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Do Investors in Mining Companies Price ESG Performance into Their Required Equity Returns?

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Abstract

In recent years, environmental, social and governance (ESG) considerations have become more prominent in capital markets, particularly in sectors with high environmental and social impacts such as mining. While prior research has examined the relationship between ESG performance and the cost of capital using broad cross-industry samples, there is limited evidence on whether ESG performance is significantly associated with required equity returns for investors in mining companies. This thesis addresses that gap by analysing the association between ESG scores and the cost of equity for publicly listed mining firms across five countries over a ten-year period. A quantitative analysis is conducted using panel regression models estimated with country-year fixed effects. The results show no statistically significant relationship between composite ESG scores, or individual E, S and G pillar scores, and mining firms' cost of equity. Overall, the findings suggest that, within this sample and period, equity investors in mining companies do not appear to systematically price ESG performance into their required equity returns.

Keywords: ESG, mining industry, cost of equity capital, equity investors, panel regression, fixed effects.
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1. Introduction

1.1 Motivation

In January 2025, the Democratic Republic of Congo suspended operations at a major Chinese-owned cobalt mine following a dam collapse that threatened the safety of residents in its second-largest city of Lubumbashi (Reuters, 2025). The mine was accused of insufficient environmental safeguards and of exposing surrounding communities to acute health and social risks. Incidents such as these are not rare in the mining industry and have occurred globally, particularly in jurisdictions with complex regulatory environments and heightened environmental vulnerability. For instance, growing concerns over the environmental footprint of Indonesia's rapidly expanding nickel mining sector have led market participants to call on the London Metal Exchange (LME) to introduce a "green nickel" premium to differentiate responsibly produced nickel from higher-emission supply, reflecting pressure for environmental accountability on the exchange where global metal contracts are traded (Deloitte, 2024). Further, the LME is actively working to refine its thresholds for "low-carbon" nickel as demand grows for more transparent and climate-aligned metal markets (Lakshmi & Dempsey, 2024). Together, these developments illustrate how issues involving ESG can rapidly translate into regulatory intervention, reputational damage, and financial consequences for mining firms. These developments also suggest public and investor scrutiny, which may translate to worsened market access and financing conditions for mining firms. The scrutiny faced by mining firms has only intensified in today's environment, wherein ESG is becoming increasingly important in financial markets. Over the past decade, ESG has evolved from a peripheral ethical consideration into a mainstream component of investment analysis. A "sea change" has been documented among the world's largest institutional investors, who now view ESG as financially material, embedded in risk pricing, and essential for long-term value creation. These large asset owners increasingly recognize that sustainability-related risks can influence portfolio-wide outcomes. This has prompted more systematic integration of ESG considerations into engagement, stewardship, and capital-allocation practices (Eccles & Klimenko, 2019).

The developments we touch on are particularly significant for the mining sector, which sits at the center of the global energy-transition supply chain. The shift toward electric vehicles, renewable-energy systems, and grid-storage technologies has sharply increased demand for minerals such as lithium, copper, and cobalt - materials indispensable for battery technologies and clean-energy infrastructure. Sustainability oriented investors and ESG themed funds are increasingly channeling capital toward mining and processing companies involved in critical-mineral supply chains, but importantly, those able to demonstrate credible environmental and social practices (Oxford, 2025). Further, a growing share of financing for critical-mineral projects now occurs through equity-based investment, reflecting both the long-duration risk profile of mining projects and the preferences of climate-aligned capital providers. This shift implies that mining firms with stronger ESG performance may benefit from improved access to funding or more favorable financing conditions, whereas weaker ESG performers may face higher capital costs or more limited investment opportunities.

Against this backdrop, understanding whether ESG performance influences the cost of equity of mining firms is both timely and relevant. If investors systematically incorporate ESG information into their risk assessments, stronger ESG performance may be associated with lower perceived risk and therefore a lower cost of equity. Conversely, if no such relationship exists, mining firms may face weaker financial incentives to improve sustainability performance despite rising stakeholder expectations.

This forms the foundation of our study, which examines whether ESG performance, both at the composite and pillar levels, affects the cost of equity for publicly listed mining firms.

1.2 Purpose of study

The purpose of this study is to examine whether ESG performance holds value relevance for mining firms by analyzing its relationship with the cost of equity capital. The cost of equity reflects investors' required return and therefore incorporates their risk perceptions, expectations, and preferences. If investors actively use ESG information in their investment decision-making, firms with stronger ESG performance may face different financing conditions than those with weaker performance. In this sense, ESG performance may represent an intangible value component, potentially enhancing firms' market perception, lowering perceived risk, or improving access to capital.

Accordingly, this study seeks to answer the following research question:

“Does ESG performance affect mining firms’ cost of equity capital, and if so, which ESG pillars drive this relationship?”

1.3 Research boundaries

The scope of this study is limited to publicly listed mining firms across multiple jurisdictions for which consistent Environmental, Social, and Governance (ESG) and financial data are available. The analysis uses annual firm-level panel data spanning the ten-year fiscal period from 2014 to 2023 (and 2015 to 2024 for dependent variables), constrained by the availability of historical ESG ratings on LSEG Eikon. This period following the Global Financial Crisis (GFC) also reflects a structural shift in global capital markets, during which investor demand for ESG information increased markedly and sustainability-related risks began to feature more prominently in institutional investment decision-making (Eccles & Klimenko, 2019).

ESG performance is measured using both composite ESG scores and the individual Environmental, Social, and Governance pillar scores provided by the LSEG database. These scores are treated as externally assessed inputs; the study does not evaluate the underlying sustainability reporting quality, disclosure practices, or the methodological design of the rating process.

Given the focus on equity financing, the empirical analysis concentrates on variables directly relevant to the cost of equity and market-based measures of firm risk. The study does not examine the cost of debt, the weighted average cost of capital (WACC), credit risk, or default probability. The cost of equity is estimated using a Capital Asset Pricing Model (CAPM)-based approach relying on realised returns and observable market data rather than implied (ex-ante) valuation models. Consequently, the final sample includes only firms with sufficient return histories to compute CAPM cost of equity, which excludes newly listed firms and those with limited trading liquidity.

1.4 Contribution

The relationship between ESG performance and cost of capital has been studied before, but the research has left significant gaps for us to fill.

Most influential studies linking ESG or CSR performance to the cost of equity rely on broad, cross-industry samples (Dhaliwal, Li, Tsang, & Yang, 2011). However, prior research argues that the financial materiality of ESG issues is industry-specific, meaning that results from diversified samples cannot automatically be inferred to sectors with distinct risk structures (Khan, Serafeim, & Yoon, 2016). Mining is one such sector: global ESG risk assessments place metals and mining among the industries with the highest environmental and social exposure, due to issues such as emissions, tailings management, water usage, and community impacts (S&P, 2020). ESG failures in mining have also been shown to produce outsized financial and reputational consequences, as illustrated by high-profile environmental incidents documented in case-based analyses such as the Vale tailings dam collapse (Davis & Guerra, 2021). While prior mining-related ESG studies examine outcomes such as financial risk, financial performance, and firm value (Fikru, Brodmann, Eng, & Grant, 2024; Fu, Yu, Guo, & Zhang, 2024; Oktadewi & Diantini, 2025), they do not directly estimate the relationship between ESG performance and firms' cost of equity capital for mining firms exclusively**.** A very recent study on ESG premia in the energy, utilities and basic materials sectors examines a similar question using a pooled multi-sector sample, but it does not provide mining-specific estimates or focus on the mining sector in isolation (Wilberg, Kjellevoll, Holz, & Neumann, 2025). Therefore, a study focusing on whether ESG performance is priced by equity investors in the mining sector remains empirically under-explored. Our study addresses this gap in the literature by focusing on mining firms, where ESG risks are financially material and central to operational continuity.

A second limitation in prior literature is the large reliance on composite ESG or CSR scores. Composite indices combine environmental, social, and governance indicators into a single weighted number, which can obscure meaningful variation across pillars. Differences in scope, measurement, and weighting across rating providers introduce noise into aggregate ESG scores (Berg, Kölbel, & Rigobon, 2022). Moreover, evidence suggests that the environmental, social, and governance pillars capture different types of information**,** and can affect financial outcomes through distinct channels. For example, prior work on the relationship between ESG scores and cost of debt find that individual ESG pillars have separate associations with firms' bond spreads and credit ratings (Apergis, Poufinas, & Antonopoulos, 2022), while other studies show that various ESG dimensions relate to risk exposure or performance in different ways (Gibson Brandon, Krueger, & Schmidt, 2021; Ramirez, Monsalve, Gonzalez-Ruiz, Almonacid, & Pena, 2022). Together, these findings suggest that the use of composite ESG measures may mask underlying pillar-level effects. Our study therefore evaluates both the composite ESG score and the individual E, S, and G components, providing more granular insight and interpretation into which sustainability dimensions, if any, relate to mining firms' cost of equity capital.

Many existing mining focused ESG studies examine firms within a single country or regulatory environment, such as China or South Africa (Evans et al., 2023). Yet ESG risks and sustainability expectations vary significantly across jurisdictions. Research on social and environmental conflict in mining demonstrates that such risks are unevenly distributed across regions and jurisdictions (Franks, et al., 2014). Moreover, literature on asset-pricing shows country-level institutional and market conditions influence expected returns, and therefore a firm's cost of equity (Bekaert, Harvey, & Lundblad, 2007). To address this limitation, our study constructs a multi-country panel of publicly listed mining firms and incorporates country–year fixed effects to absorb cross-country institutional and regulatory heterogeneity. Our study design yields broader interpretations and generalizability for mining sector studies on ESG than the geographically narrow studies available to date.

Practically, our findings are relevant for mining company managers deciding whether and where to invest in ESG initiatives, as they inform the extent to which ESG performance is associated with equity financing costs. They are also informative for investors, asset managers and ESG-oriented funds assessing whether ESG information is reflected in required returns for mining firms, and thus whether ESG signals in this sector are financially meaningful for portfolio construction and risk management. Finally, we expand the existing base of mining focused ESG literature which can be used by both researchers and practitioners as a reference point for future empirical work and policy or investment decisions.

2. Empirical Theory and Literature Review

In 2004, and in response to a call from Kofi Anan, 20 financial institutions came together and produced a United Nations report titled, “Who Cares Wins” (Gillan, Koch, & Starks, 2021). Importantly, the report made the term ESG official. It outlined environmental issues (“E”) as those related to climate change and the need for climate regulation, social issues (“S”) as those related to workplace health and safety, and corporate governance issues (“G”) as those related to board structure, accountability, and corruption (UN, 2004). Since it became official, the term ESG has attracted attention from academia, policymakers, and the public, and has been incorporated into the practices of many firms (Aboud, Saleh, & Eliwa, 2023). Our thesis focuses on the mining industry, whose players often face scrutiny for the environmental and social impact of their activities, as seen in the example of the Chinese-owned cobalt mine in Lubumbashi (Reuters, 2025).

In a similar environment that led to the term ESG, the crises of the 2000s reflected the need for more trust and ethics in business, and in so doing, strengthened the focus on the *stakeholder theory*. Established by Freeman in 1984, the stakeholder theory focuses on how different groups with a stake in the activities of a business interact to create value (Parmar, et al., 2010). In terms of ESG and cost of equity, the stakeholder theory points to better ESG performance, leading to a lower cost of equity. First, ESG performance and compliance increase mutual trust, and cooperation between the firm and stakeholders, reducing implicit and explicit costs (Evans et al., 2023). Second, a strong relationship with stakeholders increases the avoidance of negative outcomes, reduces risk, and creates more predictably stable returns (Fama, 1970). We can apply the stakeholder theory to our earlier Chinese-owned cobalt mine example. If the Chinese company had had a stronger relationship with stakeholders, including better compliance, cooperation, and trust, the stakeholder theory suggests that the negative outcome could have been avoided. It also suggests that even if it was inevitable, the consequences could have been mitigated.

Stakeholders further play an important role in the association between higher ESG scores and the cost of equity capital through the investor-base theory. The investor-base theory suggests that firms with wider investor appeal enjoy better risk diversification and lower required return (Merton, 1987; Heinkel, Kraus, & Zechner, 2001). First, ESG disclosure and performance strengthen firm legitimacy and reputation (Kuruppu, Milne, & Tilt, 2019), which can attract investment from institutional investors. Firms with a higher concentration of institutional owners benefit from a lower cost of equity. In terms of the ESG ratings themselves, they play an important role due to the active monitoring done by institutional investors (Allen, Bernardo, & Welch, 2000). Second, the disclosure of high ESG ratings allows firms to have a larger pool of potential investors, including 'green investors', who apply ethical or environmental screens to potential investments (Sharfman & Fernando, 2008). Firms with larger pools of investors benefit from a lower cost of equity.

In the mining industry, the investor-base theory manifests itself in several ways. Mining firms share many similarities with classical 'sin' industries - tobacco, alcohol, gaming - like environmental damage, social conflict, and litigation risk. With regards to the investor pool, many investors have screening processes that explicitly or implicitly exclude these sectors (Hong & Kacperczyk, 2009). For mining firms, this means that if they are considered 'sin' stocks, or if their ESG scores lead to their exclusion from potential investors, the pool of investors diminishes. In turn, remaining investors share more risk among themselves and the cost of equity increases (Merton, 1987). In a similar fashion, even if investors do not exclude the mining industry entirely, they may demand a carbon emissions premium. This means that if a mining company's Environmental score is poor, their required rate of return may be higher (Bolton & Kacperczyk, 2021). This points to a higher cost of equity.

The cost of capital describes both the expected rate of return demanded by a firm's investors, as well as the rate used by a firm's investors to discount future cash flows. The higher the cost of capital, the more future cash flows are discounted, and the lower the firm's value is. From an investor's perspective, the rate of return of a given company must be at least as high as that of a comparable risk. From a company perspective, the cost of equity is the price of equity financing, just as the interest rate is the price of debt financing (Sharfman & Fernando, 2008).

There are generally two ways of calculating a company's cost of equity: (i) the ex-post realized-returns method and, (ii) the ex-ante implied method (Sharfman & Fernando, 2008). The ex-ante implied method uses the company's current market price to derive the cost of equity. It finds the discount rate which would make the present value of expected future cash flows equal to the current market price, calculated through the dividend-discount model (Botosan, Plumlee, & Wen, 2011). The ex-post realized returns method is based on historical realized returns. It works on the idea that if we look at historical returns, the different shocks cancel each other out, and the answer provides a good estimate of future expected returns. The most common approach to using the ex-post realized returns method is through the Capital Asset Pricing Model (CAPM), which is the approach we follow in this study (Elton, 1999).

The agency theory describes the problem of information asymmetry as an agent having more information than the principal, such as with managers and investors (Jensen & Meckling, 1976). While high ESG ratings affect a firm's relationship with stakeholders, the ratings themselves are important because they point to a change in information asymmetry (Cho, Lee, & Pfeiffer, 2013). By providing information on ESG, ratings should theoretically reduce the lack of non-financial information provided by traditional financial reports, and in so doing, reduce the information asymmetry (Li, Zhao, Ye, Li & Tao, 2024). That said, while lower information asymmetry generally lowers the cost of equity (Fu, Kraft, & Zhang, 2012), in practice the disclosure of ESG ratings has been found to increase information asymmetry (Cho, Lee & Pfeiffer, 2013). This is because the information disclosed can be hard to assess and judge, and inconsistencies in 3rd party ratings create confusion that results in investors not trusting the ratings (Agapova, King, & Ranta, 2025; Pan, Chen, & Sinha, 2023). This implies that in practice, whether an ESG score is high or low does not matter.

Early empirical studies have found that firms with stronger practices in areas related to ESG, such as Environmental Risk Management (ERM), and Corporate Social Responsibility (CSR), as well as ESG itself are associated with improved financial outcomes and reduced cost of equity capital.

Firstly, firms engaging in stronger ERM have been found to experience lower systematic risk and lower weighted average cost of capital, including equity, compared to peers with weaker environmental management (Sharfman and Fernando, 2008). This association is also found for firms with stronger CSR performance, where higher CSR ratings and the initiation of standalone CSR reporting are associated with a lower implied cost of equity capital (El Ghoul, Guedhami, Kwok, & Mishra, 2011; Dhaliwal et al., 2011). Regarding ESG scores, the introduction of ESG ratings in China has been found to significantly reduce firms' cost of equity through the mitigation of information asymmetry and perceived operational risk (Li, Zhao, Ye, Li & Tao, 2024). This association has stronger effects among high-pollution and non-state-owned firms.

Furthermore, past studies have also found that generally, investors expect ESG investments to underperform the market, implying a lower required return (Giglio, et al., 2025). Between mid 2021 to late 2023, the average expected 10-year annualised return of ESG investments relative to the overall stock market was -2.1%. Similarly, another paper finds that firms with lower CO_2 emissions (thereby better environmental performance) earn lower average stock returns because investors focus mainly on familiar, near-term risks and do not fully price long-run carbon transition risk and therefore imply that ESG/CSR firms face a lower cost of capital (Bolton and Kacperczyk., 2021).

In contrast, some research finds no clear link between Corporate Social Performance (CSP) and firms' cost of equity (Humphrey et al., 2012). Comparing UK firms with high and low CSP ratings, the paper reports no significant differences in risk-adjusted returns or equity risk and concludes that adopting stronger CSP does not materially raise or reduce firms' required equity returns. This adds mixed evidence of whether ESG performance is priced in the cost of capital.

Prior research also suggests industry effects on ESG performance. It has been cited that industry is highly correlated with ESG scores to the point that firms are best evaluated relative to their industry average rather than on raw scores alone, underscoring the importance of industry when interpreting ESG outcomes (Borghesi, Houston, & Naranjo, 2014). This is supported by prior cost of capital literature which suggests that the industry membership is one of three constructs, alongside firm financial leverage and firm size, most likely to affect any sample of firms' costs of capital (Gebhardt, Lee, & Swaminathan, 2001).

Overall, prior literature largely supports the view that improved ESG is associated with lower cost of equity capital, with some mixed evidence. Moreover, it highlights that industry differences are significant and is a control frequently used across these studies.

Past literature points to a general negative association between higher ESG ratings and the cost of equity capital. Yet, while theory points to a similar association in mining firms, in practice, past mining specific ESG literature shows mixed evidence, where some studies find risk-reducing benefits of higher ESG ratings, while others find no clear performance gains or even negative valuation effects.

In theory, industry experts suggest that solid ESG policies are a means of expanding mining firms' available capital pool, as lender and institutional investors are increasingly prioritizing ESG compliance when allocating funding and making capital allocation decisions (Barich, 2021; Leonida, 2022). Past literature has also argued that higher ESG ratings in mining firms are associated with sounder governance structures and reduced agency problems, which in turn lower financial risk (Fu, Yu, Guo, & Zhang, 2024).

That said, in practice, past literature comparing ESG-rated and unrated mining companies has found no significant association between ESG ratings and standard financial performance indicators, and that these ESG rated mining firms are not necessarily more profitable, nor do they enjoy cheaper financing (Fikru, Brodmann, Eng, & Grant, 2024).

First, for mining firms in South Africa, no statistically significant positive relationship has been found between higher overall ESG scores and financial performance. While the Governance pillar has been found to be positively associated with firm performance, the Environmental and Social pillars have been found to show no significant effects (Evans et al., 2023). Interestingly, the study highlights that aggregated ESG measures may obscure distinct effects of individual pillars. Emissions and shareholder responsibility tend to be negatively associated with financial performance, whereas human rights and CSR strategy show positive relationships.

Further, a recent study examines a similar research question for the energy, utilities and basic materials sectors, using a global pooled panel from these sectors and an implied cost of equity and cost of debt measure. They find that aggregate ESG scores are not significantly related to firms' cost of capital, but that the environmental pillar is associated with a lower cost of equity and debt, while the social pillar is linked to a higher cost of debt (Wilberg et al., 2025).

Moreover, in Indonesian mining firms, better ESG performance has been found to be associated with lower firm value. Investors have been found to perceive ESG initiatives as short-term cost burdens, rather than value-creating strategies. This is especially true for firms with low profitability (Oktadewi et al., 2025).

Beyond ESG scores themselves, mining companies are increasingly grouped with other carbon-intensive 'new sin' industries that may be screened out by norm-constrained or sustainability-oriented investors. Recent work on European sin stocks extends the traditional sin categories, for example alcohol, tobacco and gambling, to include oil and gas, metals and mining, coal and uranium as carbon-intensive 'new sin' sectors. Their results show that these new sin stocks are indeed treated differently by investors, with some institutions excluding these stocks according to ownership patterns. In addition, majority of equity owner types for these 'new sin' stocks are individual investors or corporations, who might not require the same ESG mandates as larger institutional investors like pension funds or similar institutions (Sagbakken & Zhang, 2022; Hong & Kacperczyk 2009). However, the study does not find a statistically significant sin-stock return premium for either traditional or new sin stocks relative to the market or sector peers. This contrasts with the classic sin-stock evidence in prior studies which show that shunned industries earn higher expected returns, consistent with exclusion raising their required returns that is also found in another paper which suggests that socially aware investors will eliminate firms with poor CSR performance from their portfolios, increasing the companies' cost of capital. (Heinkel et al., 2001). Following asset-pricing theory, higher expected stock returns correspond to a higher cost of equity, so the traditional sin-stock literature implies a channel through which exclusion can increase firms' cost of equity; yet the more recent European evidence for carbon-intensive "new sin" sectors such as metals and mining does not show a clear or robust premium, leaving the implications for mining firms' cost of equity empirically ambiguous.

This contrast in findings between broader, cross-sector ESG-cost of capital studies and findings in prior studies specific to mining further motivates our reason for this study and is used for the development of our study hypotheses.

3. General Hypotheses

The empirical theory and literature review lead to mixed conclusions. Empirically, while stronger stakeholder relationships, and a larger investor base point to the association being negative, the agency theory suggests ESG scores increase information asymmetry. While the literature review suggests that in general, higher ESG scores are associated with a lower cost of equity capital due to reduced systematic risk, this association is less clear mining firms, where ESG has been found to have no association with firm performance, and a negative association with firm value.

Due to these mixed results, we have decided to formulate our first hypothesis as two-tailed in the following:

***H1**: There is a significant relationship between mining firms' ESG score and its cost of equity capital.*

Since past literature has mostly focused on aggregate ESG scores despite E, S, G having found to have distinct impacts on cost of equity capital, we further formulate our following hypotheses in the following:

***H2**: There is a significant relationship between mining firms' Environmental (E) score and its cost of equity capital.* ***H3**: There is a significant relationship between mining firms' Social (S) score and its cost of equity capital.* ***H4**: There is a significant relationship between mining firms' Governance (G) score and its cost of equity capital.*

4. Methodology

4.1 Sample Data

For our primary data collection, we used the London Stock Exchange Group (LSEG) database. We initially collected data on overall ESG, and specific E, S, and G scores for mining companies over 10 fiscal years from 2014 to 2023. We subsequently collected data for the dependent variables of cost of equity (and equity beta for additional analysis) for fiscal years 2015 to 2024 for each company and then collected data on control variables of leverage, size and profitability for the same fiscal years as the main explanatory variables, 2014 to 2023, for each company. We did this to later construct a panel dataset with the explanatory variables (ESG, E, S, G and control variables) as lagged variables by 1 fiscal year to the dependent variables (cost of equity and equity beta). We motivate this use of lagged variables in our panel data construction to reduce simultaneity and reverse causality concerns.

The initial search found a sample of 4074 companies, after which several sorting and cleaning steps followed:

First, we decided to focus on mining companies in the UK, USA, South Africa, Australia, and Canada as these countries represent the largest sectors for mining and have deep capital markets with sufficient historical data and liquid equity trading activity. This reduced the sample size to 2460.

Second, we manually sorted through the types of companies included in the search, removing any companies that the software had inaccurately labelled as a 'mining company', such as pure play metal refining companies, leaving only companies with extractive mining operations. This reduced the sample size to 1784 companies. Further, we removed companies with missing data for either E, S, G, or cost of equity. With our study going back 10 years, and including individual scores for E, S, and G, as well as the overall score, this step significantly restricted the number of companies, leaving a final sample size of 86 companies and 860 firm-year observations.

Finally, for missing data in cells for the control variables, we then manually input data using S&P Capital IQ, matching the input value with the respective company and fiscal year.

Table 1: Sample Size by Step

Step	Description	Sample size
1	ESG data for mining companies over last 10 years	4074
2	Reducing sample to mining companies in the UK, USA, Australia, Canada, and South Africa	2460
3	Sorting through mining company types in LSEG's "mining & metals" industry to only include pure mining companies. This removed company types like "Agricultural & Farm Machinery", "Food Retail" etc.. Final types include "Diversified Metals & Mining", "Gold", "Precious Metals & Minerals", "Steel", "Silver", "Copper", and "Coal & Consumer Fuels".	1784
4	Removing companies with missing ESG or cost of equity data	86
5	Manually inputting missing data regarding control variables with S&P Capital IQ	86

Table 2: Geographical Distribution of the Sample

Country	Number of Companies
Australia	36
Canada	24
South Africa	9
United Kingdom	9
United States of America	8
Total	**86**

Once the data was collected, we organized it into a panel data format using index match formulas on Microsoft Excel. This reduced the likelihood of manual mistakes. The panel data consisted of one row per company per respective fiscal year (860 firm-year rows), followed by country, cost of equity, overall ESG, E, S, G, and our control variables. Our final regressions had total observations of 812, where 'Null' values in the panel were dropped for control variables that contained this value for any specific firm-year. A separate panel data was created using the same format but with the cost of equity column replaced with equity beta, which was used for an additional analysis regression. Furthermore, our thesis collects ESG performance data from a single database, LSEG, to maintain consistency in grading methodology. Past research illustrates that third party ratings are often inconsistent, providing different scores (Agapova et al., 2025; Pan et al., 2023).

4.2 Measures

LSEG (or Refinitiv, which was acquired by LSEG) has been used in several studies studying the relationship between ESG scores and firm cost of capital (Apergis et al., 2022; Ramirez et al., 2022; Wilberg et al., 2025). LSEG determines a company's ESG score (and individual E, S, and G score) through looking at publicly traded data. The process of arriving at a final score includes 4 main steps.

First, the LSEG analysts look at over 870 company-level measures, with a focus on a subset of 186 company-level measures that are most comparable and material, per industry. In this step, LSEG treats underlying data points in the following: (i) Boolean data is sorted with questions such as "Does the company have a water efficiency policy?", answered with "yes" or "no", and then assigned a numeric value, 1 or 0; (ii) Numeric data is standardized using a percentile ranking system; (iii) Each measure is given a polarity indicating whether a high score is positive or negative.

For the second step, a percentile rank scoring method is used to calculate 10 main theme scores. The scoring method considers three factors: (i) the number of companies worse than the current one, (ii) the number of companies with the same value, (iii) the number of companies with no value at all. The main themes of most importance for the "metals and mining" industry are "Resource Use" in the environmental pillar, "Human Rights" in the social pillar, and "Management" in the governance pillar.

In the third step, a weight is assigned to each category, based on how material each category is to the specific industry. This is done through industry-materiality matrix, where high impact themes get a higher magnitude score, and lower impact themes get a lower magnitude score. The magnitude scores are then normalized to category weights, which add-up to equal 1 for each industry group. Our sample was taken from the "metals & mining" industry on LSEG, which assigned the highest magnitude scores to the main themes of Resource Use, Emissions, Human Rights, and Management, as seen in Table 4 (LSEG, Environmental, Social and Governance scores from LSEG, 2024).

In the final step, each ESG pillar score is calculated using the 10 main themes. That is, each theme is associated with one of the pillars, and that pillar's score is computed considering all of its assigned themes (LSEG, 2024).

Table 3: LSEG Main Theme Categories

	Pillar		
	Environmental, 'E'	*Social, 'S'*	*Governance, 'G'*
Categories	• Resource use • Emissions • Innovation	• Workforce • Human rights • Community • Product Responsibility	• Management • Shareholders • Corporate Social Responsibility Management

Table 4: Metals & Mining Magnitude Scores

Metals & Mining Industry	Main Theme	Magnitude Score	Category Weights
Environmental	Resource Use Emissions Innovation	10 2 2	0.16 0.03 0.03
Social	Workforce Human Rights Community Product Responsibility	7 10 5 2	0.12 0.16 0.08 0.04
Governance	Management Shareholders CSR Management	10 3 2	0.16 0.05 0.03

4.3 Cost of Equity Capital

Our thesis calculates the cost of equity using the Capital Asset Pricing Model (CAPM). The use of CAPM to find the cost of equity is common in past research regarding environmental responsibility (Humphrey, Lee, & Shen, 2012; Koch & Bassen, 2013; Sharfman & Fernando, 2008). We justify its use over other methods such as the ex-ante implied cost of equity method based on its use in past research, as well as its relevance in practice. CAPM has been found to be by far the most popular method of finding the cost of equity among CFOs, who 'always' or 'almost always' use it. Other methods like the dividend-discount model, on which the ex-ante method is based, are in practice backed by few firms in practice (Graham & Harvey, 2001). Our sample also makes the use of the ex-ante method difficult, as it requires large amounts of analyst data, lacking in our sample which goes 10 years back for companies across multiple countries.

We retrieve the cost of equity data from LSEG for each company for each respective fiscal year (2015 to 2024). The Weighted Average Cost of Capital (WACC) cost of equity is the return a firm theoretically pays its equity investors and is calculated by multiplying the equity risk premium of the market with the beta of the stock, plus an inflation adjusted risk free rate. The WACC equity risk premium (ERP) is calculated as the forecast of excess equity market return over a long horizon for the equity market in each country based on the aggregate market valuation combined with long-term forecasts of GDP and inflation.

$$ERP = \left(R_m - R_f^{adj}\right)$$
$$r_e = R_f^{adj} + \beta \times \left(R_m - R_f^{adj}\right)$$

4.4 Equity Beta

In our additional analysis, we tested H1-4 using equity beta as our dependent variable instead of the cost of equity. We derived equity beta from LSEG for each company for each respective fiscal year (2015 to 2024), where it is computed as the Capital Asset Pricing Model (CAPM) beta and represents levered equity beta. The CAPM beta is the measure of how much the stock moves for a given move in the market. It is the covariance of the security price movement in relation to the market's price movement, computed using historical stock data. Although unlevered equity beta, which measures the systematic risk of the firm's underlying operations without the impact of financial leverage, is used in prior similar studies to reduce the effect of firm-specific capital structure decisions, we faced data limitations in obtaining a reliable sample of unlevered equity beta (Sharfman and Fernando, 2008). This was due to our long 10-year lookback period that would require making large assumptions to construct unlevered equity beta, such as by decomposing the WACC and its respective weightage of debt and equity annually. Instead, we added leverage (Debt/Equity) as a control variable to control firm-specific capital structure choices.

4.5 Use of lagged independent variables

As highlighted previously, our independent variables are lagged by one fiscal year relative to the dependent variable. We adopt this lag structure to reduce simultaneity and reverse-causality concerns. In practice, ESG scores and firm characteristics such as size, leverage, and profitability may both influence, and be influenced by, a firm's cost of equity if they are measured in the same year. By using ESG and control variables from year *t–1* to explain the cost of equity in year *t*, we ensure that the regressors are measured before the outcome and are less likely to react immediately to the same shocks that drive the error term. This method is consistent with common practice in observational panel-data research, where lagged explanatory variables are frequently used as an attempt to address endogeneity concerns, even though they do not fully resolve such issues (Bellemare, Masaki, & Pepinsky, 2017). Despite employing lagged variables, we acknowledge that such endogeneity concerns cannot be fully eliminated and that, given our research design, the analysis should be interpreted as correlational rather than strictly causal.

4.6 Control Variables

We retrieved the control variables of Size, Leverage and Profitability from the LSEG database for each company for each respective fiscal year (2014 to 2023) and later manually input missing data from S&P Capital IQ. To study the relationship between ESG scores and cost of equity capital, it is important to control for variables that may affect the cost of equity. Our thesis controls for size, leverage, and profitability. Size may impact the cost of equity as it is often correlated with financial factors that affect the cost of equity. For example, larger firms tend to have more stable cash flows and lower risk, while smaller firms exhibit higher volatility and growth potential (El Ghoul et al., 2011). It has also been cited that larger firms receive greater stakeholder attention and possess more resources to engage with ESG measures (Bansal, 2005). Leverage should be controlled as debt influences beta, and higher risk leads to higher required returns for investors (Sharfman & Fernando, 2008). We include profitability as a control variable, consistent with prior ESG and cost of capital research that treats profitability as a standard determinant of firms' financing conditions and information environment. This prior study includes return on assets (ROA) as a control for firms' financial performance in their regression analyses. Another prior study incorporates ROA and other performance measures as controls in their cost-of-debt specifications (Dhaliwal et al., 2011; Wilberg et al., 2025). Given that our paper focuses specifically on the cost of equity, we use return on equity (ROE) as a profitability proxy that is more directly aligned with equity holders' returns. As such, if we don't control for size, leverage, and profitability our results may reflect size differences.

Table 5: Variable Definitions and Sources:

Control Variable	*Definition*	*Source*
Size	The sum of market value for all relevant instrument level share types, calculated by multiplying the requested share types by the latest price - unlisted shares, default, outstanding, listed, issued, and free float share types are included. Standardised currency to USD.	LSEG, S&P Capital IQ Pro
Profitability (ROE)	Return on average total equity - Measures a company's profitability by calculating income before discontinued operations and extraordinary items, divided by average total shareholders' equity, multiplied by 100.	LSEG, S&P Capital IQ Pro
Leverage (D/E)	Total debt percentage divided by the value of total shareholders' equity, including minority interest and hybrid debt, multiplied by 100.	LSEG, S&P Capital IQ Pro

4.7 Research Model

To test hypotheses *H1-4*, we estimate linear panel regressions (PanelOLS) models, with country-year fixed effects and control variables for firm size, leverage, and profitability.

We estimate the following baseline models:

H1: Composite ESG Score

$$\text{H1: } COE_{jt} = \alpha + \beta_1 ESG_{jt-1} + \beta_2 ln(Size)_{jt-1} + \beta_3 Leverage_{jt-1} + \beta_4 Profitability_{jt-1} + \mu_{cy} + \varepsilon_{jt}$$

H2-4: ESG Pillar Scores

$$\text{H2: } COE_{jt} = \alpha + \beta_1 E_{jt-1} + \beta_2 ln(Size)_{jt-1} + \beta_3 Leverage_{jt-1} + \beta_4 Profitability_{jt-1} + \mu_{cy} + \varepsilon_{jt}$$

$$\text{H3: } COE_{jt} = \alpha + \beta_1 S_{jt-1} + \beta_2 ln(Size)_{jt-1} + \beta_3 Leverage_{jt-1} + \beta_4 Profitability_{jt-1} + \mu_{cy} + \varepsilon_{jt}$$

$$\text{H4: } COE_{jt} = \alpha + \beta_1 Gjt_{-1} + \beta_2 ln(Size)_{jt-1} + \beta_3 Leverage_{jt-1} + \beta_4 Profitability_{jt-1} + \mu_{cy} + \varepsilon_{jt}$$

Where COEjt is the cost of equity for firm j at year t, estimated using the Capital Asset Pricing Model (CAPM), ESG_{jt-1} is the lagged composite ESG score for firm j at year t–1, E_{jt-1}, S_{jt-1}, and G_{jt-1} are the lagged Environmental, Social, and Governance pillar scores for firm j at time t–1, $ln(Size)_{jt-1}$ refers to natural logarithm of firm j's Size at year t-1 and μcy represents country-year fixed effects.

Our model builds on prior research linking ESG performance to firms' cost of capital. Prior studies have investigated the effect of corporate social responsibility on the cost of equity using a large cross-sectional sample of US firms (El Ghoul et al., 2011). They employed pooled OLS regressions with year and industry fixed effects and estimate the implied (ex-ante) cost of equity using analyst earnings forecasts and stock prices. Their model is robust and widely cited, but it is limited by its single-country focus and lack of firm or country-level heterogeneity controls beyond fixed time and sector effects (El Ghoul et al., 2011).

Other prior research has examined the relationship between environmental risk management (ERM) and the weighted average cost of capital (WACC) among large US firms using cross-sectional OLS regressions (Sharfman & Fernando, 2008). Such studies used a CAPM based cost of equity measure and provides important theoretical grounding on the link between environmental management and firm risk but lacks a panel dimension and does not account for unobserved time-varying factors (Sharfman & Fernando, 2008).

Past papers have also focused on ESG ratings and the cost of debt (COD) in the mining industry using descriptive and comparative statistics, finding that ESG-rated mining firms differ from unrated peers in size, profitability, and risk exposure (Fikru et al., 2024). However, their analysis does not focus on the association of ESG scores on cost of equity, provides only descriptive evidence of a potential relationship with COD and does not estimate an econometric model (Fikru et al., 2024).

A very recent study proposes a panel regression framework to study ESG and the cost of capital in the energy, utilities and basic materials sectors (Wilberg et al., 2025). They compute an implied cost of equity from analyst forecasts and market prices and estimate pooled OLS models with firm-clustered standard errors and fixed effects for broad geographic regions and industries, as well as various firm-level and macroeconomic controls. Methodologically, their approach illustrates the importance of controlling location and sector-specific heterogeneity in multi-country ESG - cost of capital studies. At the same time, their use of region fixed effects and pooled industries is suitable for broad sector comparisons rather than mining-specific pricing. In a single industry setting like ours, industry dummies are redundant, and region dummies group together countries and years that may differ substantially in regulation, risk premia and market conditions.

Building on these studies, our paper employs a linear panel regression, PanelOLS model, estimated on a panel data of mining firms, with country-year fixed effects, allowing us to control for unobserved macroeconomic and institutional heterogeneity across countries and over time. This approach captures within-country variation in mining firms' ESG performance and cost of equity while mitigating omitted variable bias arising from differences in regulatory environments or market conditions. We adopt a CAPM-based cost of equity measure which has been used in prior similar studies, rather than an implied COE that relies on consistent analyst forecast coverage across countries and faces data availability and accuracy issues over the 10-year lookback period with lagged variables. We do not include firm-fixed effects in the baseline regression to prevent over-absorbing cross-sectional variation in ESG scores, which could leave too little within-firm variation to estimate the coefficients precisely. However, in robustness checks we re-estimate the model with both firm and country–year fixed effects to analyse any potential differences from the baseline model.

We cluster standard errors at the firm level to account for potential autocorrelation and heteroskedasticity within firms over time. In panel datasets such as ours, observations belonging to the same firm are typically not independent, as shocks to a firm's cost of equity, risk characteristics, or ESG performance may persist across years. Ignoring this dependence could lead the model to underestimate the true variability in the data, producing standard errors that are too small and t-statistics that are overstated, thereby increasing the risk of Type I errors (Petersen, 2009; Cameron & Miller, 2015). Clustering standard errors at the firm level addresses this issue by allowing error terms for the same firm to be correlated across years, while still treating errors across different firms as independent. This adjustment is particularly important in our empirical setting, where firms are observed over multiple fiscal years and may exhibit persistent ESG practices, financial structures, or market-based risk patterns.

Because prior research provides mixed evidence on the direction of the relationship between ESG performance and firms' cost of equity, we do not impose a directional expectation on the coefficients in our hypotheses. Given the absence of this consistently supported theoretical sign, our hypotheses are tested using two-tailed tests, evaluating whether a statistically significant relationship exists rather than predicting whether the effect is positive or negative.

5. Results & Analysis

5.1 Descriptive Statistics

The average (mean) cost of equity was 9.4%, with a standard deviation of 5.1%. This shows moderate variability between companies' cost of equity. The descriptive statistics also highlight significant variability across ESG performance (scores). The average ESG score was 46.572, with a standard deviation of 24.170, showing rather significant variability in ESG performance between companies. The lowest average score was the average Environmental (E) score at 40.926, followed by Social (S) at 46.833, and Governance (G) at 54.1. 'E' also had the highest variability with a standard deviation of 28.793, followed by S with a standard deviation of 26.285, and G with the lowest standard deviation, of 23.348. The range of different ESG scores, as seen by substantial standard deviation, suggests sufficient diversity of ESG performance between mining firms to test our hypotheses. The average profitability was -9%, with a standard deviation of 218%. The average leverage (D/E) was 0.682 and the standard deviation was 8.568. The average beta was 1.242, implying an overall higher risk than the market. The standard deviation for beta was 0.856.

Table 6: Descriptive Statistics

	Mean	**Median**	**Std**	**Min**	**Max**
Cost of Equity	0.094	0.092	0.051	-0.024	0.294
ESG	46.572	50.254	24.170	2.590	90.218
Size (USD)	7466564697.779	914972023.650	21225264319.215	2230672.255	232000000000.000
Profitability	-0.090	0.021	2.175	-60.882	7.495
Leverage D-E	0.682	0.155	8.568	0.000	244.719
Beta	1.242	1.163	0.856	-0.906	5.011
E	40.926	45.014	28.793	0.000	90.378
S	46.833	45.977	26.285	0.545	96.494
G	54.100	55.311	23.348	2.412	98.043

5.2 Multicollinearity Diagnostics

Table 7: Pearson Correlation Matrix

Variables	(1) ESG	(2) COE	(3) Beta	(4) ln(Size)	(5) Profitability	(6) Leverage	(7) E	(8) S	(9) G
(1) ESG	1.000								
(2) COE	0.076**	1.000							
(3) Beta	0.158***	0.796***	1.000						
(4) ln(Size)	0.555***	0.048	0.050	1.000					
(5) Profitability	0.099***	-0.011	-0.007	0.064*	1.000				
(6) Leverage	-0.041	0.053	0.052	-0.070**	0.117***	1.000			
(7) E	0.951***	0.147***	0.210***	0.506***	0.084**	-0.034	1.000		
(8) S	0.952***	0.055	0.133***	0.526***	0.088**	-0.031	0.876***	1.000	
(9) G	0.761***	-0.036	0.044	0.462***	0.103***	-0.054	0.612***	0.607***	1.000

Table 8: Variance Inflation Factors (VIF) Results - Regression 1-4 (H1-4)

Variable	H1: ESG	H2: E	H3: S	H4: G
ESG	1.439	-	-	-
E	-	1.338	-	-
S	-	-	1.378	-
G	-	-	-	1.276
ln (Size)	1.436	1.340	1.379	1.270
Leverage D–E	1.020	1.020	1.020	1.021
Profitability	1.025	1.023	1.024	1.027

To ensure that multicollinearity does not bias the regression estimates, we ran a series of diagnostic tests by computing a Pearson correlation matrix between all variables used in our regressions (H1-4), excluding firm beta which would later be used for robustness checking, and Variance Inflation Factors (VIFs) for all explanatory variables across the four regression specifications (H1–H4).

The Pearson correlation matrix (Table 7) shows generally mild to moderate correlations among the main regression variables. As expected, the three ESG pillar indicators (E, S, and G) are strongly correlated with the composite ESG score (correlations above 0.75 and significant at the 1 percent level). This is intuitive given that E, S, and G are the components used to construct the aggregated ESG measure and supports our reasoning for running the regressions for H2-4 on each pillar separately. This way, we ensure the correlations between the explanatory variables used jointly within each regression are well below conventional multicollinearity thresholds. For example, ln(Size), Leverage D–E, and Profitability all display correlations below 0.20 in absolute value with ESG, E, S, and G. No bivariate correlation exceeds ±0.60 among variables that appear together in any single regression equation, indicating that multicollinearity is unlikely to distort the coefficient estimates.
To complement the correlation analysis, we computed VIF values for each independent variable across the four regression models (Table 8). A VIF value above 10 is commonly considered indicative of high multicollinearity while values between 5 and 10 may signal moderate concern (Hair, Black, Babin, & Anderson, 2014). Across all four hypotheses (H1–H4), all VIF scores fall between 1.020 and 1.439, which is below conservative thresholds. The highest VIF observed, 1.439 for ESG in the H1 model, is still indicative of very low collinearity. Similarly, ln(Size), Leverage D–E, and Profitability consistently exhibit VIF values near 1.0, suggesting that these controls do not introduce multicollinearity risk.

5.3 Residual Analysis

When performing a panel linear regression, there are key assumptions made, called the Gauss-Markov assumptions. These assumptions are that (i) the relationship is linear, (ii) there is homoscedasticity, (iii) there is no autocorrelation, (iv) there is no endogeneity. In addition, we also often assume approximate normality of residuals which supports the use of the usual t- and F-tests for inference. To test whether our regression model fits some of these assumptions, we do a residual analysis test (Graph 1).

For H1, in terms of linearity, the LOESS line stays close to zero across the fitted values, with a mean of 0.0, and median of –0.05. This suggests that the relationship between ESG and cost of equity, as well as the control variables, is linear. Further, the spread of residuals is consistently around zero - interquartile range of –2.23 to 2.06. This suggests that there are no issues of heteroscedasticity and therefore that the assumption of homoscedasticity holds. The residuals are not clustered, and seem randomly scattered, suggesting that the residuals are independent.

In terms of normality of residuals, skewness was 0.194, and kurtosis was 4.891. For a perfectly normal distribution, skewness should be close to 0 and kurtosis close to 3. This suggests that residuals are nearly symmetric, with a slightly heavier tail than a perfect normal distribution. This means that residuals are approximately symmetric but with more extreme observations than a normal distribution.

5.4 Regression Results

To test our first hypothesis - H1: There is a significant relationship between mining firms' ESG score and its cost of equity capital - we regress company ESG scores on cost of equity, with control variables: Size, Leverage, Profitability. We include country-year fixed effects.

We start our analysis of the regression results with R^2 (within). R^2 (within) provides the percentage of within-firm variation over time that our model explains. Since our baseline model includes country-year fixed effects, this means the percentage of within-firm change that our regressors explain *after* taking out all the country-year shocks. The R^2 (within) for the regression was –1.02%. The negative value stems from one of two possibilities: (i) our model fits less well than a simple within-mean model, (ii) the fixed effects absorb most of the variation. Overall, our regressors have very little explanatory power over the within-firm variation in cost of equity.

We further look into our model's F-tests. F-tests check whether a group of variables are helpful as a whole. The F-statistic (robust) was 3.55 with a p-value of 0.0070. F-statistic (robust) tests evaluate whether we would still see a pattern in the data if all the coefficients were zero, i.e., by chance. A p-value of 0.0070 shows that there is less than 0.7% probability of seeing such a pattern by chance. Therefore, although our regressors explained very little of the variation in our dependent variable, they do still show information on the cost of equity.

For our main coefficients, ESG was found to have a statistically insignificant correlation with cost of equity ($p = 0.48$). The only control variable of statistical significance was Leverage, which had a coefficient of 0.0004 with a p-value of 0.0005. This suggests that more levered firms face a higher cost of equity.

With regard to H1, we cannot reject H0. There is no significant relationship between the overall ESG score and the cost of capital.

Hypothesis 2 looks at whether there is a significant relationship between cost of equity capital and a company's environmental performance, 'E'. The regression of companies' 'E' score on cost of equity reveals a weak-positive relationship at a 10% significance level.

Our R^2 (within) for H2 was –0.65%. Similarly to H1, this reveals that our regressors explain very little of the within-firm variation in cost of equity. The percentage is however slightly larger than for H1, suggesting that this model explains slightly more of the within-firm variation in cost of equity than our first model. Now that we have two models, we can discuss adjusted R^2. Adjusted R^2 tells us whether the predictors actually improve the model, i.e. whether the different variables help explain the dependent variable. The adjusted R^2 is slightly increased in H2 at –4.71% compared to –6.06% in H1. Thus, though the difference is minimal, our second model investigating 'E' score explains more of the variation in cost of equity than our first model investigating the overall 'ESG' score.

In terms of coefficient, a one-point increase in 'E' score is associated with a 2.47% increase in cost of equity. This has a p-value of 0.10, and is thus insignificant at a 5% significance level, but significant at a 10% significance level. Our control variable of Leverage is positive and statistically significant, with a p-value of 0.0003.

The F-statistic (overall) is statistically significant, suggesting that our variables jointly explain the variation in the cost of equity. Further, F-statistic (robust) is 0.002, illustrating that there is a 0.2% probability of seeing such a pattern by chance. Thus, while the explanatory power is low, our variables do provide information on the cost of equity.

With regard to H2, we reject H0 at a 10% significance level but cannot reject H0 at a 5% significance level. There is a weak-positive statistically significant relationship between cost of equity and Environmental performance at a 10% significance level.

The regression for H3 looks into the relationship between cost of equity and companies' Social performance.

Our R^2 (within) for H3 was –1.01%. This suggests that our regressors explain very little of the over-time variation in cost of equity. The adjusted R^2 value for H3 was –6.21%. This is the lowest across our 4 models, suggesting that H3 investigating the relationship between 'S' and the cost of equity, explains the least variation in cost of equity.

The F-test (robust) is 0.008, so there is an 0.8% probability of seeing such a pattern by chance.

In regard to coefficients, 'S' was found to have a statistically insignificant relationship with cost of equity, with a p-value of 0.6626. Leverage shows a statistically significant relationship.

With regard to H3, we cannot reject H0. We find no significant relationship between cost of equity and Social performance.

H4 investigates the relationship between cost of equity and 'G' performance. We find no statistically significant relationship, with a p-value of 0.2519.

The R^2 (within) was –0.26%. Though this suggests that our regressors explain very little of the variation in cost of equity, the value is the highest across our 4 models. This means that it explains the within-firm variation in cost of equity slightly better than our other models. That said, the explanatory power remains significantly low. The adjusted R^2 for H4 was –5.85%.

The F-statistic (overall) was significant, thus our model's variables jointly explain the variability in cost of equity. The F-test (robust) was 0.0052, thus there is a 0.52% probability of seeing the same pattern by chance.

Regarding H4, we cannot reject H0. There is no significant relationship between Governance score and cost of equity capital.

Table 9: Baseline regression results

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**	**Hypothesis 4**
	COE_{jt}	COE_{jt}	COE_{jt}	COE_{jt}
ESG score	0.0123	-	-	-
	(0.4828)			
E Score	-	0.0247	-	-
		(0.1020)		
S Score	-	-	0.0073	-
			(0.6626)	
G Score	-	-		-0.0148
				(0.2519)
In(Size)	0.0161	-0.0502	0.0392	0.1363
	(0.9173)	(0.7532)	(0.7990)	(0.3463)
Profitability	-0.0005	-0.0006	-0.0005	-0.0003
	(0.4975)	(0.4538)	(0.5222)	(0.6437)
Leverage	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0005)	(0.0003)	(0.0005)	(0.0008)
R^2 (within)	-0.0102	-0.0065	-0.0101	-0.0026
Adj. R^2	-0.0606	-0.0471	-0.0621	-0.0585
F-statistic	1.9091	4.3731***	1.6342	2.2869*
	(0.1070)	(0.0017)	(0.1637)	(0.0585)
F-statistic (robust)	3.5540***	4.2658***	3.4741***	3.7286***
	(0.0070)	(0.0020)	(0.0080)	(0.0052)
Country-year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No
Observations	812	812	812	812
Firms	86	86	86	86

5.5 Robustness Checks

To ensure our results are reliable, we have done robustness checks, first adding firm-level fixed effects. Firm-level fixed effects control for unobserved, time-invariant firm characteristics, isolating within-firm changes. Examples of what firm fixed effects control for are company culture, long-term strategy, and investor perception. Our baseline model, H1, included country-year fixed effects and found a statistically insignificant relationship between overall ESG score and firms' cost of equity. The first robustness check, adding firm-level fixed effects, similarly found a statistically insignificant relationship. This remains true for the relationship between cost of equity and 'E', 'S', and 'G' (H2-4). With results remaining consistent throughout our hypotheses, this points to our baseline model, and its results remain valid. An important difference between our baseline model and our robustness check adding firm-level fixed effects is that our R^2 (within) increases across all four models. This means that our robustness check model with firm-level fixed effects explains more of the within-firm variation in cost of equity.

This robustness check shows that adding firm fixed effects significantly improves overall model fit. An F-test comparing the baseline country–year fixed effects model with the firm- and country–year fixed effects model rejects the null that the firm effects are jointly zero ($F(85, 673) = 9.61$, $p < 0.001$), indicating the presence of important firm-specific heterogeneity in the cost of equity. However, the ESG coefficient remains small and statistically insignificant in this specification, so our main conclusion that ESG performance is not significantly associated with mining firms' cost of equity remains unchanged. This suggests that our baseline findings are robust even when firm fixed effects are included in addition to country-year fixed effects.

Table 10: Regression results with added firm-fixed effects

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**	**Hypothesis 4**
	COE_{jt}	COE_{jt}	COE_{jt}	COE_{jt}
ESG	0.0185	-	-	-
	(0.3941)			
E	-	0.0211	-	-
		(0.1848)		
S	-	-	0.0158	-
			(0.4492)	
G	-	-	-	-0.0077
				(0.6114)
In(Size)	-0.9816***	-1.0083***	-0.9781***	-0.9591***
	(0.0037)	(0.0027)	(0.0041)	(0.0043)
Leverage D-E	4.691e-0.5	4.172e-05	4.563e-05	4.559e-05
	(0.4933)	(0.5349)	(0.5190)	(0.5123)
Profitability	-0.0003	-0.0003	-0.0003	-0.0002
	(0.4692)	(0.4599)	(0.4876)	(0.5868)
R^2 (within)	0.0096	0.0172	0.0084	0.0155
Adj R^2	-0.1683	-0.1648	-0.1681	-0.1704
F-statistic	5.5363***	6.0684***	5.5883***	5.2400***
	(0.0002)	(0.0001)	(0.0002)	(0.0004)
F-statistic (robust)	3.7233***	3.8360***	3.7211***	3.3647***
	(0.0052)	(0.0043)	(0.0053)	(0.0097)
Country-year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	812	812	812	812
Firms	86	86	86	86

As a second robustness check, we re-estimated the baseline regressions for H1–H4 using a pooled panel OLS specification in which the country–year fixed effects were removed, while keeping all other model components unchanged. The purpose of this test is to assess whether the country-year fixed effects in the primary specification were absorbing a substantial share of the usable variation in the data. In fixed-effects models, especially those with high-dimensional effects such as country-year interactions, much of the between-firm and between-year variation is eliminated, which can inflate standard errors and weaken coefficient significance (Wooldridge, 2010). By estimating a model without these fixed effects and comparing it directly to our baseline results, we can assess whether the insignificance of the ESG variables is driven by over-absorption of variation rather than a genuine absence of relationship.

Our results remain consistent with the initial regression model with the exception of the statistically significant result regarding our H2. The ‘E’ variable had a positive coefficient of 0.0286 significant at 5% ($p = 0.0385$). This suggests that part of the insignificance of the 'E' in our initial regression may have been due to the loss of variation from the country-year fixed effects. However, our other coefficients remain consistently insignificant. This suggests that overall, the earlier statistically insignificant results were not driven by our country-year fixed effects.

Table 11: Regression results excluding fixed effects

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**	**Hypothesis 4**
	COE_{jt}	COE_{jt}	COE_{jt}	COE_{jt}
ESG	0.0141	-	-	-
	(0.4166)			
E	-	0.0286**	-	-
		(0.0385)		
S	-	-	0.0068	-
			(0.6662)	
G	-	-	-	-0.0167
				(0.2664)
In(Size)	0.0460	-0.0512	0.0862	0.2034
	(0.7882)	(0.7560)	(0.6120)	(0.2042)
Leverage D-E	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0007)	(0.0004)	(0.0008)	(0.0015)
Profitability	-0.0006	-0.0007	-0.0005	-0.0004
	(0.4465)	(0.3955)	(0.4813)	(0.6193)
R^2 (within)	-0.0110	-0.0069	-0.0103	-0.0035
Adj R^2	0.0033	0.0195	0.0010	0.0046
F-statistic	1.9058	5.2763***	1.4582	2.2152*
	(0.1075)	(0.0003)	(0.2131)	(0.0657)
F-statistic (robust)	3.1576**	4.0945***	3.0632**	3.5438***
	(0.0137)	(0.0027)	(0.0161)	(0.0071)
Country-year fixed effects	No	No	No	No
Firm fixed effects	No	No	No	No
Observations	812	812	812	812
Firms	86	86	86	86

5.6 Additional Analysis

Since our baseline model calculates cost of equity (COE) through the CAPM (using beta as the measure of a firm's systematic risk relative to the market), an additional analysis that replaces COE with equity beta as the dependent variable, keeping all else equal, allows us to deconstruct the components of the market risk premium (MRP) and risk-free rate (Rf) from the CAPM COE, and test whether ESG performance affects companies' systematic risk (equity beta) directly. This analysis is supported prior studies, where equity beta is used as a secondary hypothesis and as the dependent variable to see if the transmission of the effect of explanatory variables (environmental risk management) on cost of capital is primarily through equity beta (Sharfman and Fernando, 2008). Our reasoning is also motivated by our use of a cross-country sample of firms, where the differences in MRP and Rf could have an unaccounted effect on skewing the COE dependent variable, despite our use of country-year fixed effect controls.

However, as equity beta is significantly and highly correlated to cost of equity (0.796), as earlier reflected, we do not expect a large deviation in results from the baseline regressions.

The results of our additional analysis are in line with our initial baseline model regression. ESG, and E, S, G remain statistically insignificant, while leverage maintains statistical significance. R^2 (within) remains low in this regression as it did in the baseline regression, in this regression. This indicates that the results from our baseline model are not noticeably driven by variation in the CAPM cost of equity calculation itself.

Table 12: Regression results with Beta as dependent variable

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**	**Hypothesis 4**
	COE_{jt}	COE_{jt}	COE_{jt}	COE_{jt}
ESG	0.0039	-	-	-
	(0.1848)			
E	-	0.0043	-	-
		(0.1029)		
S	-	-	0.0034	-
			(0.2077)	
G	-	-	-	-0.0002
				(0.9177)
In(Size)	-0.0116	-0.0145	-0.0096	0.0085
	(0.6914)	(0.6190)	(0.7403)	(0.7531)
Leverage D-E	7.171e-05***	7.094e-05***	7.07e-05***	7.216e-05***
	(0.0004)	(0.0003)	(0.0005)	(0.0006)
Profitability	-8.043e-05	-8.052e-05	-7.598e-05	-5.611e-05
	(0.5171)	(0.5183)	(0.5369)	(0.6363)
R^2 (within)	-0.0152	-0.0079	-0.0203	-0.0078
Adj R^2	-0.0535	-0.0457	-0.0543	-0.0634
F-statistic	3.2330**	4.6593***	3.0945**	1.4513
	(0.0121)	(0.0010)	(0.0153)	(0.2153)
F-statistic (robust)	4.0901***	4.4660***	4.0860***	3.5210***
	(0.0028)	(0.0014)	(0.0028)	(0.0074)
Country-year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No
Observations	810	810	810	810
Firms	86	86	86	86

6. Discussion

Our thesis aimed to answer whether ESG performance affects mining firms' cost of equity capital and if so, which ESG pillars explain this effect. Our results consistently point to one conclusion: no, ESG performance does not affect mining firms' cost of equity capital. Our robustness checks stress that the lack of association is robust, and that our results are reliable.

Our conclusion fits well with our hypotheses, which we left without direction (i.e., two-tailed). Revisiting the reasoning behind this, while ESG has been found to be associated with a lower cost of equity, the key difference between our study and past literature is our focus on mining firms. Previous research shows that in mining firms, ESG has had no association with firm performance, and a negative association with firm value. Empirically, there is also theory that points to the conclusion that ESG performance will not have a negative association with cost of equity. The agency theory posits that while the presence of ESG scores may theoretically reduce the information asymmetry between a company and its investors, the lack of consistency among different 3rd party scores has the opposite effect. Investors cannot trust the scores and are confused by the different scores. This supports the conclusion of our results that ESG scores will have no significant correlation with cost of equity.

That said, and as previously mentioned, the empirical theory and past literature were mixed in their conclusions. On the other side of the argument, ESG scores had been previously found to be associated with lower cost of equity capital. The stakeholder theory and investor-based theory support this conclusion as the potential for a wider base of investors, and wider focus on matters of importance of stakeholders is associated with more trust, and a lower cost of equity. Our results were, however, very clear: ESG performance does not have a statistically significant impact on cost of equity. The contradiction between this side of the argument and our results may stem from several factors. It may be that even if these theories are real, when applied in the mining industry they are weak in practice. With regards to the investor-base theory, 'green' investors may simply exclude the entire mining industry due to its 'sin industry' nature. If the entire mining industry is excluded from investor portfolios, a better ESG score will not have an impact. With inconsistent ESG scores among 3rd parties, excluding the entire sector due to lack of certainty regarding actual ESG performance would make sense. For the stakeholder theory, a possible explanation may be that ESG performance is increasingly seen as a basic hygiene factor and not a competitive advantage, thus rendering relatively better ESG performance unimportant.

Practically, there are also other plausible reasons for a lack of significant association between ESG scores and cost of equity in mining firms. It is possible that ESG risk is overshadowed by other more dominant sources of risk in this industry. Commodity price cycles, country risk and operational uncertainties can be large and highly priced in, which may make any incremental ESG effect too small to detect with our data and model. Equally, it can be the case that cost of equity is not the main channel that ESG risks are priced in, but potentially other channels like cost of debt, which we do not explore in this study. Moreover, a typical mining equity investor may have already accepted substantial ESG controversy as part of the sector, implying that the usual ESG-related return premia may be weaker. Finally, ESG scores in mining are subject to considerable measurement error and disclosure bias, and ESG risks may materialise over very long horizons or as infrequent high-magnitude events, rather than in a stable annual premium.

6.1 Leverage

In contrast to the weak results between ESG and cost of equity, one control variable consistently showed a statistically significant, positive association with cost of equity: Leverage. The relationship between leverage and cost of equity is basic finance. More leverage leads to more financial risk, which leads to a higher equity beta, and a higher cost of equity. The statistical significance between leverage and cost of equity suggests that mining investors treat traditional financial risk as primary, and that ESG remains for background information. This leads to the possible explanation of our results being that mining investors simply do not care enough about ESG for it to have a statistically significant impact on cost of equity.

6.2 Explanatory Power

Our baseline and robustness check regression models had low Adj R^2 and R^2 (within) values. This means that our explanatory variables (ESG and control variables) together explain little of the variation in our cost of equity estimate. There are some potential reasons for this.

First, our study uses a CAPM-based cost of equity (COE) estimate that is based on realized returns, whereas more recent similar studies use implied (or ex-ante) cost of equity estimates, which is derived from financial models like the dividend discount models or residual income models based on analysts' forecasts and current stock prices. This measure often represents market expectations about future returns. Market expectations might be smoother and less volatile estimate to model than realized returns, which can be noisy and capture many short-run, firm-specific and market-wide shocks that we do not model explicitly. This makes it harder for a set of independent variables to explain a large proportion of its variance, potentially explaining our lower R^2 values.

Second, our study focuses on a single industry, mining, whereas prior papers that examine a similar research question largely examine cross-industry samples, with fixed effects on industry. With a cross-industry study, there is naturally a much wider range of variation in the dependent variable, COE, due to different industries having different risk profiles, capital structures, and exposures to ESG factors. A model that includes industry fixed effects or other industry-specific control variables can capture a large portion of this between industry variation. Explaining a larger total variation (spread across industries) makes it easier to achieve a higher R^2. By contrast, listed mining firms are relatively similar in their business models and risk exposures, which limits cross-sectional variation in the cost of equity that can be picked up by firm-level variables such as ESG, size, leverage and profitability. We also find that removing fixed effects does not materially increase the R^2, suggesting that the low explanatory power is not driven by the fixed-effects structure, but by the combination of noisy dependent variables, a limited set of regressors and a relatively homogeneous single industry sample.

Last, other explanatory variables that affect the cost of equity in mining firms may have been left out. Our study focuses on ESG performance and a small set of standard firm-level controls (size, leverage and profitability). In reality, there are other variables that influence mining firms' cost of equity that we are not able to include, such as commodity price shocks, firm-specific growth opportunities, asset tangibility, stock liquidity, detailed governance characteristics or more granular country and regulatory risk measures. Some of these factors are difficult to measure consistently across countries and over time, and adding many additional variables in a relatively small, single-industry panel also risks overfitting. The exclusion of these determinants likely contributes to the low R^2 values and means that our models should be interpreted as focusing on the ESG-COE relationship, rather than explaining most of the variation in mining firms' cost of equity.

7. Conclusion

7.1 Contributions

Our contribution to existing literature is 3-sided. First, our study focused on a previously ignored industry in terms of ESG and cost of capital: the mining industry. Our results point to the conclusion that in the mining industry, ESG has no significant impact on cost of equity. Our results suggest that mining investors remain traditional in their evaluation of investments. The focus on countries in which mining the industry has a large presence - South Africa, Australia, the United Kingdom, the Unites States of America, Canada - allows us to present a global representation of the relationship between ESG performance and cost of equity. With these countries also presenting financial hubs for the mining industry, it also allows our results to provide an extensive overview of the mining industry's capital markets. We conclude that even in the most mining-intensive markets, ESG does not have a significant impact on the cost of equity. Finally, we contributed to the literature by focusing on both the overall ESG score and individual E, S, and G pillars. Our results found no negative association throughout, and even a positive, significant relationship between 'E' score and cost of equity at the 10% level.

7.2 Limitations

Looking back on our study, we faced several limitations.

To mitigate potential simultaneity and reverse causality, we lagged ESG and control variables by one year relative to the cost of equity (COE). This assumes that ESG information for fiscal year t–1 is fully incorporated into investors' expectations for t. In practice, fiscal year-ends differ across firms and countries, and ESG ratings may be updated with a delay. As a result, our lag structure may not perfectly align with the timing between ESG signals and the market's COE expectations, which can attenuate estimated effects and bias coefficients towards zero.

Our analysis relies on ESG scores from a single provider (LSEG) due to data availability issues with other providers to retrieve a large enough sample size for ESG data on mining firms over 10 fiscal years. Different rating agencies often disagree on ESG assessments, use distinct indicators and weights, and may emphasise different aspects of environmental or social risk. If LSEG's methodology underweights mining specific ESG risks such tailings, water use, community conflict or systematically differs from how investors themselves interpret ESG information, our ESG measures may contain substantial measurement error. In addition, we use the combined ESG score and do not explicitly incorporate Refinitiv's separate 'ESG controversies' metric, which adjusts scores based on negative news coverage. To the extent that major controversies trigger strong investor reactions while being only imperfectly captured in our ESG measure, downside ESG risk for some firms may be understated in our analysis. This may reduce our ability to detect any true relationship between ESG performance and cost of equity.

Our sample includes only publicly listed mining firms for which both financial data and LSEG ESG scores are available over the sample period. This effectively restricts the analysis to larger, better-known firms that report consistently and are covered by ESG data providers, while excluding smaller, privately held, unrated or delisted mining companies. As a result, our findings may not be generalisable to the broader population of mining firms, particularly junior or private miners that may rely more heavily on alternative financing and face different ESG and risk profiles. In addition, several subjective decisions were required during data cleaning and variable construction, for example, how to handle missing values, fiscal-year mismatches and extreme observations which introduces the possibility of researcher bias despite our efforts to apply consistent rules across the dataset.

Although our panel has 812 firm-year observations, it covers only 86 firms and 50 country-year clusters across five countries. When clustering standard errors at the firm level and absorbing country-year fixed effects, the effective number of independent clusters is modest. This limits statistical power and makes it harder to detect economically small effects, even if they exist. It also means that our results should be interpreted with caution when generalising beyond the countries and period studied.

Our sample period may precede a fuller integration of ESG risks into equity pricing for mining firms. Regulatory frameworks, investor mandates and voluntary initiatives around climate and human rights in mining are evolving quickly. It is possible that ESG considerations will become more strongly priced in the cost of equity in future years than during our historical 10-year window. Our findings therefore reflect an early stage of ESG integration in mining and may not capture later shifts in investor behaviour.

We estimate the cost of equity using a CAPM-based approach, which is supported by prior literature, and we complement this by using equity beta directly as a proxy for systematic risk in an additional analysis section. However, our study is limited by not being able to implement alternative cost of equity measures, such as implied cost of equity based on forward looking analyst earnings forecasts and price-based valuation models, which has been the approach used in more recent literature. Analyst forecast coverage for mining firms in our multi-country sample is sparse and inconsistent over the 10-year period, which makes implied COE estimates unreliable. If implied COE measures capture investor expectations differently from our CAPM-based estimates, our conclusions about the ESG-COE relationship may be sensitive to the chosen COE proxy.

7.3 Suggestions for Future Research

Our thesis focused on whether there was a significant relationship between overall ESG, or either of its three pillars, with mining companies' cost of equity capital. The scope of our study was mining companies in the United States of America, the United Kingdom, South Africa, Australia and Canada, with a timeline stretching 10 years. As our conclusion was that there is no significant relationship between overall ESG, or the social and governance pillars, a first suggestion for future research would be to investigate what *does* impact the cost of equity of mining companies. This is to say, what factors *do* have a significant relationship with mining companies' cost of equity capital. We found that leverage had a consistently significant positive relationship with cost of equity. The coefficient was significant but small. It could therefore be useful for future research to focus on factors that may be significant and with a large coefficient, so as to provide a useful view on what has a large and significant impact on mining companies' cost of equity. A second suggestion would be to look at the other side of the matter and investigate what significant impact ESG has on other financial aspects of mining companies. We found that there was no significant relationship between ESG and cost of equity specifically, but perhaps there are other financial aspects with which ESG does have a significant relationship. This could also be a useful study to conduct for non-financial aspects, such as employee wellbeing or reputation as seen by investors or customers. Such a study could investigate whether a higher ESG score has a significant relationship with one such non-financial metric. Further, as we find a stronger relationship between a mining firm's environmental score and cost of equity, a third suggestion would be to investigate why environmental aspects seem more important to equity investors than social or governance performance. For example, it could be that environmental crises, such as oil spills, are considered by equity investors to be more destructive than perhaps a crisis in management. A final suggestion would be regarding the ESG scores themselves. We retrieved these from LSEG's database, but as third-party ESG ratings are often contradicting between different parties and considered by investors to be unreliable, as mentioned earlier, it may be useful to instead conduct an event study. An example could be an event study in which an event affects either of the three pillars and investigate said event's impact on the cost of equity.

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9. Appendix

Appendix A: Tables and Graphs

Graph 1: Residuals vs Fitted (Baseline Regression):

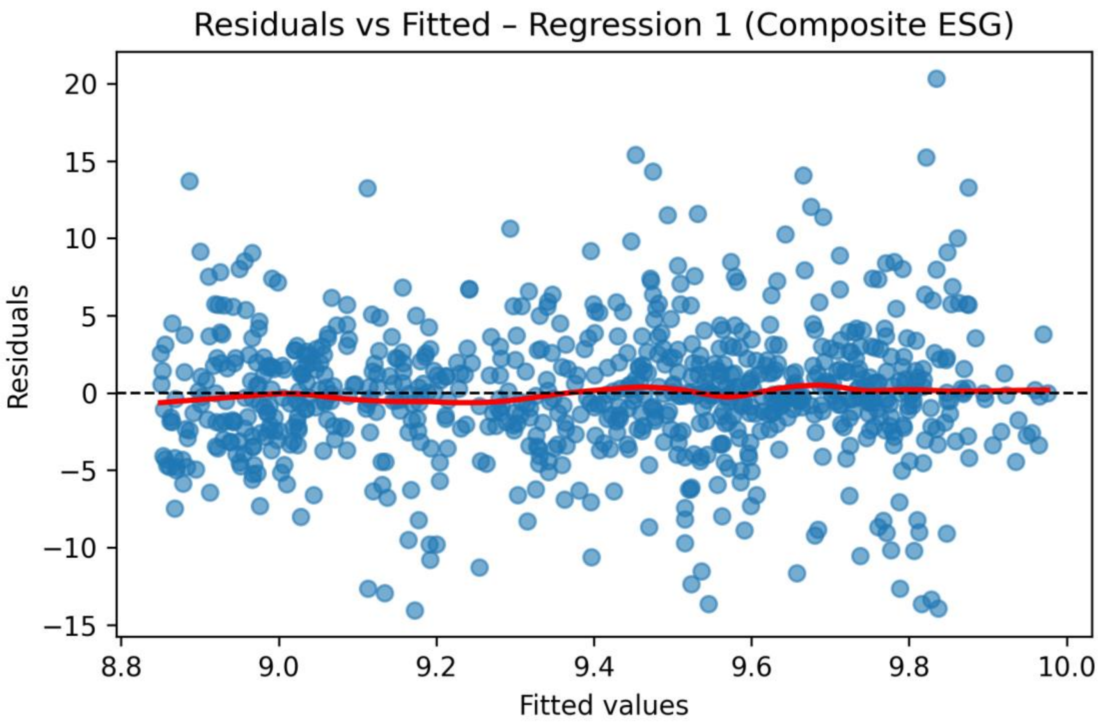

Table 13: Summary of Residuals (Baseline Regression):

	Regression 1
Minimum	-14.158336
1st Quartile	-2.321248
Median	-0.050756
Mean	-0.0
3rd Quartile	2.063123
Maximum	20.408136
Skewness	0.194439
Kurtosis	4.89143

Appendix B: Gen AI Statement

Our thesis uses Generative AI in a limited capacity to clarify and confirm. The model used was GPT-5.1 by Chat GPT. We used it in the following ways:

Prompt A: Clarifying use of F-test.

- *Prompt:* From my understanding, F-tests are used to show whether fixed effects are needed. Please clarify.
- *Answer*: Short version: your understanding is on the right track, but it's a bit too narrow. An F-test isn't "for fixed effects" per se—it's a general tool for testing whether a group of coefficients is jointly zero in a nested linear model. Fixed effects is just one very common place where that question comes up.
- Prompt A illustrates how we used GPT-5.1 to clarify our understanding of certain concepts. A risk, as seen from its answer, is that the scope of information it uses to answer can go beyond the scope of a study. That is, it gives an answer in the general sense, not specific to our study. To mitigate this risk, we consistently double-checked its answer with the literature review, and our own knowledge.

Prompt B: Asking if discussion of results provided was sufficient.

- *Prompt:* In our discussion of results (for our panel regression), we focused on whether the result was significant, the r squared (within), adjusted r squared, f-test, and f-test robust. Does this provide enough insight or should we add more?
- *Answer*: Short answer: that's a solid start, but you'll almost certainly strengthen the discussion by adding a few more panel-specific elements—especially around model choice, inference quality, and practical meaning.
- Prompt B illustrates how we used GPT-5.1 to confirm that our explanations provided enough insight on our regression results. This was mainly to ensure the reader understands to a large extent what the figures are saying. As seen again, one risk from using AI is that its answer provides a more general answer. In this instance, it suggested we improve elements that were already included in our thesis. Thus, as mentioned earlier, we always double-checked the answers with our own knowledge.

Prompt C: Checking the validity of descriptive statistics calculated values.

- *Prompt:* For our results section on descriptive statistics, can you run through our panel data to check if our computed descriptive statistics was done correctly? I will upload our csv panel data here.
- Answer: Summarised: I've gone through your CSV and recomputed the basic descriptive statistics for the numeric variables in your panel.

Here's what I get for the full sample (using all 860 rows, and listwise per variable, so N differs when there are missing values): (Proceeds to list table values)

- Prompt C was used to verify our coded descriptive statistics table on Python had correctly produced the right values by separately uploading our panel data set on GPT-5.1 to independent produce values that we used to crossmatch with our values to verify that we had not made a human/coding error.

Prompt D: Asking GPT-5.1 for support on Python, the statistical software used to

produce the regression result.

- *Prompt:* How do I get the natural logarithm for a size explanatory variable in python when running my regression?
- *Answer:* Use np.log() on your size variable before (or inside) the regression – np.log is the natural log in Python. Summarised: (Adds code to import pandas and create code line:
  # Create the natural log of Size (assuming the column is called 'Size_USD') df["ln_size"] = np.log(df["Size_USD"])
  Key points:
  np.log(x) = natural logarithm ln(x).
  Make sure your size variable is strictly positive before logging (drop or adjust zeros/negatives).
- Prompt D was used for coding support on Python to help create the natural logarithm transformation for the size variable we had in our panel data to a 'ln_Size' variable with help of GPT-5.1.

Prompt E: Clarifying terminology specific to mining literature.

- Prompt: What does tailing event/tailings mean in mining literature? I notice the term frequently
- Answer: Summarised: 2. Tailing event / Tailings dam failure / Tailings spill
  When you see "tailings event", "tailings incident", or similar in mining/ESG literature, it almost always refers to: A material incident involving tailings, such as: a tailings dam failure, a breach, a spill/release of tailings to the environment or a major stability/safety incident at a tailings facility.
  Examples often cited:

Fundão dam (Samarco, Brazil, 2015)

Brumadinho dam (Vale, Brazil, 2019)

In ESG/panel datasets, a "tailings event" variable might be: a dummy = 1 in years when the firm had such an incident, or a count of tailings-related incidents, or a severity-weighted index.

- Prompt E was used to clarify, using GPT-5.1, mining specific terminology that had appeared frequently when reading previous literature so as to avoid confusion between the econometric term ‘tailing/tail risk’ and a mining term ‘tailings event’.