusing on high Scope 1 industries, we find a positive and significant coefficient for family-controlled firms whether or not they have high environmental preferences. The coefficients indicate that low E families have 30-34% (51-54%) higher total (Scope 1) emissions than widely held firms and high E families have 35-37% (52-54%) higher total (Scope 1) emissions than widely held firms. There is no statistically significant difference between these categories of family E preferences. These results mirror those in Table 5. Where expected marginal abatement costs are high, there is suggestive evidence that family firms are *dirtier* than widely held ones even when their owners have strong environmental preferences.

In columns 5 through 8, we present results for low Scope 1 industries where the marginal costs of becoming more *clean* are expected to be low. Again, we find suggestive evidence that environmental preferences matter. In all specifications, we find positive but insignificant coefficients for the low E family, suggesting 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 10% lower total emissions (statistically insignificant), and 24% lower Scope 1 emissions (statistically significant).[21]

Taken together, our results provide suggestive evidence that controlling owners' willingness to act on their environmental preferences depends on the expected cost to make their firm *cleaner*. When expected costs to be even more *clean* are high, even strong pro-environmental preferences do not override the drift towards *dirty*. Only when the costs of becoming *cleaner* are

[21] In untabulated tests, where we split industries based on direct emissions only, we find a similar pattern. There is a statistically significant difference between low and high E families only in low direct emission industries where the costs of becoming cleaner are arguably low. In this alternative industry split, we find positive and significant coefficients for low E families and negative and insignificant coefficients for high E families.

expected to be low do our results suggest 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

Our tests use LLM-based environmental preference scores that are not based on standardized data sources, such as earnings calls or mandatory disclosures. A potential concern 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 weight sources from wealthier countries or based on 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. While we cannot rule out all types of bias from the use of a LLM-based measure, in this section we construct an alternative family environmental preference score that controls for potential biases such as language and test whether our results hold using this alternative environmental preference score.

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.[22]

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— family firms never have lower emissions performance than widely held firms, and those families with low environmental preferences have significantly higher carbon emissions than those of widely held firms. Thus, the negative relation between preferences and emissions persists after stripping out the effects of English language, country income, family wealth, and firm size.

B. Alternative CCPI Score

We also test an alternative CCPI score as a country level indicator for expected marginal abatement costs. Specifically, we use only the "emissions" category from the CCPI score to sort firms into low and high CCPI groups, by country. Table A2 in Appendix A replicates the Table 5

[22] We note that 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.

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.

Our findings are salient given the widespread prevalence of controlled firms globally and the fact that global emissions growth now comes primarily from developing countries (Copeland, Shapiro, and Taylor, 2022) where controlled firms are the most common (Lins, 2003).

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Figure 1
Percent of Firms Reporting Carbon Emissions

This figure reports the percentage of firms that report CO2-equivalent emissions from 2010 to 2024 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 3,086 (in 2010) and 4,510 firms (in 2021). All data are from LSEG.

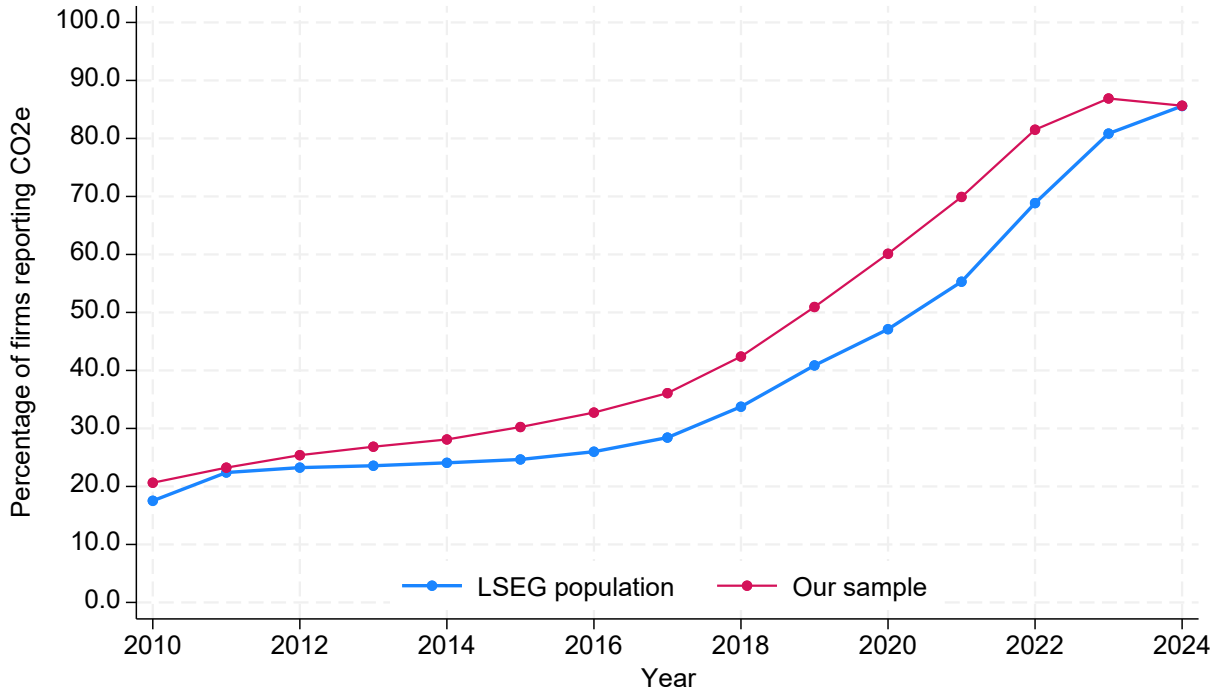

Figure 2
Family Control Around the World

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.

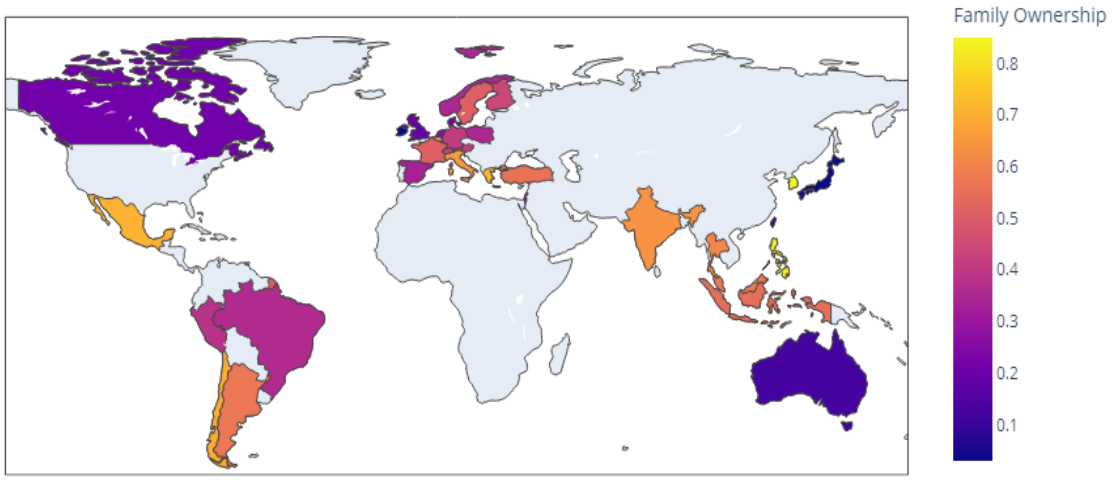

Table 1
Summary Statistics

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 covers the years 2023 and 2024. Ownership categories do not add to 100% due to rounding. All variables are described in Appendix Table A1.

Panel A: Summary Statistics

	Mean	Median	SD	N
A. Environmental Performance				
Firm Reports CO2e	0.89	1.00	0.32	7,232
Scope 1 and 2 Emissions				
CO2e	1,699,683	83,950	7,377,957	6,444
Log (CO2e)	11.28	11.35	2.80	6,434
Log (CO2e / Revenue)	3.73	3.61	2.15	6,434
Log (CO2e), Low CCPI Countries	11.88	11.99	2.57	3,064
Log (CO2e), High CCPI Countries	10.72	10.71	2.88	3,205
Log (CO2e), Low Scope 1 Industries	10.38	10.50	2.36	3,155
Log (CO2e), High Scope 1 Industries	12.14	12.29	2.92	3,279
Scope 1 Emissions				
CO2e	1,456,396	26,316	6,961,248	6,318
Log (CO2e)	10.20	10.23	3.30	6,236
Log (CO2e / Revenue)	2.61	2.36	2.68	6,236
B. Ownership				
Family-controlled	0.42	0.00	0.49	7,232
Government-controlled	0.07	0.00	0.25	7,232
Other-controlled	0.06	0.00	0.24	7,232
Widely Held	0.46	0.00	0.50	7,232
C. Family Owners' Environmental Preferences				
Family E Preference	16.60	11.00	11.72	2,230
Low E Family	0.15	0.00	0.36	7,232
High E Family	0.15	0.00	0.36	7,232
Inconclusive E Family	0.11	0.00	0.31	7,232
D. Other Firm Characteristics				
Total Assets (in $ million)	9,642	2,379	26,353	7,232
Log (Total Assets)	21.64	21.59	1.64	7,232
Log (Revenue)	7.37	7.38	1.78	7,232
Cash	0.15	0.11	0.14	7,232
Tangibility	0.31	0.27	0.22	7,232
Leverage	0.26	0.24	0.40	7,232
Profitability	0.04	0.04	0.15	7,232
Dual Class Shares	0.16	0.00	0.36	7,232

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	4,807	30
Australia	0.18	0.00	0.04	0.78	0.05	0.02	0.11	45.7	4,337	442
Austria	0.42	0.26	0.11	0.21	0.16	0.26	0.00	58.2	7,859	38
Belgium	0.65	0.06	0.08	0.21	0.06	0.06	0.54	55.0	11,013	71
Brazil	0.42	0.07	0.15	0.37	0.09	0.08	0.25	61.7	10,302	202
Canada	0.26	0.02	0.10	0.62	0.11	0.15	0.01	31.6	7,748	502
Chile	0.71	0.14	0.00	0.14	0.07	0.04	0.61	68.7	8,919	56
Denmark	0.22	0.07	0.25	0.47	0.11	0.09	0.02	75.6	7,525	92
Finland	0.38	0.11	0.11	0.39	0.20	0.15	0.04	61.1	4,003	107
France	0.56	0.08	0.07	0.29	0.29	0.24	0.03	57.1	25,468	272
Germany	0.48	0.07	0.09	0.36	0.03	0.07	0.38	65.8	19,024	346
Greece	0.68	0.27	0.00	0.05	0.05	0.57	0.05	60.3	5,421	37
India	0.66	0.12	0.02	0.20	0.28	0.33	0.05	70.3	3,520	918
Indonesia	0.59	0.18	0.08	0.16	0.37	0.14	0.08	57.2	4,555	102
Ireland	0.15	0.00	0.00	0.85	0.12	0.02	0.00	51.4	14,776	82
Israel	0.44	0.07	0.10	0.39	0.03	0.03	0.38	n/a	4,239	61
Italy	0.69	0.21	0.03	0.07	0.09	0.11	0.48	50.6	10,146	174
Japan	0.09	0.01	0.03	0.87	0.06	0.02	0.01	42.1	17,487	825
Luxembourg	0.50	0.00	0.08	0.42	0.04	0.13	0.33	65.1	9,103	48
Malaysia	0.65	0.17	0.06	0.13	0.38	0.24	0.03	38.6	3,227	240
Mexico	0.68	0.00	0.00	0.32	0.04	0.09	0.56	55.8	7,366	114
Netherlands	0.25	0.00	0.17	0.58	0.09	0.11	0.04	70.0	16,428	106
Norway	0.38	0.09	0.13	0.40	0.13	0.18	0.07	67.5	6,476	110
Peru	0.33	0.22	0.00	0.44	0.00	0.33	0.00	n/a	2,783	36
Philippines	0.89	0.04	0.00	0.08	0.21	0.68	0.00	70.7	8,932	53
Poland	0.39	0.39	0.09	0.13	0.22	0.17	0.00	44.4	8,913	46
Singapore	0.50	0.28	0.00	0.22	0.28	0.20	0.02	n/a	8,310	108
South Korea	0.83	0.06	0.01	0.09	0.31	0.46	0.05	30.0	17,560	280
Spain	0.43	0.09	0.13	0.35	0.09	0.11	0.22	63.4	15,680	108
Sweden	0.48	0.02	0.07	0.44	0.28	0.12	0.08	69.4	3,434	362
Switzerland	0.47	0.06	0.07	0.41	0.24	0.17	0.06	61.9	9,991	236
Taiwan	0.16	0.05	0.04	0.76	0.09	0.03	0.03	36.9	8,028	296
Thailand	0.64	0.17	0.02	0.17	0.26	0.33	0.05	61.4	4,859	222
Turkey	0.66	0.20	0.09	0.05	0.16	0.43	0.07	43.8	7,670	112
U.K.	0.19	0.00	0.10	0.71	0.01	0.01	0.17	62.4	8,950	669

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 covers the years 2023 and 2024. 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	-0.029
	(-1.35)
Government-controlled	-0.042
	(-1.49)
Other-controlled	0.015
	(0.73)
Log (Total Assets)	0.002
	(0.23)
Log (Revenue)	0.050***
	(6.52)
Cash	-0.123**
	(-2.49)
Tangibility	0.090*
	(1.87)
Leverage	0.004
	(0.36)
Profitability	0.127***
	(4.23)
Dual Class Shares	0.026
	(1.25)
Country FE	Yes
SASB Industry FE	Yes
Year FE	Yes
N	7,232
Adjusted R^2	0.191

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 for the years 2023 and 2024. 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. 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	0.158**	0.148**	0.180*	0.170*
	(2.20)	(2.18)	(1.82)	(1.77)
Government-controlled	-0.041	-0.050	-0.082	-0.091
	(-0.31)	(-0.38)	(-0.54)	(-0.59)
Other-controlled	0.309**	0.287**	0.130	0.111
	(2.31)	(2.21)	(0.69)	(0.59)
Log (Total Assets)	0.145***	0.393***	0.207***	0.378***
	(7.60)	(5.74)	(7.35)	(4.21)
Log (Revenue)		0.728***		0.813***
		(9.74)		(9.49)
Cash	-0.212	-0.385	-0.694**	-0.806***
	(-0.77)	(-1.59)	(-2.43)	(-2.90)
Tangibility	2.912***	2.819***	3.113***	3.058***
	(7.86)	(7.76)	(7.95)	(7.97)
Leverage	-0.062	-0.047	-0.184***	-0.173***
	(-1.34)	(-1.04)	(-3.06)	(-2.92)
Profitability	-1.530***	-1.115***	-1.853***	-1.592***
	(-4.17)	(-3.38)	(-3.18)	(-3.07)
Dual Class Shares	0.060	0.070	0.101	0.108
	(0.65)	(0.75)	(0.74)	(0.82)
Country FE	Yes	Yes	Yes	Yes
SASB Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,434	6,434	6,236	6,236
Adjusted R^2	0.608	0.773	0.612	0.745

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 for the years 2023 and 2024. 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. 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	0.236***	0.215**	0.308**	0.291**
	(2.74)	(2.61)	(2.59)	(2.47)
High E Family	0.104	0.099	0.072	0.065
	(1.33)	(1.30)	(0.58)	(0.53)
Inconclusive E Family	0.128	0.127	0.161	0.158
	(1.35)	(1.43)	(1.34)	(1.34)
Government-controlled	-0.044	-0.054	-0.091	-0.099
	(-0.33)	(-0.41)	(-0.59)	(-0.64)
Other-controlled	0.309**	0.288**	0.131	0.112
	(2.31)	(2.21)	(0.70)	(0.60)
Log (Total Assets)	0.148***	0.395***	0.214***	0.383***
	(7.39)	(5.75)	(7.17)	(4.25)
Log (Revenue)		0.729***		0.815***
		(9.75)		(9.51)
Cash	-0.200	-0.375	-0.672**	-0.783***
	(-0.73)	(-1.53)	(-2.31)	(-2.76)
Tangibility	2.910***	2.817***	3.108***	3.054***
	(7.84)	(7.74)	(7.93)	(7.95)
Leverage	-0.059	-0.045	-0.178***	-0.168***
	(-1.31)	(-1.00)	(-3.03)	(-2.89)
Profitability	-1.540***	-1.124***	-1.863***	-1.604***
	(-4.21)	(-3.41)	(-3.18)	(-3.08)
Dual Class Shares	0.058	0.068	0.099	0.107
	(0.64)	(0.74)	(0.72)	(0.80)
Country FE	Yes	Yes	Yes	Yes
SASB Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,434	6,434	6,236	6,236
Adjusted R^2	0.608	0.773	0.612	0.745
Low vs. High E Family (*p*-value)	(0.056)	(0.088)	(0.051)	(0.062)

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 for the years 2023 and 2024. The subsamples are based on a country's score on the Climate Change Performance Index (CCPI). 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. 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	0.206	0.171	0.315**	0.302*	0.106	0.096	0.215	0.207
	(1.59)	(1.39)	(2.14)	(2.10)	(1.11)	(1.13)	(1.56)	(1.58)
High E Family	0.203**	0.188**	0.334***	0.328***	-0.140**	-0.138*	-0.241**	-0.241**
	(2.50)	(2.47)	(3.42)	(3.46)	(-2.15)	(-1.91)	(-2.54)	(-2.35)
Inconclusive E Family	0.181	0.181	0.295*	0.293*	-0.064	-0.096	-0.100	-0.129
	(1.58)	(1.64)	(1.93)	(1.94)	(-0.35)	(-0.63)	(-0.56)	(-0.67)
Government-controlled	0.139	0.128	0.103	0.099	-0.168	-0.188	-0.316	-0.343
	(0.92)	(0.79)	(0.54)	(0.51)	(-1.13)	(-1.33)	(-1.40)	(-1.53)
Other-controlled	0.492***	0.453***	0.461**	0.448**	0.032	0.032	-0.329*	-0.334*
	(3.53)	(3.41)	(2.59)	(2.58)	(0.25)	(0.25)	(-2.04)	(-2.04)
Log (Total Assets)	0.182***	0.436***	0.226***	0.298**	0.101***	0.397***	0.229***	0.495***
	(8.48)	(5.46)	(7.84)	(2.64)	(3.24)	(3.50)	(4.00)	(4.05)
Log (Revenue)		0.717***		0.919***		0.681***		0.714***
		(7.45)		(8.06)		(6.56)		(7.32)
Cash	-0.641*	-0.770**	-1.056***	-1.097***	0.273	-0.020	-0.300	-0.524
	(-1.86)	(-2.79)	(-4.97)	(-5.68)	(0.93)	(-0.07)	(-0.70)	(-1.11)
Tangibility	3.266***	3.147***	3.432***	3.400***	2.819***	2.773***	3.058***	3.026***
	(5.99)	(5.96)	(5.34)	(5.56)	(6.04)	(5.79)	(6.09)	(5.94)
Leverage	-0.008	0.006	-0.131**	-0.126**	-0.374	-0.426	-0.733*	-0.753*
	(-0.21)	(0.19)	(-2.50)	(-2.57)	(-1.19)	(-1.33)	(-2.05)	(-2.10)
Profitability	-1.018***	-0.689*	-1.153**	-1.053**	-2.361***	-1.718***	-3.099***	-2.616***
	(-3.08)	(-1.89)	(-2.15)	(-2.15)	(-5.07)	(-4.19)	(-4.29)	(-3.98)
Dual Class Shares	-0.024	0.015	-0.176	-0.164	0.132	0.135	0.279**	0.277**
	(-0.12)	(0.07)	(-0.99)	(-0.96)	(1.17)	(1.14)	(2.62)	(2.59)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SASB Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,205	3,205	3,130	3,130	3,064	3,064	2,952	2,952
Adjusted R^2	0.642	0.795	0.597	0.747	0.597	0.753	0.656	0.757
Low vs. High E Family (*p*-value)	(0.970)	(0.829)	(0.830)	(0.773)	(0.018)	(0.024)	(0.008)	(0.009)

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 the years 2023 and 2024. Firms are grouped into high (low) Scope 1 industries if the industry's total Scope 1 emissions account for greater (less) 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). All variables are described in Appendix Tables A1. 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	0.291**	0.260**	0.434***	0.415***	0.174	0.162	0.199	0.183
	(2.67)	(2.66)	(3.00)	(2.96)	(1.66)	(1.51)	(1.31)	(1.18)
High E Family	0.346**	0.331**	0.431**	0.420**	-0.104	-0.106	-0.265**	-0.272**
	(2.24)	(2.19)	(2.08)	(2.06)	(-1.31)	(-1.28)	(-2.38)	(-2.36)
Inconclusive E Family	0.488***	0.464***	0.568**	0.553**	-0.220*	-0.209*	-0.254	-0.247
	(3.47)	(3.67)	(2.70)	(2.70)	(-2.01)	(-1.92)	(-1.58)	(-1.56)
Government-controlled	0.037	0.007	-0.071	-0.090	-0.195	-0.196	0.011	0.012
	(0.23)	(0.04)	(-0.35)	(-0.44)	(-0.81)	(-0.84)	(0.05)	(0.05)
Other-controlled	0.333	0.286	0.180	0.148	0.272*	0.269*	0.098	0.093
	(1.67)	(1.55)	(0.75)	(0.63)	(1.84)	(1.84)	(0.44)	(0.42)
Log (Total Assets)	0.192***	0.504***	0.263***	0.442***	0.100***	0.271***	0.169***	0.328***
	(6.96)	(4.80)	(6.77)	(3.73)	(3.43)	(2.97)	(4.01)	(3.34)
Log (Revenue)		0.663***		0.808***		0.811***		0.823***
		(6.82)		(7.42)		(7.76)		(9.07)
Cash	-0.293	-0.439	-0.274	-0.380	-0.164	-0.329	-0.991**	-1.117***
	(-0.76)	(-1.45)	(-0.93)	(-1.31)	(-0.55)	(-1.11)	(-2.49)	(-2.86)
Tangibility	2.880***	2.792***	3.449***	3.405***	2.848***	2.780***	2.775***	2.722***
	(6.43)	(6.40)	(8.11)	(8.22)	(5.37)	(5.32)	(5.00)	(4.89)
Leverage	0.035	-0.057	-0.474	-0.527	-0.074*	-0.060	-0.156***	-0.144***
	(0.11)	(-0.17)	(-1.24)	(-1.36)	(-1.96)	(-1.61)	(-3.69)	(-3.70)
Profitability	-1.890***	-1.396***	-2.568***	-2.257***	-1.357***	-1.074***	-1.613***	-1.398**
	(-3.33)	(-2.73)	(-3.85)	(-3.61)	(-3.93)	(-3.03)	(-2.85)	(-2.64)
Dual Class Shares	-0.006	0.011	0.025	0.036	0.149	0.153	0.154	0.157
	(-0.07)	(0.12)	(0.21)	(0.31)	(1.39)	(1.40)	(0.85)	(0.92)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SASB Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,279	3,279	3,208	3,208	3,155	3,155	3,028	3,028
Adjusted R^2	0.623	0.779	0.610	0.742	0.456	0.713	0.338	0.626
Low vs. High E Family (*p*-value)	(0.651)	(0.567)	(0.991)	(0.978)	(0.009)	(0.012)	(0.004)	(0.006)

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 covers the years 2023 and 2024. 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, $\varepsilon_{Family\ (2)}$	0.180***	0.165**	0.258**	0.245**
	(2.86)	(2.68)	(2.60)	(2.50)
High E Family, $\varepsilon_{Family\ (2)}$	0.089	0.093	0.040	0.042
	(1.28)	(1.41)	(0.35)	(0.37)
Inconclusive E Family	0.089	0.093	0.119	0.119
	(1.07)	(1.17)	(1.14)	(1.15)
Government-controlled	-0.090	-0.095	-0.137	-0.142
	(-0.72)	(-0.75)	(-0.98)	(-0.99)
Other-controlled	0.273**	0.254**	0.091	0.076
	(2.15)	(2.05)	(0.52)	(0.43)
Log (Total Assets)	0.144***	0.393***	0.208***	0.380***
	(7.48)	(5.65)	(7.30)	(4.19)
Log (Revenue)		0.727***		0.812***
		(9.67)		(9.46)
Cash	-0.203	-0.379	-0.685**	-0.797***
	(-0.74)	(-1.55)	(-2.38)	(-2.84)
Tangibility	2.916***	2.823***	3.116***	3.060***
	(7.78)	(7.69)	(7.88)	(7.91)
Leverage	-0.059	-0.045	-0.179***	-0.169***
	(-1.31)	(-1.00)	(-3.02)	(-2.87)
Profitability	-1.536***	-1.118***	-1.859***	-1.595***
	(-4.22)	(-3.41)	(-3.20)	(-3.09)
Dual Class Shares	0.072	0.081	0.113	0.120
	(0.82)	(0.91)	(0.88)	(0.96)
Country FE	Yes	Yes	Yes	Yes
SASB Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,434	6,434	6,236	6,236
Adjusted R^2	0.607	0.772	0.612	0.745
Low vs. High E Family (*p*-value)	(0.187)	(0.279)	(0.081)	(0.098)

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 and 2024.

Variable	Description	Source
A. Environmental Performance		
Firm Reports CO2e	A dummy variable equal to one if a firm reports CO2-equivalent emissions.	LSEG[23]
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 or equal to the median, and zero otherwise.	GPT, Perplexity

[23] 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.

High E Family	A dummy variable equal to one if the sum of the LLM generated family owner's ownership preferences is greater than the median, and zero otherwise.	GPT, Perplexity
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 for the years 2023 and 2024. The subsamples are based on a country's score on the GHG Emissions Category of the Climate Change Performance Index (CCPI). 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. 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	0.236**	0.219***	0.416***	0.419***	0.071	0.048	0.090	0.064
	(2.81)	(3.13)	(5.75)	(6.60)	(0.43)	(0.29)	(0.39)	(0.28)
High E Family	0.164	0.150	0.335***	0.338***	-0.086	-0.077	-0.240*	-0.238
	(1.74)	(1.72)	(3.50)	(3.89)	(-0.81)	(-0.71)	(-1.78)	(-1.69)
Inconclusive E Family	0.146	0.153	0.263*	0.262*	0.071	0.025	0.014	-0.040
	(1.29)	(1.35)	(1.87)	(1.84)	(0.32)	(0.12)	(0.06)	(-0.17)
Government-controlled	0.071	0.056	0.053	0.056	-0.090	-0.084	-0.288	-0.296
	(0.41)	(0.32)	(0.26)	(0.27)	(-0.57)	(-0.52)	(-1.17)	(-1.18)
Other-controlled	0.393**	0.369**	0.335	0.339	0.164	0.148	-0.114	-0.142
	(2.36)	(2.32)	(1.67)	(1.74)	(0.73)	(0.71)	(-0.37)	(-0.47)
Log (Total Assets)	0.184***	0.366***	0.219***	0.191	0.111***	0.423***	0.255***	0.564***
	(9.30)	(3.70)	(8.08)	(1.48)	(3.14)	(4.11)	(4.13)	(5.10)
Log (Revenue)		0.797***		1.030***		0.660***		0.664***
		(6.86)		(8.05)		(7.81)		(7.92)
Cash	-0.807**	-0.896**	-1.288***	-1.274***	0.197	-0.153	-0.097	-0.398
	(-2.31)	(-2.94)	(-5.73)	(-6.04)	(0.70)	(-0.54)	(-0.19)	(-0.74)
Tangibility	3.324***	3.236***	3.350***	3.362***	2.666***	2.589***	2.714***	2.648***
	(5.91)	(6.06)	(4.78)	(5.14)	(6.53)	(6.29)	(6.13)	(6.09)
Leverage	-0.008	0.004	-0.116*	-0.118**	-0.355	-0.410	-0.777**	-0.802**
	(-0.20)	(0.11)	(-2.10)	(-2.31)	(-1.29)	(-1.52)	(-2.33)	(-2.49)
Profitability	-1.076**	-0.828*	-0.953*	-0.992**	-2.186***	-1.597***	-3.129***	-2.685***
	(-2.94)	(-2.05)	(-1.95)	(-2.22)	(-5.02)	(-4.42)	(-4.77)	(-4.36)
Dual Class Shares	0.077	0.101	-0.032	-0.035	0.056	0.046	0.293**	0.281**
	(0.49)	(0.65)	(-0.20)	(-0.23)	(0.42)	(0.35)	(2.43)	(2.38)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SASB Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,060	3,060	2,977	2,977	2,931	2,931	2,828	2,828
Adjusted R^2	0.656	0.809	0.603	0.756	0.580	0.747	0.633	0.747
Low vs. High E Family (*p*-value)	(0.150)	(0.183)	(0.412)	(0.409)	(0.322)	(0.415)	(0.175)	(0.201)

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 LLMs 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 LLMs 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.

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