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ESG Performance and Corporate Financial Performance: Disentangling Sector Effects

Shritha Shetty Puvvadi

Oakridge International School Newton Campus

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ABSTRACT

This paper examines the relationship between Environmental, Social and Governance (ESG) performance and corporate financial performance using a panel dataset of S&P 500 companies for the period 2015 to 2023, comprising approximately 2,614 firm-year observations. The study employs two empirical approaches: sorting firms into portfolios by ESG quartile, and fixed-effects panel regression on three financial performance measures, namely Return on Assets (ROA), Tobin's Q, and Return on Equity (ROE). The portfolio sort shows that firms in the highest ESG quartile earn 6.2 percentage points lower stock returns and 0.86 percentage points lower ROA than firms in the lowest ESG quartile. However, panel regressions with both industry and firm fixed effects show that the ESG coefficient is statistically insignificant across all six main specifications. The observed negative univariate association is driven by systematic sectoral differences: ESG-intensive industries such as Utilities and Energy are structurally lower-return, while ESG-light sectors such as Information Technology are structurally higher-return. A pillar-level breakdown provides marginal cross-sectional evidence of a positive association between environmental performance and ROA, but this is not robust to firm fixed effects. The results indicate that, once firm- and industry-specific heterogeneity is controlled for, ESG performance neither improves nor harms corporate financial performance for large-cap U.S. firms. These findings emphasise the importance of methodological rigour, especially the use of fixed-effects controls, in ESG research.

Keywords: Corporate financial performance, ESG, Fixed effects, Panel data, Portfolio sorting, S&P 500

1. Introduction

Environmental, Social and Governance (ESG) considerations have moved from a peripheral concern to a central factor in corporate strategy and investment decision-making. Surveys of corporate practice report that a large majority of executives now regard sustainability as central

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to business strategy, and that a growing share of large firms identify climate change as a material financial risk (Morgan Stanley Institute for Sustainable Investing, 2026; Institute of Sustainability Studies, 2025). Strong ESG performance is increasingly associated with real commercial benefits rather than merely reputational ones, including lower capital costs, improved access to financing, and greater long-term resilience (Think Parallax, 2026; TRC Companies, 2026).

The S&P 500 (Standard & Poor's 500) is a stock-market index tracking the performance of 500 leading companies listed on U.S. exchanges, representing approximately 80% of the total market capitalisation of U.S. public companies. Because these firms are large, widely held, and subject to extensive disclosure, they provide a natural setting in which to test whether ESG performance is linked to financial performance. Yet the theoretical predictions are ambiguous. On the one hand, firms with strong ESG practices may avoid regulatory and reputational risk, attract and retain talent, and enjoy a lower cost of capital, all of which could raise profitability. On the other hand, ESG investments impose real costs —cleaner technology, higher labour standards, and stronger oversight— that could reduce profitability, at least in the short run. Because theory does not deliver a clear answer, the question is ultimately empirical.

This paper studies the ESG–performance relationship using data on 333 large U.S. companies from 2015 to 2023. The empirical strategy proceeds in two stages. First, a portfolio sort ranks firms by ESG score each year, divides them into quartiles, and compares the average financial performance of the highest-ESG group against the lowest. Second, panel regressions measure the effect of ESG while holding constant firm size, leverage, age, industry, and year. The central result is that the simple comparison suggests high-ESG firms perform worse, but this apparent effect disappears once industry and firm characteristics are controlled for. The reason is that certain industries, such as Utilities, tend to have high ESG scores but structurally low profitability, while others, such as Information Technology, tend to have lower ESG scores but structurally high profitability.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 describes the data and sample. Section 4 defines the variables. Section 5 presents descriptive statistics. Section 6 sets out the methodology and the equations tested. Section 7 presents the empirical findings. Section 8 discusses the results and their limitations, and Section 9 concludes.

2. Literature Review

The empirical literature on ESG and financial performance is extensive and, on balance, mixed. Friede, Busch, and Bassen (2015) synthesised evidence from more than 2,000 primary studies

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and found that roughly 63% reported a positive ESG–performance relationship, while close to 38% reported null or mixed results. This heterogeneity motivates continued empirical work using rigorous methods.

Several studies report a positive association between ESG and firm value. Aydoğmuş, Gülay, and Ergun (2022) analysed 1,720 firms between 2013 and 2021 and found that the composite ESG score is positively and significantly correlated with firm value, with the Social and Governance pillars driving the effect, while the Environmental pillar was positively related to profitability but not to firm value. Whelan, Atz, and Clark (2021) reviewed more than 1,000 studies published between 2015 and 2020 and concluded that ESG performance is generally associated with better operating metrics such as ROE, ROA, and stock price, and offers downside protection during crises. Dalal and Thaker (2023) studied 65 Indian firms in the NSE 100 ESG Index between 2015 and 2017 and found that higher ESG scores were positively associated with both ROA and Tobin's Q. Koundouri, Pittis, and Plataniotis (2022) compared European ESG leaders with the broader market and reported that strong ESG performance was associated with better profitability and valuation.

Evidence from the energy and power sector is more mixed. Naeem and Cankaya (2022) examined 192 global energy and power-generation firms between 2008 and 2019 and found that ESG scores were positively related to ROE but negatively related to pretax ROA and Tobin's Q, suggesting that ESG may benefit shareholders while weighing on operational profitability. In contrast, Zhao et al. (2018) studied 20 listed Chinese power-generation firms and found that ESG performance was positively related to financial performance measured by return on capital employed.

A further strand of research emphasises context and mechanisms. Shin, Moon, and Kang (2022) used data from 4,978 firms across 48 countries and showed that national culture moderates the ESG–performance relationship, which is stronger in individualistic and masculine cultures and weaker in high power-distance and high uncertainty-avoidance cultures. Yin, Li, and Su (2023) found that ESG performance positively affected the stock returns of Chinese listed firms, partly mediated by financial performance and innovation capability, with stronger effects for non-state-owned and eastern-region firms. Zhou, Liu, and Luo (2022) reported that ESG improvements raised firm market value, with financial performance and operating capacity acting as mediating channels. At the global level, Bolla, Jahan, Chaudhary, Kumar, and Anandan (n.d.) analysed roughly 9,000 firms across 40 countries between 2008 and 2023 and found that ESG performance was positively correlated with corporate resilience and long-term financial success.

Alongside this largely positive evidence, an influential body of work reports null or negative findings and highlights methodological pitfalls. Hong and Kacperczyk (2009) found that "sin

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stocks" earn positive abnormal returns, contrary to a simple ESG-helps narrative. Pedersen, Fitzgibbons, and Pomorski (2021) showed that ESG-sorted portfolios need not outperform once investor preferences are impounded in prices. Edmans (2011) documented that employee satisfaction —a social dimension of ESG— predicted abnormal returns, implying markets do not always fully price intangibles. Khan, Serafeim, and Yoon (2016) argued that only industry-material ESG issues are related to performance. Albuquerque, Koskinen, and Zhang (2020) found that high-ESG firms exhibited lower return volatility during the COVID-19 crisis, a result echoed for Asian markets by Broadstock, Chan, Cheng, and Wang (2021) and Umar, Gubareva, and Teplova (2021). Crucially, Berg, Kölbel, and Rigobon (2022) documented substantial disagreement across ESG rating providers, with pairwise correlations averaging only about 0.54, which helps explain why studies using different ratings reach different conclusions. The present study contributes to this debate by applying transparent panel methods to a clean sample of large U.S. firms and by distinguishing carefully between naive and properly controlled comparisons.

3. Data and Sample

The dataset covers 333 companies that were constituents of the S&P 500 index over the fiscal years 2015 to 2023, yielding approximately 2,614 firm-year observations after cleaning. For each firm in each year, the data include the composite ESG score and its three pillar scores (Environmental, Social, Governance), together with financial information such as total assets, total debt, net income, market capitalisation, revenue, and cash flow. Firm-level classification variables include the GICS sector (11 industry groups), year of establishment, and headquarters location.

Several standard cleaning decisions were made. First, a small number of observations with negative computed firm age, arising from spin-offs or restructurings after the sample start, were removed. Second, all continuous variables were winsorised at the 1st and 99th percentiles to limit the influence of outliers, which are especially pronounced in ROE and Tobin's Q. Third, ESG scores were lagged by one year in the regressions to mitigate reverse causality, so that the regression sample effectively runs from 2016 to 2023. Fourth, observations with missing lagged ESG scores or missing controls were dropped from the relevant regressions.

Table 1 reports the distribution of firms across the 11 GICS sectors, together with the average ESG score, ROA, and Tobin's Q in each sector. This table is central to interpreting the later results.

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Table 1. Distribution of Firms Across Industries, With Average ESG and Performance

GICS Sector	N	ESG Score (mean)	ROA (mean)	Tobin's Q (mean)
Communication Services	124	3.240	0.0641	2.070
Consumer Discretionary	222	3.913	0.0713	2.591
Consumer Staples	105	4.484	0.1020	2.958
Energy	183	4.489	0.0307	1.532
Financials	497	3.133	0.0366	1.126
Health Care	332	3.695	0.0802	3.510
Industrials	427	3.948	0.0793	2.433
Information Technology	208	3.399	0.0890	3.679
Materials	176	4.671	0.0645	1.606
Real Estate	220	3.992	0.0385	1.927
Utilities	228	5.026	0.0212	0.906

Note. This table shows, for each of the 11 GICS industries, the number of firm-year observations (N), the average ESG score, the average ROA, and the average Tobin's Q. The sample covers 2015–2023 for firms with an available ESG score.

A striking pattern emerges when the ESG-score and ROA columns are read together. Utilities have the highest average ESG score (about 5.03) but the lowest average ROA (about 2.1%). Energy also combines a high ESG score (about 4.49) with a low ROA (about 3.1%). At the opposite end, Information Technology has a relatively low ESG score (about 3.40) but a high ROA (about 8.9%), and Consumer Staples combines a high ESG score with a high ROA (about 10.2%). This tendency for high-ESG industries to have lower profitability, and vice versa, is the single most important fact in the analysis: a naive comparison of high- and low-ESG firms that ignores industry will wrongly attribute sectoral differences to ESG itself.

4. Variable Definitions

This section defines every variable used in the analysis. There are three kinds of variables: outcome (dependent) variables that measure financial performance; the ESG variables of interest; and control variables that capture other firm characteristics affecting performance. Table 2 summarises each variable, its definition, and how it is measured. Tobin's Q is computed following the widely used approximation of Chung and Pruitt (1994) as the sum of market capitalisation and total debt divided by total assets.

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Table 2. Definitions and Measurement of Variables

Variable	Definition	Measurement	Role
ROA	Return on assets; profitability relative to assets	Net Income / Total Assets	Dependent
ROE	Return on equity; profitability for shareholders	Net Income / Shareholders' Equity	Dependent
Tobin's Q	Market value relative to book value of assets	(Market Cap + Total Debt) / Total Assets	Dependent
ESG Score	Composite ESG performance rating (lagged)	Provider rating, t−1	Independent
Environmental	Environmental pillar score (lagged)	Provider sub-rating, t−1	Independent
Social	Social pillar score (lagged)	Provider sub-rating, t−1	Independent
Governance	Governance pillar score (lagged)	Provider sub-rating, t−1	Independent
Size	Firm size	ln(Total Assets)	Control
Leverage	Financial leverage	Total Debt / Total Assets	Control
Firm Age	Age since incorporation	ln(Year − Year founded + 1)	Control
Industry (GICS)	Industry group (11 sectors)	S&P GICS classification	Fixed effect
Year	Fiscal year	Calendar year (2016–2023)	Fixed effect

Note. All continuous variables are winsorised at the 1st and 99th percentiles. "ln" denotes natural logarithm; "t−1" denotes a one-year lag. Market Cap is the total stock-market value of the firm's equity.

5. Descriptive Statistics

Table 3 reports summary statistics for the main variables, computed on the winsorised sample of firm-years with an available ESG score. For each variable it reports the number of observations, the mean, the standard deviation (SD), and the minimum, median, and maximum values.

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Table 3. Summary Statistics

Variable	N	Mean	SD	Min	Median	Max
ESG Score	2,726	3.891	1.402	0.650	3.780	8.560
Environmental Score	2,283	3.365	1.913	0.003	3.010	9.570
Social Score	2,679	3.176	2.014	0.145	2.740	9.702
Governance Score	2,726	7.087	0.843	2.504	7.150	9.056
ROA	2,973	0.060	0.086	−0.438	0.046	1.496
ROE	2,973	0.101	2.644	−65.364	0.146	38.380
Firm Size (ln Assets)	2,973	10.196	1.499	3.921	10.115	15.170
Leverage	2,973	0.317	0.216	0.000	0.311	2.439
Firm Age (ln)	2,969	3.934	0.838	0.693	3.932	5.481
Asset Turnover	2,814	0.610	0.518	0.020		4.212

Note. Summary statistics on the winsorised sample of firm-years with an ESG score, covering 2015–2023. SD is the standard deviation. The Environmental and Social scores have fewer observations because the data provider did not rate every firm on those pillars in every year. The Governance pillar is scored on a higher scale by the provider, which explains its higher mean.

The composite ESG score averages 3.89 (SD 1.40). ROA averages 5.9% with a median of 4.6%, while ROE is far more volatile (SD 2.64), which is why ROA is treated as the primary accounting measure and ROE as a robustness check. The average firm has a log-asset size of about 10.2 (roughly $26 billion in assets), leverage of 0.32, and a log age of 3.93 (about 51 years since incorporation).

6. Methodology and the Equations Tested

This study investigates the relationship between ESG performance and corporate financial performance using a panel-data regression technique. Panel data combine cross-sectional and time-series dimensions, observing the same firms over multiple years, which allows the model to account for firm-specific heterogeneity (Baltagi, 2005). The analysis proceeds in two stages: a portfolio sort and a panel regression.

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6.1 Step One: Portfolio Sorting

In the first stage, firms are ranked by ESG score each year and divided into four equal groups (quartiles). Quartile 1 (Q1) contains the 25% of firms with the lowest ESG scores; Quartile 4 (Q4) contains the 25% with the highest. The average performance of Q4 is then compared with that of Q1.

Equation 1: Assigning firms to quartiles

For each firm i in year t, the quartile assignment is:

$$Q(i,t) = \lceil 4 \times \mathrm{rank}_t(ESG(i,t)) / N_t \rceil \qquad (1)$$

where Q(i,t) is the quartile (1–4) of firm i in year t; $\mathrm{rank}_t(ESG(i,t))$ is the firm's rank by ESG score within year t (1 = lowest); N_t is the number of firms with an ESG score in year t; and ⌈ ⌉ denotes rounding up to the nearest integer. Sorting within each year prevents the secular rise in average ESG scores (from about 2.9 in 2015 to about 4.8 in 2022) from confounding ESG rank with calendar time.

Equation 2: The stock-return proxy

Because the dataset does not include a ready-made stock return, an approximate return is constructed from the year-over-year change in market capitalisation:

$$Stock\_Return(i,t) = [\, Market\_Cap(i,t) / Market\_Cap(i,t-1) \,] - 1 \qquad (2)$$

This proxy captures the change in equity value but excludes dividends and is affected by share issuance and buybacks. It is used only in the portfolio sort, never in the regressions, and is flagged as a limitation.

Equation 3: Comparing the top and bottom groups (Welch t-test)

To test whether the Q4–Q1 difference is statistically meaningful, a Welch two-sample t-test is used:

$$t = (\, \bar{y}(Q4) - \bar{y}(Q1) \,) / \sqrt{(\, s^2(Q4)/n(Q4) + s^2(Q1)/n(Q1) \,)} \qquad (3)$$

where $\bar{y}(Q4)$ and $\bar{y}(Q1)$ are the mean performance of the top and bottom ESG groups; $s^2(Q4)$ and $s^2(Q1)$ are their variances; and n(Q4) and n(Q1) are their sample sizes. The Welch version is used because it does not assume equal variances across the two groups, which is appropriate given that high- and low-ESG portfolios contain different industries with different volatilities.

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6.2 Step Two: Panel Regression

The portfolio sort does not account for differences in industry, size, leverage, or age between high- and low-ESG firms. Panel regression addresses this by estimating the effect of ESG while holding these characteristics constant. The general static panel model may be written as:

$$y(i,t) = \beta' x(i,t) + \mu_i + \lambda_t + \varepsilon(i,t) \qquad \text{(4a)}$$

where y(i,t) is the dependent variable, x(i,t) is a vector of explanatory variables, μ_i is the firm- (or industry-) specific effect, λ_t is the time-specific effect, and ε(i,t) is the idiosyncratic error. Three performance measures (ROA, Tobin's Q, ROE) are tested under two fixed-effects structures (industry-and-year, and firm-and-year), giving six main specifications.

The six main equations (Table 6)

Equations 4–6 use industry fixed effects, which give each of the 11 industries its own baseline so that firms are compared with others in the same industry:

$$ROA(i,t) = \alpha + \beta_1 ESG(i,t-1) + \beta_2 Size(i,t) + \beta_3 Leverage(i,t) + \beta_4 ln(Age)(i,t) + \Sigma\gamma_k Industry_k + \Sigma\delta_t Year_t + \varepsilon(i,t) \qquad (4)$$

Column (1) of Table 6: dependent variable ROA, industry and year fixed effects.

$$Tobin's\ Q(i,t) = \alpha + \beta_1 ESG(i,t-1) + \beta_2 Size(i,t) + \beta_3 Leverage(i,t) + \beta_4 ln(Age)(i,t) + \Sigma\gamma_k Industry_k + \Sigma\delta_t Year_t + \varepsilon(i,t) \qquad (5)$$

Column (3) of Table 6: dependent variable Tobin's Q, industry and year fixed effects.

$$ROE(i,t) = \alpha + \beta_1 ESG(i,t-1) + \beta_2 Size(i,t) + \beta_3 Leverage(i,t) + \beta_4 ln(Age)(i,t) + \Sigma\gamma_k Industry_k + \Sigma\delta_t Year_t + \varepsilon(i,t) \qquad (6)$$

Column (5) of Table 6: dependent variable ROE, industry and year fixed effects.

Equations 7–9 replace industry fixed effects with firm fixed effects, which give each firm its own baseline and absorb everything about the firm that does not change over time. This is a stricter test, identifying the ESG effect only from within-firm changes over time:

$$ROA(i,t) = \alpha + \beta_1 ESG(i,t-1) + \beta_2 Size(i,t) + \beta_3 Leverage(i,t) + \beta_4 ln(Age)(i,t) + \mu_i + \delta_t + \varepsilon(i,t) \qquad (7)$$

Column (2) of Table 6: dependent variable ROA, firm and year fixed effects.

$$Tobin's\ Q(i,t) = \alpha + \beta_1 ESG(i,t-1) + \beta_2 Size(i,t) + \beta_3 Leverage(i,t) + \beta_4 ln(Age)(i,t) + \mu_i + \delta_t + \varepsilon(i,t) \qquad (8)$$

Column (4) of Table 6: dependent variable Tobin's Q, firm and year fixed effects.

$$ROE(i,t) = \alpha + \beta_1 ESG(i,t-1) + \beta_2 Size(i,t) + \beta_3 Leverage(i,t) + \beta_4 ln(Age)(i,t) + \mu_i + \delta_t + \varepsilon(i,t) \quad (9)$$

Column (6) of Table 6: dependent variable ROE, firm and year fixed effects.

In these equations, α is the intercept; β_1 is the coefficient of interest, measuring how performance changes when last year's ESG score rises by one point; β_2–β_4 are the coefficients on the controls Size, Leverage, and Age; $\Sigma\gamma_k Industry_k$ is the set of industry effects (Equations 4–6); μ_i is the firm effect (Equations 7–9); $\Sigma\delta_t Year_t$ (or δ_t) is the set of year effects; and $\varepsilon(i,t)$ is the error term. The index i denotes firms (1 to 333) and t denotes years (2016 to 2023).

The two pillar equations (Table 7)

To check whether a single pillar drives performance even when the composite does not, the ESG score is replaced by its three pillars —Environmental (E), Social (S), and Governance (G)— and the ROA regression is re-estimated under both fixed-effects structures:

$$ROA(i,t) = \alpha + \beta_1 E(i,t-1) + \beta_2 S(i,t-1) + \beta_3 G(i,t-1) + \beta_4 Size + \beta_5 Leverage + \beta_6 ln(Age) + \Sigma\gamma_k Industry_k + \Sigma\delta_t Year_t + \varepsilon(i,t) \quad (10)$$

Column (1) of Table 7: pillars entered separately, industry and year fixed effects.

$$ROA(i,t) = \alpha + \beta_1 E(i,t-1) + \beta_2 S(i,t-1) + \beta_3 G(i,t-1) + \beta_4 Size + \beta_5 Leverage + \beta_6 ln(Age) + \mu_i + \delta_t + \varepsilon(i,t) \quad (11)$$

Column (2) of Table 7: pillars entered separately, firm and year fixed effects.

Here E, S, and G are the lagged Environmental, Social, and Governance scores. Entering all three together tests whether each pillar has an independent effect after accounting for the other two.

6.3 Standard Errors

All regressions employ cluster-robust standard errors clustered at the firm level. Because each firm is observed many times, its yearly observations are not fully independent; clustering by firm corrects for this serial correlation so that statistical significance is not overstated (Petersen, 2009).

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7. Empirical Findings

7.1 Portfolio Sort Results

Table 4 reports the average ESG score and the average of each performance measure for the four ESG quartiles, pooled across 2015–2023. A clear pattern appears in the Stock Return column: mean returns decline from 17.9% in Q1 to 11.7% in Q4, a difference of 6.2 percentage points. ROA declines more modestly, from 6.3% in Q1 to 5.4% in Q4, while ROE shows no clear monotonic pattern.

Table 4. Pooled Portfolio Means by ESG Quartile

ESG Quartile	ESG Score (mean)	Stock Return	ROA	ROE
Q1 (Low)	2.347	0.1787	0.0629	0.1455
Q2	3.474	0.1550	0.0602	0.1728
Q3	4.348	0.1065	0.0562	0.1801
Q4 (High)	5.426	0.1167	0.0543	0.1484

Note. Firms are sorted into quartiles by ESG score within each year, then pooled across 2015–2023. Q1 is the lowest-ESG group; Q4 is the highest. Stock Return is the market-capitalisation-change proxy from Equation 2. All variables are winsorised at the 1st and 99th percentiles.

Table 5 formally tests the difference between the high-ESG (Q4) and low-ESG (Q1) portfolios using Welch t-tests. The Stock Return difference of −6.2 percentage points is highly significant ($t = -3.20$, $p = 0.001$). The ROA difference of −0.86 percentage points is significant at the 5% level ($t = -2.15$, $p = 0.032$). The ROE difference is economically small and statistically insignificant ($t = 0.08$, $p = 0.934$).

Table 5. Difference-in-Means Tests: High-ESG (Q4) vs. Low-ESG (Q1)

Variable	Q4 High Mean	Q1 Low Mean	Difference (Q4−Q1)	Std. Error	t-statistic	p-value
Stock Return (Mkt Cap Δ) ***	0.1167	0.1787	−0.0620	0.0194	−3.20	0.001
ROA **	0.0543	0.0629	−0.0086	0.0040	−2.15	0.032
ROE	0.1484	0.1455	0.0030	0.0362	0.08	0.934

*Note. Welch two-sample t-tests of the difference in mean performance between the top ESG quartile (Q4) and the bottom quartile (Q1), pooled across 2015–2023. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

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Taken together, the portfolio sort suggests that higher-ESG firms earn lower stock returns and lower ROA. However, this univariate association may be confounded by systematic differences between high- and low-ESG firms, most obviously in sectoral composition. The panel regressions address these confounds.

7.2 Main Panel Regression Results

Table 6 reports the six main regressions. Columns (1), (3), and (5) use industry and year fixed effects; columns (2), (4), and (6) use firm and year fixed effects. Below each coefficient, the cluster-robust t-statistic is reported in parentheses.

Table 6. Panel Regression of Firm Performance on Composite ESG

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable:	ROA	ROA	Tobin's Q	Tobin's Q	ROE	ROE
ESG Score (t−1)	0.00406	0.00110	0.0316	−0.0347	0.0311	−0.0266
	(1.46)	(0.62)	(0.39)	(−0.74)	(1.42)	(−0.98)
Size (ln Assets)	−0.01925***	−0.01485	−0.8757***	−0.4383***	−0.0243	−0.1568**
	(−6.70)	(−1.54)	(−8.91)	(−3.39)	(−1.00)	(−2.41)
Leverage	−0.01994	−0.16859***	0.5657	−0.1470	−0.2040	−1.0794**
	(−0.97)	(−4.99)	(0.94)	(−0.22)	(−1.23)	(−2.57)
Firm Age (ln)	0.00447	0.01763	−0.0511	0.0772	0.0365*	−0.1006
	(1.29)	(1.27)	(−0.55)	(0.33)	(1.79)	(−0.69)
Firm FE	No	Yes	No	Yes	No	Yes
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,614	2,614	2,600	2,600	2,614	2,614
R^2 / within-R^2	0.217	0.050	0.430	−0.031	0.012	0.006

*Note. Estimates of Equations 4–9. Columns (1), (3), (5) include industry and year fixed effects; columns (2), (4), (6) include firm and year fixed effects. All regressions include Size, Leverage, and ln(Firm Age) as controls. Cluster-robust t-statistics (clustered by firm) are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. For firm-FE columns, R^2 is the within-R^2.*

The central finding is that the coefficient on lagged ESG is statistically insignificant in all six specifications. Under industry fixed effects, the ESG coefficient is 0.00406 for ROA (t = 1.46),

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0.0316 for Tobin's Q (t = 0.39), and 0.0311 for ROE (t = 1.42). Under firm fixed effects, the coefficients attenuate further and change sign for Tobin's Q and ROE, remaining insignificant throughout. The negative univariate association documented in Table 5 therefore disappears once industry or firm heterogeneity is controlled for, confirming that it reflects sectoral composition rather than an independent ESG effect.

The control variables behave as expected, which reassures that the model is well specified. Size enters negatively and highly significantly for ROA under industry fixed effects (β = −0.019, t = −6.70) and for Tobin's Q under both structures, consistent with the size effect. Leverage is significantly negative for ROA under firm fixed effects (β = −0.169, t = −4.99) and for ROE under firm fixed effects (β = −1.079, t = −2.57), consistent with the costs of financial distress. Firm Age is generally small and imprecisely estimated. The large sample (about 2,614 observations) gives ample power to detect an ESG effect if one existed, which strengthens confidence in the null result.

7.3 Pillar Decomposition

Table 7 disaggregates the composite ESG score into its Environmental, Social, and Governance pillars in the ROA regression.

Table 7. Pillar Decomposition: ESG Pillars and Return on Assets

Dependent Variable: ROA	(1) Industry FE	(2) Firm FE
Environmental Score (t−1)	0.00353*	−0.00015
	(1.92)	(−0.10)
Social Score (t−1)	−0.00195	−0.00082
	(−1.46)	(−0.71)
Governance Score (t−1)	0.00007	0.00077
	(0.02)	(0.18)
Size (ln Assets)	−0.02070***	−0.02753***
	(−6.79)	(−3.27)
Leverage	−0.03063	−0.20155***
	(−1.57)	(−5.29)
Firm Age (ln)	0.00440	0.00507
	(1.22)	(0.41)
Firm FE	No	Yes
Industry FE	Yes	No

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Year FE	Yes	Yes
Observations	2,153	2,153
R^2 / within-R^2	0.242	0.047

*Note. The composite ESG score is replaced by its three pillars, each lagged one period. Column (1) uses industry and year fixed effects; column (2) uses firm and year fixed effects. All regressions include Size, Leverage, and ln(Firm Age) as controls. Cluster-robust t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

Under industry fixed effects, the Environmental pillar is positive and marginally significant ($\beta = 0.00353$, $t = 1.92$, $p = 0.055$), while the Social and Governance pillars are insignificant. However, under firm fixed effects the Environmental coefficient falls to essentially zero ($\beta = -0.00015$, $t = -0.10$), and the other pillars remain insignificant. The marginal environmental effect therefore reflects between-firm heterogeneity rather than a within-firm causal relationship, consistent with the null result for the composite score.

8. Discussion

The findings admit several interpretations. First, the null aggregate result is consistent with a substantial part of the ESG–performance literature. Friede et al. (2015) report that approximately 38% of primary studies find no significant relationship, and Berg et al. (2022) show that ESG rating providers disagree substantially, with pairwise correlations averaging about 0.54. Such measurement noise attenuates estimated coefficients toward zero and helps explain why many specifications fail to detect an effect.

Second, the contrast between the significant negative univariate association and the null multivariate result underscores the importance of controlling for sectoral composition. In this sample, high-ESG sectors (Utilities, Materials, Energy) are structurally lower-return, while low-ESG sectors (Information Technology, Communication Services, Financials) are structurally higher-return. A researcher reporting only the univariate result would wrongly conclude that ESG destroys firm value.

Third, the null within-firm result under firm fixed effects is a strong test of causality. Firm fixed effects absorb all time-invariant firm characteristics —business model, culture, geographic footprint, managerial style— and identify the ESG coefficient purely from within-firm changes over time. The absence of a systematic association is inconsistent with strong versions of the "doing well by doing good" hypothesis in this sample.

Several limitations should be noted. First, the stock-return variable used in the portfolio sort is a proxy computed from the change in market capitalisation; it excludes dividends and is affected by share issuance and buybacks, and a more rigorous test would use total returns from a

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dedicated pricing database. Second, the ESG scores come from a single provider, and given the documented disagreement across providers (Berg et al., 2022), the results may not be robust to alternative data sources. Third, the sample is restricted to large-capitalisation U.S. firms, so the conclusions may not generalise to smaller or non-U.S. firms. Fourth, the analysis focuses on contemporaneous performance with a one-year lag, whereas ESG effects may operate over longer horizons.

9. Conclusion

This study examined the effect of ESG performance on the financial performance of S&P 500 firms during 2015–2023, using portfolio sorting and panel regression on three performance measures (ROA, Tobin's Q, and ROE). The results consistently indicate that, once firm and industry characteristics are controlled for, ESG performance has no statistically significant effect on corporate financial performance.

The portfolio sort initially suggested a negative association, with high-ESG firms earning lower stock returns and lower ROA than low-ESG firms. However, this association is driven by sector composition: ESG-intensive industries such as Utilities and Energy are structurally lower-return, while ESG-light sectors such as Information Technology are structurally higher-return. These differences vanished once fixed effects were introduced, and the ESG coefficient was insignificant in all six specifications. The one partial exception —a marginally significant Environmental effect on ROA in the cross-section— disappeared under firm fixed effects, pointing to between-firm differences rather than a causal relationship.

These results align with a large part of the existing literature that finds no consistent link between ESG and performance, and contribute to the debate by showing that methodology —especially the treatment of sectoral composition— is crucial in shaping conclusions. Reporting only univariate results risks misleading findings. Future research should incorporate multi-provider ESG scores to address rating disagreement, extend the time horizon to capture long-run ESG effects, and broaden the sample beyond large-cap U.S. firms to test generalisability.

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