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# Essays in Sustainable Finance and ESG modeling

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# Abstract

Department Of Economics and Management

Doctor of Philosophy

**Essays in Sustainable Finance and ESG Modeling**

By Nicholas J Downing

Environmental, social, and governance (ESG) information has become increasingly important to investors, corporations, academics, and policymakers. As financial markets increasingly rely on non-financial information to assess corporate sustainability and risk, this dissertation examines how ESG measures are constructed, interpreted, and incorporated into financial analysis. Using econometric and empirical finance methods, the three chapters investigate the relationship between corporate governance and ESG performance, the role of missing data in ESG measurement, and the implications of incomplete emissions information for asset pricing. The first chapter examines whether board diversity and network centrality are associated with firms' environmental and social performance, finding significant relationships between corporate governance structures and ESG outcomes. The second chapter evaluates alternative approaches to missing-value imputation in ESG data and finds that machine-learning methods, particularly K-nearest-neighbors imputation, can improve the accuracy of emissions measures and materially affect resulting ESG scores. The third chapter extends this analysis to financial markets by examining whether missing emissions information is associated with equity returns. Using international firm-level data, the analysis develops emissions and missing-data factors within a Fama–French-style framework and finds evidence that incomplete emissions information is associated with distinct return patterns. Taken together, the chapters demonstrate that the economic interpretation of ESG information depends not only on firms' underlying sustainability characteristics but also on corporate governance, data construction, and disclosure quality. The dissertation highlights the importance of accounting for these factors when using ESG information in financial research and investment analysis.

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# Chapter 1

# Introduction

ESG data are widely used across financial markets as benchmarks for investment decisions, reference points for policy design, and inputs for academic research. Research showing that board gender diversity and directors' network connections influence firms' environmental and social performance underscores that ESG scores are routinely interpreted as indicators of governance quality and real sustainability outcomes. Given their growing influence, it is essential that these data are of high quality and used to their full potential. This requires careful scrutiny of how ESG information is collected, processed, and aggregated into composite scores. Without such scrutiny, empirical analyses risk conflating genuine differences in firm behavior and governance with artifacts of data construction or disclosure. This dissertation therefore studies how corporate governance affects environmental and social performance and how ESG and emissions scores are constructed and interpreted, examining how both real outcomes and their measurement jointly influence economic inference and market outcomes.

The first paper, published in the *Journal of Sustainable Finance & Investment* in year 2025, examines the relationship between corporate governance and the environmental and social performance of companies. Using firm-level panel data, it focuses on board gender diversity and directors' network positions as channels through which governance can affect sustainability outcomes. The analysis shows that firms with more gender-diverse boards and better-connected directors exhibit higher environmental and social performance, suggesting that governance structures play a meaningful role in shaping real ESG outcomes rather than simply affecting disclosure.

The second paper, published in *Finance Research Letters* in year 2025, studies the role of missing data in ESG datasets and its implications for the construction of emissions scores. It compares traditional imputation approaches with machine learning methods using both simulations and real-world ESG data. The results show that missing values materially affect

emissions scores and that firms with more complete disclosure—often larger firms—receive systematically higher scores, indicating the presence of size-related biases driven by data availability.

The third paper, currently circulated as a working paper, examines whether emissions-related return premia reflect underlying environmental risk or disclosure behavior. Using a factor-based asset pricing framework, it shows that missing emissions disclosure behaves as a priced characteristic, with return dynamics that closely resemble those of conventional emissions-based factors. These findings suggest that emissions premia may partly reflect disclosure patterns rather than pure environmental exposure.

Evidence that corporate governance, such as board gender diversity and directors' network positions, shapes corporate environmental and social performance implies that ESG scores are often used as proxies for the real effects of governance on sustainability results. Understanding how ESG data are constructed and how missing or incomplete information is handled is therefore essential for credible economic inference about the role of governance in shaping environmental and social performance. Empirical studies that rely on ESG scores implicitly assume that these measures accurately reflect the underlying firm behavior, including board structure, decision-making, and sustainability practices. When this assumption fails, estimated relationships can capture differences in disclosure practices, data availability, or score construction methodologies rather than genuine differences in environmental or social performance driven by governance choices. This distinction has direct implications for policy analysis, as ESG metrics are increasingly used to evaluate corporate governance reforms, guide environmental and social regulation, and assess the progress of firms toward sustainability objectives. If ESG scores imperfectly reflect real performance, policies and market decisions based on these measures can misidentify both risks and best practices.

The findings of this dissertation are relevant to several groups that rely on ESG data for decision-making. For academic researchers, the results highlight the importance of accounting for data construction and missingness when using ESG measures in empirical analysis, particularly in studies of firm performance and asset pricing. For investors, the results suggest that ESG scores and emissions-based signals may partially reflect disclosure quality rather than underlying sustainability risk, with implications for portfolio allocation and risk assessment. For regulators and policy makers, the analysis underscores the need for greater transparency and consistency in ESG reporting standards, as well as caution when using ESG metrics as benchmarks for regulation or policy evaluation.

Together, the three essays show that environmental and social performance, its measurement, and its pricing are jointly determined by governance structures, data availability, and disclosure incentives, and that ignoring any one of these dimensions risks biased inference in

research, policy evaluation, and investment decision-making.

# Chapter 2

# The Importance of Board Diversity and Network Centrality in ESG Data

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**Abstract**

This paper aims to identify some of the determinants of firm performance on social and environmental issues. Specifically, we look at the effects of corporate boards' gender diversity and of corporate directors' social networks as captured by network centrality measures. We focus on a sample of Italian listed companies over the period 2010-2020 and find evidence of a positive relationship between gender diversity and a firm's Environmental (E) and Social (S) scores suggesting that social and environmental responsibility is higher when there are more women on the corporate board. As to board members' social networks, network centrality measures appears to be positively linked to the E and S scores. This information is valuable not only to the company itself but also to policy makers who are interested in improving firms' environmental and social performance.

## 2.1 Introduction

In this paper, we study the relationship between the composition and diversity of firms' board of directors and two aspects of firms' sustainability, their environmental and social performance. We run the analysis using a sample of Italian listed firms, for which environmental and social scores are available, and use network theory and resource dependency theory to frame the evidence.

Nowadays, sustainability is at the core of the economic and policy debate because it has become increasingly critical for organizations' relevance and competitiveness in today's world. Indeed, there is growing recognition that the prosperity of our global society does not depend just on the level of GDP, but also how that GDP is garnered, which requires corporations to be conscious of their impact on the environment as well as on the society in which they operate (Biju et al., 2024; Tu et al., 2024). According to the Intergovernmental Panel on Climate Change (IPCC), holding temperatures to only "2 degrees Celsius above pre-industrial" levels would "require a dramatic shift in public and private investments" (Masson-Delmotte et al., 2018). The growing recognition of the importance of meeting this challenge has increased the attention to firm governance in relation to environmental and societal risks and has catalyzed substantial capital toward sustainable development (Daugaard and Ding, 2022; Rau and Yu, 2023; Li et al., 2021; Mariappan et al., 2025; Nasri and Sassi, 2025). On this respect, the economic literature has identified several variables that appear to improve sustainability, and we contribute to the literature by analyzing the relationship between individual firm environmental and social performance, on the one hand, and, on the other, the composition of its board of directors which is responsible for making major decisions, setting policies and providing oversight and strategic guidance to the organization.

The composition of corporate boards and in particular the implications of board connections and gender diversity have been extensively studied by the literature on firms' financial performance (Adams and Ferreira, 2009; Hillman and Dalziel, 2003; Alhossini et al., 2021; Post and Byron, 2015; Sieweke et al., 2024), among others). The evidence on their impact on firms' sustainability is not as broad and, most importantly, inconclusive. Furthermore, as discussed below, the most important insights come from studies of sustainability reporting and disclosure and not so much from studies of actual goals' achievements.

Corporate board diversity remains a very dynamic area of corporate governance and, unsurprisingly, a very hot topic in academic research as well. Among the benefits of diversity that the literature has identified, the most relevant channel for firm sustainability is the improved and more thorough access to information that a diverse board can ensure, which may lead to that *superior* knowledge enabling agents to implement value-creating strategies that

are mutually good for profits, people, and the planet. Besides gender diversity, to measure corporate boards' access to information, we use network theory and centrality measures to capture directors' exposure to information from other firms. Social networks are a valuable form of social capital (Burt, 2000; Tsai and Ghoshal, 1998; Kilduff and Brass, 2010) and in corporate finance, they are broadly viewed as contributing to financial performance just through information flows across corporate board members (Hillman and Dalziel, 2003).

In this paper, we add to the studies of determinants of firms' sustainability by examining the role of corporate boards' characteristics on firms' environmental and social performance via the lenses of gender diversity and social network analysis. Our fundamental argument is that the gender composition of the board and the positioning of firm's directors within a network of interconnected directors affects the firm's environmental and social performance. Resource dependency and network theories provide a theoretical foundation to this statement. According to the resource dependence theory, the most critical function of a board is the provision of resources. In principle, a more diverse board has access to a broader set of resources, including information and insights. Also, board composition, and therefore the provision of specific resources, which is directly related to firm performance (Lu et al., 2022; Singh and Guha, 2019; Federo and Aguilera, 2025; Hill et al., 2015), depends on context and environmental needs. The social network theory adds to this in that it implies that a well-networked board member can be a better advisor and monitor because a higher number of connections improves the access to information and increases overall influence (Amin et al., 2020; Lu et al., 2022). These theories place board diversity and directors' centrality in a specific perspective such that decision-making by boardrooms that are too homogeneous will be sub-optimal (Amin et al., 2020) and lead to inferior governance and performance. On a larger scale, this view links the 2007-08 global financial crises "to poor corporate governance practices, arising from lack of diversity, independence and transparency in corporate boardrooms" (Elmagrhi et al., 2019). Firms therefore have a rationale for seeking diverse and well connected board members able to access the information that is necessary to maximize their performance in a world that increasingly values environmentally and socially conscious behavior (Hill et al., 2015).

To assess a company's sustainability and ethical performance, we rely on the environmental, social, and governance (ESG) scores that are viewed as a synthetic measure of a company potential for significant and sustainable growth. The ESG scores that we use in our analysis are taken from Thomson Reuters Eikon platform, which has a long-time coverage of companies and assigns a quantitative metric to firms' environmental, social and governance efforts based on more data sources than common alternatives such as the Bloomberg and the MSCI ESG scores. Compared to the rest of the literature using these scores, we restrict the

attention to the environmental and social elements of the metric and exclude the governance aspects because of their potential endogeneity with respect to the composition of the board of directors due to reverse causality. In addition, whereas most studies look at ESG scores as an aggregate, we look at their environmental and social components separately. This gives a more accurate understanding of where the influence is strongest and avoids offsetting effects and other biases. Also, by focusing on the environmental (E) and social (S) scores separately we get around a potential source of bias related to the weighting of the ESG components that data providers employ to construct the aggregate ESG measures (Billio et al., 2020).
Although, we exclude the governance component of the ESG scores, studying the implications of board members' links and diversity on firm environmental and social efforts may still raise endogeneity issues due to omitted variables related to companies' culture. As an example, more female directors on the board and more environmentally and socially responsible policies might result from some unobserved aspect of a company's culture. This issue is dealt with in two ways. First, we use a fixed-effect (FE) model to control for unobserved, time-invariant company-specific characteristics. Second, we exploit an important regulatory change (Law 120 of 2011; so-called "Golfo-Mosca Act") that mandated gender quotas for boards of directors in public and private companies starting from 2012.
We find that the presence of board connections, captured by a positive Degree centrality, is a strong predictor of both environmental and social performance. However, in the case of the E-score, the relationship appears non-linear: the positive effect diminishes progressively as directors serve on an increasing number of boards. This finding aligns with the "attention scarcity and busy directors" hypothesis proposed by (Fich and Shivdasani, 2006), which suggests that directors with numerous external mandates tend to provide weaker monitoring, ultimately harming firm performance. In contrast, we do not observe a similar diminishing effect for the S-score. In addition, board positioning within the interlock network, measured through Betweenness centrality, is also positively associated with both environmental and social outcomes, further reinforcing the role of network embeddedness in shaping ESG performance. Finally, we find a positive correlation between ESG scores and the proportion of female directors on the board. Instrumental variable regressions support a causal interpretation of this relationship, particularly in the case of environmental performance.
This paper contributes to the literature in many respects. First, we add to the literature on the relationship between board gender diversity and sustainability, whose findings are inconclusive. Second, we show that directors' social connections do matter. Directors sitting on several boards help in terms of firm environmental performance, i.e. energy usage and efficiency, waste reduction and carbon footprint reduction. Instead, although boards may play a bridge-spanning role across firms and therefore mediate and control information flows,

they do not appear to help in terms of social performance.
Overall, these findings are important for firms but also for policy makers, investors, consumers, and everyday citizens. As to firms, our results suggest that there are different strategies in terms of board composition that firms can pursue to improve the environmental and social pillars of their ESG score. Relevant for policy makers, we find that interlocking directorate may bring some benefit to society in terms of firms adopting more sustainable business practices. Last, the evidence that we provide can help investors, consumers and citizens to identify firms with a greater potential for significant and sustainable growth.
The rest of the paper is organized as follows. In Section 2 we review the literature and discuss the hypotheses that we test. In Section 3 we outlay the model and describe the data. In Section 4 we present and discuss the results. In Section 5 we conclude by drawing implications for policy and a road map for future research.

## 2.2 Literature Review

### 2.2.1 Background

The impact of climate change facing the international community is global in scope and unprecedented in scale. In fact, holding temperatures at two degrees above pre-industry levels would require a dramatic shift in public and private investments from fossil fuels to more climate-friendly alternatives (Masson-Delmotte et al., 2018). Besides this, it necessitates coordinated actions and collaborative efforts from various societal stakeholders to strengthen the global response to climate developments. Hence, the transition to a low-carbon and climate-resilient economy represents a "grand challenge" (George et al., 2016) facing humanity.
The growing recognition of this challenge has drawn increasing attention to environmental and social risks combined with governance issues and catalysed substantial capital towards sustainable development (Daugaard and Ding, 2022). To meet the growing demand for this form of responsible finance, ESG scores have been developed to assess firms' progress towards sustainable development goals [1]
At the heart of the debate on sustainability and socially responsible behavior there are two issues. The first relates to the provision of economic goods vs. social goods (Machado and Davim, 2023). The second concerns the role that governments should play to foster firms' environmentally and socially responsible behavior (Daugaard and Ding, 2022; González and

[1] In general, ESG scores are employed to evaluate individual companies but can also be applied to evaluate countries and regions (Daugaard and Ding, 2022).

Martinez, 2004). These issues rose in response to the unprecedented growth in size and power of corporations and to concerns over the role of "big businesses" in society (Acquier et al., 2011; Daugaard and Ding, 2022). As these concerns become increasingly pressing, interest grew as to firms' determinants of environmentally and socially responsible behavior. Corporate boards play a crucial role in shaping firms' values and mission and in setting strategies (Finkelstein et al., 2009), and therefore one can expect directors to have a say on environmental and social matters.

In this paper, we test whether board gender diversity and directors' connections to other firms are related to greater sustainability in terms of environmental objectives and social impact compared to firms with less diverse and less interconnected boards. The rationale for this comes from the resource dependence theory, according to which board composition is affected by context and environmental needs and different board composition results in different corporate outcomes Singh (2007); Lu et al. (2022), and from network theory, according to which directors' participation in the boards of several firms may improve access to information and increase influence (Ramsawak et al., 2023).

Corporate board gender diversity and directors' connections to other firms have been studied extensively in relation to financial outcomes (Post and Byron, 2015; Ramsawak et al., 2023), but not as thoroughly in relation to environmental and social performance. In this respect, we intend to contribute to the growing literature on the drivers of ESG scores (explicitly allowing for the likely endogeneity of governance), which are of interest not only to academics and investors, but also to policy makers and regulators pursuing progress towards a sustainable world as they are key levers to improve policy design (Daugaard and Ding, 2022). Needless to say, that most action towards sustainability have been undertaken by companies themselves with no common guidelines, governmental support, or independent verification (González and Martinez, 2004).

**Hypotheses Development**

In a world of growing influence of firms, understanding whether and how certain characteristics influence their environmental and social performance is necessary. Corporate boards play a potentially critical role in this sense as they bridge the gap between the management of a firm and its stakeholders. Nevertheless, the effects of board gender diversity and of directors' network centrality on environmental and social performances are under-researched. In this paper, we argue that the positioning of a firm's directors within a network of interconnected directors as well as their gender have an influence on the firm's environmental and social score. This comes from the fact that today's world is more complex and interconnected than it has ever been in history and we can expect these complexities and interconnected-

ness to have wide ranging implications whose assessment has started only recently for data availability reasons.

**Board Network Centrality**

A network can be described in a straightforward manner. According to (Salancik, 1995), "networks are constructed when individuals, whether organizations or humans, interact. When many individuals are involved, the resulting structure can be analyzed to derive many facts about the individuals or the network." Information flows, influences, interpersonal and interorganizational relationships are facilitated within a network because "the links between individuals are the channels by which information is communicated, resources are exchanged, new relationships are formed, and existing relationships are leveraged" (Larcker et al., 2013). The way in which firms may benefit from these networks and from their directors' position within a network can be best understood in terms of resource dependency theory, according to which when resources are scarce and economies of scale exist with regard to resources, organizations are more likely to establish ties with other organizations (Hillman et al., 1999). Within this framework, the primary purpose of the board is to provide resources to the firm (Salancik and Pfeffer, 1978). (Hillman et al., 1999) goes a step further by stating that all the benefits from interlocking directors —reduced uncertainty, reduced transaction costs, access to information, increased consideration in the regulatory process, increased government contracts, reputation, prestige, etc., have an effect on performance. The knowledge, expertise, and connections of directors enable them to provide advice to management, which can directly apply to a firm's performance in terms of sustainability. Boards that are more connected should be able to gather information that they can then pass on to managers to improve various aspects of their corporate social responsibility score (Amin et al., 2020).
While resource dependency theory rationalizes firms' participation in networks, network theory can help us characterize empirically the connections among the board members of different firms. More specifically, network theory "quantifies" the relationships between the nodes of a network. Network theory defines networks in terms of graphs which are collections of nodes connected by links or edges from which we can derive an adjacency matrix, $A = [a_{ij}]$. An adjacency matrix is a matrix with rows and columns labeled by graph vertices, with a 1 or 0 in position $a_{ij}$ depending on whether $i$ and $j$ are adjacent or not (Weisstein, 2007).
For our purposes, each firm is represented by a node. If a firm has a director who is on the board of another company, a link is created between those two firms, and information can flow from node to node through such a link. In this setting, a piece of information from one node can be transferred to another node that is on the opposite end of the network through a series of interconnected nodes. The more interlocking directors a firm has, the more nodes

or firms are connected to that firm. This allows both to receive and disseminate information through the network at a high speed, which enables sharing and learning about industry trends or else (Dong and Yang, 2016). Essentially, the idea is that the flow of knowledge outside the firm is integrated into the firm through a knowledge network (Dong and Yang, 2016).

To measure directors' positioning in a network, we rely on two centrality measures from network theory: Degree and Betweenness. Degree is a network centrality measure based on the number of direct links that one node in a network has with any other node. In the case of corporate boards, it tells whether the board of a firm shares any member with the board of another firm. High Degree scores imply very connected board members who are likely to hold significant amounts of information or who can quickly connect with the wider network. Technically, the Degree of firm $i$ is the sum of its connections with all other firms. A firm with a high Degree either has many board members who are members of other boards or has board members who are members of many other boards. The higher the Degree is, the more the information that a company comes into direct contact with is (Shahgholian et al. (2015)). Formally, the $i$-th firm's Degree can be defined as follows:

$$Degree_i = \sum_{j=1}^{n} a_{ij} \tag{2.1}$$

where $n$ is the total number of nodes in the network. $a_{ij}$ is $i, j$-th element of the adjacency matrix and is either 0 or 1, depending on whether $i$ and $j$ share a board member (Zhang and Luo, 2017). Degree centrality reflects the local knowledge around a focal firm (Dong and Yang, 2016; Rowley, 1997).

Betweenness centrality measures the number of times a node (firm) lies on the shortest path between other nodes (firms) (Zhang and Luo, 2017). In the case of corporate boards, it captures whether a firm serves as a key broker between other firms and tells how important the firm is regarding the flow of information within the network, i.e., its ability to control and influence the flow of information (Dong and Yang, 2016). A high score implies that board members are very influential. Firm $i$ has a high level of Betweenness if that firm serves as a channel through which other firms can connect with each other. Hence, other firms find firm $i$ to be on the shortest path to their pursuit to connect with other firms. Formally, firm $i$'s Betweenness with respect to all pairs of firms $j$ and $k$ is measured as follows:

$$Betweenness_i = \sum_{j>k} \frac{g_{j,k}(i)}{g_{jk}} \tag{2.2}$$

where $g_{jk}$ is the total number of shortest paths from firm $j$ to firm $k$ and $g_{jk}(i)$ is the number

of those paths that pass through the $i$-th firm (Zhang and Luo, 2017).

Boards that are well-positioned in a network are able to benefit from the information shared among the network members to advance their knowledge. They may have access to information before it is formally released (Renneboog and Zhao, 2011) or to critical news that will allow more effective decision-making (Carpenter and Westphal, 2001).

(Rowley, 1997) shows that the central position of a company's board members in a network increases the firm's efficiency in responding to multiple stakeholder demands. Also, well-connected boards may motivate and assist top management with better information and incentives, improving innovative outcomes (Chang and Wu, 2021). Resource dependency theory provides that board members bring strategic resources and information to assist management. Network theory asserts that board connections determine the access to information and ultimately influence economic outcomes through informational advantages (Bjørnskov and Sønderskov, 2013; Amin et al., 2020).

It is on this ground that we argue that an advantage in terms of network centrality results in *better* information which may translate into improvements in sustainability policies and therefore ESG performance. Related to this line of reasoning are the studies by (Sun et al., 2020; Amin et al., 2020; Harjoto and Wang, 2020). Specifically, using a sample of 4851 firms listed on the Shenzhen Stock Exchange, (Sun et al., 2020) show that board interlocks have a positive affect on firms' Corporate Social Responsibility (CSR) reporting; using data of 3000 publicly traded U.S. companies between 2002 and 2013, (Amin et al., 2020) document the informational advantage of being part of a network and that firms with a well-connected board exhibit a better CSR performance (Tschopp and Huefner (2015)); last, with data from UK FTSE 350 index from 2007 to 2018, (Harjoto and Wang, 2020) find a evidence of a relationship between board networks and ESG performance.

Summing up, it is common ground in the literature that social interactions matter for economic activity and that networks function as "conduits for information diffusion and resource exchange across individuals and organizations" and thereby enhance economic and CSR performance. In this paper, we focus on board members' centrality within a network of firms and look at how this affects firms' environmental and social scores. This leads us to our first hypothesis.

**Hypothesis 1 - Network Centrality:** Network centrality among board members is positively related to Environmental and Social scores.

**Board Diversity**

In the literature there is no agreement on the theoretical framework to link board diversity to environmental and social performance and a multi-theoretical framework is essential.

Generally speaking, the interest for corporate boards stems from the observation that sustainability oriented firms exhibit higher market value and better financial performance (Zhang et al., 2013). This has led to studies aimed at understanding how boards' composition could affect firm social responsibility and whether board differences could result in different performance (Terjesen et al., 2016; Provasi and Harasheh, 2021; Harjoto et al., 2015; McGuinness et al., 2017). We refer to (Fernández-Torres et al., 2025) and references therein for a state-of-art review on the topic. In principle, by increasing board diversity firms could broaden their access to information and this could help achieve certain goals. Also, if female directors have a preference for sustainability, their presence in firms' boards may increase the pressure on managers to improve firm environmental performance and social performance. However, there is evidence that female directors are more independent and (Adams and Ferreira, 2009) argue that independence comes with costs and benefits, and there is thus no reason to expect the average firm to benefit from adding more women to its board. Overall, the empirical evidence on this is mixed.

(Cucari et al., 2017) find a negative relationship between women on corporate boards and ESG disclosure in a sample of 54 Italian-listed companies from 2011 to 2014, which they attribute to the fact that there is more to a person than just their gender. Instead, (Manita et al., 2018) find a non significant relationship in a sample of 379 firms from the Standard & Poor's 500 Index over the period 2010-2015. On the positive effect side of the evidence, there are (Barako and Brown, 2008) and (Kiliç et al., 2015) who report a positive correlation between women on the board and CSR reporting in samples of 40 Kenyan and 25 Turkish banks, respectively. Using Australian data, Rao and Tilt (2016) find that companies with more female directors exhibit higher levels of corporate social responsibility and rationalize this finding on the basis that board diversity increases the variety of questions raised by board members when compared to more homogeneous boards (Carter et al., 2003).

For gender diversity to matter, men and women must differ in their approaches to management and directorship. (Adams and Funk, 2012) find that Swedish female directors differ in their core values from male directors. They are more benevolent and universally concerned, but less power-oriented than men. They are less traditional and security-oriented and slightly more risk-loving than their male counterparts. However, Swedish female directors appear different from the average Swedish woman in the population.

Female directors are generally found to be more interested in helping the community, which increases company morale and improves the firm's image and public reputation. For example, (Devicienti et al., 2019) find that female managers are more responsive to employees' needs and limit involuntary part-time work, increase full-time employment, and allow more part-time arrangements to employees at their request. Still, "the underlying motives as to why

women may be more charitable than men remain unclear. Perhaps the notion of giving as a source of female empowerment has some merit" (Williams, 2003). Other researchers show that gender differences in decision-making can be attributed to different levels of aversion to risk. For example, (Zalata et al., 2019) find that female CEO financial reporting behavior is more accurate due to higher risk aversion rather than greater moral sensitivity.
There is some agreement that as a result of their "relational abilities", women appear to be more concerned with a broader set of stakeholders (Galbreath, 2011). Such gender differences in perceptions of community interests can lead to heterogeneous decision-making outcomes. Furthermore, board gender diversity can increase the wealth of experiences, not just in terms of information, that directors can leverage on to increase firm performance (Ferrero-Ferrero et al., 2015) as well as sustainability.
For all these reasons, in this paper we want to provide more evidence on the link between board gender diversity and firm's environmental and social scores. This leads us to the second hypothesis that we test.
**Hypothesis 2 - Board Diversity:**
Board gender diversity has a positive effect on Environmental and Social scores.

## 2.3 Model and Data

### 2.3.1 The Empirical Model

To measure the effects of corporate board gender diversity and network centrality, we estimate a fixed effect (FE) model, which we specify as follows:

$$Y_{i,t} = \beta_0 + \beta_1 G_{i,t} + \beta_2 N^c_{i,t} + \beta_3 X_{i,t-1} + \beta_4 B_{i,t} + \eta_i + \tau_t + \varepsilon_{i,t} \tag{2.3}$$

where $Y_{i,t}$ is an environmental (E) or social (S) score, ranging between 0 and 100, and capturing firm $i$ environmental and social performance in year $t$. Gender diversity and network centrality are captured by $G_{i,t}$ and $N^c_{i,t}$, respectively. The diversity variable $G_{i,t}$ consists of a vector of dummy variables capturing the quartiles of a firm's share of female directors on the board. Specifically, each dummy indicates the quartile into which the firm's proportion of female directors falls. This dummy-based specification allows us to analyze the effect of different female shares on the E and S scores without imposing a linear relationship. Also, it allows for the fact that when female board members are too few their voices may go unheard and therefore they may be unable to affect company policies in a meaningful way (Konrad et al. (2008)). As to board member connections, $N^c_{i,t}$, we use the two measures of network centrality that we have described earlier, i.e. Degree and Betweenness.

Consistent with the corporate governance and ESG literature, several control variables are included to account for observable firm characteristics that may influence ESG performance. Board size is included because larger boards may possess a broader range of expertise and resources but may also face coordination problems. The proportion of independent directors controls for board monitoring quality and governance independence. Firm size, proxied by the number of employees, captures organizational scale and the greater public scrutiny typically faced by larger firms. Finally, leverage controls for financial constraints and capital structure, which may influence firms' ability and willingness to undertake ESG investments. $X_{i,t-1}$ denotes a set of firm control variables that include the number of employees, board size, independent board members, and leverage. The variables leverage and number of employees are lagged one year to avoid simultaneity issues due to omitted variables and also to allow for some lag before these factors affect companies' environmental and social policies and their scores. Leverage is defined by total debt divided by total total equity. $B_{i,t}$ denotes instead a set of board characteristics which could influence performance in terms of sustainability. These include board size and the share of independent directors.
Unobserved and time non-varying firm fixed effects are captured by $\eta_i$, whereas $\tau_t$ denotes the time effect common to all companies. Last, $\varepsilon_{i,t}$ is the classical error term that is assumed to be independently and identically distributed.
Firm fixed effects are employed to control for unobserved time-invariant firm characteristics that may influence ESG performance. While this specification strengthens causal identification by reducing omitted-variable bias, it also removes cross-sectional variation across firms. Consequently, the estimated coefficients should be interpreted primarily as within-firm effects over time rather than differences between firms.
We use an FE model to control for any endogeneity related to unobserved, time invariant firm characteristics that may affect both the left-hand-side and the right-hand-side variables. To counteract further any endogeneity issue, as mentioned earlier, we restrict our focus to the environmental and social elements of the ESG scores. In fact, as Adams et al. (2010b) put it, governance structures (including corporate board composition) are usually chosen to solve the firm governance problems. Last, as additional check, we run instrumental variable (IV) regressions using the Golfo-Mosca law on board quotas.

### 2.3.2 The Data

The empirical analysis is based on data from three sources, BoardEx, Thomson Reuters Eikon and corporate reports. BoardEx collects detailed information on the boards of directors of companies around the world and allows us to recover corporate board networks,

where each board is a node and two boards are connected if the same individual sits on both boards. It is based on this information that we compute the Degree and Betweenness metrics of network centrality for each firm. We retrieve board composition for Italian companies from BoardEx data and corporate reports for the period 2010 to 2020. The number of Italian companies varies from 105 in 2010 to 233 in 2020.

Thomson Reuters Eikon is the most comprehensive data set for appraising firms' ESG performance. It encompasses 80 percent of the global market capitalization, spans nearly 20 years, and includes 450 different ESG metrics. ESG data are collected and organized according to 10 themes, which are then grouped into three larger pillars, i.e. environment, social, and governance. The environmental pillar consists of resource use, emissions, and innovation. The social pillar comprises workforce, human rights, community, and product responsibility. Governance, which, however, we omit from our analysis, consists of management, information disclosures, auditing, and compliance issues. All scores range from 0 to 100: the higher the value is, the better the performance is. Besides ESG scores, Thomson Reuters collects other firm and economic data that we use as control variables in our regressions. Thomson Reuters data are available for a number of Italian companies that goes from 26 in 2010 to 124 in 2020. We note that Thomson Reuters scores typically take up to five years to become definitive, as they may be subject to revisions during that time. Accordingly, we end our sample period in 2020 to ensure data reliability.

After merging the two datasets and dropping the firms that are observed for only one year, we are left with a sample that covers 23 firms in 2010 going up to 99 in 2020.

### 2.3.3 Summary Statistics

Table 2.1 reports means, medians and standard deviations of the variables that we use in the analysis. As to sustainability measures, Social scores tend to have larger values than Environmental scores with smaller standard deviation. As to network centrality measures, Degree captures the number of directors who sit on the board of other firms and the number of boards they sit on. It has a mean value of 2.63 and median value of 2.00, which implies that around one-third of firm board members sit on the board of other firms, on average. Betweenness measures how important a firm is regarding the flow of information within the network. A firm has a high level of Betweenness if it serves as a channel through which other firms can connect with each other. Firms with high Betweenness can control and influence the flow of information between other firms (Dong and Yang (2016)). Betweenness varies significantly across firms and increases sharply over time. It exhibits a large standard deviation and contains several outliers.

The table then presents summary statistics for the share of female directors. Over the full sample period, the overall mean is 29%, with a standard deviation of 14 percentage points. However, this average masks a clear upward trend such that the share of female directors increases from just over 4% in 2010 to 37% by 2020.

Last, the table reports summary statistics for few firm level variables that we include in our regressions as controls. Board size is around 12, on average, with median 11 and standard deviation of 4.These figures should be interpreted with caution, as BoardEx records all directors who were active at any point during the year. As a result, board renewals or director replacements within a year may inflate the reported board size. To address this potential issue, we conduct several robustness checks to ensure that our results are not affected. On average, 54.27% of directors are independent directors and 77.79% are non executive directors. Other variables that we consider are the number of full-time employees and leverage.

**Table 2.1:** Descriptive Statistics

| **Variable** | **Mean** | **Median** | **St.dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| *Sustainability measures* | | | | | |
| Environmental score | 59.81 | 64.86 | 25.89 | 0 | 98.91 |
| Social score | 63.41 | 67.26 | 21.59 | 4.18 | 96.30 |
| *Centrality measures* | | | | | |
| Degree | 2.63 | 2.00 | 2.18 | 0 | 11.00 |
| Betweenness | 116.61 | 7.13 | 196.20 | 0 | 1320.52 |
| *Board diversity* | | | | | |
| Female directors share | 0.29 | 0.33 | 0.14 | 0 | 0.67 |
| *Control variables* | | | | | |
| Board size | 12.04 | 12.00 | 4.31 | 4.00 | 31.00 |
| Independent directors (%) | 54.60 | 55.56 | 19.84 | 0 | 95.83 |
| Non-executive directors (%) | 78.58 | 81.82 | 13.74 | 22.22 | 100.00 |
| Full-time employees (thousands) | 20.92 | 6.10 | 32.50 | 0.01 | 165.06 |
| Leverage | 1.61 | 1.25 | 1.73 | -3.83 | 11.81 |

Table 2.2 reports the correlation between the Environmental and Social scores, Degree, Betweenness and the share of female directors on the corporate board. As expected, the Environmental and Social scores are strongly correlated ($\rho = 0.7412$), suggesting some overlap in firms' performance across these dimensions.

Although, there are no serious problems of collinearity between the network centrality variables and the board gender dummies, the high correlation between Degree and Betweenness centrality ($\rho$= 0.7492) may reflect some structural overlap of these two network metrics, consistent with the intuition that more connected directors often serve as critical intermediaries in board networks.

Both Degree and Betweenness centrality show modest positive correlations with the social

score ($\rho$= 0.2848 and $\rho$= 0.2425, respectively), and weaker associations with the environmental score. Also the share of female directors is weakly positively correlated with both sustainability outcomes, particularly environmental score ($\rho$= 0.0186), and only moderately with social score ($\rho$ = 0.1771). These low correlations, especially for environmental performance, suggest that gender diversity alone may not be a strong predictor of firm sustainability performance when considered in isolation. However, it may still play a more nuanced or indirect role, potentially interacting with other board characteristics or firm-specific factors.

**Table 2.2:** Correlation Matrix

| | **Env. score** | **Soc. score** | **Degree** | **Betweenness** | **Female share** |
|---|---|---|---|---|---|
| **Environmental score** | 1 | | | | |
| **Social Score** | 0.7412 | 1 | | | |
| **Degree** | 0.1752 | 0.2848 | 1 | | |
| **Betweenness** | 0.1344 | 0.2425 | 0.7492 | 1 | |
| **Female share** | 0.0186 | 0.1771 | 0.1325 | 0.2528 | 1 |

## 2.4 Results

### 2.4.1 Network Analysis Results

Table 2.3 reports the results of our FE regressions of the Environmental and Social scores on the network centrality measures. The E-Score regressions in columns (1) and (2) and the S-Score regressions in columns (4) and (5) include only the network centrality measures and the firm fixed effects. For what concerns degree centrality we allow for a non-linear effect based on the "attention scarcity and busy directors" theory of (Fich and Shivdasani, 2006) who show that when directors hold three or more external seats, board monitoring weakens and firm performance suffers. This "busyness effect" dilutes directors' time and attention, leaving insufficient bandwidth for non-financial issues such as ESG, ultimately dragging down ESG ratings. To allow for this, we include in the regression a dummy that takes on value 1 if Degree is positive. Depending on the year, the share of firms with positive Degree varies between 70% in 2011 and 93% in 2016. With respect to Betweenness centrality, the existing literature does not provide theoretical or empirical grounds for expecting a non-linear relationship with ESG outcomes. On the contrary, one could reasonably argue that increases in Betweenness should consistently enhance a firm's ability to extract or provide value through its strategic position within the board network. As a firm's Betweenness rises, so does its potential influence over information flow, agenda setting, and cross-firm norm diffusion. This increasing centrality likely reinforces positive ESG behavior

due to heightened legitimacy concerns, greater stakeholder scrutiny, and the transmission of prevailing sustainability norms. Importantly, there appears to be no clear saturation point beyond which additional Betweenness would diminish these effects, supporting the use of a linear specification.

In the regressions in columns (3) and (6) we add time-varying firm characteristics, i.e., board size, the share of independent board members, and lagged number of employees, which proxies for firm size, and lagged leverage, which captures the capital structure and proxies for default risk. We also include year fixed effects to control for any time-variant omitted variables that are constant across entities but vary over time and could bias the coefficients of other time-varying variables included in the regressions that are correlated with them.

Our results confirm our hypothesis of a positive relationship between environmental and social performance and network centrality. Degree centrality matters: firms with directors sitting on the board of other firms have an E-score that is more than 15% higher than average [2]. However, the relationship is non-linear and the positive effect gradually weakens as directors hold seats on an increasing number of boards [3]. In contrast, there is no evident diminishing effect for the S-score. In fact, firms with a positive degree centrality exhibit social scores that are 6 to 11% higher than those of firms with zero degree centrality.

For what concerns the variable Betweenness, it is generally statistically and economically significant. Moving from the 25th to the 50th percentile of the distribution of Betweenness raises the E-score by 20% of the mean and the S-score by 22%. Betweenness centrality exhibits a highly right-skewed distribution with a long upper tail. To assess the robustness of our results to extreme values, we winsorize the variable at the 95th percentile. As shown in Table A.3 of the Appendix, the results remain unchanged.

These results are consistent with those of (Sun et al., 2020) and (Amin et al., 2020) who focus on the relationship between board centrality and CSR performance and reporting. Our finding of positive coefficients supports network theory's conjecture that firms can gain an information advantage based on their position in a network (Salancik, 1978) and this may ultimately improve their performance (Larcker et al., 2013). More specifically, the fact that Betweenness is significant in both the Environmental and Social score regressions suggests that mediating information flows by playing a bridge-spanning role provides directors with

[2] The E-score mean is 59.8. The coefficient of the the dummy (I(Degree>0) varies between 8.5 and 10.5, which implies that companies with Degree>0 have an E-score that is between 8.5 and 10.5 higher than the E-score of those with a Degree=0. Hence, they have an E-score that is 14.2-17.6% higher than the average.

[3] As an example, based on the estimates of Column (3) of Table 2.3, if we take two firms with a Degree equal to 2 and to 4 (the median and 75th percentile of the distribution of degree), their E-scores are respectively 5.4 and 2.3 points higher than the score of a company with Degree=0.

knowledge that enables them to steer their firm toward outcomes aligned with environmental and social values. Similarly, the significance of Degree centrality indicates that simply having more direct board connections can facilitate access to diverse perspectives and best practices, reinforcing firms' responsiveness to social expectations through increased exposure to peer influence and normative pressures.

### 2.4.2 Board Diversity Results

Table 2.4 reports the results of our FE regressions of the Environmental and Social scores on the board diversity quartile dummies. Columns (1) and (4) present the most parsimonious regression specification where we control only for firm fixed effects. The regressions in the other columns include also firm characteristics (board size, the share of independent directors, and lagged number of employees and leverage; columns (2) and (5)) and time fixed effects (columns (3) and (6)). Firm and time fixed effects control for any unobserved, time invariant firm characteristics and for time varying variables, respectively, that may correlate with female presence on corporate boards and bias our estimates of the board diversity dummy coefficients.

The omitted dummy for the share of female directors corresponds to the first quartile, which reflects firms with a very low proportion of women in the board. This group serves as the reference category against which the coefficients of the other quartile dummies are interpreted. Based on the results in columns (1) and (2), increasing the share of female directors is associated with a higher Environmental score. Specifically, compared to firms in the first quartile—those with less than 21% female board representation—firms in the second (22–33%), third (34–40%), and fourth quartiles (above 40%) have significantly higher E-scores. The magnitude of the difference is substantial, corresponding to approximately 12%, 13%, and 18% of the mean E-score, respectively. The results for the Social score are both qualitatively and quantitatively similar to those for the E-score, showing a comparable positive association with higher quartiles of female board representation. Including year dummies lowers the coefficient estimates and makes gender diversity insignificant. This could be expected because, although firm boards are renewed in different years, female presence increases steadily over time which makes the female share dummies likely to capture aggregate shocks.

In Table A.1 of the Appendix, we replicate the analysis using terciles instead of quartiles to divide the distribution of the share of female directors. The results remain unchanged, confirming the robustness of our findings.

### 2.4.3 Combined regression results

In the regressions reported in Table 2.5, we include both the centrality measures, capturing directors' connections and the firm's positioning in networks, and the dummies for board shares of female directors, capturing diversity of experiences and perspectives and the potential to cater to a broader and more diverse set of stakeholders. As usual, we control for firm fixed effects, some firm characteristics and for time fixed effects. In the Environmental score regressions in columns (1) and (2), degree centrality is statistically significant and the effect is similar to that of the regressions without the gender diversity dummies. The same holds for Betweenness and the gender dummies, which however become insignificant when including the time effects, possibly due to the fact that both Betweenness and board diversity increase over time and the year dummies correlate and capture these and any other aggregate trend.

As to the Social score regression in columns (3) and (4) of Table 2.5, including the gender dummies makes the coefficients of the Degree>0 dummy and of Betweenness slightly smaller. The evidence on board diversity is essentially unaffected as the estimated coefficients are not statistically different from those reported in Table 2.4. This implies that when it comes to social issues directors' connections do not have a significant bearing, whereas increasing the share of female directors significantly improves firms' attention for societal concerns. However, like before, including time effects makes the coefficients of the gender dummies smaller and insignificant.

### 2.4.4 Instrumental Variable Analysis

In Tables 6 and 7 we deal with the potential endogeneity of the share of female directors with an instrumental variable strategy based on a quasi-experimental policy change. To be specific we exploit two reforms setting quotas on the "less represented gender" in corporate boards. The first is Law 120/2011 (also called Golfo-Mosca law, after the names of the two legislators who promoted it in the Italian Parliament), which was passed in August 2011 and came into force in August 2012. It applied to listed companies and state-owned enterprises for three consecutive board renewals since its enactment and set a quota of 20% for the first board renewal and of 33% for the second and third renewals.[4] In 2019, the Annual Budget Law extended the application of the gender quotas for three more board renewals and raised the percentage of directors of the "less represented gender" to 40%. The enforcement of the gender quotas is entrusted to the Equal Opportunity Department of the Italian Government,

[4]According to the Italian Civil Code (Art. 2383), the members of the boards of listed companies are appointed for a maximum term of three years.

which can issue a warning to the company if the quota is not respected. If the company fails to adjust its board composition, the Government has a mandate to remove some directors so that the renewed board follows the law.

The policy is well suited to serve as a valid instrument, as it influences the share of women on corporate boards (instrument relevance) but does not directly affect firms' environmental and social scores (exclusion restriction). To create variation in the instrument that is not collinear with year dummies, we interact the policy which is a time-varying, plausibly exogenous shock with firms' board composition before the policy, as follows:

$$Z_{i,t} = max(0, Quota_t - Share\ of\ women_{i,p}) \tag{2.4}$$

where:

$$Quota_t = \begin{cases} 0 & \text{if } t < 2012 \\ 0.20 & \text{if } 2012 \leq t < 2015 \\ 0.33 & \text{if } 2015 \leq t \leq 2018 \\ 0.40 & \text{if } t \geq 2019 \end{cases} \tag{2.5}$$

and:

$$Share\ of\ women_{i,p} = \begin{cases} Share\ of\ women_{i,t-1} & \text{if } t < 2012 \\ Share\ of\ women_{i,2011} & \text{if } 2012 \leq t < 2015 \\ Share\ of\ women_{i,2014} & \text{if } 2015 \leq t \leq 2018 \\ Share\ of\ women_{i,2018} & \text{if } t \geq 2019 \end{cases} \tag{2.6}$$

The instrument, $Z_{i,t}$, captures firm-specific exposure to the quota that varies across firms within the year depending on how far the firm was from compliance before the policy. The share of women on boards is lagged to avoid simultaneity and mechanical endogeneity. Using the contemporaneous share would make the instrument a direct function of the endogenous variable, undermining identification. By contrast using board composition from a period prior to the policy ensures that the instrument is predetermined, as it captures how binding the quota is based on a board structure that was set before the quota became effective. This preserves the causal interpretation of our instrument.

Table 2.5 results are generally robust to the use of an instrument. Table 2.6 reports the result from the estimation of the E-score regression, whereas Table 7 reports the results from the estimation of the S-score regression. Since we have a single instrument we replace the gender quota dummies with the *share* of female directors and estimation results of the

baseline OLS-FE models without and with year fixed effects are in Columns (1) and (4) of the tables, respectively. Coefficient estimates are statistically and economically similar to those reported in Table 2.5 based on the specification with quartile dummies.

Columns (2) and (5) show first stage estimates from the regression of the share of female directors on the instrument, with and without year dummies. The relationship between the share of female directors and the instrument (defined as the distance from the gender quota prior to the board renewal following the approval of the law) is negative and statistically significant. This implies that firms which were further below the quota threshold before the renewal tended to have a lower share of female directors even after the board was reappointed. This suggests that the adjustment toward compliance with the quota was slow and probably incomplete or uneven, possibly reflecting differences in firm-level commitment to gender diversity, enforcement intensity, or structural barriers to rapid adjustment.

In the E-score regressions (Table 2.6), the instrument performs well in the first-stage regressions. Its relevance is supported by robust first-stage F-statistics of 4.82 and 12.42 across different model specifications. While the F-statistic of 4.82, obtained from a model with firm fixed effects only, falls below the conventional threshold of 10, the F-statistic rises to 12.42 when time fixed effects are included, indicating a sufficiently strong instrument in this richer specification. Furthermore, endogeneity tests generally yield statistically significant p-values, supporting the rejection of the null hypothesis of exogeneity and justifying the use of an IV approach over OLS in the baseline specification. In the second-stage IV-FE regressions (Columns (3) and (6) of Table 2.6), the coefficient on female board share remains positive and statistically significant in column (3), and though imprecise in column (6), it retains a large magnitude. Overall, these results provide credible evidence that greater gender diversity on boards leads to improved environmental outcomes, and that this relationship is not entirely driven by unobserved firm characteristics or reverse causality.

Network centrality indicators also offer consistent insights. The positive and significant coefficient of the Degree $> 0$ dummy suggests that having board members with any connections matters, while the small, negative sign on the linear Degree term points to nonlinearity in the value of additional connections. Betweenness centrality—indicating strategic influence within the board network—is also positively associated with environmental scores, reinforcing the idea that more central and better-connected boards may facilitate stronger environmental strategies.

Table 2.7 presents results from regressions of firms' social performance on board gender diversity and directors' network centrality, using the same fixed effects and IV specifications as in the environmental score analysis. In the baseline OLS-FE model (Column (1) and (4)), the share of female directors is positively and significantly associated with the social

score, suggesting that gender-diverse boards are linked to stronger social performance. In the IV-FE model in Column (3), the estimated effect of female board representation remains positive and statistically significant, although the instrument exhibits limited strength (F = 5.55), suggesting that the results should be interpreted with some caution. When year fixed effects are included (Column 6), the second-stage coefficient becomes negative and statistically insignificant. However, also the endogeneity test p-value rises to 1.0000. This suggests weaker identification in the more saturated specification and casts some doubt on the robustness of the causal effect for social performance.

Network centrality variables display patterns that are consistent across both environmental and social domains. The dummy for having at least one board connection Degree $> 0$ is positively and significantly associated with the Social score, while the linear degree term is small or negative—pointing to diminishing marginal benefits from additional connections. Betweenness centrality, capturing a board member's brokerage position, also shows positive effects, though its significance is somewhat sensitive to specification, particularly in the IV models.

Taken together, the findings from both the Environmental and Social score regressions reveal several consistent mechanisms. First, gender diversity on boards is positively associated with ESG outcomes in OLS-FE models. The IV-FE regressions provide evidence of a causal effect, especially for the environmental dimension, where the relationship remains significant and robust across all specifications. For the social score, the IV results are more mixed: while in the first-stage the instrument remains strong, the second-stage estimates are sensitive to the inclusion of time fixed effects. Second, network centrality, particularly the presence of any board connection, but also the strategic influence captured by Betweenness, is a robust predictor of higher ESG scores across both dimensions consistent with our hypothesis that network interactions can function as conduit for information and resource exchanges across organizations. These results suggest that firms with more diverse and well-connected boards are better positioned to adopt and implement sustainability-related strategies.

## 2.5 Policy implications and concluding remarks

Corporate board networks and gender diversity can have an impact on the type and amount of information flowing to a firm and therefore affect its performance. Traditionally, performance has been assessed using operational and financial measures. However, recent studies have shown that firm performance is associated also with other factors, such as environmental, social, and governance activities. ESG activities enhance firms' financial stability, market value, and efficiency (Chouaibi and Chouaibi, 2021; Feng and Wu, 2023;

**Table 2.3:** Fixed Effects Regressions of Environmental and Social Scores on Centrality Measures

| | **Environmental Score** | | | **Social Score** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Degree | -1.458** | -1.280* | -1.554** | -0.446 | 0.080 | -0.275 |
| | (0.662) | (0.676) | (0.681) | (0.534) | (0.551) | (0.457) |
| I(Degree > 0) | 9.294*** | 10.498*** | 8.541*** | 4.903** | 7.342*** | 3.625* |
| | (2.616) | (2.712) | (2.643) | (2.379) | (2.473) | (2.021) |
| Betweenness | 1.776*** | 1.668*** | 0.696 | 2.332*** | 1.886*** | 0.241 |
| | (0.481) | (0.485) | (0.519) | (0.439) | (0.445) | (0.394) |
| Board size | | -0.761** | -0.164 | | -1.069*** | -0.138 |
| | | (0.345) | (0.344) | | (0.316) | (0.263) |
| Independent board members | | -0.085 | -0.159** | | -0.035 | -0.148*** |
| | | (0.066) | (0.065) | | (0.060) | (0.049) |
| Employees (lagged 1yr) | | -0.048 | 0.147* | | -0.041 | 0.233*** |
| | | (0.082) | (0.082) | | (0.075) | (0.062) |
| Leverage (lagged 1yr) | | -0.688 | -0.216 | | -1.134 | -0.469 |
| | | (0.752) | (0.742) | | (0.689) | (0.568) |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Year FE | N | N | Y | N | N | Y |
| N. firms | 99 | 77 | 77 | 99 | 77 | 77 |
| N. obs. | 462 | 356 | 356 | 462 | 356 | 356 |
| R-squared | 0.07 | 0.12 | 0.27 | 0.12 | 0.21 | 0.54 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Wong et al., 2021) and may create value by increasing shareholder wealth or maximizing shareholder utility (Gillan et al., 2021).

Previous research on board network centrality and gender diversity have looked mainly at financial performance and corporate social responsibility disclosure. The evidence from studies considering ESG outcomes is limited and mixed. This paper adds to the literature by highlighting how these variables impact environmental and social scores and their interaction, in a sample of Italian listed firms over the period from 2010 to 2020.

The first area of interest in this paper is the effect that a company's position in a network of firms can have on its Environmental and Social scores. In other words: do connections with other firms through board members improve the access to the information and resources necessary to raise its social and environmental scores? Based on our evidence, the answer is yes. We find that the network measurements of Degree and Betweenness influences firms' Environmental and Social scores. This suggests that boards that play a bridge-spanning role across other firms place them in an advantageous position to attain effectively both environmental and social sustainability. Also, having directors sitting on the boards of other companies improves firms' environmental and social performance. However, the positive

**Table 2.4:** Fixed Effects Regressions of Environmental and Social Scores on Board Diversity (a)

| | **Environmental Score** | | | **Social Score** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| F quartile 2 | 6.339*** | 6.928*** | -0.713 | 9.625*** | 11.005*** | 1.924 |
| | (1.696) | (1.936) | (2.572) | (1.478) | (1.672) | (1.938) |
| F quartile 3 | 8.426*** | 7.634*** | -1.835 | 12.484*** | 12.630*** | 0.795 |
| | (1.881) | (2.093) | (2.803) | (1.639) | (1.808) | (2.112) |
| F quartile 4 | 11.085*** | 10.584*** | -2.205 | 17.055*** | 18.044*** | 2.046 |
| | (2.257) | (2.443) | (3.297) | (1.966) | (2.110) | (2.484) |
| Board size | | -0.403 | -0.222 | | -0.330 | -0.106 |
| | | (0.360) | (0.346) | | (0.311) | (0.260) |
| Independent board members | | -0.149** | -0.159** | | -0.148** | -0.155*** |
| | | (0.070) | (0.067) | | (0.061) | (0.051) |
| Employees (lagged 1yr) | | 0.057 | 0.177** | | 0.095 | 0.253*** |
| | | (0.084) | (0.082) | | (0.073) | (0.061) |
| Leverage (lagged 1yr) | | -0.608 | -0.247 | | -1.159* | -0.375 |
| | | (0.750) | (0.759) | | (0.648) | (0.572) |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Year FE | N | N | Y | N | N | Y |
| N. firms | 99 | 77 | 77 | 99 | 77 | 77 |
| N. obs. | 462 | 356 | 356 | 462 | 356 | 356 |
| R-squared | 0.09 | 0.10 | 0.23 | 0.22 | 0.29 | 0.54 |

*Notes:* Female directors' shares dummies are based on the quartiles of the female directors' share distribution, corresponding to 21%, 33%, and 40%.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

effect on the Environmental score suffers when they are sitting on too many boards.

Hence, contrary to common belief we find that interlocking boards may have a positive impact on society. Interlocking boards are typically viewed as symptom of a corporate elite running the multinational companies in their own interest, which raises feelings of distrust in corporations as institutions (Adams et al., 2010a). However, it is interesting to see that this same corporate structure can benefit society and that corporate networks can be used to improve the environmental and social impact of firms' activities and the well being of their stakeholders. Therefore, people pessimistic attitude towards interlocking directorates is not unavoidable. With the right incentives and efforts, these same interlocked structures can be used to the good of society and not just of a select few.

The second area of interest of this paper pertains to gender diversity in positions of power throughout society. This has been an important issue for decades. We live in an era where some of such diversity is increasing, but it is important to examine this change thoroughly as many simply assume that increasing diversity automatically has a positive effect on all aspects of a company's performance. Then, it is important to test the impact of gender

diversity on firms' sustainability. The research conducted here does support the claim that female directors improve companies' performance on environmental and social scores.

Overall, our findings are consistent with the predictions of network and resource dependency theories (Hillman et al., 1999; Pfeffer and Salancik, 2015) and also with some papers on the effects of board networks and gender diversity on corporate social responsibility (Harjoto and Wang, 2020; Harjoto et al., 2015; Bear et al., 2010; Amin et al., 2020; Barako and Brown, 2008; Sun et al., 2020). More specifically, our study provides evidence that board interlocks may be an important channel for information spillovers and together with female board representation may improve firms' sustainability when it comes to environmental and social goals.

Our findings regarding board positioning within networks have implications for both firms and policy makers. As to firms, our results suggest that there are different strategies that firms can pursue to improve the Environmental and Social pillars of their ESG score. If they are weak in their Environmental score or Social score, for example, they could consider improving their position in the corporate board network. That could enable them access to information that they are lacking to develop a more effective environmental policy. Policy-wise, our results imply that promoting board independence and limiting directorate interlocks may weaken information sharing between management and directors, thus reducing the valuable spillover effects of board connections, although admittedly, as mentioned, interlocks raise concerns of anti-competitive conducts.

The implications of the evidence regarding female board representation are as subtle. In this paper, we find an effect on environmental and social outcomes. However, in the literature, the estimated effects of board diversity on firms' performance vary substantially across empirical specifications and methods, and also depends on firm characteristics. Mixed results should come as no surprise, given that gender diversity is strongly related to board independence, which has no obvious impact on firm performance (Adams et al., 2010b). Furthermore, mandatory board gender quotas like any regulation that forces firms to do something that they currently do not do is likely to impose some costs. For example, mandatory hiring of female directors does not guarantee that the new directors are even just as qualified as the incumbent ones.

A further limitation concerns the upward trend observed in Refinitiv ESG scores during the sample period. Although year fixed effects are included in several specifications to account for common temporal shocks, improvements in ESG scores over time may partially reflect changes in reporting practices, disclosure requirements, or provider methodology rather than genuine improvements in sustainability performance. Consequently, the results should be interpreted with this consideration in mind. Similarly, the proportion of female directors

increased throughout the sample period. Since both female board representation and ESG scores exhibit positive time trends, part of their observed association may reflect common underlying trends rather than a purely causal relationship. Although specifications including year fixed effects mitigate this concern, the possibility of residual time-related confounding cannot be completely excluded.

In conclusion, this paper raises a number of opportunities for future research. First of all, the fact that the Environmental score responds more than the Social score to network centrality raises the question of why the former is affected more than the latter. Is it an issue of type of peer effects and information or of differences in the adaptability of policies? Further investigation is also needed to understand the drivers of the non-linearity between the number of board connections and environmental performance, as well as the reasons why this non-linearity is not observed in relation to social performance. In addition, the differential response suggests that more research is needed on the three ESG pillars and on their components to gain a more thorough understanding of how to improve ESG performance for firms facing different challenges. More specifically, further research could investigate which components of the Environmental and Social pillar respond the most to firm's network centrality, whether it is resource use, emissions, or innovation. Moreover, given the potential divergence among ESG scores, further research could focus on considering ESG scores from alternative providers. While this study examines board network centrality and board gender diversity both independently and jointly within the same regression specifications, it does not explicitly examine whether the effect of one depends upon the other. Future research could therefore investigate interaction effects between board network centrality and gender diversity to determine whether the influence of network position on ESG performance varies according to the level of female board representation. Future work should also investigate whether board gender diversity moderates the relationship between board network centrality and ESG performance through explicit interaction effects. Such an approach may provide additional insight into the complementary roles of board composition and board connectivity in shaping ESG outcomes. Besides these issues, we believe that deepening our understanding of the relationship between board gender diversity and network centrality would help firms and policy makers to better predict how changes in one of these features would affect firm outcomes, reducing speculation on firm management and government intervention. In general, a clearer understanding the determinants of ESG would enable an optimal implementation of ESG practices at the firm level as well as from a policy level. If firms are able to identify which pillars and themes are their weaknesses, this type of research would enable them to design strategies to improve these areas. Last, new research is called for on Directive 2014/95/EU on disclosure of non-financial information which came into force in Italy in 2017

(Carungu et al., 2022), (Venturelli et al., 2017). Such policy regarding the disclosure of ESG data has undoubtedly had an impact and it would be critical to know how this policy is affecting the economy and firm ESG behavior.

**Table 2.5:** Combined Effects on Environmental and Social Scores

| | **Environmental Score** | | **Social Score** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Degree | -1.202** | -1.527** | -0.084 | -0.318 |
| | (0.589) | (0.601) | (0.501) | (0.460) |
| I(Degree > 0) | 9.407*** | 8.397*** | 5.220** | 3.684* |
| | (2.669) | (2.662) | (2.269) | (2.035) |
| Betweenness | 1.417*** | 0.696 | 1.440*** | 0.339 |
| | (0.487) | (0.526) | (0.414) | (0.403) |
| F quartile 2 | 5.764*** | -0.488 | 9.775*** | 2.202 |
| | (1.921) | (2.568) | (1.633) | (1.964) |
| F quartile 3 | 5.940*** | -1.367 | 10.283*** | 1.132 |
| | (2.101) | (2.770) | (1.786) | (2.119) |
| F quartile 4 | 8.455*** | -1.420 | 15.100*** | 2.540 |
| | (2.465) | (3.276) | (2.096) | (2.505) |
| Board size | -0.408 | -0.169 | -0.455 | -0.142 |
| | (0.355) | (0.347) | (0.302) | (0.265) |
| Independent board members | -0.171** | -0.154** | -0.182*** | -0.161*** |
| | (0.069) | (0.067) | (0.058) | (0.051) |
| Employees (lagged 1yr) | 0.035 | 0.151* | 0.090 | 0.235*** |
| | (0.083) | (0.082) | (0.070) | (0.062) |
| Leverage (lagged 1yr) | -0.613 | -0.224 | -1.042* | -0.382 |
| | (0.737) | (0.755) | (0.627) | (0.577) |
| Firm FE | Y | Y | Y | Y |
| Year FE | N | Y | N | Y |
| N. firms | 77 | 77 | 77 | 77 |
| N. obs. | 356 | 356 | 356 | 356 |
| R-squared | 0.16 | 0.27 | 0.35 | 0.54 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 2.6:** IV-FE Regressions of Environmental Scores

| | (1) Without Year FE | | | (2) With Year FE | | |
|---|---|---|---|---|---|---|
| | Env. Score | Female Share (1st Stage) | Env. Score (2SLS) | Env. Score | Female Share (1st Stage) | Env. |
| Female share | 21.140*** | | 145.563** | -0.057 | | |
| | (5.771) | | (68.565) | (8.621) | | |
| Z | | -0.238** | | | -0.343*** | |
| | | (0.105) | | | (0.096) | |
| Degree | -1.187** | -0.0012 | -1.294 | -1.524** | 0.004 | |
| | (0.591) | (0.007) | (1.007) | (0.611) | (0.004) | |
| I(Degree > 0) | 9.356*** | 0.092*** | -1.588 | 8.987*** | -0.009 | |
| | (2.736) | (0.029) | (7.566) | (2.742) | (0.020) | |
| Betweenness | 1.344*** | 0.015*** | -0.500 | 0.792 | -0.006 | |
| | (0.482) | (0.005) | (1.297) | (0.527) | (0.004) | |
| Board size | -0.564 | -0.016*** | 1.437 | -0.210 | 0.002 | |
| | (0.350) | (0.004) | (1.243) | (0.355) | (0.003) | |
| Independent board members | -0.171** | 0.005*** | -0.730** | -0.167** | 0.002*** | |
| | (0.071) | (0.001) | (0.328) | (0.069) | (0.000) | |
| Employees (t-1) | 0.032 | -0.003*** | 0.418* | 0.140* | 0.001 | |
| | (0.081) | (0.001) | (0.251) | (0.081) | (0.001) | |
| Leverage (t-1) | -0.823 | 0.008 | -1.552 | -0.394 | -0.004 | |
| | (0.731) | (0.008) | (1.305) | (0.756) | (0.006) | |
| Firm FE | Y | Y | Y | Y | Y | |
| Year FE | N | N | N | Y | Y | |
| N. firms | 71 | 71 | 71 | 71 | 71 | |
| N. observations | 325 | 325 | 325 | 325 | 325 | |
| R-squared | 0.18 | 0.38 | | 0.27 | 0.75 | |
| F-test (excluded instrument) | | | 4.82 | | | |
| Endogeneity test (p-val) | | | 0.0000 | | | |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 2.7:** IV-FE Regressions of Social Scores

| | (1) Without Year FE | | | (2) With Year FE | | |
|---|---|---|---|---|---|---|
| | Social Score | Female Share (1st Stage) | Social Score (2SLS) | Social Score | Female Share (1st Stage) | So |
| Female share | 36.324*** | | 118.195** | 8.753*** | | |
| | (4.661) | | (48.910) | (6.283) | | |
| Z | | -0.238** | | | -0.343*** | |
| | | (0.105) | | | (0.096) | |
| Degree | -0.055 | -0.001 | -0.126 | -0.330 | 0.004 | |
| | (0.478) | (0.007) | (0.718) | (0.445) | (0.004) | |
| I(Degree > 0) | 4.465** | 0.092*** | -2.735 | 3.937* | -0.009 | |
| | (2.209) | (0.029) | (5.397) | (1.998) | (0.020) | |
| Betweenness | 1.320*** | 0.015*** | 0.107 | 0.402 | -0.006 | |
| | (0.389) | (0.005) | (0.925) | (0.384) | (0.004) | |
| Board size | -0.675** | -0.016*** | 0.642 | -0.229 | 0.002 | |
| | (0.283) | (0.004) | (0.887) | (0.259) | (0.003) | |
| Independent board members | -0.160*** | 0.005*** | -0.527** | -0.148*** | 0.002*** | |
| | (0.057) | (0.001) | (0.234) | (0.050) | (0.000) | |
| Employees (t-1) | 0.104 | -0.003*** | 0.358** | 0.235*** | 0.001 | |
| | (0.065) | (0.001) | (0.179) | (0.059) | (0.001) | |
| Leverage (t-1) | -1.443** | 0.008 | -1.922** | -0.746 | -0.004 | |
| | (0.591) | (0.008) | (0.931) | (0.551) | (0.006) | |
| Firm FE | Y | Y | Y | Y | Y | |
| Year FE | N | N | N | Y | Y | |
| N. firms | 71 | 71 | 71 | 71 | 71 | |
| N. observations | 325 | 325 | 325 | 325 | 325 | |
| R-squared | 0.40 | 0.38 | | 0.56 | 0.75 | |
| F-test (excluded instrument) | | | 5.55 | | | |
| Endogeneity test (p-val) | | | 0.0005 | | | |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

# Chapter 3

# Missing Value Imputation in Environmental, Social, and Governance Data: An Impact on Emissions Scores

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**Abstract**

This paper addresses the challenge of missing value imputation in environmental, social, and governance (ESG) data from The London Stock Exchange Group (LSEG) and its impact on category scores. First, using simulations, I compare traditional and machine learning (ML) imputation methods and show that ML methods consistently outperform traditional imputation approaches. Applying these methods to missing real-world ESG data, I recalculate emission scores and uncover notable discrepancies from LSEG-reported values, suggesting that LSEG's methodology may unintentionally favor firms with more complete disclosures. Moreover, I identify a pattern that companies with larger market capitalization tend to have lower rates of missing data and receive higher emissions scores. These results show a potential missing data bias in ESG data that favors larger firms and the importance of imputing missing data with ML techniques to reach category scores that more closely capture actual sustainability performance.

## 3.1 Introduction

The demand for non-financial data is increasing as investors and policy makers seek to address ethical and environmental problems in the modern economy (Azémar and Giroud, 2023; Alliance, 2020; Khatib, 2024, 2025). ESG data sets have satisfied this demand, but not without controversy (Kotsantonis and Serafeim, 2019). To obtain consistent results, high-quality data is necessary, and the widespread occurrence of missing data challenges the accurate calculation of ESG scores with up to 50 percent of the key performance indicators (KPI) in ESG data affected by missing values (Berg et al., 2020; Refinitiv, 2022; Kotsantonis and Serafeim, 2019; Crippa, 2023). There are a growing number of studies that contribute theoretically by exploring methods of imputation of missing values in ESG data and its link to greenwashing (Caprioli et al., 2024; Gopal, 2020; Emmanuel et al., 2021).

Although previous studies have highlighted the importance of missing information in ESG datasets, relatively little is known about how alternative imputation methods affect the resulting ESG scores and the potential implications for firm evaluation. To address this gap, this study makes two principal contributions to the literature.

First, this study compares traditional and machine learning approaches for imputing missing values in LSEG's emissions dataset using a simulation framework to determine which methods most accurately recover missing observations. Second, it applies the best-performing imputation methods to real-world emissions data to examine how the treatment of missing values affects emissions scores and whether current scoring methodologies may introduce systematic biases related to firm size and disclosure completeness. Together, these analyzes provide new evidence on the role of missing data in ESG measurement and its implications for researchers and practitioners. This study specifically looks at the emissions category scores for LSEG dataset.

Although there is a growing literature on the benefits of ESG practices in financial and stock market performance (Saini et al., 2022; Sandberg et al., 2023; Tahmid et al., 2022; Cheng et al., 2019; Lian and Weng, 2024), there are other studies that show that ESG practices can have a negative or no relationship with firm performance (Duque-Grisales and Aguilera-Caracuel, 2021; Revelli and Viviani, 2015). The occurrence of missing data and their imputation could contribute to inconsistency of results (Sahin et al., 2022a). Machine learning (ML) models have been shown to be beneficial for estimating missing values. Recent advances in the analysis of big data using ML have created yet unexplored opportunities to apply ML to ESG data (Emmanuel et al., 2021; Maharana et al., 2022; Bryzgalova et al., 2022; Rubin, 1976; Caprioli et al., 2024; Gopal, 2020; Suresh et al., 2019).

A peer comparison-based ranking system within a sector, such as the London Stock

Exchange Group (LSEG), will be influenced by missing values (Refinitiv, 2022; Berg et al., 2020). This can lead to firms receiving higher ESG scores, not necessarily due to better performance, but simply because they provide more complete data than their peers. This goes against the claims of LSEG in their brochures and website, so it is in the interest of rating agencies as well to take seriously the problem of missing data (Refinitiv, 2022; London Stock Exchange Group, 2023). LSEG states that the transparency thresholds for the KPIs that are used in the calculation of category scores are 5 percent present for numerical data and 7 percent present for boolean data but does not infer any problem arising from missing data (Refinitiv, 2022).

Two potential approaches to assess the quality of an imputation method are simulation to predict known missing data and the use of imputed unknown data to predict other known variables. I first run a simulation comparing imputation methods, K Nearest Neighbors (KNN), Multiple Iteration Chain Equation (MICE), Decision Tree (DT), Simple Median imputation (Simple), and Zero imputation (Zero). The simulation shows that the machine learning methods, KNN, MICE, DT, outperform simple and zero imputation. These five models are then used to impute actual missing data in the LSEG ESG dataset where the true values are unknown. The imputed data set is used to recalculate the emission category score by applying the LSEG peer-ranking system. The new recalculated scores are compared with the original scores provided by LSEG to determine a divergence in scores based on the inclusion of imputed data.

ML models provide recalculated scores that differ from traditional simple median and zero imputation. This indicates that the scores provided by LSEG could not capture the overall sustainability performance due to the impact of missing data. In fact, ESG data are known to be biased in favor of larger firms (Dobrick et al., 2023), which could be due to missing data, as larger firms have more resources to collect and report information to rating agencies such as LSEG, and they are highly regulated by governments and are closely monitored by investors (Busch et al., 2024; Matsumura et al., 2014).

This study makes several key contributions to the growing literature on the imputation of missing ESG data. First, it adds to the ongoing discussion on imputation methods (see, for example,(Caprioli et al., 2024; Gopal, 2020; Emmanuel et al., 2021; Crippa, 2023)) by introducing an important but previously overlooked perspective: comparing imputed results with actual scores provided by LSEG. To date, the literature has largely overlooked this aspect, yet this comparison reveals that missing data in LSEG's dataset has an unacknowledged impact on category scores.

Additionally, this paper provides a simulation that compares different ML methods to impute missing values in the ESG data.

Furthermore, it contributes to the growing effort to identify the most effective methods to evaluate missing data in ESG datasets more broadly. Although the focus is on LSEG, the findings have the potential to inform approaches to address missing data issues from other ESG providers.

This paper is also the first to show a relationship between firms with higher market capitalization that tend to have a lower missing data percentage and higher emissions scores. This could indicate that missing data is one of the channels that causes the large firm bias in ESG scores detected by (Dobrick et al., 2023).

Finally, this research is important because policy makers, investors, and researchers use the emissions score and environmental pillar as a benchmark for overall climate impact (Organisation for Economic Co-operation and Development, 2022; Mazzotta and Brogi, 2021). They should take into account the missing data effect and its connection with market capitalization. These biases could result in portfolio distortion by favoring large-cap firms creating a capital feedback loop by investing in firms with better disclosure, not necessarily better emissions performance (Sahin et al., 2021; Akgun, 2021).

The remainder of the paper is organized as follows. Section 2 describes the data and methods used. Section 3 discusses the results, and Section 4 concludes.

## 3.2 Data

LSEG groups and ranks the KPIs into category scores that aggregate into pillars and then a final ESG score at the level of the industry group (Refinitiv, 2022). Industry groups are defined by the Refinitiv Business Classification Scheme (Refinitiv, 2022).

The emission category score is important because emission data tend to be reported and standardized consistently across different sectors (Kotsantonis and Serafeim, 2019; Berg et al., 2020). Emission data are key to the construction of the environmental pillar and are used regularly by investors as a proxy to measure the risk of climate change (Amel-Zadeh and Serafeim, 2018; Krueger et al., 2020).Category scores are the basis for the pillar scores, so any issue within a category score would also influence the pillar score and the final ESG score.

The data used in this analysis are from the global machinery sector and cover the years 2017 to 2023. The machinery industry group was selected because it has various regulatory environments, firm sizes, and emissions levels, making it ideal for evaluating the effect of missing data (Lavin and Montecinos-Pearce, 2021). Table A.1 displays all KPIs in the data set and the type of data, Boolean or numerical, and the percentage missing for that particular KPI. Further analysis was carried out using the 22 variables in the emission category shown

in Table A.2.

Tables 3.1 show the total missing values in the dataset. This indicates the potential missing information that is not being considered when calculating the ESG scores.

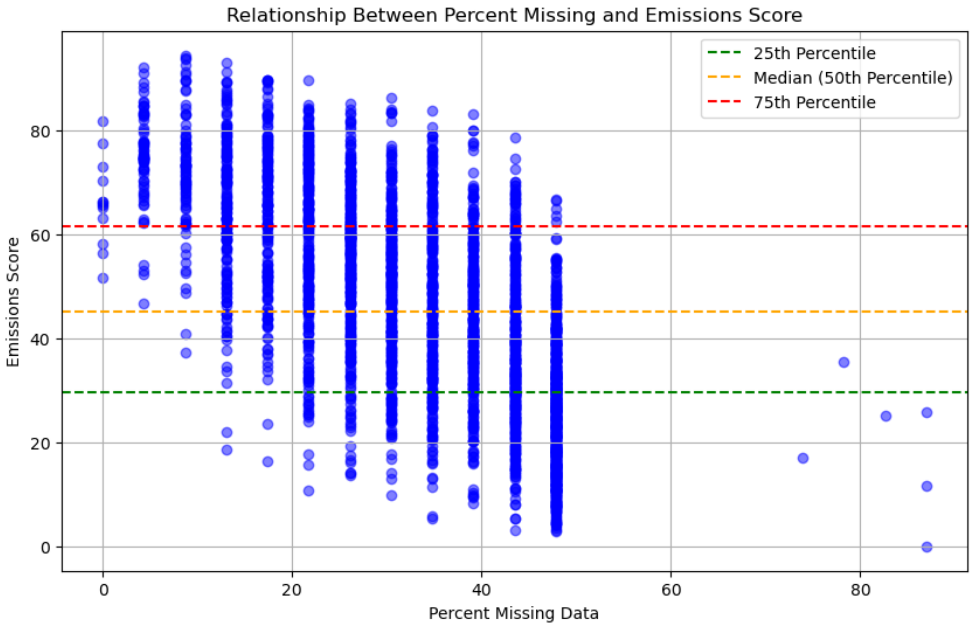
**Table 3.1:**
Missing Data Summary for Machinery Sector: 2017-2023

| Metric | Value |
|---|---|
| Total values in dataset | 453,492 |
| Total missing values | 98,646 |
| Total missing percentage | 21.75% |

*This table presents a summary of missing and present data for the Machinery sector over the 2017–2020 period.*

Figure 3.1 shows the relationship between missing data and emission category scores. This scatter plot indicates a negative relationship between missing data and emission scores. In addition, it shows that different quartiles of emission scores are characterized by different percentages of missing data. Quartiles with a higher percentage of missing data have lower emissions category scores.

**Figure 3.1:**
Missing Data and Emissions Category Score Scores 2017-2023



## 3.3 Imputation Methods

Different ML methods have been considered. First, KNN imputer uses a classification mechanism based on measuring the distance to the closest examples in a training data set (Emmanuel et al., 2021; Rahman and Davis, 2013; Hastie et al., 2009).

Second, the MICE imputer is a method for taking multiple estimates of an imputation and creating a distribution of the results.

Third, DT imputer is non-parametric and predicts a value by learning simple decision rules from data features. It is also referred to as a piecewise constant approximation (Pedregosa et al., 2011a; Suresh et al., 2019; Woods et al., 2021).

In addition to ML methods, the results for Simple Median Imputation (Simple), which uses the median of a column to fill in place of missing data (Emmanuel et al., 2021). Finally, Zero imputer is the imputation of a zero in place of missing data (Emmanuel et al., 2021). A more detailed description of the methods can be found in Appendix B.

These ML models were chosen for being less complex compared to black-box models such as random forest or gradient boosting models (Lantz, 2019; van Buuren and Groothuis-Oudshoorn, 2011; Molnar, 2022). This helps to create a baseline on which to build on with future research (Jerez et al., 2010; Saar-Tsechansky and Provost, 2007; Molnar, 2022).

## 3.4 Empirical Set-Up

The five methods are compared by simulation. The simulation analyzes the data for 2017 to 2023 together and then again for each year separately. This simulation assumes that the data are completely missing at random, which, I acknowledge, may not be the case for ESG datasets (Gopal, 2020). Ten percent of the known data are removed. Each method is then used to predict the missing ten percent. The simulation is performed on an aggregate level, evaluating all the data together and also on a yearly basis. This is done to check for variations over time. Some ML methods can also perform better with more data. The aggregate measure gives more weight to years that have more data (Hyndman and Koehler, 2006). However, computing by year takes into account changes that could take place from year to year (Kowarik and Templ, 2016). Different ML models also perform better or worse depending on the total amount of data used (Bernico et al., 2019). Each execution of the simulation consisted of five iterations. The complete simulation was then repeated six times using different random seeds, generating different missing-data patterns for each repetition. Consequently, the results reported in Table 2 represent the average over 30 independent simulation iterations, thereby reducing the influence of any single random realization.

The predicted value for each method is compared with the real value using the root mean squared error (RMSE) and $R^2$ evaluation metrics. These methods are commonly used to compare the performance of ML models (Jerez et al., 2010). The lower the RMSE the higher the similarity the predicted values have to the known values. The closer $R^2$ is to 1, the more accurate the method predicts missing values.

The five approaches are used again to impute actual missing data in the data set. This data is then used to recalculate the category scores for the emission category. Recalculation is performed following the LSEG methodology to assess category scores (Refinitiv, 2022). To compare the recalculated scores for each method with the original scores, the scores are organized into quartiles (which also correspond to the ESG ratings categories for LSEG). Each quadrant corresponds to an LSEG letter rating, A,B,C,D (Refinitiv, 2022) being equivalent to quartiles 4,3,2,1. This enables for the comparison of the scores with imputed data with the original scores using a confusion matrix. The confusion matrix determines whether a score from the original data set remained in the same quartile (or letter grade) after using imputed data. The number of scores that remained in the same quartile after imputation is divided by the total number of scores compared in the confusion matrix. This percentage is referred to as the accuracy score. The accuracy score is used to determine the amount of divergence created by the recalculated scores for each of the imputation approaches. The accuracy scores do not imply a closer prediction to a ground truth but show a bias in the data regarding missing values. I also acknowledge that regulatory environments or listing standards influence the completeness of the data. Analyzing this would require data organized by country, which is beyond the scope of this paper.

To ensure consistency with the LSEG methodology, the category scores were recalculated using the same underlying KPI scoring and aggregation procedure described by LSEG. The present analysis is conducted exclusively at the category level (i.e., prior to the application of sector-specific category weightings used to construct overall ESG scores). Consequently, the sector-dependent weighting mechanisms do not affect the recalculated category scores examined in this study. For comparison purposes, both the original and imputed datasets were processed using the same category-level calculation methodology, ensuring that any observed differences arise solely from the treatment of missing data rather than differences in the weighting scheme. A summary of the LSEG ESG score construction methodology and its relationship to the category-level calculations used in this study is provided in Appendix E.

Finally, a fixed-effects regression is estimated that connects missing emission score data with market capitalization.

$$\text{EmissionsMissing}_i = \beta_0 + \beta_1 \cdot \text{MarketCap}_i + \beta_2 \cdot \text{EPS}_i + \beta_3 \cdot \text{OpProfit}_i + \beta_4 \cdot \text{CertDummy}_i + \gamma_{\text{year}} + \varepsilon_i \tag{3.1}$$

$\text{EmissionsMissing}_i$ is the percentage of missing emissions data by firm per year. $\text{MarketCap}_i$ is the variable of interest that is the market capitalization of each firm by year. Earnings per share ($\text{EPS}_i$), operating profit ($\text{OpProfit}_i$) and ($\text{CertDummy}_i$) are control variables inspired by (Dobrick et al., 2023). ($\text{CertDummy}_i$) is a dummy variable that is 1 if a firm has some percentage of its activities covered by a Quality Management System (QMS) and an Environmental Management System (EMS) and 0 if not. $\gamma_{\text{year}}$ represents year fixed effects (absorbed) and $\varepsilon_i$ is the error term. The control variables were inspired by the regression used by (Dobrick et al., 2023) when measuring size bias in ESG data. Firm-level control was not applied because firm-fixed effects absorb all time-invariant characteristics of each firm (Wooldridge, 2010). In this case, I want to capture the fact that larger firms generally have fewer missing data than smaller firms, and a firm-fixed effect would prevent that.

## 3.5 Main Results

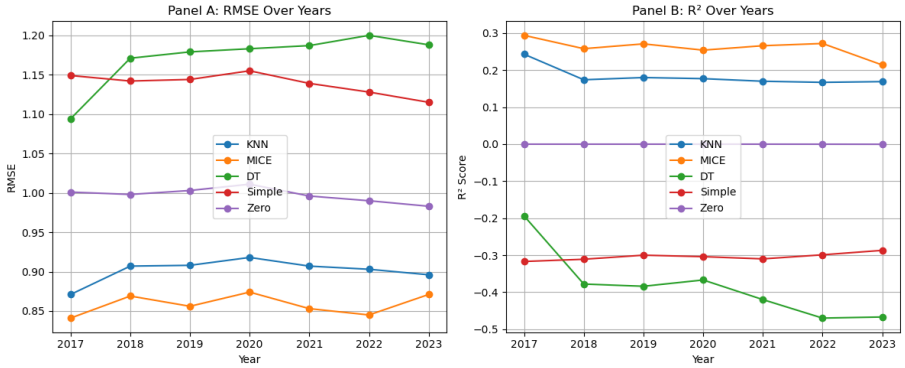
The results of the five methods suggest that KNN is the best performer w.r.t. RMSE and $R^2$ metrics; see Table 3.2. KNN has both the lowest RMSE and the $R^2$ closest to 1, with values of 0.601 and 0.635, respectively. The Simple Imputer is the worst performing method, according to this simulation, though it is commonly used. Figure 3.2 is a simulation of the same data set by year. The MICE model has performed best for most years. The simple and zero imputation methods still perform worse than the KNN and MICE models. In addition, there is a decrease in the comparative performance of the DT model when the data are analyzed by year. This could be due to some ML models performing better with more data. However, a pattern still persists that ML outperforms traditional approaches.

**Table 3.2:**
Simulation of Imputation Methods Aggregate Metrics

| Imputer | RMSE | $R^2$ |
|---|---|---|
| KNN Imputer | 0.601 | 0.635 |
| MICE Imputer | 0.759 | 0.419 |
| Decision Tree Imputer | 0.874 | 0.227 |
| Simple Imputer | 1.085 | -0.192 |
| Zero Imputer | 0.995 | 0.000 |

*This table compares the RMSE and $R^2$ metrics for different imputation methods.*

**Figure 3.2:**
RMSE and $R^2$ for each Imputation model by Year




Based on the results of the simulation, I evaluate how these approaches perform when imputing actual missing data.

**Table 3.3:**
Accuracy Values by Year

| Imputer | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
|---|---|---|---|---|---|---|---|
| KNN All Data | 0.38 | 0.39 | 0.37 | 0.38 | 0.38 | 0.40 | 0.37 |
| MICE All Data | 0.47 | 0.46 | 0.42 | 0.41 | 0.42 | 0.39 | 0.37 |
| Decision Tree Data | 0.50 | 0.56 | 0.54 | 0.47 | 0.47 | 0.48 | 0.42 |
| Simple All Data | 0.66 | 0.73 | 0.58 | 0.55 | 0.53 | 0.53 | 0.46 |
| Zero All Data | 0.86 | 0.87 | 0.84 | 0.81 | 0.80 | 0.73 | 0.67 |

*This table shows the accuracy values from the confusion matrices by year, comparing predicted values from the model with the actual scores from LSEG.*

The category scores that are recalculated with the imputed data correspond to different levels of accuracy to the original scores based on the approach used to impute. The less accurate approaches in the simulation, zero/simple imputation, have the highest level of similarity to the original scores, as expected. More accurate models of imputation, KNN,

MICE, have lower levels of accuracy when compared to the original scores. Table 3.3 shows these trends, presenting each model's accuracy score for each year from 2017 to 2023. To state this more directly, as the quality of imputation increases, the similarity of the recalculated scores to the original score decreases.

Figure 3.3 shows the comparison of scores by quartile and Table 3.4 shows the Pearson's correlation coefficient for the data.

**Figure 3.3:**
Comparison of Actual vs Predicted Scores by Quartile (2017)

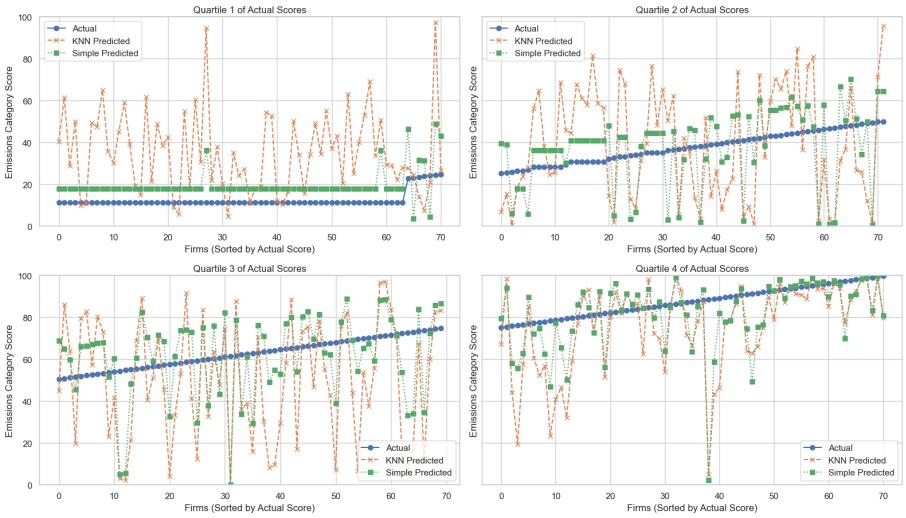



**Table 3.4:**
Correlation by Quartile

| Quartile | Correlation KNN | Correlation Simple | Avg Actual Score |
|---|---|---|---|
| 1 | -0.055 | 0.483 | 12.5 |
| 2 | 0.046 | 0.297 | 37.7 |
| 3 | 0.023 | 0.203 | 62.7 |
| 4 | 0.484 | 0.381 | 87.5 |

*This table shows the correlation between predicted and actual scores by quartile, for both KNN and simple approaches, along with the average actual score.*

Table 3.5 shows the trend that the firms with the highest market capitalization have the least missing data and the highest emissions scores. This supports the argument that missing data could be one possible channel for the size bias in ESG data.

**Table 3.5:**
Average Actual, KNN, Simple scores by Quartile with Market Cap, and Emissions Missingness (2017–2021)

| Year | Quartile | Actual | KNN | Simple | Market Cap | Emissions % |
|---|---|---|---|---|---|---|
| 2017 | 1 | 87.5 | 75.6 | 81.6 | 9.75e+11 | 19.85 |
| 2017 | 2 | 62.7 | 50.0 | 61.6 | 2.43e+11 | 36.23 |
| 2017 | 3 | 37.7 | 39.4 | 37.5 | 2.84e+11 | 46.28 |
| 2017 | 4 | 12.5 | 35.1 | 19.6 | 7.96e+10 | 51.15 |
| 2018 | 1 | 87.5 | 80.6 | 85.1 | 7.83e+11 | 19.37 |
| 2018 | 2 | 62.5 | 45.7 | 59.6 | 2.19e+11 | 34.39 |
| 2018 | 3 | 38.4 | 38.4 | 38.9 | 5.59e+10 | 43.79 |
| 2018 | 4 | 13.3 | 35.5 | 17.8 | 1.47e+11 | 49.28 |
| 2019 | 1 | 87.4 | 73.8 | 78.8 | 7.92e+11 | 20.29 |
| 2019 | 2 | 62.4 | 48.1 | 58.4 | 1.65e+11 | 33.95 |
| 2019 | 3 | 37.6 | 39.3 | 42.9 | 1.20e+11 | 40.58 |
| 2019 | 4 | 12.6 | 38.6 | 20.0 | 1.42e+11 | 49.49 |
| 2020 | 1 | 87.5 | 74.6 | 78.6 | 1.08e+12 | 21.06 |
| 2020 | 2 | 62.5 | 52.9 | 61.3 | 1.45e+11 | 32.88 |
| 2020 | 3 | 37.6 | 35.0 | 40.6 | 1.04e+11 | 40.57 |
| 2020 | 4 | 12.6 | 37.5 | 19.7 | 2.68e+11 | 48.57 |
| 2021 | 1 | 87.5 | 75.1 | 78.9 | 1.26e+12 | 19.23 |
| 2021 | 2 | 62.5 | 50.9 | 59.3 | 7.37e+10 | 32.48 |
| 2021 | 3 | 37.6 | 37.5 | 41.5 | 2.57e+11 | 39.85 |
| 2021 | 4 | 12.6 | 36.5 | 20.4 | 3.23e+11 | 47.99 |
| 2022 | 1 | 87.4 | 75.1 | 78.1 | 7.90e+11 | 22.61 |
| 2022 | 2 | 62.3 | 52.7 | 58.3 | 7.94e+11 | 31.33 |
| 2022 | 3 | 37.3 | 38.3 | 43.4 | 2.20e+11 | 35.14 |
| 2022 | 4 | 12.4 | 33.6 | 19.7 | 1.66e+11 | 40.21 |
| 2023 | 1 | 87.6 | 72.9 | 75.1 | 4.66e+11 | 28.04 |
| 2023 | 2 | 62.8 | 50.6 | 56.9 | 4.23e+11 | 31.31 |
| 2023 | 3 | 38.0 | 41.8 | 46.2 | 1.64e+11 | 29.98 |
| 2023 | 4 | 12.7 | 35.4 | 22.6 | 7.40e+10 | 34.12 |

*This table presents actual scores, KNN and simple predicted scores, along with market capitalization and emissions missingness over the 2017–2023 period.*

**Table 3.6:**
Regression on Emissions Data Missingness (Standardized Variables)

| Variable | Coefficient | Std. Error | t | p-value |
|---|---|---|---|---|
| Market Cap (z) | -0.1119 | 0.0162 | -6.93 | 0.000 |
| Earnings per Share (z) | 0.0317 | 0.0162 | 1.96 | 0.050 |
| Operating Profit (z) | -0.0512 | 0.0164 | -3.11 | 0.002 |
| Certification Dummy | -1.0310 | 0.0330 | -31.29 | 0.000 |
| Constant | 0.3560 | 0.0192 | 18.52 | 0.000 |
| Fixed Effects: Year (absorbed) | | | | |
| Observations: 2,930 | | | | |
| $R^2 = 0.2923$ Adjusted $R^2 = 0.2899$ Root MSE = 0.8406 | | | | |

*Note: Dependent variable is standardized emissions missingness. All continuous variables are standardized. Year fixed effects are absorbed.*

Table 3.6 shows that market capitalization has an inverse relationship with missing data in the emission category score. The result is significant.

## 3.6 Conclusion and Further Development

Using different imputation methods, I highlight the impact of missing data in computing ESG category scores from LSEG. More sophisticated ML methods provide imputed data that lead to a significant deviation from the original LSEG scores. This indicates that there is missing data bias that rewards firms for providing more data and not necessarily an accurate representation of their sustainability performance. I also show that the firms that provide less missing data have a higher market capitalization. Refinement of imputation models is essential to capture the effect of missing data in ESG datasets. In addition, creating simulations with missing patterns that more closely reflect the missing patterns in the ESG data would improve further analysis.

# Chapter 4

# The Role of Missing Emissions Data as a Priced Risk Factor

This chapter is co-authored with Juan-Angel Jimenez-Martin, with the author as first and corresponding author. A version of this chapter is currently under review at *Economic Modelling*.

The research was presented at the **12th International Conference on CSR, Sustainability, Ethics, and Governance**, Limerick, Ireland, 17–19 June 2026.

**Abstract**

This paper examines how missing emissions data affects the pricing of environmental information in equity markets. Using firm-level data from 23 developed countries during the period 2015-2023, we constructed two systematic risk factors, an Emission Factor and a Missing Data Factor, within a Fama-French-style portfolio sorting procedure, which jointly control size, exposure to emissions, and disclosure quality. We show that the missing emission factor is highly priced and exhibits return dynamics that closely mirror those of the emissions factor. We further construct a framework inspired by Goldstein and Yang (2017) how the missingness and emissions score influence the returns. Our findings caution against interpreting emissions-based return premia as clean evidence of priced carbon risk without accounting for data construction and disclosure.

## 4.1 Introduction

A growing asset pricing literature examines whether environmental, social, and governance (ESG) characteristics represent priced risk factors in equity markets. In this literature, cor-

porate carbon emissions have received particular attention, motivated by climate policy risk, uncertainty in transition, and growing investor demand for sustainable investment strategies. Early studies document a positive "carbon premium," in which companies with higher emissions earn higher average returns, consistent with investors who require compensation for regulatory and transition risks (Bolton and Kacperczyk, 2021).

However, this interpretation has been challenged by (Aswani et al., 2024), who show that the carbon premium is highly sensitive to emissions measurement choices and data sources. In particular, the return–emissions relationship disappears largely when using firm-disclosed emissions rather than data collected by a ratings agency like the London Stock Exchange Group (LSEG), Bloomberg, or Sustainalytics, suggesting that emissions premia may reflect data construction and disclosure patterns rather than priced environmental risk. At the core of this disagreement is the quality of information that is being used to assess the carbon impact of firms.

This paper builds on this critique by explicitly examining the role of missing emissions data. We show that emissions-based factors are closely linked to disclosure patterns and that missingness itself is a priced characteristic in equity markets. By constructing a Missing Emissions factor alongside a conventional emissions factor, we demonstrate that disclosure gaps are a central mechanism underlying emissions-related return premia. Our analysis uses emissions data and scores from the LSEG ESG database.

The implications of asset pricing of the characteristics of ESG are described by (Giese et al., 2019, 2021), who argue that ESG affects the valuation of assets through three channels: cash-flow effects, risk (discount-rate) effects, and investor preference effects. Importantly, this framework emphasizes that the effects of ESG depend critically on measurement choices, sectoral exposure, and data quality. (Giese et al., 2021) states that the key issues that underlie the E pillar score include issues related to the management of carbon emissions.

Within this framework, missing emissions data can influence returns primarily through all three channels. High missingness increases the uncertainty about environmental exposure of firms, obscuring future regulatory costs and transition risks. This raises the estimation risk and perceived downside risk, leading investors to demand higher expected returns. In contrast, firms with more complete emissions disclosure reduce information asymmetry and uncertainty, potentially lowering required returns. Poor disclosure quality will also influence the confidence of sustainable investors in the emissions score as a reliable benchmark for firm environmental performance.

This paper builds on the logic of (Grossman and Stiglitz, 1980; Goldstein and Yang, 2017): in markets where information is costly or imperfect, prices reflect not only fundamentals but also the availability and quality of data. Missing emissions data, by shaping investor

expectations and influencing factor construction, can thus behave like a priced signal rather than mere noise.

(Pástor et al., 2021) develop an equilibrium model for sustainable investment in which sustainable investors are willing to accept lower expected returns in exchange for holding portfolios that better reflect their values. Despite the lower expected return for sustainable investment strategies, green assets still outperform when positive shocks hit the ESG factor, which captures changes in customers' tastes for green products and investors' tastes for green holdings (Pástor et al., 2022; Pástor et al., 2021).

This paper draws on the valuation channels described by (Giese et al., 2019), the information risk model by (Goldstein and Yang, 2017), and the sustainable equilibrium model by (Pástor et al., 2021) to explain how missing data in LSEG's emissions category are priced in excess returns.

Further, the disclosure literature suggests that emissions non-reporting is unlikely to be random. (Olesiewicz et al., 2021) model carbon disclosure as missing not at random using machine learning and demonstrate that non-disclosure correlates systematically with firm characteristics, implying that naive treatment of missing data induces bias. (Ma et al., 2024) provide evidence from China that the disclosure of carbon itself conveys information interpreted by investors. They find that the quality of carbon information can alter a firms stock price. More broadly, (Goldstein and Yang, 2017) show in noisy rational expectations models that equilibrium expected returns depend on information precision. These studies collectively imply that emissions missingness may affect expected returns not only through underlying transition exposure, but also through disclosure-induced information risk. The model used in this paper is solved under a Rational Expectations Equilibrium (REE) in which prices aggregate the information available to market participants.

(Sahin et al., 2022b) provide a seminal contribution by demonstrating that missing ESG data is neither random nor meaningless. Using LSEG firm-level ESG data, they show that conventional ESG scores implicitly treat missing values as neutral and introduce an explicit "missing pillar" to capture non-disclosure behavior. Importantly, (Sahin et al., 2022b) establish that missingness itself conveys information and should be treated as a firm characteristic rather than a data limitation.

Complementing this insight, (Benuzzi et al., 2025) show that the ESG outcomes are highly sensitive to the methodological choices used to handle missing data. Using detailed ESG key performance indicators (KPIs), they demonstrate that common practices, such as zero-imputation and score rescaling, mechanically alter ESG scores, firm rankings, and correlations across pillars. KPIs are the base variables that LSEG collects to construct their scores. In particular, treating missing values as zeros artificially strengthens the correlations

between ESG dimensions. Together, these papers establish that missing ESG data is a structural feature of ESG datasets and a key driver of empirical ESG results. They also imply that asset pricing tests using ESG scores may inadvertently price disclosure behavior rather than fundamental sustainability characteristics.

This paper builds directly on the insights of (Sahin et al., 2022b) and (Benuzzi et al., 2025) by examining whether missing emissions data is priced in equity markets. While (Sahin et al., 2022b) shows that missing ESG data is informative at the score level and (Benuzzi et al., 2025) demonstrate that missing data treatment materially alters ESG measures, we extend these insights to asset pricing factor construction and return predictability.

(Downing, 2025) highlights that missing emissions data specifically distorts emissions scores and conventional imputation choices can systematically overstate or understate firm-level emissions. (Caprioli et al., 2024) further demonstrate that conventional handling or ignoring of missing ESG data and, by extension, emissions data, distorts scores underscoring that missing data can meaningfully shape asset pricing tests. (Gopal, 2020) also found that the imputation of missing data in ESG datasets had a downstream application in firm performance and portfolio allocation, indicating the presence of a distorting effect caused by the missing data itself.

Our approach also draws on the literature that examines how ESG factors should be constructed and what they truly capture. (Yang and Jiménez-Martin, 2022) show that the performance of the ESG factor depends critically on whether raw data, aggregated scores, or specific methodological choices are used in factor construction. They emphasize that ESG "risk factors" are not invariant objects but are shaped by data availability and modeling decisions. Similarly, (Lioui and Tarelli, 2022) argue that ESG factors often reflect broader economic characteristics such as industry composition, size, or growth opportunities—rather than pure sustainability risk. Their work cautions against interpreting ESG factor returns without careful consideration of the underlying data structure. We add to this line of thinking by including missing data into the variables necessary for consideration when construction Emissions or ESG risk factors.

We construct a missing emission factor and an emissions factor within a Fama–French-style framework and examine their joint pricing implications. We built two emissions factors, one based on the LSEG emissions scores and the other based on the total CO2 emissions data also provided by LSEG. Through these factors, we are able to control for both firm size and influences of missingness and emissions scores on each other. We show that the missing emission factor is highly priced and exhibits return dynamics that closely mirror those of the emissions factor. Once missingness is explicitly accounted for, the standalone pricing effect of emissions scores weakens substantially. We further construct a framework inspired by

(Goldstein and Yang, 2017) how the missingness and emissions score influence the returns.

These findings suggest that emissions premia partly reflect disclosure-related risk rather than pure environmental exposure. More broadly, our results highlight that emissions data quality and missingness in particular is a major concern for asset pricing research and should be given direct analysis to determine it's effects rather than treated as an implementation detail.

Furthermore, our findings highlight that emissions scores cannot be interpreted independently of disclosure quality. Failure to account for missing emissions data risks conflating environmental performance with reporting behavior, potentially overstating or mischaracterizing the nature of carbon-related risk premia.

This research is relevant to anyone who relies on emissions data as a benchmark for evaluation or decision-making. For investors, emissions metrics are often used to construct portfolios, manage climate-related risk exposure, and satisfy sustainability requirements. If emissions scores embed disclosure patterns or missing data effects, portfolio allocations may reflect reporting behavior rather than true environmental risk. For policymakers and regulators, emissions data are increasingly used to monitor corporate performance, design climate-related regulations, and assess progress toward environmental targets. Understanding how missingness affects these measures is therefore essential for ensuring that policy decisions are based on accurate signals. For academic researchers, the findings highlight the importance of accounting for data construction and disclosure quality when using emissions variables in empirical analysis, particularly in studies of asset pricing, corporate performance, and climate risk.

This paper is organized as follows. Section 2 presents the theoretical framework and methodology, Section 3 describes the data, Section 4 presents the results, and Section 5 concludes.

## 4.2 Theoretical framework

### 4.2.1 Theoretical framework: emissions, missingness, and asset pricing

This section develops a conceptual framework linking (i) emissions-related transition risk, (ii) disclosure-induced information risk arising from emissions data missingness, and (iii) their interaction in asset pricing. First, we describe how emissions exposure affects firm value through transition risk. Second, we introduce emissions disclosure quality and measurement noise. Third, we decompose total uncertainty into transition-related and disclosure-related

components. Fourth, we map these components into an equilibrium asset-pricing representation. Finally, we derive three testable implications: an emissions premium, a missingness premium, and a conditional interaction between the two.

We build on the ESG asset-pricing framework of (Giese et al., 2019, 2021), who argue that ESG characteristics affect equity returns through three channels: (i) cash-flow effects, (ii) risk (discount-rate) effects, and (iii) investor preference effects. Their empirical analysis uses MSCI ESG ratings for more than 1,600 large- and mid-cap developed-market firms in the MSCI World Index from December 2006 to December 2019, controlling for size and industry. Adapting this framework to corporate emissions, we distinguish between emissions exposure and emissions missingness as related but distinct sources of priced information.

Corporate emissions proxy for exposure to transition and regulatory risk because they are linked to the likelihood of future regulation, technological substitution, and shifts in consumer demand. High-emission firms face greater expected carbon pricing, compliance costs, capital expenditures for abatement, and potential stranded assets (Gollier and Tirole, 2015; Pástor et al., 2021; Bolton and Kacperczyk, 2021). Through the cash-flow channel, higher emissions therefore reduce expected future cash flows by increasing operating and investment costs associated with environmental adjustment. (Pástor et al., 2021) show that climate risk can command a premium when perceived as systematic, but that realized return patterns depend on investor beliefs and sustainability preferences.

Emissions also affect the riskiness of cash flows. Uncertainty about the timing and severity of climate policy, the pace of technological change, and demand reallocation increases earnings volatility and downside risk for high-emission firms (Bolton and Kacperczyk, 2021; Giese et al., 2019, 2021). If transition risk is systematic, exposure to emissions commands a risk premium in equilibrium (Pástor et al., 2021; Bolton and Kacperczyk, 2021). (Bolton and Kacperczyk, 2021) states that the stocks of firms with high emissions are shunned by socially responsible investors and that the resulting exclusion of these firms presents higher stock returns.

When emissions are accurately measured and fully disclosed, standard asset-pricing intuition therefore predicts a positive relationship between emissions and expected returns: emissions proxy for systematic transition risk, and investors require compensation for bearing it.

However, recent theoretical and empirical work highlights an important qualification for this prediction. In equilibrium models with investor preferences for sustainability, such as (Pástor et al., 2021; Pástor et al., 2022), green assets can command lower expected returns because they are preferred by investors and therefore become relatively expensive. In these frameworks, investor demand for sustainable assets acts similarly to a non-pecuniary

preference, driving up prices and compressing expected returns for greener firms.

At the same time, empirical evidence suggests that realized returns on green assets have, at least over certain periods, been higher than those of brown assets (Pástor et al., 2022). This apparent contradiction arises because changes in investor preferences—specifically, increasing demand for sustainable investing—generate capital gains for green firms. As demand for sustainable assets rises unexpectedly, their prices increase, leading to realized returns that exceed those implied by long-run equilibrium risk premia. Conversely, brown assets may experience negative revaluation effects as they become less desirable (Pástor et al., 2021; Pástor et al., 2022).

This distinction between expected and realized returns is crucial for interpreting emissions-related return patterns. While transition risk models predict that high emission firms should offer higher expected returns as compensation for risk, periods of increasing demand for sustainability can generate higher realized returns for low emission (green) firms. As a result, observed return differentials may reflect both risk premia and demand-driven price dynamics.

In practice, emissions data are frequently incomplete and missing not at random. Missingness correlates with firm size, governance quality, regulatory exposure, and expected performance (Sahin et al., 2022b; Olesiewicz et al., 2021; Caprioli et al., 2024; Downing, 2025; Gopal, 2020; Ma et al., 2024). Moreover, ESG score construction methodologies can mechanically embed disclosure patterns through imputation and normalization procedures (Benuzzi et al., 2025). As a result, observed emissions measures reflect both environmental performance and reporting behavior. (Caprioli et al., 2024), through the use of machine learning imputation indicates that missing data could prevent analysts from objectively differentiating companies' performance in terms of ESG Scoring

Missing emissions data affect asset pricing through two related mechanisms. First, non-disclosure may itself be informative. Firms can strategically withhold emissions information in response to regulatory, reputational, or cost considerations (Ma et al., 2024; Sahin et al., 2022b). In this case, the absence of emissions data conveys information about the underlying exposure to transition risk and disclosure incentives (Olesiewicz et al., 2021; Caprioli et al., 2024).

Second, incomplete disclosure increases estimation risk. When investors face imperfect or noisy information about fundamentals, equilibrium prices reflect the precision of available information. In the Grossman–Stiglitz framework, imperfect information must be compensated in equilibrium because investors require a premium to hold assets whose payoffs are more difficult to estimate (Grossman and Stiglitz, 1980). More broadly, models of information disclosure and noisy rational expectations show that expected returns depend on the precision of public and private signals available to investors (Goldstein and Yang, 2017).

Foundational information-risk models similarly demonstrate that lower disclosure quality increases required returns by raising uncertainty about future cash flows (Easley et al., 2004; Lambert et al., 2007). Emissions missingness therefore contributes to a distinct information-risk premium.

Emissions exposure and emissions missingness interact in determining expected returns. In a noisy rational expectations equilibrium, prices aggregate information from multiple signals, and the precision of public disclosure affects how strongly fundamentals are reflected in prices (Goldstein and Yang, 2017). When emissions are observed with high precision, measured exposure closely reflects true transition risk, and pricing primarily operates through the systematic risk channel. When emissions are missing or measured with noise, total valuation uncertainty increases because investors must infer both the level of emissions exposure and the reliability of disclosure. In such settings, expected returns reflect both transition risk and information risk, and the pricing of emissions depends on disclosure quality.

Taken together, this framework yields three empirical implications. First, firms with higher emissions exposure should earn higher expected returns, reflecting compensation for transition risk. Second, firms with greater emissions data missingness should earn higher expected returns, reflecting disclosure-induced information risk. Third, the emissions premium is conditional on disclosure quality and is strongest when emissions are more precisely disclosed.

### 4.2.2 Fundamentals and Transition Risk

We develop a unified asset pricing framework in which (i) emissions exposure affects firm cash flows through transition risk, and (ii) missing emissions data affects the precision with which investors infer that exposure.

The model embeds an emissions disclosure structure into a standard noisy rational expectations environment. We follow the Constant Absolute Risk Aversion (CARA) normal setup also adding a term to account for emissions preferences, and equilibrium derivations follow standard arguments in the noisy rational expectations literature (see, (Goldstein and Yang, 2017). The model combines preference-based ESG demand in the spirit of (Pástor et al., 2021) with a noisy rational expectations framework based on (Goldstein and Yang, 2017), allowing emissions exposure to be both economically relevant and imperfectly observed.

There are two dates, $t = 1$ and $t = 2$. At $t = 1$, a risk-free asset and a risky asset trade competitively. The risky asset is in fixed supply $Q \geq 0$ and pays stochastic cash flow $\tilde{v}_i$ at $t = 2$.

Let $\tilde{E}_i$ denote firm $i$'s true (unobserved) emissions exposure. Emissions affect firm value

because they influence expected future cash flows through carbon pricing, regulatory compliance costs, technological substitution, and stranded asset risk.

We model the risky payoff as

$$\tilde{v}_i = \bar{v} - \phi \tilde{E}_i + \tilde{u}_i, \tag{4.1}$$

where $\bar{v}$ is a deterministic baseline payoff, $\phi > 0$ measures the sensitivity of firm value to emissions exposure and $\tilde{u}_i \sim \mathcal{N}(0, \tau_u^{-1})$ captures non-climate fundamentals.

Assume

$$\tilde{E}_i \sim \mathcal{N}(\mu_E, \tau_E^{-1}). \tag{4.2}$$

with $\tilde{E}_i$ and $\tilde{u}_i$ independent. The parameter $\tau_E$ denotes prior precision about emissions exposure, and $\tau_u$ captures non-climate fundamental risk.

The unconditional variance of firm value equals

$$\mathrm{Var}(\tilde{v}_i) = \phi^2 \tau_E^{-1} + \tau_u^{-1}. \tag{4.3}$$

Higher emissions exposure increases payoff sensitivity to transition shocks and therefore increases economic risk.

### 4.2.3 Emissions Disclosure and Missingness

The key innovation of the model is the structure of emissions disclosure. Investors do not observe $\tilde{E}_i$ directly. Instead, they observe a publicly reported emissions signal

$$\tilde{y}_i = \tilde{E}_i + \tilde{\eta}_i, \; with \; \tilde{\eta}_i \sim \mathcal{N}(0, \tau_{\eta,i}^{-1}), \tag{4.4}$$

where $\tilde{y}_i$ denotes the firm's reported emissions disclosure and $\tilde{\eta}_i$ captures reporting noise, estimation error, or incomplete coverage. $\tau_{\eta,i}$ denotes disclosure precision. Higher $\tau_{\eta,i}$ implies more reliable emissions reporting. We assume that disclosure precision depends on emissions data completeness:

$$\frac{\partial \tau_{\eta,i}}{\partial M_i} < 0, \tag{4.5}$$

where $M_i$ measures the missingness of emissions data. This assumption is economically and empirically grounded. Incomplete emissions reporting typically reflects boundary exclusions, estimation gaps, or unverified components, all of which increase measurement variance. Higher $M_i$ indicates a higher percentage of missing data. Empirically, firms with lower sus-

tainability disclosure quality exhibit greater dispersion and disagreement in environmental ratings (Christensen et al., 2021), while carbon-intensive firms with less transparent disclosure exhibit stronger pricing of carbon risk (Bolton and Kacperczyk, 2021). More broadly, information precision is a central determinant of asset pricing in noisy rational expectations models (Goldstein and Yang, 2017).

Thus, emissions exposure determines economic risk, while missingness determines informational precision.

### 4.2.4 Information Structure

In the spirit of (Goldstein and Yang, 2017), there are three types of traders:

- Informed traders (mass $\mu \in [0, 1]$),
- Uninformed traders (mass $1 - \mu$),
- Liquidity traders supplying $\tilde{x} \sim \mathcal{N}(0, \tau_x^{-1})$. The noise trading provides the randomness that makes the rational-expectation equilibrium partially revealing, which is crucial to sustain trading in equilibrium as stated in (Goldstein and Yang, 2017).

Informed trader $j$ observes a private signal, $\tilde{s}_j$, of the value of a company:

$$\tilde{s}_j = \tilde{v}_i + \tilde{\varepsilon}_j, \; with \, \tilde{\varepsilon}_j \sim \mathcal{N}(0, \tau_\varepsilon^{-1}). \tag{4.6}$$

The private signal $\tilde{s}_j$ is an unbiased but noisy signal of the firm's terminal payoff, where $\tilde{\varepsilon}_j$ represents idiosyncratic information noise with precision $\tau_\varepsilon$. $\tilde{v}_i$ denotes the true stochastic terminal payoff (fundamental value) of firm $i$ at time $t = 2$. All shocks are mutually independent. All strategic traders have CARA utility with risk aversion $\gamma > 0$. The subscript $i$ indexes firms, while $j$ indexes investors.

### 4.2.5 Equilibrium Pricing

As Goldstein and Yang (2017), we conjecture a linear rational expectations equilibrium price of the form

$$\tilde{p}_i = p_0 + p_y \tilde{y}_i + p_v \tilde{v}_i + p_x \tilde{x}, \tag{4.7}$$

The coefficients $p_0, p_y, p_v$, and $p_x$ are equilibrium constants determined by rational expectations and market clearing. According to Equation 4.7, the asset price depends on the public emission signal, the fundamental value, and random supply.

Define the price-implied signal

$$\tilde{s}_p = \frac{\tilde{p}_i - (p_0 + p_y \tilde{y}_i)}{p_v} = \tilde{v}_i + \rho^{-1}\tilde{x}, \qquad \rho = \frac{p_v}{p_x}. \tag{4.8}$$

The price-implied signal $\tilde{s}_p$ is the noisy estimate of firm $i$'s fundamental value that investors can extract from the equilibrium price after netting out the component driven by public disclosure. $\rho$ measures the informativeness of the price. It represents the signal-to-noise ratio of the information revealed by the market. The price therefore reveals a noisy signal of firm value with precision

$$\tau_p = \rho^2 \tau_x. \tag{4.9}$$

Given the information available to each investor, Bayesian updating combines the prior distribution with the observed signals to form posterior expectations of firm value and emissions. Given investors' posterior beliefs obtained through Bayesian updating, the standard CARA-normal framework implies that optimal portfolio demand is proportional to expected risk-adjusted returns and inversely proportional to posterior uncertainty.. Consequently, improvements in disclosure quality affect asset prices not by changing cash flows directly, but by changing investors' beliefs and the precision with which those beliefs are formed.

Under CARA-normal preferences with ESG considerations, investor demand is

$$D = \frac{E(\tilde{v}_i \mid \mathcal{I}) - \tilde{p}_i - \theta\, E(\tilde{E}_i \mid \mathcal{I})}{\gamma \operatorname{Var}(\tilde{v}_i \mid \mathcal{I})}. \tag{4.10}$$

The additional term $\theta\, E(\tilde{E}_i \mid \mathcal{I})$ captures investors' preferences over firms' emissions exposure. The parameter $\theta \geq 0$ measures the strength of ESG preferences: investors derive disutility from holding high-emissions ("brown") assets and therefore require additional compensation to hold them. Equivalently, investors behave as if they evaluate an emissions-adjusted payoff, $\tilde{v}_i - \theta \tilde{E}_i$.

At this point, ESG demand is fully embedded into the model. Relative to the standard noisy rational expectations framework (e.g., (Goldstein and Yang, 2017)) but similar to (Pástor et al., 2022; Pástor et al., 2021), this specification introduces a preference-based demand shifter that is independent of cash flows and risk. In the benchmark model, asset demand depends only on expected payoffs and perceived risk. Here, demand also depends directly on expected emissions exposure, reflecting non-pecuniary preferences for sustainability. We maintain CARA preferences but assume investors derive utility from an emissions-adjusted payoff. Unlike (Pástor et al., 2022; Pástor et al., 2021), who do not model uncertainty about ESG characteristics, emissions exposure in our framework is not directly observed and must be inferred from noisy disclosure.

This modification preserves the tractability of the CARA-normal structure while generating an additional channel through which emissions affect prices: beyond their impact on cash flows (through $\phi$) and information (through $\tau_{\eta,i}$), emissions now also affect equilibrium prices through investor tastes.

For informed investors, $\mathcal{I}_I = \{\tilde{y}_i, \tilde{s}_i, \tilde{s}_p\}$, while uninformed investors observe $\mathcal{I}_U = \{\tilde{y}_i, \tilde{s}_p\}$.

The information structure therefore creates three distinct sources of information available to market participants: (i) public emissions disclosures, (ii) private information held only by informed investors, and (iii) information revealed through equilibrium prices. The interaction of these signals determines investors' posterior beliefs about firm value and emissions exposure. These posterior beliefs directly determine portfolio demand under CARA preferences and, through market clearing, determine equilibrium prices and expected returns.

**Informed Investors.**

A fraction $\mu$ of investors observes a private signal

$$\tilde{s}_i = \tilde{v}_i + \tilde{\varepsilon}_i, \qquad \tilde{\varepsilon}_i \sim \mathcal{N}(0, \tau_\varepsilon^{-1}). \tag{4.11}$$

Given signals $(\tilde{y}_i, \tilde{s}_i, \tilde{s}_p)$, the posterior precision equals $\tau_v + \tau_\varepsilon + \tau_\eta + \rho^2\tau_x$, and demand becomes

$$D_I = \frac{\tau_\varepsilon \tilde{s}_i - \tau_\eta \tilde{y}_i + \rho^2\tau_x \tilde{s}_p - (\tau_v + \tau_\varepsilon + \tau_\eta + \rho^2\tau_x)\tilde{p}_i - \theta\left(\tau_\eta \tilde{y}_i + \tau_E \mu_E\right)}{\gamma}. \tag{4.12}$$

**Uninformed Investors.**

Uninformed investors observe only $(\tilde{y}_i, \tilde{s}_p)$ and their posterior precision equals $\tau_v + \tau_\eta + \rho^2\tau_x$ . Their demand is

$$D_U = \frac{\rho^2\tau_x \tilde{s}_p - \tau_\eta \tilde{y}_i - (\tau_v + \tau_\eta + \rho^2\tau_x)\tilde{p}_i - \theta\left(\tau_\eta \tilde{y}_i + \tau_E \mu_E\right)}{\gamma}. \tag{4.13}$$

Differently from (Goldstein and Yang, 2017), the signal $\tilde{y}_i$ is negatively related to the company's value, $\tilde{v}_i$, specifically, larger $\tilde{y}_i$ implied lower , $\tilde{v}_i$, therefore the demand functions for both informed, Equation (4.12), and uninformed, Equation (4.13), traders reflects that a higher $\tilde{y}_i$ is 'bad news', reducing their desire to hold assets. The final step is to aggregate the demands of informed and uninformed investors. Market clearing requires aggregate demand to equal the exogenous asset supply. Solving this fixed-point problem simultaneously determines the equilibrium price coefficients, which summarize how public information, private

information, and liquidity trading are incorporated into market prices.

**Market Clearing.**

$$\int_0^{\mu} D_I \, dj + (1-\mu) D_U + \tilde{x} = Q. \tag{4.14}$$

Solving the fixed-point system yields a unique partially revealing equilibrium with coefficients

$$p_0 = -\frac{\gamma Q + \theta \tau_E \mu_E}{\mu \tau_\varepsilon + \tau_v + \tau_\eta + \rho^2 \tau_x}, \tag{4.15}$$

$$p_y = \frac{\tau_\eta (1-\theta)}{\mu \tau_\varepsilon + \tau_v + \tau_\eta + \rho^2 \tau_x}, \tag{4.16}$$

$$p_v = \frac{\mu \tau_\varepsilon + \rho^2 \tau_x}{\mu \tau_\varepsilon + \tau_v + \tau_\eta + \rho^2 \tau_x}, \tag{4.17}$$

$$\rho = \frac{\mu \tau_\varepsilon}{\gamma}. \tag{4.18}$$

The equilibrium coefficients link the information environment to asset pricing. Substituting the equilibrium price into investors' expected returns shows that the cost of capital depends on two distinct channels. The first is an information channel, whereby more precise disclosure reduces uncertainty and therefore lowers the risk premium required by investors. The second is a preference channel, whereby investors who dislike emissions require additional compensation to hold firms with higher expected emissions exposure. Equation (4.19) combines these two mechanisms into a single expression for expected returns. Following standard noisy REE arguments, expected excess return equals for company $i$

$$E(\tilde{v}_i - \tilde{p}_i) = \frac{\gamma Q}{\mu \tau_\varepsilon + \tau_v + \tau_{\eta,i} + \left(\frac{\mu \tau_\varepsilon}{\gamma}\right)^2 \tau_x} + \theta \, E(\tilde{E}_i). \tag{4.19}$$

The second term in Equation (4.19) reflects ESG-driven demand. The model therefore predicts that disclosure quality and ESG preferences are complementary rather than independent mechanisms: disclosure determines how accurately investors identify emissions-intensive firms, while ESG preferences determine how strongly that information is capitalized into prices. Firms with higher expected emissions exposure must offer higher expected returns to compensate investors for holding "brown" assets. ESG preferences therefore introduce a demand-based component to expected returns, distinct from the risk-based component captured by the first term.

Further, Equation (4.19), defines the cost of capital, the numerator reflects the aggregate risk-bearing capacity, while the denominator represents the precision or the information sources, rather than the realized values of the signals themselves. The cost of capital in this model is driven by the average risk perceived by traders. Disclosure reduces this perceived risk by providing more information, which lowers the cost of capital. This risk-reduction effect happens as long as the signal is informative, regardless of the direction of that information.

Importantly,

$$\frac{\partial E[R_i]}{\partial \tau_{\eta,i}} < 0. \tag{4.20}$$

Greater disclosure precision lowers the cost of capital. Since

$$\frac{\partial \tau_{\eta,i}}{\partial M_i} < 0, \tag{4.21}$$

it follows that

$$\frac{\partial E[R_i]}{\partial M_i} > 0. \tag{4.22}$$

Further, ESG preferences interact with disclosure precision. Since

$$\frac{\partial E(\tilde{E}_i)}{\partial \tau_{\eta,i}} \neq 0, \tag{4.23}$$

disclosure affects not only perceived risk but also the strength of ESG-driven demand. Higher precision improves investors' ability to identify high-emissions firms, amplifying the ESG premium.

Thus,

$$\frac{\partial^2 E[R_i]}{\partial \tau_{\eta,i}\, \partial \theta} < 0. \tag{4.24}$$

The model implies that ESG premia are not only driven by investor preferences, but also by the informativeness of sustainability disclosure, linking greenium dynamics to information frictions.

### 4.2.6 Interaction Between Emissions and Missingness

Emissions exposure affects payoff sensitivity through $\phi$, while missingness affects information precision through $\tau_{\eta,i}$. The total posterior precision depends jointly on both channels.

A first-order linearization of equilibrium expected returns yields

$$E[R_i] = \beta_0 + \beta_1 E_i + \beta_2 M_i + \beta_3 (E_i \times M_i), \tag{4.25}$$

where the interaction term arises because the pricing of emissions exposure depends on disclosure precision. The $E_i$ term comes from equation 1, the $M_i$ term comes from equations 23 through 26. The interaction term $E_i \times M_i$ arises from a first-order approximation of the nonlinear equilibrium return function, equation 23, reflecting that emissions exposure and the disclosure precision jointly determine expected returns.

**Construction of risk factors**

We construct two factor portfolios: an Emissions Factor and a Missing Emissions Factor. Both factors are formed using a 2×2×2 sorting procedure, analogous to the standard Fama–French portfolio construction methods (Fama and French, 1993). Similar multi-way sorting approaches have been employed in the literature: (Khandelwal et al., 2023) use a 2×3×3 method sorting first by size, then by book-to-market, and finally by ESG score; (Simlai, 2025) perform a 2×2 sort using size and ESG scores to evaluate their effects on returns; and (Rudkin et al., 2025) use a 2×2 sorting procedure first by ESG score and then by a known characteristic such as momentum or value.

For the Missing Factor, firms are first divided into small and large groups based on market capitalization. Within each size group, firms are then sorted by emissions scores (LowE/HighE), and within each size–emissions cell, firms are further sorted by the percentage of missing emissions data (LowM/HighM). The Missing Factor is calculated as the average return difference between the low-missingness and high-missingness portfolios across all four size–emissions cells. Firms with more complete emissions disclosure are treated as low-missingness firms in the long portfolio, whereas firms with a high proportion of missing emissions data are included in the short portfolio.

Similarly, for the Emissions Factor, firms are first sorted by size, then by missingness (LowM/HighM), and finally by emissions score within each size–missingness cell. The Emissions Factor is computed as the average return difference between low- and high-emission portfolios across all four size–missingness cells, where low-emission (green) firms form the long portfolio and high-emission (brown) firms form the short portfolio.

This 2×2×2 sorting procedure ensures that each factor captures variation in firm returns conditional on the other characteristics, providing a cleaner separation of emissions exposure and emissions data missingness. The resulting factors are then used in regression analyzes to assess whether emissions and missingness provide overlapping or distinct information about

expected stock returns.

There are two iterations of the Emissions factor, the first being based on emissions scores provided by LSEG and the other on the raw emissions data also provided by LSEG. The point of this is to be able to determine if raw data is a more accurate predictor of transaction risk than emissions scores.

### Testable Hypotheses

The noisy rational expectations equilibrium yields three empirical implications.

**H1: Missingness Premium (Information Risk).** From the cost-of-capital expression,

$$\frac{\partial E[R_i]}{\partial \tau_{\eta,i}} < 0, \qquad \frac{\partial \tau_{\eta,i}}{\partial M_i} < 0, \tag{4.26}$$

so

$$\frac{\partial E[R_i]}{\partial M_i} > 0. \tag{4.27}$$

Higher emissions data missingness lowers disclosure precision, raises valuation uncertainty, and increases required returns.

**Hypothesis H1:** Firms with greater exposure to the Missingness Factor earn higher expected returns.

**H2: Emissions Premium (Transition Risk).** Because firm value depends on emissions through

$$\tilde{v}_i = \bar{v} - \phi \tilde{E}_i + \tilde{u}_i, \tag{4.28}$$

higher emissions increase exposure to systematic transition risk. If transition risk is priced, firms with greater emissions exposure earn higher expected returns.

In the empirical analysis, emissions exposure is proxied using two alternative factors: one constructed from emissions scores and one constructed from raw emissions intensity (total $CO_2$ emissions scaled by revenue). Comparing these two measures allows us to assess whether market-based emissions scores or accounting-based raw emissions data more accurately capture transition risk in asset prices.

**Hypothesis H2:** Firms with greater exposure to the Emissions Factor earn higher expected returns.

**H3: Conditional Emissions Pricing.** Total expected return depends jointly on emissions exposure and disclosure precision. A first-order expansion implies

$$E[R_i] = \beta_0 + \beta_1 E_i + \beta_2 M_i + \beta_3 (E_i \times M_i). \tag{4.29}$$

Because missingness reduces the precision of emissions as a signal of transition exposure, the marginal pricing of emissions weakens as missingness increases.

**Hypothesis H3:** The emissions-related return premium is decreasing in emissions data missingness. Equivalently, the coefficient on the interaction between the Emissions Factor and the Missingness Factor is negative.

Taken together, Hypotheses H1–H3 imply that emissions exposure and emissions data missingness are jointly priced. Emission exposure loads on a transition risk factor, emissions data missingness loads on an information risk factor, and disclosure quality determine the extent to which emissions measures capture transition risk rather than information risk.

### Panel Model

The empirical specifications are designed as reduced-form tests of the noisy rational expectations equilibrium developed in Section 2. In the model, expected excess returns in Equation (4.19) depend on total information precision. Two firm-level components drive the cross-sectional variation in expected returns: (i) transition risk exposure through emissions sensitivity, embedded in fundamentals via $\tilde{v}_i = \bar{v} - \phi \tilde{E}_i + \tilde{u}_i$, and

(ii) disclosure precision $\tau_{\eta,i}$, which depends negatively on emissions data missingness $M_i$.

Because neither transition exposure nor disclosure precision is directly observable, the empirical analysis constructs factor portfolios that proxy for systematic variation in each component. The *Emissions Factor* (lagged by one year) captures common return variation among firms with similar emissions exposure and proxies for systematic transition risk. The *Raw Emissions Factor* (lagged by one year) is constructed as total $CO_2$ emissions divided by total revenue, providing a measure of carbon intensity. The *Missingness Factor* (lagged by one year) captures common return variation associated with differences in emissions disclosure completeness and proxies for variation in disclosure precision $\tau_{\eta,i}$.

We estimate fixed-effects panel regressions of firm-level excess returns:

$$ExcessReturn_{i,t} = \alpha + \beta_1 Factor_{i,t-1} + \boldsymbol{\gamma}' \mathbf{X}_{i,t} + \delta_t + \phi_s + \phi_c + \varepsilon_{i,t}, \tag{4.30}$$

where $ExcessReturn_{i,t}$ denotes firm $i$'s return in period $t$ in excess of the risk-free rate. $Factor_{i,t-1}$ denotes either the Emissions Factor, Raw Emissions Factor, or Missingness Factor, lagged by one year.

The empirical analysis controls for the Fama–French five-factor model factors, including the market factor (MKT), Small Minus Big (SMB), High Minus Low (HML), Robust Minus Weak (RMW), and Conservative Minus Aggressive (CMA). SMB captures the size premium, HML represents the value premium based on book-to-market ratios, RMW reflects differences in operating profitability, and CMA captures differences in firms' investment behavior.

$\mathbf{X}_{i,t}$ includes the five Fama–French factors (Mkt–RF, SMB, HML, RMW, CMA) as well as firm-level controls such as profitability, market capitalization, and shareholders' equity. The terms $\delta_t$, $\phi_s$, and $\phi_c$ denote year, sector, and country fixed effects, respectively. The coefficients $\beta_1$ are reduced-form estimates of risk premia associated with exposure to transition risk and disclosure-induced information risk. They do not directly estimate structural parameters such as $\phi$ or $\tau_{\eta,i}$, but test whether cross-sectional variation in these components is reflected in expected returns.

To mitigate endogeneity concerns, we lag emissions variables by 12 months, ensuring that emissions information predates realized returns. This timing structure aligns with the delayed availability of ESG disclosures and reduces reverse causality. Additionally, we include standard Fama-French risk factors to control for systematic risk exposures.

When both factors and their interaction are included, the specification corresponds to a linearization of the model-implied return:

$$ExcessReturn_{i,t} = \alpha + \beta_1 Factor_{i,t-1} + \beta_3 (E_i \times M_i) + \boldsymbol{\gamma}' \mathbf{X}_{i,t} + \delta_t + \phi_s + \phi_c + \varepsilon_{i,t}, \quad (4.31)$$

where emissions exposure affects payoff sensitivity and missingness affects disclosure precision. The interaction term tests whether the pricing of emissions exposure varies with disclosure quality, as implied by the equilibrium. All regressions are estimated by OLS with MacKinnon–White heteroskedasticity-robust standard errors (HC3). Identification comes from within-industry, within-year, and within-country variation.

**Split-Sample Tests by Disclosure Precision**

The theoretical framework implies that the emissions premium depends on disclosure precision $\tau_{\eta,i}$. Because $\partial \tau_{\eta,i} / \partial M_i < 0$, missingness partitions firms into high- and low-precision regimes. To allow for flexible, non-parametric tests of this mechanism, we implement split-sample regressions along two dimensions: (i) disclosure precision (proxied by the Missingness Factor), and (ii) emissions exposure (proxied by the Emissions Factor and Raw Emissions Factor).

First, firms are split into high and low-missingness groups based on the median of the

Missingness Factor. Within each subsample, we estimate excess return regressions including the Emissions Factor and Raw Emissions Factor as the primary regressors. The model predicts that the emissions premium should be stronger when the disclosure precision is high (low missingness).

Second, firms are split into high and low-emissions groups based on the median of the Emissions Factor. Within each regime, we estimate regressions including the Missingness Factor. Because disclosure precision affects total valuation uncertainty, the information-risk premium may differ across emissions regimes. The regression model otherwise follows the specification above.

If the theoretical mechanism holds, the emissions premium should be economically larger in the low-missingness subsample, while the missingness premium should be present independently of emissions exposure. This design mirrors the model's prediction that transition risk and disclosure precision jointly determine equilibrium expected returns.

## 4.3 Data

### 4.3.1 Data Sources

The data in this analysis come from two sources. The London Stock Exchange Group ESG database and the Fama French Database through Dartmouth University. This consists of the top 23 developed economics in North America, Europe, and Asia. The sample consists of 6,994 firms from 23 developed markets (table A.6 in Appendix C lists the countries). All data is for the years 2015 to 2023. All return-based variables are measured at a monthly frequency, while emissions-related data and missingness are reported annually. Monthly financial and return data are then matched to the corresponding annual emissions observations for each firm-year.

LSEG was selected because, unlike many commercial ESG databases that primarily distribute aggregated ESG scores, it provides access to the underlying KPI-level observations together with explicit identification of missing values. This level of transparency is essential for the present study, as the proposed Missing Data Factor is constructed directly from the observed pattern of missing KPI disclosures rather than from aggregated ESG scores alone. Although ESG ratings are known to diverge between providers due to differences in methodologies and weighting schemes, the objective of this study is not to compare ESG ratings between vendors, but to examine how missing KPI data influence the construction and pricing of ESG information. A summary of the relevant LSEG data structure is provided in Appendix B.

All financial variables were obtained from the LSEG Fundamentals database. To ensure comparability between firms from different countries, financial variables were expressed in U.S. dollars (USD), consistent with the currency denomination of the global Fama-French risk factors. LSEG performed exchange rate conversions using its standardized historical exchange rate methodology prior to data extraction.

### 4.3.2 Construction of Emissions and Missingness Measures

The emissions category score is based on a set of underlying key performance indicators (KPIs), but the specific KPIs used vary between industries. Table A.3 in Appendix C lists the entire set of emissions-related variables and identifies whether each variable is boolean or numerical. Each industry group uses a different subset of these variables. For example, firms in the banking services industry are evaluated using 14 emissions-related variables, whereas firms in the metals and mining industry are evaluated using 23. As a result, missing data must be measured within industry groups rather than across the entire sample.

We define missingness as the percentage of emissions-related KPIs without reported values, calculated at the firm-year level using only the variables relevant to the firm's industry classification. This approach is consistent with the internal scoring methodology of LSEG and avoids conflating missingness between incomparable KPI sets. Missingness is computed by dividing the number of missing KPI observations (with respect to both boolean and numerical variables) by the total number of relevant emissions variables for that industry.

For illustration, consider Far Limited (FAR.AX), an Australian firm in the oil and gas industry. Table A.4 reports the 25 emissions-related variables used to construct the emissions score for this industry. For each year, the missingness measure is calculated as the fraction of these variables for which no data is reported. This procedure is repeated for all firms and years in the sample.

Because the treatment of missing numerical observations is central to the proposed Missingness Factor, appendix 2 illustrates the LSEG scoring procedure. Missing numerical KPIs receive an implicit zero contribution during score aggregation, whereas boolean variables are recorded as zero when unanswered. This distinction motivates us to treat missingness as an economically meaningful issue rather than a purely statistical one.

LSEG constructs ESG metrics using a peer comparison scoring framework. Raw firm data are first evaluated within peer groups in the global industry to form category scores. These category scores are then aggregated into pillar scores, which in turn determine the overall ESG score. Emissions scores are a category score within the environmental pillar and therefore are industry-relative, reflecting differences in production technologies, regulatory

environments, and reporting practices across sectors.

The monthly frequencies for the risk-free rate and the five Fama French factors (Mkt–RF), (SMB), (HML), (RMW) and (CMA)—are obtained from the Fama French developed markets database through the University of Dartmouth. Fama French factors are exogenous. Firm-level returns and accounting variables, including market capitalization and shareholder equity, are sourced from LSEG and matched to factor data by firm and date. Monthly firm-level excess returns are computed as the difference between raw returns and the risk-free rate. All factor and control variables are converted to decimal form, where appropriate.

Market capitalization is measured as the total market value of a firm's outstanding equity. Operating profit is measured as operating income before interest and taxes, as reported by LSEG. Shareholder equity is measured as the total common equity reported on the firm's balance sheet. These variables are included to control for differences in firm size, profitability, and financial structure that may influence expected returns independently of emissions disclosure quality. Although profitability ratios such as ROA or ROE are frequently used in the literature, operating profit was selected because the analysis focuses on firms' operating scale and financial capacity rather than accounting efficiency.

Operating profit is included as a control for the firm's absolute earnings capacity rather than profitability ratios. Because market capitalization is included separately in the regression, the model partially controls for firm size. In addition, all continuous variables are standardized prior to estimation, reducing the influence of scale differences.

### 4.3.3 Sample Characteristics

Table 4.1 reports the number of firms per year included in the final sample. The number of companies increases over time, reflecting the expanded coverage of ESG by LSEG, with a total of 6,994 unique companies observed over the sample period.

Tables 4.2 and 4.3 provide summary statistics for the emissions-based, financial, and market variables, showing substantial variation across firms, particularly in size-related measures such as market capitalization and equity.

The descriptive statistics reveal substantial heterogeneity across firms, particularly in market capitalization, shareholder equity, and operating profit, justifying the inclusion of standardized financial controls in the regression models. The prevalence of missing emissions observations further motivates the construction of the Missingness Factor.

| Year | Number of Firms |
|---|---|
| 2015 | 2,948 |
| 2016 | 3,506 |
| 2017 | 2,092 |
| 2018 | 4,656 |
| 2019 | 5,210 |
| 2020 | 6,169 |
| 2021 | 6,511 |
| 2022 | 6,630 |
| 2023 | 3,299 |
| **Total Unique Firms** | 6,994 |

**Table 4.1:** Number of firms per year and total unique firms in the dataset

**Table 4.2:** Descriptive Statistics: Emissions & Financial Variables

| Variable | N | Mean | Std |
|---|---|---|---|
| EmissionsFactor | 482,875 | 3.167e-04 | 1.169e-02 |
| EmissionRawDataFactor | 482,875 | 6.637e-04 | 1.291e-02 |
| MissingFactor | 482,875 | -1.885e-04 | 9.902e-03 |
| Total_CO2_Revenue | 260,484 | 6.782e+02 | 3.476e+04 |
| Excess_Return | 482,875 | -9.734e-02 | 1.709e-01 |
| Operating Profit | 145,666 | 3.651e+10 | 1.698e+11 |
| Company Market Capitalization | 481,418 | 1.222e+11 | 7.280e+11 |
| Shareholder Equity | 463,277 | 9.547e+10 | 6.683e+11 |

**Table 4.3:** Descriptive Statistics: Market / Factor Variables

| Variable | N | Mean | Std |
|---|---|---|---|
| Mkt-RF | 482,875 | 6.145e-01 | 4.813e+00 |
| SMB | 482,875 | -2.192e-01 | 1.583e+00 |
| HML | 482,875 | -2.535e-02 | 3.362e+00 |
| RMW | 482,875 | 3.559e-01 | 1.508e+00 |
| CMA | 482,875 | 1.140e-01 | 2.135e+00 |

### 4.3.4 Financial/Factor Data, Emissions Scores and Missing Data

Table 4.4 highlights the correlation structure, indicating that the emissions-based factors exhibit meaningful relationships with standard Fama–French factors (notably HML and

CMA), while their direct correlation with returns remains relatively modest, suggesting potential indirect channels of influence through systematic risk exposures.

Several other patterns are notable. First, the Emissions Factor and the Raw Emissions Factor exhibit a moderately strong negative correlation, reflecting differences in how emissions exposure is measured using scores versus raw data. Second, the Missingness Factor is positively correlated with both emissions-based factors, indicating that firms with higher emissions exposure also tend to exhibit greater data incompleteness.

Importantly, the Missingness Factor is negatively correlated with excess returns, consistent with the presence of an information-risk premium. In contrast, the Raw Emissions Factor is negatively correlated with returns, while the score-based Emissions Factor is positively correlated, foreshadowing the differing behavior observed in the regression results. This divergence is consistent with the interpretation that raw emissions more cleanly capture transition risk, whereas emissions scores also embed disclosure quality and ESG-related demand effects.

Correlations with the Fama–French factors further support this interpretation. The Emissions Factor is positively associated with value (HML) and investment (CMA), while the Raw Emissions Factor exhibits the opposite pattern. This suggests that score-based measures are more closely aligned with broader ESG and style tilts, whereas raw emissions capture a distinct dimension of risk exposure.

Figure 4.1 illustrates the accumulated returns of the constructed factors over time. The figure shows that the emissions-based factors and the Missingness Factor exhibit related but distinct dynamics, reflecting their shared dependence on underlying emissions data as well as their differing economic interpretations. The co-movement between factors is consistent with the correlations reported in Table 4.4, but deviations over time highlight the importance of distinguishing between transition risk and disclosure-induced information risk.

The "Return" series in Figure 4.1 represents the equal-weighted cross-sectional average of firms' cumulative excess returns at each point in time. It serves as a descriptive benchmark for the evolution of average firm performance relative to the constructed factor portfolios. It does not correspond to a tradable portfolio but instead summarizes the average excess return across firms in the sample.

Overall, the correlation structure and return dynamics indicate that emissions exposure and emissions data missingness are closely related but distinct dimensions of firm characteristics. Their joint behavior reflects both the underlying economic linkage between emissions and disclosure incentives and the role of data construction methodologies in shaping ESG-based measures.

**Table 4.4:** Correlation Matrix: Emissions, Financial, and Market Variables

| | EmF | RawF | MissF | $CO_2$ | Ret | Profit | MktCap | Equity | Mkt-RF | SMB | HML | RMW | CMA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EmF | 1.000 | | | | | | | | | | | | |
| RawF | -0.402 | 1.000 | | | | | | | | | | | |
| MissF | 0.278 | 0.159 | 1.000 | | | | | | | | | | |
| $CO_2$ | 0.006 | 0.003 | -0.001 | 1.000 | | | | | | | | | |
| Ret | 0.130 | -0.072 | -0.115 | 0.008 | 1.000 | | | | | | | | |
| Profit | 0.005 | -0.005 | 0.013 | -0.005 | -0.041 | 1.000 | | | | | | | |
| MktCap | 0.008 | 0.002 | 0.013 | -0.007 | -0.026 | 0.689 | 1.000 | | | | | | |
| Equity | 0.003 | -0.000 | 0.007 | -0.005 | -0.035 | 0.680 | 0.825 | 1.000 | | | | | |
| Mkt-RF | 0.188 | 0.083 | -0.266 | 0.003 | 0.292 | -0.005 | 0.005 | -0.000 | 1.000 | | | | |
| SMB | -0.166 | -0.099 | -0.203 | -0.003 | 0.220 | -0.016 | -0.010 | -0.011 | 0.154 | 1.000 | | | |
| HML | 0.464 | -0.478 | 0.376 | -0.001 | 0.080 | 0.003 | 0.004 | -0.002 | -0.076 | 0.154 | 1.000 | | |
| RMW | 0.105 | 0.204 | 0.017 | 0.005 | -0.021 | 0.006 | 0.003 | 0.004 | 0.068 | -0.369 | -0.562 | 1.000 | |
| CMA | 0.523 | -0.541 | 0.368 | -0.002 | 0.007 | 0.003 | -0.002 | -0.003 | -0.319 | -0.038 | 0.807 | -0.289 | 1.000 |

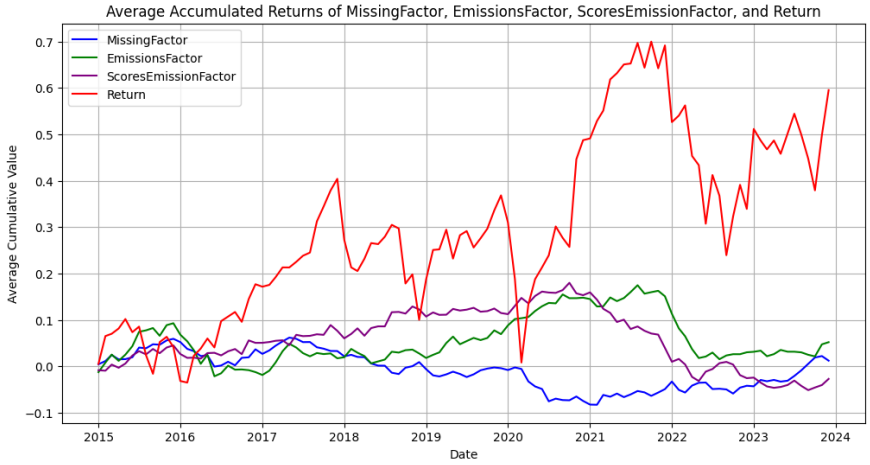



**Figure 4.1:** Accumulated Returns

To further examine whether missingness captures economically significant differences across firms, Figure 4.2 and Table 4.5 compare average emissions scores across groups defined jointly by market capitalization and missing emissions-data. Firms are partitioned using the median market capitalization and the sample mean percentage of missing emissions observations. The results show that missingness dominates firm size in explaining variation in emissions scores. Even large-cap firms with high missingness exhibit substantially lower average emissions scores than small-cap firms with low missingness. This pattern suggests that disclosure completeness is a more important determinant of emissions scores than firm size alone, reinforcing the motivation to treat missingness as a priced firm characteristic rather than a secondary data issue.

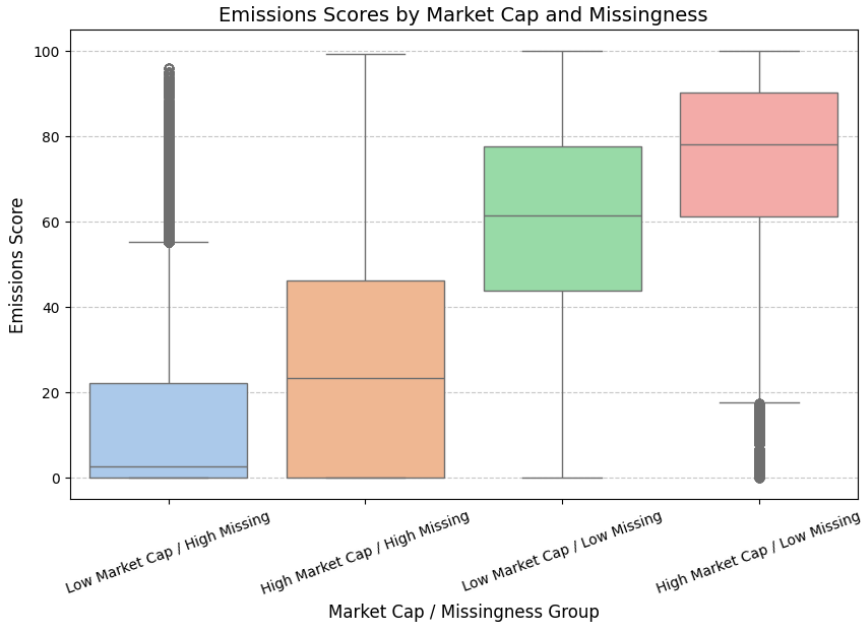



**Figure 4.2:** Size vs Missingness

**Table 4.5:** Summary of Emissions Score by Market Cap and Missingness Groups

| Group | Observations | Avg Emissions | Avg Market Cap | Avg Percent Miss |
|---|---|---|---|---|
| High Market Cap / High Missing | 91,666 | 27.30 | $1.14\times10^{11}$ | 44 |
| High Market Cap / Low Missing | 140,229 | 73.67 | $3.38\times10^{11}$ | 18 |
| Low Market Cap / High Missing | 178,513 | 13.35 | $7.79\times10^{8}$ | 46 |
| Low Market Cap / Low Missing | 53,382 | 60.06 | $1.06\times10^{9}$ | 21 |

### 4.3.5 Model Diagnostics

Before estimating the panel regressions, we examine potential multicollinearity among the explanatory variables. Variance inflation factors (VIFs), reported in Appendix A Table A.1 and Table A.2, indicate that multicollinearity is not a major concern. In the initial $2 \times 2$ factor construction, the Emissions and Missing Factors exhibit moderate VIF values below the conventional threshold of 10. After extending the factor construction to the $2 \times 2 \times 2$ specification, all factor VIFs fall below 3, indicating that the additional sorting dimension substantially reduces collinearity while preserving the economic interpretation of the factors. These results support the robustness of the subsequent regression estimates.

## 4.4 Panel Regressions

### 4.4.1 Baseline Panel Regression Results

Building on the descriptive analysis in Section 3, this section examines whether emissions exposure and disclosure-related missingness are systematically associated with expected returns. The analysis proceeds from the baseline regression model to additional robustness tests before interpreting the results within the theoretical framework.

Table 4.6 reports the baseline panel regressions relating excess returns to the Missingness Factor, the Emissions Factor, and their interaction. The table provides the initial evidence regarding whether disclosure quality and emissions exposure are priced after controlling for the standard Fama–French risk factors and firm characteristics.

**Table 4.6:** Emissions, Missingness, and Excess Returns

| **Dependent Variable: Excess Return** | (1) Missing Factor | (2) Emissions Factor | (3) Interaction M |
|---|---|---|---|
| **Missing Factor** | **-0.0398**** | | **-0.0556***** |
| | (0.019) | | (0.020) |
| **Emissions Factor** | | -0.0126 | -0.0108 |
| | | (0.016) | (0.017) |
| **Missing × Emissions** | | | **4.9645***** |
| | | | (1.759) |
| Mkt–RF | 0.9445*** | 0.9437*** | 0.9452*** |
| | (0.005) | (0.004) | (0.005) |
| SMB | 0.5883*** | 0.5833*** | 0.5918*** |
| | (0.013) | (0.013) | (0.013) |
| HML | 0.1835*** | 0.1832*** | 0.1880*** |
| | (0.013) | (0.013) | (0.013) |
| RMW | -0.0962*** | -0.0964*** | -0.0911*** |
| | (0.017) | (0.017) | (0.017) |
| CMA | -0.1467*** | -0.1446*** | -0.1535*** |
| | (0.018) | (0.018) | (0.018) |
| Operating Profit | -0.0015*** | -0.0015*** | -0.0015*** |
| | (0.000) | (0.000) | (0.000) |
| Market Capitalization | 0.0036*** | 0.0036*** | 0.0036*** |
| | (0.000) | (0.000) | (0.000) |
| Shareholders' Equity | -0.0014*** | -0.0014*** | -0.0014*** |
| | (0.000) | (0.000) | (0.000) |
| Observations | 355,585 | 355,585 | 355,585 |
| R-squared | 0.196 | 0.196 | 0.196 |
| Robust Standard Errors | HC3 | HC3 | HC3 |

*Notes:* This table reports OLS regressions of excess returns on the missing data factor, the emissions factor, and their interaction. All specifications include year, industry, and country fixed effects. Robust HC3 standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Across all specifications, the Missingness Factor remains statistically significant, whereas the Emissions Factor alone is not. The interaction term is positive and statistically significant, indicating that the pricing of emissions depends on disclosure quality. These results

provide the first evidence that disclosure precision moderates the pricing of transition risk.

### 4.4.2 Additional Evidence and Robustness

To better understand the interaction between emissions and disclosure quality, the sample is divided according to the median level of emissions-data missingness. In Table 4.7, Panel A uses an emission factor derived from raw $CO_2$ emissions and Panel B uses an emissions factor based on LSEG emissions scores similar to Table 4.6. This is done to isolate the effects of the two missingness subgroups and to see whether using raw $CO_2$ or emissions scores is better able to capture transition risk.

We also observe a jump in the R-squared between Tables 4.6 and 4.7. The regressions reported in Table 4.7 are estimated separately for firms with relatively low and high levels of emissions-data missingness. Splitting the sample reduces cross-sectional heterogeneity within each subsample, resulting in a higher explanatory power relative to the regressions reported in Table 4.6.

**Table 4.7:** Lagged Emissions Factors: Raw $CO_2$ vs. Emissions Scores (Split by Missingness)

| **Panel A: Raw $CO_2$ Emissions Factor** | | |
|---|---|---|
| **Dependent Variable: Excess Return** | (1) Low Missing (%) | (2) High Missing (%) |
| **Emission Raw Data Factor** | **-0.1919**$^{***}$ | **-0.0618**$^{**}$ |
| | (0.0272) | (0.0303) |
| Mkt–RF | 0.0097$^{***}$ | 0.0100$^{***}$ |
| SMB | 0.0058$^{***}$ | 0.0071$^{***}$ |
| HML | 0.0049$^{***}$ | 0.0042$^{***}$ |
| RMW | 0.0024$^{***}$ | 0.0027$^{***}$ |
| CMA | 0.0002 | -0.0003 |
| Operating Profit | -0.0015$^{**}$ | -0.0037$^{***}$ |
| Market Capitalization | 0.0035$^{***}$ | 0.0071$^{***}$ |
| Shareholders' Equity | -0.0014$^{***}$ | -0.0031$^{***}$ |
| Observations | 99,131 | 97,223 |
| R-squared | 0.614 | 0.574 |

| **Panel B: Emissions Score Factor** | | |
|---|---|---|
| **Dependent Variable: Excess Return** | (1) Low Missing (%) | (2) High Missing (%) |
| **Emissions Score Factor** | **0.0544**$^{**}$ | **-0.1444**$^{***}$ |
| | (0.0249) | (0.0315) |
| Mkt–RF | 0.0098$^{***}$ | 0.0104$^{***}$ |
| SMB | 0.0064$^{***}$ | 0.0106$^{***}$ |
| HML | 0.0047$^{***}$ | 0.0033$^{***}$ |
| RMW | 0.0026$^{***}$ | -0.0008$^{***}$ |
| CMA | -0.0002 | -0.0033$^{***}$ |
| Operating Profit | -0.0016$^{***}$ | -0.0023$^{**}$ |
| Market Capitalization | 0.0034$^{***}$ | 0.0042$^{***}$ |
| Shareholders' Equity | -0.0014$^{***}$ | -0.0012 |
| Observations | 177,512 | 163,247 |
| R-squared | 0.592 | 0.488 |

*Notes:* This table reports OLS regressions of excess returns on lagged emissions factors. Panel A uses a factor constructed from raw $CO_2$ emissions, while Panel B uses emissions scores. Samples are split by the median level of emissions data missingness. All specifications include year, industry, and country fixed effects. Robust standard errors (HC3) are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

### 4.4.3 Interpretation of Empirical Results

The empirical results provide evidence consistent with the theoretical framework linking transition risk and disclosure-induced information risk to expected returns. In particular, the findings align closely with the structure of Equation (4.19), where expected returns are inversely related to total information precision;

$$\mu\tau_\varepsilon + \tau_v + \tau_{\eta,i} + \rho^2\tau_x,$$

and where emissions exposure and missingness enter through distinct but interacting channels.

**Missingness and Information Risk.** Across specifications, the Missingness Factor exhibits a statistically significant relationship with excess returns, consistent with Hypothesis H1. In particular, the negative coefficient in Table 4.6 reflects the construction of the factor (long low-missingness, short high-missingness). Economically, this implies that firms with higher emissions data missingness earn higher expected returns.

This result follows directly from the theoretical mechanism governing disclosure precision. In the model, emissions disclosure is observed through the noisy signal in Equation (4.4), with precision $\tau_{\eta,i}$. Missingness reduces this precision, i.e.,

$$\frac{\partial\tau_{\eta,i}}{\partial M_i} < 0,$$

which in turn lowers total posterior precision and increases the cost of capital:

$$\frac{\partial E[R_i]}{\partial\tau_{\eta,i}} < 0.$$

Thus, a higher missingness increases valuation uncertainty by weakening the informational content of $\tilde{y}_i$, forcing investors to rely more heavily on noisier signals such as $\tilde{s}_p$ (price-implied information) and private signals $\tilde{s}_i$. This reduction in overall precision increases the required returns. The empirical behavior of the Missingness Factor therefore provides direct support for the information-risk channel embedded in the noisy rational expectations equilibrium.

**Emissions and Transition Risk.** The results for emissions-based factors reflect the role of emissions exposure in determining fundamental risk through Equation (1),

$$\tilde{v}_i = \bar{v} - \phi\tilde{E}_i + \tilde{u}_i,$$

and the associated contribution to payoff variance,

$$\mathrm{Var}(\tilde{v}_i) = \phi^2 \tau_E^{-1} + \tau_u^{-1}.$$

Higher exposure to emissions increases the sensitivity of firm value to transition shocks (through $\phi \tilde{E}_i$), raising the fundamental risk $\tau_v^{-1}$ and thus increasing the expected returns.

The Raw Emission Factor (Panel A of Table 4.7) exhibits a consistently negative and statistically significant coefficient in both low and high missingness subsamples. Given the factor construction (long low-emissions, short high emissions firms), this implies that high emissions firms earn higher expected returns. This is directly consistent with the model's prediction that emissions proxy for systematic transition risk and therefore command a positive risk premium.

In contrast, the Emission Score Factor (Panel B) displays a sign reversal across subsamples. This instability suggests that emissions scores do not align cleanly with $\tilde{E}_i$, but instead reflect a mixture of true exposure to emissions and quality of disclosure. Because emissions scores are constructed using incomplete and imputed data, they are effectively noisy transformations of $\tilde{y}_i$, and therefore inherit variation from $\tau_{\eta,i}$ in addition to $\tilde{E}_i$. As a result, their relationship to the expected returns depends on the underlying level of precision of the disclosure.

**Interaction Between Emissions and Missingness.** The interaction term in Table 4.6 is positive and statistically significant, indicating that the price of emissions exposure depends on the quality of the disclosure, consistent with Hypothesis H3.

This finding is directly implied by the equilibrium structure of Equation (4.19). The total precision depends jointly on the fundamentals related to emissions (through $\tau_v$ and $\tau_E$) and the precision of disclosure (through $\tau_{\eta,i}$). When missingness is high (low $\tau_{\eta,i}$), the signal $\tilde{y}_i$ becomes less informative about $\tilde{E}_i$, weakening the mapping from observed emissions to true transition exposure. In this case, the marginal effect of emissions on expected returns is attenuated because investors cannot accurately infer $\tilde{E}_i$ from the available data.

In contrast, when the missingness is low (high $\tau_{\eta,i}$), the public signal becomes more precise, allowing emissions measures to reflect the true exposure more accurately. This strengthens the pricing of emissions through the transition risk channel. The positive interaction coefficient therefore reflects the complementarity between emissions exposure and disclosure precision in determining equilibrium expected returns.

**Green Demand and ESG-Based Measures.** The differing behavior of the two emissions-based factors is also consistent with recent equilibrium models of sustainable investing. While

the theoretical framework predicts that higher emissions (higher $\tilde{E}_i$) increase expected returns through risk, models such as (Pástor et al., 2021; Pástor et al., 2022) explain that investor preferences can distort this relationship.

In these models, strong demand for sustainable companies ("green") increases their prices and reduces their expected returns, independently of the fundamentals. Emissions scores, which are directly related to ESG ratings and widely used by investors, are more likely to embed this preference-driven component. As a result, the Emission Score Factor can capture both $\tilde{E}_i$ and demand-driven pricing effects, leading to deviations from the pure risk-based prediction and contributing to the observed sign reversals.

**Raw vs. Score-Based Emissions Measures.** Comparing the two measures, the Raw Emission Factor appears to provide a cleaner proxy for $\tilde{E}_i$ and therefore for the transition risk. Because it is constructed directly from emissions scaled by revenue, it is less affected by noise in $\tilde{y}_i$ induced by missingness and scoring methodologies. Its consistent sign in all subsamples indicates that it more reliably captures the fundamental risk component that enters $\tilde{v}_i$.

In contrast, the Emission Score Factor is more sensitive to variation in $\tau_{\eta,i}$ and therefore more exposed to information noise and methodological artifacts. This is consistent with the correlation structure in Table 4.4, where the emissions scores exhibit stronger relationships with missingness-related variables than the raw emissions measures.

**Summary.** Together, the results support the joint role of transition risk and information risk in asset pricing. The missing factor behaves according to theoretical predictions related to the precision of disclosure $\tau_{\eta,i}$, while emissions-based factors capture the variation in fundamental risk through $\tilde{E}_i$ and $\phi$. The interaction between the two reflects their combined effect on the total precision of the information in equilibrium. Raw emissions measures provide a more stable mapping to transition risk, whereas score-based measures reflect a combination of risk, information, and preference-driven effects.

## 4.5 Conclusion

- This paper examines how missing emissions data affect the pricing of environmental information in equity markets. Using firm-level data from 23 developed countries during the period 2015–2023, we construct three systematic risk factors—a monthly *Emissions Factor* based on emissions scores, a *Raw Emissions Factor* based on total $CO_2$ emissions scaled by

revenue, and a *Missing Emissions Factor*. These factors are designed to separately capture transition risk and disclosure-induced information risk within a unified empirical framework. The analysis is guided by a noisy rational expectations model of information precision (Easley et al., 2004; Lambert et al., 2007; Grossman and Stiglitz, 1980; Goldstein and Yang, 2017), which predicts that both fundamental risk and disclosure quality jointly determine expected returns.

Our results provide strong evidence that missing emissions data constitutes a priced source of systematic risk. Assets with higher exposure to the Missing Emissions Factor earn significantly different returns, consistent with investors requiring compensation for increased information and estimation risk. This finding aligns closely with the theoretical predictions that a lower disclosure precision increases the cost of capital. Moreover, the Missing Factor remains robust across specifications and plays a central role in explaining cross-sectional variation in returns, highlighting the importance of explicitly accounting for data quality in ESG-based asset pricing.

The evidence on emissions-related premia is more nuanced and depends on how emissions exposure is measured. When using emissions scores, the estimated premium is sensitive to disclosure quality, and even changes sign across subsamples. In contrast, the Raw Emission Factor exhibits a consistent negative relationship with returns across both low- and high-missingness regimes. This stability suggests that raw emissions-based measures more accurately capture underlying transition risk, while emissions scores are more heavily influenced by disclosure practices, missing data, and methodological adjustments embedded in ESG scoring frameworks.

These results are consistent with the theoretical framework developed in this paper. Emissions exposure affects expected returns through transition risk, while missingness affects the precision of the information available to investors. When disclosure quality is high, emissions measures more closely reflect true exposure to transition risk. However, when missingness is high, emissions measures become noisier signals and their pricing weakens, with the Missing Factor absorbing the information-risk component. The significant interaction effects observed in the data support the prediction that the pricing of emissions is conditional on disclosure precision.

Importantly, the results also align with recent equilibrium models of sustainable investing (**?**Pástor et al., 2022), which show that investor demand for green assets can distort realized returns. In particular, strong demand for low-emission ("green") firms can lead to lower expected returns for such firms and higher valuations, even when transition risk would predict the opposite. This mechanism helps explain why emissions score-based factors exhibit sign reversals, as they capture not only transition risk, but also market-wide sustainability prefer-

ences. In contrast, the Raw Emissions Factor appears less sensitive to these demand-driven effects and more closely aligned with the underlying risk-based channel.

Overall, our findings caution against interpreting emissions-based return premia as clean evidence of priced carbon risk without accounting for data construction and disclosure quality. Missing emissions data are not random and play a central role in shaping ESG scores, factor behavior, and asset pricing outcomes. Ignoring missingness risks conflating disclosure incentives with true environmental exposure and may lead to misleading inferences about the pricing of climate risk.

These results have important implications for researchers, investors, and data providers. For empirical asset pricing, incorporating disclosure quality is essential to disentangle transition risk from information risk. For investors, reliance on ESG scores without accounting for missing data may introduce unintended exposures driven by reporting behavior rather than fundamentals. More broadly, improving the transparency and completeness of emissions disclosure is critical to ensure that ESG metrics serve as reliable inputs for risk measurement and portfolio allocation.

Future research could extend this framework to other ESG dimensions and to emerging markets, where disclosure practices and regulatory environments differ substantially. Further work could also examine how improvements in reporting standards affect the relative importance of transition risk and information risk over time. Explicitly modeling missing data remains a key requirement for advancing ESG asset pricing.

# Appendix A

# The Importance of Board Diversity and Network Centrality in ESG Data

## A.1 Robustness Checks

**Table A.1:** Fixed Effects Regressions of Environmental and Social Scores on Board Diversity (a) (Terciles)

| | **Environmental Score** | | | **Social Score** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| F Third 2 | 6.904*** | 7.921*** | 0.615 | 11.848*** | 12.757*** | 4.650** |
| | (1.722) | (1.831) | (2.485) | (1.464) | (1.540) | (1.857) |
| F Third 3 | 9.283*** | 8.472*** | -1.216 | 15.014*** | 14.869*** | 3.153 |
| | (1.659) | (1.783) | (2.559) | (1.410) | (1.500) | (1.912) |
| Board size | | -0.508 | -0.242 | | -0.459 | -0.185 |
| | | (0.347) | (0.345) | | (0.292) | (0.258) |
| Independent board members | | -0.123* | -0.161** | | -0.113** | -0.147*** |
| | | (0.067) | (0.065) | | (0.056) | (0.049) |
| Employees (lagged 1yr) | | 0.080 | 0.181** | | 0.137* | 0.264*** |
| | | (0.084) | (0.081) | | (0.071) | (0.061) |
| Leverage (lagged 1yr) | | -0.492 | -0.189 | | -0.955 | -0.245 |
| | | (0.743) | (0.756) | | (0.625) | (0.564) |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Year FE | N | N | Y | N | N | Y |
| N. firms | 99 | 77 | 77 | 99 | 77 | 77 |
| N. obs. | 462 | 356 | 356 | 462 | 356 | 356 |
| R-squared | 0.09 | 0.12 | 0.24 | 0.26 | 0.33 | 0.54 |

*Notes:* Female directors' shares dummies are based on the thirds of the female directors' share distribution, corresponding to 25% and 35%.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A.2:** Combined Effects on Environmental and Social Scores (Terciles)

| | **Environmental Score** | | **Social Score** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Degree | -1.292** | -1.543** | -0.232 | -0.356 |
| | (0.587) | (0.599) | (0.490) | (0.454) |
| I(Degree > 0) | 9.084*** | 8.383*** | 4.659** | 3.487* |
| | (2.656) | (2.649) | (2.217) | (2.010) |
| Betweenness | 1.395*** | 0.734 | 1.355*** | 0.350 |
| | (0.485) | (0.519) | (0.405) | (0.394) |
| F Third 2 | 6.673*** | 0.703 | 11.308*** | 4.662** |
| | (1.849) | (2.463) | (1.544) | (1.869) |
| F Third 3 | 6.673*** | -0.840 | 12.413*** | 3.255* |
| | (1.855) | (2.522) | (1.548) | (1.913) |
| Board size | -0.486 | -0.187 | -0.553* | -0.213 |
| | (0.344) | (0.346) | (0.287) | (0.263) |
| Independent board members | -0.144** | -0.155** | -0.142** | -0.150*** |
| | (0.066) | (0.065) | (0.055) | (0.049) |
| Employees (lagged 1yr) | 0.055 | 0.155* | 0.126* | 0.247*** |
| | (0.083) | (0.082) | (0.069) | (0.062) |
| Leverage (lagged 1yr) | -0.510 | -0.161 | -0.867 | -0.252 |
| | (0.733) | (0.751) | (0.612) | (0.570) |
| Firm FE | Y | Y | Y | Y |
| Year FE | N | Y | N | Y |
| N. firms | 77 | 77 | 77 | 77 |
| N. obs. | 356 | 356 | 356 | 356 |
| R-squared | 0.17 | 0.27 | 0.38 | 0.55 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A.3:** Combined Effects on Environmental and Social Scores — Winsorized Betweenness at 99th Percentile (Robustness Check)

| | **Environmental Score** | | | | **Social Score** | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Degree | -1.202** | -1.527** | -1.292** | -1.543** | -0.084 | -0.318 | -0.232 | -0.356 |
| | (0.589) | (0.601) | (0.587) | (0.599) | (0.501) | (0.460) | (0.490) | (0.454) |
| I(Degree > 0) | 9.407*** | 8.397*** | 9.084*** | 8.383*** | 5.220** | 3.684* | 4.659** | 3.487* |
| | (2.669) | (2.662) | (2.656) | (2.649) | (2.269) | (2.035) | (2.217) | (2.010) |
| Betweenness ≤ 99th pctile | 1.417*** | 0.696 | 1.395*** | 0.734 | 1.440*** | 0.339 | 1.355*** | 0.350 |
| | (0.487) | (0.526) | (0.485) | (0.519) | (0.414) | (0.403) | (0.405) | (0.394) |
| F Quartile 2 | 5.764*** | -0.488 | | | 9.775*** | 2.202 | | |
| | (1.921) | (2.568) | | | (1.633) | (1.964) | | |
| F Quartile 3 | 5.940*** | -1.367 | | | 10.283*** | 1.132 | | |
| | (2.101) | (2.770) | | | (1.786) | (2.119) | | |
| F Quartile 4 | 8.455*** | -1.420 | | | 15.100*** | 2.540 | | |
| | (2.465) | (3.276) | | | (2.096) | (2.505) | | |
| F Third 2 | | | 6.673*** | 0.703 | | | 11.308*** | 4.662** |
| | | | (1.849) | (2.463) | | | (1.544) | (1.869) |
| F Third 3 | | | 6.673*** | -0.840 | | | 12.413*** | 3.255* |
| | | | (1.855) | (2.522) | | | (1.548) | (1.913) |
| Board size | -0.408 | -0.169 | -0.486 | -0.187 | -0.455 | -0.142 | -0.553* | -0.213 |
| | (0.355) | (0.347) | (0.344) | (0.346) | (0.302) | (0.265) | (0.287) | (0.263) |
| Independent board members | -0.171** | -0.154** | -0.144** | -0.155** | -0.182*** | -0.161*** | -0.142** | -0.150*** |
| | (0.069) | (0.067) | (0.066) | (0.065) | (0.058) | (0.051) | (0.055) | (0.049) |
| Employees (lagged 1yr) | 0.035 | 0.151* | 0.055 | 0.155* | 0.090 | 0.235*** | 0.126* | 0.247*** |
| | (0.083) | (0.082) | (0.083) | (0.082) | (0.070) | (0.062) | (0.069) | (0.062) |
| Leverage (lagged 1yr) | -0.613 | -0.224 | -0.510 | -0.161 | -1.042* | -0.382 | -0.867 | -0.252 |
| | (0.737) | (0.755) | (0.733) | (0.751) | (0.627) | (0.577) | (0.612) | (0.570) |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | N | Y | N | Y | N | Y |
| N. firms | 77 | 77 | 77 | 77 | 77 | 77 | 77 | 77 |
| N. obs. | 356 | 356 | 356 | 356 | 356 | 356 | 356 | 356 |
| R-squared | 0.16 | 0.27 | 0.17 | 0.27 | 0.37 | 0.56 | 0.40 | 0.57 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A.4:** Combined Effects on Environmental and Social Scores — Winsorized Board Size at 90th Percentile (Robustness Check)

| | **Environmental Score** | | | | **Social Score** | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Degree | -1.044* | -1.337** | -1.166** | -1.367** | -0.050 | -0.236 | -0.235 | -0.288 |
| | (0.581) | (0.591) | (0.579) | (0.588) | (0.499) | (0.456) | (0.489) | (0.451) |
| I(Degree > 0) | 9.675*** | 8.816*** | 9.377*** | 8.737*** | 5.399** | 3.885* | 4.891** | 3.659* |
| | (2.631) | (2.621) | (2.621) | (2.607) | (2.263) | (2.024) | (2.215) | (1.997) |
| Betweenness | 1.326*** | 0.608 | 1.321*** | 0.651 | 1.404*** | 0.294 | 1.329*** | 0.303 |
| | (0.481) | (0.519) | (0.480) | (0.511) | (0.414) | (0.400) | (0.405) | (0.392) |
| F Quartile 2 | 6.120*** | 0.071 | | | 10.285*** | 2.501 | | |
| | (1.832) | (2.529) | | | (1.576) | (1.953) | | |
| F Quartile 3 | 6.906*** | -0.260 | | | 11.205*** | 1.717 | | |
| | (1.988) | (2.739) | | | (1.709) | (2.116) | | |
| F Quartile 4 | 9.013*** | -0.625 | | | 15.688*** | 2.936 | | |
| | (2.391) | (3.232) | | | (2.057) | (2.496) | | |
| F Third 2 | | | 6.999*** | 1.121 | | | 11.691*** | 4.794** |
| | | | (1.809) | (2.413) | | | (1.529) | (1.849) |
| F Third 3 | | | 7.302*** | -0.285 | | | 13.093*** | 3.502* |
| | | | (1.787) | (2.483) | | | (1.511) | (1.903) |
| Board size $\leq 18^{a}$ | -1.696*** | -1.642*** | -1.680*** | -1.657*** | -0.951** | -0.824* | -0.936** | -0.876** |
| | (0.555) | (0.543) | (0.551) | (0.539) | (0.477) | (0.420) | (0.466) | (0.413) |
| Independent board members | -0.167** | -0.138** | -0.139** | -0.137** | -0.186*** | -0.155*** | -0.144*** | -0.143*** |
| | (0.067) | (0.065) | (0.065) | (0.064) | (0.058) | (0.050) | (0.055) | (0.049) |
| Employees (lagged 1yr) | 0.068 | 0.186** | 0.082 | 0.191** | 0.102 | 0.251*** | 0.131* | 0.263*** |
| | (0.082) | (0.081) | (0.082) | (0.081) | (0.071) | (0.063) | (0.070) | (0.062) |
| Leverage (lagged 1yr) | -0.460 | 0.042 | -0.378 | 0.090 | -0.993 | -0.263 | -0.846 | -0.156 |
| | (0.728) | (0.744) | (0.724) | (0.738) | (0.626) | (0.575) | (0.612) | (0.565) |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | N | Y | N | Y | N | Y |
| N. firms | 77 | 77 | 77 | 77 | 77 | 77 | 77 | 77 |
| N. obs. | 356 | 356 | 356 | 356 | 356 | 356 | 356 | 356 |
| R-squared | 0.19 | 0.29 | 0.19 | 0.29 | 0.36 | 0.55 | 0.38 | 0.56 |

*Note*: [a] Board size is winsorized at the 90th percentile (18 directors). Values above 18 are set equal to the most frequent firm-level value below 18.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A.5:** Combined Effects on Environmental and Social Scores — Excluding Firms with More Than 90,000 Employees (Robustness Check)

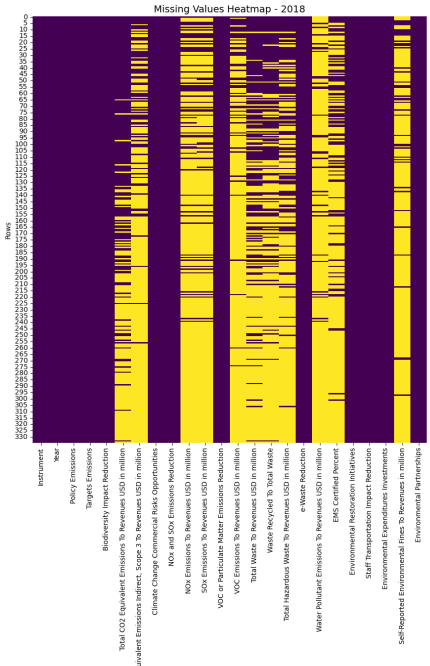
| | **Environmental Score** | | | | **Social Score** | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Degree | -1.832*** | -2.143*** | -2.015*** | -2.186*** | -0.302 | -0.392 | -0.574 | -0.472 |
| | (0.680) | (0.693) | (0.676) | (0.692) | (0.567) | (0.523) | (0.552) | (0.519) |
| I(Degree > 0) | 12.137*** | 10.879*** | 11.686*** | 10.897*** | 5.744** | 3.966* | 5.126** | 3.890* |
| | (3.005) | (2.962) | (2.971) | (2.943) | (2.507) | (2.237) | (2.425) | (2.205) |
| Betweenness | 1.641*** | 0.911 | 1.637*** | 0.973* | 1.686*** | 0.509 | 1.639*** | 0.545 |
| | (0.540) | (0.588) | (0.536) | (0.584) | (0.451) | (0.444) | (0.438) | (0.438) |
| F Quartile 2 | 6.628*** | -0.584 | | | 10.345*** | 1.562 | | |
| | (2.042) | (2.802) | | | (1.704) | (2.116) | | |
| F Quartile 3 | 8.226*** | -0.052 | | | 11.922*** | 1.329 | | |
| | (2.369) | (3.080) | | | (1.976) | (2.327) | | |
| F Quartile 4 | 9.743*** | -1.135 | | | 16.040*** | 2.237 | | |
| | (2.597) | (3.540) | | | (2.166) | (2.674) | | |
| F Third 2 | | | 8.358*** | 1.622 | | | 12.462*** | 4.533** |
| | | | (2.008) | (2.791) | | | (1.639) | (2.091) |
| F Third 3 | | | 8.514*** | 0.554 | | | 13.784*** | 3.761* |
| | | | (2.000) | (2.796) | | | (1.632) | (2.094) |
| Board size | -1.029** | -0.701 | -1.215*** | -0.762* | -0.501 | -0.114 | -0.776** | -0.268 |
| | (0.431) | (0.426) | (0.421) | (0.437) | (0.360) | (0.322) | (0.343) | (0.327) |
| Independent board members | -0.201*** | -0.182** | -0.168** | -0.185*** | -0.194*** | -0.164*** | -0.143** | -0.158*** |
| | (0.075) | (0.072) | (0.071) | (0.070) | (0.062) | (0.055) | (0.058) | (0.052) |
| Employees (lagged 1yr) | -0.140 | 0.005 | -0.129 | 0.003 | 0.107 | 0.273*** | 0.118 | 0.261** |
| | (0.137) | (0.136) | (0.136) | (0.135) | (0.115) | (0.102) | (0.111) | (0.101) |
| Leverage (lagged 1yr) | -0.890 | -0.477 | -0.795 | -0.382 | -1.310** | -0.652 | -1.181* | -0.531 |
| | (0.784) | (0.803) | (0.776) | (0.800) | (0.654) | (0.607) | (0.633) | (0.599) |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | N | Y | N | Y | N | Y |
| N. firms | 74 | 74 | 74 | 74 | 74 | 74 | 74 | 74 |
| N. obs. | 315 | 315 | 315 | 315 | 315 | 315 | 315 | 315 |
| R-squared | 0.22 | 0.32 | 0.23 | 0.32 | 0.40 | 0.58 | 0.44 | 0.59 |

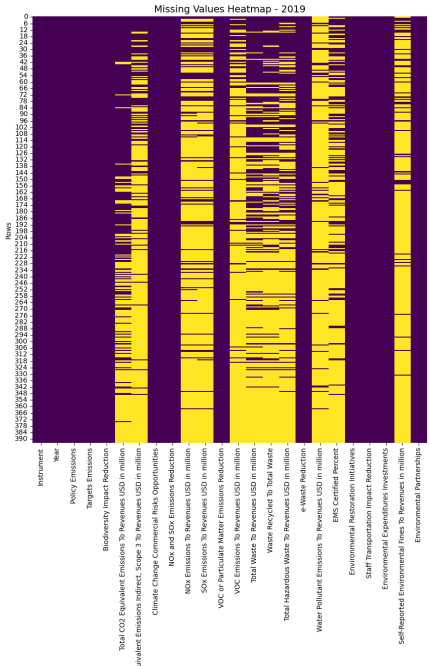
*Note*: Observations exclude firms with more than 90,000 employees (above the 90th percentile of the distribution).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

# Appendix B

# Missing Value Imputation in Environmental, Social, and Governance Data: An Impact on Emissions Scores







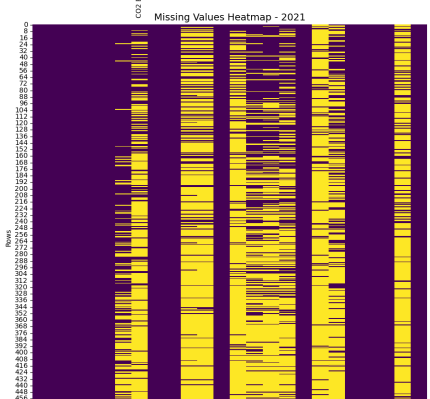
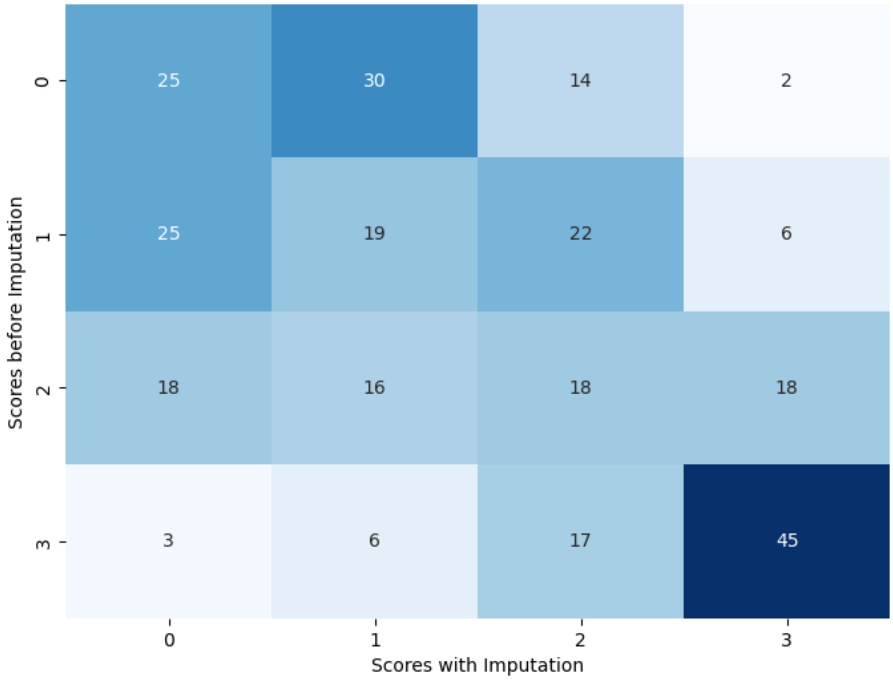


**Figure B.2:** Confusion matrix results 2017




## B.1 Methods

The K-Nearest-Neighbor algorithm (KNN) is a commonly used method for imputation. It uses a classification mechanism based on measuring the distance to the closest examples in a training data set (Rahman and Davis, 2013) (Emmanuel et al., 2021) (Hastie et al., 2009). Euclidean distance can be used to measure this distance. This is the most widely used distance measure and is considered productive and efficient (Rahman and Davis, 2013). KNN has some shortcomings. It can suffer from low precision and also associations as well as a possible long computational time.

MICE stands for multiply iterative chain equation. It is a method of taking multiple estimates of an imputation and creating a distribution of the results. It uses a bayesian ridge regression. In Bayesian Ridge Regression, the priors for the model parameters are chosen to follow gamma distributions, which are conjugate priors for the precision (inverse of variance) in a Gaussian distribution. This approach makes Bayesian Ridge Regression conceptually similar to classical Ridge Regression, but with the added benefit of a probabilistic framework that incorporates uncertainty in the estimates. (Suresh et al., 2019) (Pedregosa et al., 2011b) Decision trees are non-parametric and predict a value by learning simple decision rules from data features. It is also referred to as a piecewise constant approximation (Pedregosa et al., 2011b) (Suresh et al., 2019) (Woods et al., 2021). The decision tree is a machine learning

algorithm that illustrates all conceivable outcomes and the paths leading to those outcomes in the form of a tree structure. Missing value imputation using this method is done by building decision trees to observe the missing values of each variable, and then fills the missing values of each missing variable by using its corresponding tree (Emmanuel et al., 2021).

## B.2 Missing Data Summary

**Table A.1:** Missing Data by Percent and Type

| Column | Type | Percent Missing |
|---|---|---|
| HRC Corporate Equality Index | Numerical | 94.59 |
| Env R&D Expenditures To Revenues in million | Numerical | 92.99 |
| Employee Health & Safety Training Hours | Numerical | 92.70 |
| Gender Pay Gap Percentage | Numerical | 92.50 |
| Customer Satisfaction | Numerical | 92.35 |
| Employee Satisfaction | Numerical | 91.41 |
| Executives Cultural Diversity | Numerical | 91.31 |
| Water Recycled | Numerical | 91.01 |
| Litigation Expenses To Revenues in million | Numerical | 90.71 |
| Water Pollutant Emissions To Revenues USD in million | Numerical | 89.82 |
| Training Costs Per Employee | Numerical | 87.98 |
| Occupational Diseases | Numerical | 87.48 |
| Self-Reported Environmental Fines To Revenues in million | Numerical | 86.09 |
| VOC Emissions To Revenues USD in million | Numerical | 84.15 |
| Employees With Disabilities | Numerical | 83.71 |
| QMS Certified Percent | Numerical | 83.46 |
| Renewable Energy Use Ratio | Numerical | 82.91 |
| SOx Emissions To Revenues USD in million | Numerical | 82.27 |
| NOx Emissions To Revenues USD in million | Numerical | 81.67 |
| Lost Days To Total Days | Numerical | 78.99 |
| CO2 Equivalent Emissions Indirect, Scope 3 To Revenues USD in million | Numerical | 75.36 |
| Board Cultural Diversity, Percent | Numerical | 75.16 |
| EMS Certified Percent | Numerical | 72.78 |
| Total Renewable Energy To Energy Use in million | Numerical | 72.58 |
| Average Training Hours | Numerical | 70.99 |

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| Column | Type | Percent Missing |
|---|---|---|
| Turnover of Employees | Numerical | 66.92 |
| Total Hazardous Waste To Revenues USD in million | Numerical | 65.67 |
| CSR Sustainability External Audit | Boolean | 65.33 |
| Women Managers | Numerical | 64.63 |
| Total Donations To Revenues in million | Numerical | 63.98 |
| Trade Union Representation | Numerical | 63.69 |
| Waste Recycled To Total Waste | Numerical | 62.30 |
| GRI Report Guidelines | Boolean | 58.52 |
| Environmental Supply Chain Monitoring | Boolean | 56.68 |
| Salary Gap | Numerical | 55.09 |
| Injuries To Million Hours | Numerical | 54.55 |
| Total Waste To Revenues USD in million | Numerical | 54.05 |
| Water Use To Revenues USD in million | Numerical | 48.53 |
| Women Employees | Numerical | 44.81 |
| Nomination Committee Involvement | Numerical | 43.72 |
| Total Energy Use To Revenues USD in million | Numerical | 41.43 |
| Total CO2 Equivalent Emissions To Revenues USD in million | Numerical | 38.99 |
| Integrated Strategy in MD&A | Boolean | 34.82 |
| Non-audit to Audit Fees Ratio | Numerical | 33.28 |
| Nomination Committee Independence | Numerical | 32.29 |
| CSR Sustainability Report Global Activities | Boolean | 30.30 |
| Whistleblower Protection | Boolean | 25.48 |
| Highest Remuneration Package | Numerical | 21.76 |
| Compensation Committee Independence | Numerical | 21.31 |
| Board Meeting Attendance Average | Numerical | 17.93 |
| Internal Audit Department Reporting | Boolean | 14.51 |
| Audit Committee Independence | Numerical | 12.57 |
| Total Senior Executives Compensation To Revenues in million | Numerical | 12.32 |
| Net Employment Creation | Numerical | 9.34 |
| Average Board Tenure | Numerical | 3.23 |
| State Owned Enterprise SOE | Boolean | 3.18 |
| Veto Power or Golden Share | Boolean | 3.13 |
| Voting Cap Percentage | Numerical | 1.39 |
| Internal Promotion | Boolean | 0.35 |
| e-Waste Reduction | Boolean | 0.35 |

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| Column | Type | Percent Missing |
|---|---|---|
| NOx and SOx Emissions Reduction | Boolean | 0.35 |
| Human Rights Breaches Contractor | Boolean | 0.30 |
| Green Buildings | Boolean | 0.30 |
| Policy Freedom of Association | Boolean | 0.30 |
| Water Technologies | Boolean | 0.30 |
| Global Compact Signatory | Boolean | 0.30 |
| Env Supply Chain Partnership Termination | Boolean | 0.30 |
| Product Responsibility Monitoring | Boolean | 0.25 |
| Environmental Restoration Initiatives | Boolean | 0.25 |
| Policy Customer Health & Safety | Boolean | 0.25 |
| Policy Sustainable Packaging | Boolean | 0.25 |
| Corporate Responsibility Awards | Boolean | 0.25 |
| OECD Guidelines for Multinational Enterprises | Boolean | 0.25 |
| Renewable/Clean Energy Products | Boolean | 0.25 |
| Hybrid Vehicles | Boolean | 0.25 |
| Noise Reduction | Boolean | 0.25 |
| Environmental Partnerships | Boolean | 0.25 |
| Staff Transportation Impact Reduction | Boolean | 0.25 |
| Fundamental Human Rights ILO UN | Boolean | 0.25 |
| Policy Water Efficiency | Boolean | 0.25 |
| Targets Energy Efficiency | Boolean | 0.25 |
| Day Care Services | Boolean | 0.25 |
| Targets Diversity and Opportunity | Boolean | 0.25 |
| Supplier ESG Training | Boolean | 0.25 |
| Employees Health & Safety Team | Boolean | 0.25 |
| Policy Environmental Supply Chain | Boolean | 0.25 |
| Targets Water Efficiency | Boolean | 0.25 |
| Flexible Working Hours | Boolean | 0.25 |
| Environment Management Team | Boolean | 0.25 |
| Biodiversity Impact Reduction | Boolean | 0.25 |
| Equal Shareholder Rights | Boolean | 0.00 |
| Shareholder Rights Policy | Boolean | 0.00 |
| Anti Takeover Devices Above Two | Numerical | 0.00 |
| Auditor Tenure | Numerical | 0.00 |
| Board Functions Policy | Boolean | 0.00 |

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| Column | Type | Percent Missing |
|---|---|---|
| CEO Chairman Duality | Boolean | 0.00 |

**Table A.2:** Emissions Category with Percent Missing

| Variable | number of missing data |
|---|---|
| Environmental Expenditures Investments | 0.00 |
| VOC or Particulate Matter Emissions Reduction | 0.00 |
| Climate Change Commercial Risks Opportunities | 0.15 |
| Targets Emissions | 0.20 |
| Policy Emissions | 0.20 |
| Staff Transportation Impact Reduction | 0.25 |
| Environmental Restoration Initiatives | 0.25 |
| Environmental Partnerships | 0.25 |
| Biodiversity Impact Reduction | 0.25 |
| NOx and SOx Emissions Reduction | 0.35 |
| e-Waste Reduction | 0.35 |
| Total CO2 Equivalent Emissions To Revenues USD in million | 39.00 |
| Total Waste To Revenues USD in million | 54.05 |
| Waste Recycled To Total Waste | 62.30 |
| Total Hazardous Waste To Revenues USD in million | 65.67 |
| EMS Certified Percent | 72.78 |
| CO2 Equivalent Emissions Indirect, Scope 3 To Revenues USD in million | 75.36 |
| NOx Emissions To Revenues USD in million | 81.67 |
| SOx Emissions To Revenues USD in million | 82.27 |
| VOC Emissions To Revenues USD in million | 84.15 |
| Self-Reported Environmental Fines To Revenues in million | 86.09 |
| Water Pollutant Emissions To Revenues USD in million | 89.82 |

## B.3 Evaluation Metrics

Root Mean Square Error (RMSE) and $R^2$ score

For the evaluation of the five imputation methods (that is, KNN, MICE, DT, Simple, Zero) in part 1, I use the root mean square error (RMSE) and the score $R^2$. The Root Mean Square Error (RMSE) computes the difference between the imputed values and the actual values.

A mean squared error (MSE) measures the average squared difference between the predicted missing values and the actual value, while RMSE represents the standard deviation of the differences between the estimated missing values and the observed values. A small value as an output for this performance metric means that the estimated value is close to the real value.

For the $R^2$ score, the best possible score is 1.0 and can be negative (because the model can be worse than the average)(Pedregosa et al., 2011b). $R^2$ score determines the amount of variance between two variables. RMSE and $R^2$ are used to evaluate the performance of the imputation methods compared to each otherEmmanuel et al. (2021).

For both performance metrics, $n$ is the total number of observations at the firm level, $y_i$ is the original value, and $\hat{y}_i$ is the estimated value.

## B.4 LSEG Category Scores

An additional complication arises from the treatment of boolean variables by LSEG. Affirmative responses are recorded as one, while both negative responses and non-responses are recorded as zero. In contrast, missing numerical data are left blank. As a result, missingness in numerical emissions data provides a cleaner signal of non-disclosure than boolean variables, reinforcing the importance of explicitly accounting for missing data when constructing emissions-based measures Refinitiv (2022). Crippa (2023) specifically points out that a source of data driven greenwashing can arise from the use of traditional imputation techniques that cause biases in the scores. We see this present in the LSEG dataset. The emissions data used has a total of 50.4 percent missing. Of this, 7% is boolean and 80% is numerical. We see that a majority of the missing data is derived from the numerical variables and a majority of the present data is from the boolean data as a result of LSEG's imputation policy regarding boolean data. At this time, no steps have been taken to account for this inconsistency.

**Figure B.3:** Illustration of LSEG Category Score Construction

**Step 1: Raw ESG Data (Industry Peer Group)**

| Company | Variable 1 (Boolean) | Variable 2 (Numeric) | Variable 3 (Numeric) |
|---|---|---|---|
| A | 1 | 20 | 80 |
| B | 0 | 23 | 23 |
| C | 0 | 15 | 7 |
| D | 1 | *Missing* | 75 |

**Step 2: Initial Percentile Ranks (Within-Industry)**

| Company | Var 1 | Var 2 | Var 3 |
|---|---|---|---|
| A | 100% | 50% | 100% |
| B | 0% | 100% | 33% |
| C | 0% | 0% | 0% |
| D | 100% | – | 67% |

**Step 3: Aggregation and Final Category Score**

| Company | Total Score | Final Category Score |
|---|---|---|
| A | 250 | **100%** |
| B | 133 | **33%** |
| C | 0 | **0%** |
| D | 167 | **67%** |

*Notes:* Percentile ranks are computed within the industry peer group for each variable. Missing numerical values are excluded from the initial percentile ranking but contribute zero to the aggregated score, resulting in a de facto penalty when total scores are re-ranked to obtain the final category score. Boolean variables record both negative responses and non-responses as zero.

Figure C.1 gives a basic example of how LSEG calculates a category score and how missing data for numerical variables is treated with a de facto zero imputation. Step 1 shows raw data organized by variables and company. There is no missing values for the boolean variable as according to LSEG policy, these values are imputed with zero initially. Step 2 assigns a percentage rank based on the comparison of the raw data with one's peers. Step 3 adds those percent values and then re-ranks them a second time to create the category score. In this step, the de facto zero is implied. Although, for variable 2, company D is not taken into consideration during the peer rank of the other three companies, when the percentage of each company is added, the missing value of company D carries the same importance as the zero value for company C. These direct and implied imputations could be distorting the scores they are designed to create Benuzzi et al. (2025)

# Appendix C

# The Role of Missing Emissions Data as a Priced Risk Factor

## C.1 Variance Inflation Factors

To assess potential multicollinearity among the regressors, variance inflation factors (VIFs) were computed. The VIF measures the extent to which the variance of an estimated regression coefficient is inflated because of linear dependence with other regressors. A commonly cited rule of thumb is that VIF values above 10 indicate serious multicollinearity, while values above 5 may suggest moderate multicollinearity and values below 3 are generally safe (Kutner et al., 2005; Hair et al., 2010; Gujarati and Porter, 2009).

Tables A.1 and A.2 report VIFs for all regressors, including the Emissions Factor, Missing Factor, their interaction, firm characteristics, and Fama French risk factors. For the initial 2×2 sort, the VIFs for the Emissions and Missing Factors are 9.64 and 9.61, respectively, remaining below the threshold of 10, indicating moderate multicollinearity. While the interaction term between the Emissions and Missing Factors is well identified (VIF = 1.84), the moderate correlation between the two factors highlights that including both in a regression could inflate standard errors slightly. However, other adverse effects commonly associated with multicollinearity, such as excessively high standard errors or unstable coefficient signs, are not observed.

By introducing a 2×2×2 sorting procedure—conditioning each factor on size and the other factor, we further mitigate potential collinearity. Table A.2 shows that all VIFs in the 2×2×2 specification fall below 3, indicating that multicollinearity is no longer a concern. Notably, the interaction term between Emissions and Missing Factors remains well identified. Moreover, all major trends observed in the 2×2 regressions are preserved, suggesting that the additional sorting dimension reduces multicollinearity while retaining the explanatory power of the factors.

Although the Emissions and Missing Factors are moderately correlated in the 2×2 sort, it is common in asset pricing applications for factors to exhibit correlation while still capturing distinct

**Table A.1:** Variance Inflation Factors (2×2 Sort)

| **Variable** | **VIF** |
|---|---|
| EmissionsFactor | 9.64 |
| MissingFactor | 9.61 |
| HML | 7.43 |
| CMA | 5.65 |
| MktCap_norm | 5.23 |
| Profit_norm | 3.50 |
| Shareholders_Equity_norm | 3.19 |
| RMW | 2.51 |
| Mkt–RF | 2.00 |
| SMB | 1.36 |
| MissingFactor × EmissionsFactor | 1.84 |

**Table A.2:** Variance Inflation Factors (2×2×2 Sort)

| **Variable** | **VIF** |
|---|---|
| HML | 7.15 |
| CMA | 5.60 |
| Market Capitalization (Norm.) | 5.23 |
| Profit (Normalized) | 3.50 |
| Shareholders' Equity (Norm.) | 3.19 |
| RMW | 2.49 |
| Emissions Factor | 2.44 |
| Mkt–RF | 1.90 |
| Missing Factor | 1.79 |
| Emissions × Missing Factor | 1.44 |
| SMB | 1.38 |

*Notes:* This table reports variance inflation factors (VIFs) for the full regression specification including sector and year fixed effects. High VIFs for sector indicators reflect the inclusion of a full set of mutually exclusive industry dummies and do not indicate problematic multicollinearity among the main variables of interest.

sources of cross-sectional variation in returns (Fama and French, 1993; Cochrane, 2005). Conditioning each factor on the other and accounting for the firm size in the 2×2×2 construction further mitigates collinearity concerns.

## C.2 LSEG Category Scores

An additional complication arises from the treatment of boolean variables by LSEG. Affirmative responses are recorded as one, while both negative responses and non-responses are recorded as zero. In contrast, missing numerical data are left blank. As a result, missingness in numerical emissions data provides a cleaner signal of non-disclosure than boolean variables, reinforcing the importance of explicitly accounting for missing data when constructing emissions-based measures Refinitiv (2022). Crippa (2023) specifically points out that a source of data driven greenwashing can arise from the use of traditional imputation techniques that cause biases in the scores. We see this present in the LSEG dataset. The emissions data used has a total of 50.4 percent missing. Of this, 7% is boolean and 80% is numerical. We see that a majority of the missing data is derived from the numerical variables and a majority of the present data is from the boolean data as a result of LSEG's imputation policy regarding boolean data. At this time, no steps have been taken to account for this inconsistency.

**Figure C.1:** Illustration of LSEG Category Score Construction

**Step 1: Raw ESG Data (Industry Peer Group)**

| Company | Variable 1 (Boolean) | Variable 2 (Numeric) | Variable 3 (Numeric) |
|---|---|---|---|
| A | 1 | 20 | 80 |
| B | 0 | 23 | 23 |
| C | 0 | 15 | 7 |
| D | 1 | *Missing* | 75 |

**Step 2: Initial Percentile Ranks (Within-Industry)**

| Company | Var 1 | Var 2 | Var 3 |
|---|---|---|---|
| A | 100% | 50% | 100% |
| B | 0% | 100% | 33% |
| C | 0% | 0% | 0% |
| D | 100% | – | 67% |

**Step 3: Aggregation and Final Category Score**

| Company | Total Score | Final Category Score |
|---|---|---|
| A | 250 | **100%** |
| B | 133 | **33%** |
| C | 0 | **0%** |
| D | 167 | **67%** |

*Notes:* Percentile ranks are computed within the industry peer group for each variable. Missing numerical values are excluded from the initial percentile ranking but contribute zero to the aggregated score, resulting in a de facto penalty when total scores are re-ranked to obtain the final category score. Boolean variables record both negative responses and non-responses as zero.

Figure C.1 gives a basic example of how LSEG calculates a category score and how missing data for numerical variables is treated with a de facto zero imputation. Step 1 shows raw data organized by variables and company. There is no missing values for the boolean variable as according to LSEG policy, these values are imputed with zero initially. Step 2 assigns a percentage rank based on the comparison of the raw data with one's peers. Step 3 adds those percent values and then re-ranks them a second time to create the category score. In this step, the de facto zero is implied. Although, for variable 2, company D is not taken into consideration during the peer rank of the other three companies, when the percentage of each company is added, the missing value of company D carries the same importance as the zero value for company C. These direct and implied imputations could be distorting the scores they are designed to create Benuzzi et al. (2025)

## C.3 Tables

| Description | Type |
|---|---|
| Accidental Spills To Revenues USD in million | Numeric |
| Biodiversity Impact Reduction | Boolean |
| Cement CO2 Equivalents Emission | Numeric |
| Climate Change Commercial Risks Opportunities | Boolean |
| CO2 Equivalent Emissions Indirect, Scope 3 To Revenues USD in million | Numeric |
| Water Pollutant Emissions To Revenues USD in million | Numeric |
| Emissions Trading | Boolean |
| EMS Certified Percent | Numeric |
| Environmental Expenditures Investments | Boolean |
| Environmental Partnerships | Boolean |
| Environmental Restoration Initiatives | Boolean |
| e-Waste Reduction | Boolean |
| Flaring Gases To Revenues USD in million | Numeric |
| Total Waste To Revenues USD in million | Numeric |
| Internal Carbon Price per Tonne | Numeric |
| NOx and SOx Emissions Reduction | Boolean |
| NOx Emissions To Revenues USD in million | Numeric |
| Ozone-Depleting Substances To Revenues USD in million | Numeric |
| Policy Emissions | Boolean |
| Self-Reported Environmental Fines To Revenues in million | Numeric |
| SOx Emissions To Revenues USD in million | Numeric |
| Staff Transportation Impact Reduction | Boolean |
| Targets Emissions | Boolean |
| Total CO2 Equivalent Emissions To Revenues USD in million | Numeric |
| VOC Emissions To Revenues USD in million | Numeric |
| VOC or Particulate Matter Emissions Reduction | Boolean |
| Waste Recycled To Total Waste | Numeric |

**Table A.3:** Emissions-related metrics from the LSEG ESG database

**Table A.4:** Oil and Gas Industry Variables

| **Variable** |
|---|
| Accidental Spills To Revenues USD in million |
| Biodiversity Impact Reduction |
| Climate Change Commercial Risks Opportunities |
| CO2 Equivalent Emissions Indirect, Scope 3 To Revenues USD in million |
| Water Pollutant Emissions To Revenues USD in million |
| Emissions Trading |
| EMS Certified Percent |
| Environmental Expenditures Investments |
| Environmental Partnerships |
| Environmental Restoration Initiatives |
| e-Waste Reduction |
| Flaring Gases To Revenues USD in million |
| Total Waste To Revenues USD in million |
| Internal Carbon Price per Tonne |
| NOx and SOx Emissions Reduction |
| NOx Emissions To Revenues USD in million |
| Ozone-Depleting Substances To Revenues USD in million |
| Policy Emissions |
| Self-Reported Environmental Fines To Revenues in million |
| SOx Emissions To Revenues USD in million |
| Targets Emissions |
| Total CO2 Equivalent Emissions To Revenues USD in million |
| VOC Emissions To Revenues USD in million |
| VOC or Particulate Matter Emissions Reduction |
| Waste Recycled To Total Waste |

**Table A.5:** Sample Sizes and Monthly Cross-Sectional Regressions by Sector

| **Sector** | **Number of Firms** | **Cross-Sectional Regressions** |
|---|---|---|
| Energy | 329 | 108 |
| Industrials | 993 | 108 |
| Basic Materials | 529 | 108 |
| Consumer Cyclicals | 930 | 108 |
| Consumer Non-Cyclicals | 368 | 108 |
| Technology | 820 | 96 |
| Financials | 961 | 108 |
| Healthcare | 880 | 96 |
| Utilities | 202 | 96 |
| Real Estate | 493 | 96 |
| Academic & Educational Services | 20 | 84 |

**Table A.6:** List of Included Countries

| **No.** | **Country** |
|---|---|
| 1 | Australia |
| 2 | Austria |
| 3 | Belgium |
| 4 | Canada |
| 5 | Switzerland |
| 6 | Germany |
| 7 | Denmark |
| 8 | Spain |
| 9 | Finland |
| 10 | France |
| 11 | United Kingdom |
| 12 | Greece |
| 13 | Hong Kong |
| 14 | Ireland |
| 15 | Italy |
| 16 | Japan |
| 17 | Netherlands |
| 18 | Norway |
| 19 | New Zealand |
| 20 | Portugal |
| 21 | Sweden |
| 22 | United States of America |
| 23 | Singapore |

Figure 4.2 and Table 4.5 provide additional insight by examining emissions scores between groups defined by market capitalization and missingness. The results suggest that missing data plays a more influential role in determining emissions scores than firm size alone, reinforcing the motivation to treat missing data as an economically meaningful characteristic rather than a secondary data issue. The median company market capitalization used as the cut point is $2.53 \times 10^9$, and the mean percent of missing emissions data is 34.76%.

Figure 4.2 and Table 4.5 highlight the relationship between missing data, firm size, and emissions scores. We show that when firm size and missingness are taken into account, missingness seems to have a more substantial impact on emissions scores. This statement is explained by the fact that the average emissions scores are lower for firms with high missingness when we control for size. Even large Cap firms with high missingness have lower average emissions scores than low Cap firms with low missingness. High Cap companies with low missingness have the highest emissions scores, and low Cap companies with high missingness have the lowest emissions scores.

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