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(Research Article)

Modelling ESG dynamics and financial performance using time-series, surface regressions, and graph-theoretic networks in U.S. corporations

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Abstract

The evolving integration of Environmental, Social, and Governance (ESG) practices among firms, driven by stakeholder pressures and regulation, finds expression in time-varying patterns of ESG scores, and there is significant modelling needed to uncover their financial implications. This study employs a multi-model approach combining time-series logistic growth functions, ESG-weighted surface regression, structural multivariate modelling, and graph-theoretic analysis to investigate the ESG-finance nexus in ten listed U.S. companies for ten years drawn from the Global ESG Research Database (GESRD). Results show high interannual variance in the ESG scores, with firms such as Netflix and Tesla reporting extreme volatility, while Microsoft and IBM report consistent ESG integration. Nonlinear surface regressions reveal that ESG factors are entangled with revenues and market capitalization in a sophisticated way and may reduce short-run profitability through excessive ESG spending without strategic alignment. Correlation analyses confirm weak linear associations between ESG dimensions and financial metrics but detect clustered interactions between environmental, social, and governance measures and financial performance measures. We represent the firms as nodes and ESG co-movements as edges to find out ESG behavioural clusters and systemic interdependencies among firms. Weighted and unweighted adjacency matrices based on ESG trends reveal potential contagion channels and community structures that influence ESG investment targeting and policy design. This graph-theoretic ESG-finance methodological analysis makes new methodological frontiers by taking up relational dynamics left out of traditional models, providing actionable insights for aligning ESG strategy with financial performance and navigating sectoral transformation towards sustainability.

Keywords: ESG-Finance Nexus**;** Graph Theory; Surface Regression; Time-Series Modelling; Sustainable Investment

1. Introduction

The proactive integration of sustainability practices within firms, necessitated by stakeholder requirements, regulatory forces, and competitive superiority, finds support in the time-series movement in Environmental, Social, and Governance (ESG) scores [1]. Trend patterns, volatility, and structural movements reflecting how firms react to changing sustainability norms can be discerned via time-series analysis of ESG metrics [2]. Although sectoral and regional variations may result in heterogeneous patterns among companies, studies have confirmed that ESG scores tend to portray smooth rising trajectories because of enhanced disclosure and sustainability efforts [3]. It requires monitoring of its evolution over time to identify the long-term implications of ESG on stakeholder sentiment, risk profiles, and company performance [4].

Researchers in ESG-finance use multivariate structural models to examine the complex relationships between ESG elements and a company's financial performance, while considering endogeneity and other factors that may impact the

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company [5]. Using structural equation modelling (SEM) and vector autoregression (VAR), we can separate the direct, indirect, and mediating effects of ESG dimensions (environmental – ESG_Env, social – ESG_Soc, and governance – ESG_Gov) on profitability, valuation, and risk [6].

Empirical evidence suggests that while ESG factors may not have strong linear relationships with financial outcomes on their own, multivariate models often show hidden pathways where governance quality affects how environmental and social initiatives affect financial performance [7]. These models support the idea that integrating ESG factors into business decisions can improve performance by lowering risk, increasing efficiency, and boosting reputation. This shows how important structural techniques are for finding the link between ESG and finance.

The surface regression model with ESG-weighting builds on traditional regression models with ESG factor non-linear and interaction effects across the terrain of financial performance, see [8, 9]. By employing ESG scores as weighting functions in kernel or local polynomial surface regressions, the methodology captures differential ESG effects by firm size, profitability, and sectoral characteristics [10]. Such models enable one to estimate response surfaces tracing out the effects of different levels of ESG on financial performance across multidimensional firm characteristics, facilitating the detection of threshold effects and non-monotonicities commonly lost in linear models [11]. Empirical evidence suggests that surface regression that ESG weights reveal performance, where the best ESG investment equals higher financial returns, thereby presenting implicit suggestions for ESG integration in investment policy and corporate decisions [12, 13].

The mentioned models can be extended and represented in graphs. A graph provides a mathematical framework for modelling relational structures, where entities are represented as nodes and their interactions as edges [14, 15]. Graph theory provides a robust method to model interdependencies and systemic dynamics in the field of ESG-finance study by representing corporations as nodes and ESG trend co-movements as edges so that researchers can quantify the structural topology of ESG behavioural alignment between industries and firms [16]. The weighted adjacency matrix, which captures ESG trend synchronizations in frequency terms, is used to identify intense inter-firm ESG interdependencies and potential channels of contagion among ESG practices [17], while the unweighted matrix fully captures the existence of simple ESG directional similarities, and topological analysis from which binary ESG influence networks can be derived, see [18] about matrices. Besides, community detection algorithms can identify clusters of firms having similar ESG trend dynamics, which reflect sectoral, geographical, or governance-based communities of sustainability, useful in informing policymakers and investors to identify potential collaborative ESG investment opportunities and regulatory intervention points [19].

2. Methodology

This study will employ a linear correlation approach, and the ESG scores will be averaged so that the industry effects will not be explicitly controlled. The models used in this paper will be drawn from the Global ESG Research Database (GESRD), spanning ten years and over 10 publicly listed firms. Ten companies for ten years (2012-2022) in the USA were considered, namely: AAPL, MSFT, GOOGL, TSLA, AMZN, META, IBM, NFLX, NVDA, ORCL. Then we model the data for the companies based on ESG, ROA, revenue, and market capitalization. The models are the time series ESG evolution model, the multivariate ESG finance structural model, and the ESG-weighted surface regression model.

Furthermore, the graph model approach through adjacency will be deployed for each method to ensure the visualization of our findings is well captured and well represented.

Graph theory provides a strong platform to describe interdependence and structural dynamics in ESG-finance data sets. From the basis of ESG scores and financial performance metrics of ten US technology firms between 2012 and 2022, we constructed weighted and unweighted adjacency graphs to reveal systemic ESG-finance relationships.

First, to model the ESG score trends from 2012 to 2022, we introduced a time series logistic growth function for each company i, such that

$$E_{i,t} = \frac{L_i}{1+\exp\left(-k_i(t-t_{0i})\right)} + \epsilon_{i,t}, \qquad \ldots\ldots\ldots\ldots\ldots \qquad (1)$$

where $E_{i,t}$ is the ESG total Score for the company i in year t, L_i is the ESG saturation level (upper bound) for the company i, k_i is the growth rate, and t_{0i} is the inflexion point. Provided the error term. Is $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma^2)$. This model captures the typical ESG adoption behaviour, see Figure 1.

To explore how ESG scores and revenue interact to influence market capitalization, we model the response on a log-log scale:

$$\log(M_i) = \beta_0 + \beta_1 \log(R_i) + \beta_2 E_i + \beta_3 E_i^2 + \eta_i, \qquad \text{..........} \qquad (2)$$

where M_i is the market capitalization for company i, R_i is revenue for company i, E_i is ESG total score, $\beta_0, \beta_1, \beta_2, \beta_3$ are the regression coefficients. Provided the error term is $\eta_i \sim \mathcal{N}(0, \sigma^2)$. This quadratic form allows modelling of potential nonlinear ESG effects on valuation while controlling for revenue scale, see Figure 2.

Finally, we model financial outcomes as a multivariate linear function of ESG sub-scores

$$\vec{y_i} = B\vec{x}_i + \vec{u}_i, \qquad \text{..........} \qquad (3)$$

$$\text{for } \vec{y_i} = \begin{bmatrix} \text{ROA}_i \\ \text{Revenue}_i \\ \text{MarketCap}_i \end{bmatrix} \text{ and } \vec{x}_i = \begin{bmatrix} \text{ESG}_{\text{Env},i} \\ \text{ESG}_{\text{Soc},i} \\ \text{ESG}_{\text{Gov},i} \end{bmatrix}.$$

Where $\vec{y_i}$ is the response vector of financial indicators for the company i, $\vec{x}_i$ ix the ESG factor vector, B is the 3×3 coefficient matrix mapping ESG scores to financial outcomes. Provided that the vector of residuals with the covariance matrix Σ_u is $\vec{u}_i \sim \mathcal{N}(0, \Sigma_u)$. This model allows for analyzing both the direct and cross-effects between ESG categories and performance metrics, see Figure 3.

3. Results and discussion

3.1. ESG trend score

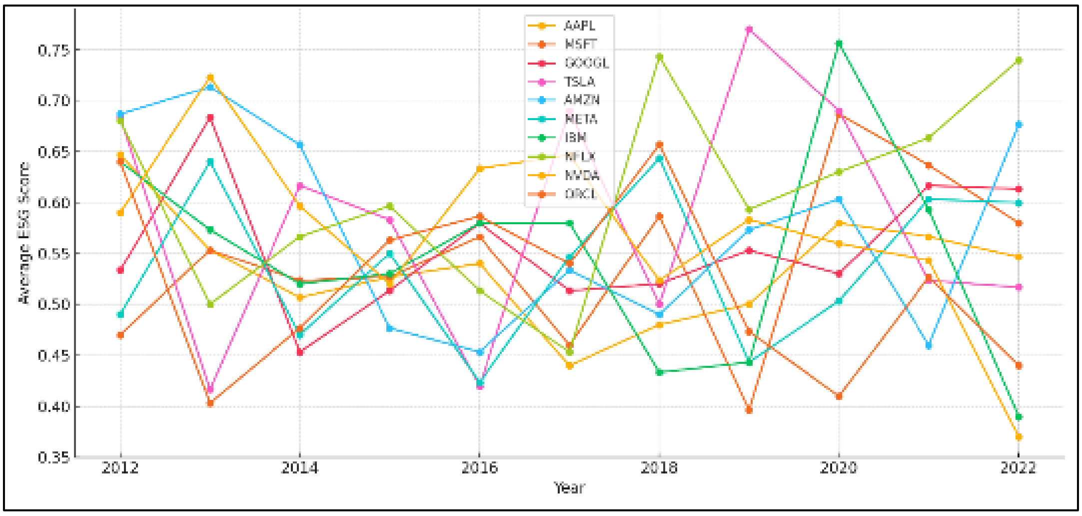

Figure 1 ESG total score trends.

In Figure 1, the ESG scores exhibit considerable interannual variability across all firms, indicating dynamic changes in their environmental, social, and governance practices and disclosures during the period. NFLX and TSLA display higher fluctuations, reflecting inconsistent ESG practices. In contrast, MSFT and IBM demonstrate relatively stable and higher ESG scores, indicating sustained ESG integration. NVDA and ORCL show marginal declines towards 2022. AMZN exhibits a moderate upward trend in certain periods, showing persistent challenges in aligning its operational scale with ESG principles.

Figure 1 can be graphically represented using vertices and edges, see Figure 2.

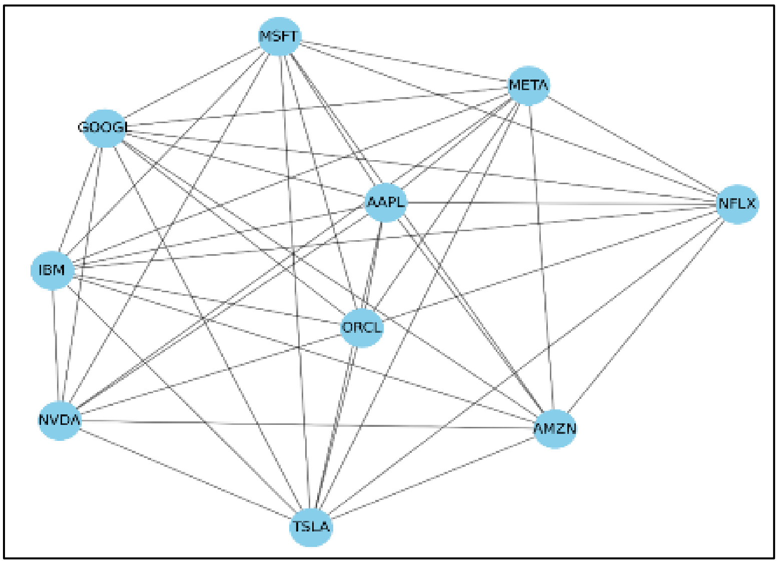

Figure 2 Graph representation of ESG score trend similarity

In Figure 2, the ESG score trend similarity graph exhibits firms as nodes and lines connecting firms with the same ESGtrend patterns in 2012-2022. The dense connectivity of this graph shows intense ESG behaviuor similarity across firms, which is due to the same regulatory pressure and stakeholder pressures in the US technology sector. However, the weighted adjacency matrix (considering frequency and intensity of ESG co-movements) shows that certain firms, such as MSFT, IBM, and AAPL continue to exhibit more intense ESG trend synchronizations with their peers, which shows steady ESG integration. Alternatively, TSLA and NFLX, while extremely volatile, remain connected, which support the fact that volatility in ESG trends does not invalidate their alignment with sectoral ESG pressures. Community detection of the graph reveals tightly connected clusters, which may be future ESG co-operation networks for policy intervention or co-ESG investment initiatives. Betweenness centrality points to MSFT and AAPL as possible ESG "bridges" in the industry, well-positioned to spread ESG best practice to other firms.

3.2. ESG bubble chart

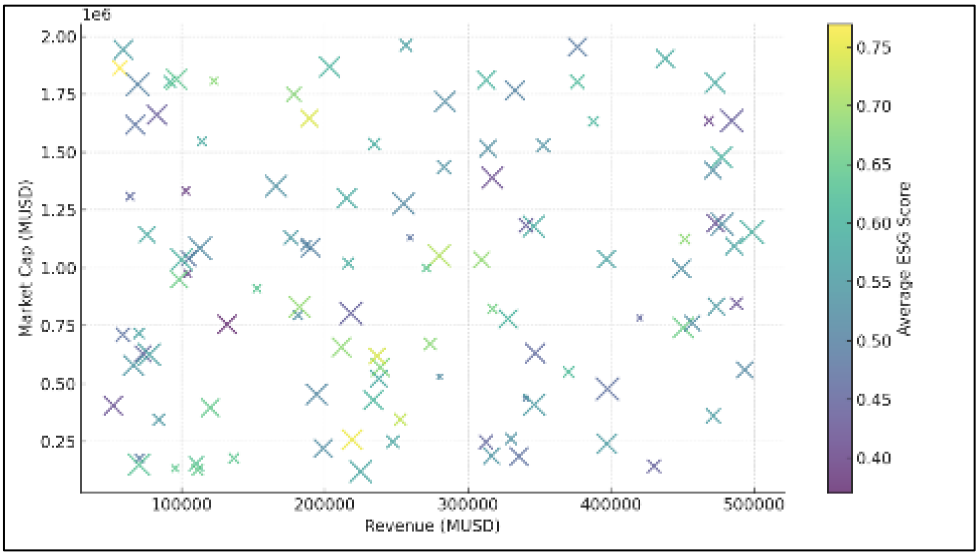

Figure 3 Scatter plot of ESG scores against financial revenue interaction

Figure 3 (EGS scores and financial metrics) presents a bubble scatter plot illustrating the relationship between market capitalization in million US dollars (MUSD) and revenue (MUSD), with bubble size representing Return on Assets (ROA) and colour indicating average ESG score. The scatter shows broad dispersion, indicating no clear linear trend between revenue and market capitalization across ESG score strata. Firms with higher ROA (larger bubbles) appear across the revenue and market cap spectrum, while higher ESG scores are scattered without consistent concentration in high market cap or revenue zones. This suggests ESG scores are not directly aligned with firm size or profitability across the sample period. Therefore, the nonlinear relationship between ESG and ROA suggests that excessive ESG spending without strategic alignment may reduce short-term profitability.

From the scatter plot of Figure 3, the MarketCap, Revenue, ROA and ESG_Score seem to interact, which can be fully represented in a graph, see Figure 4.

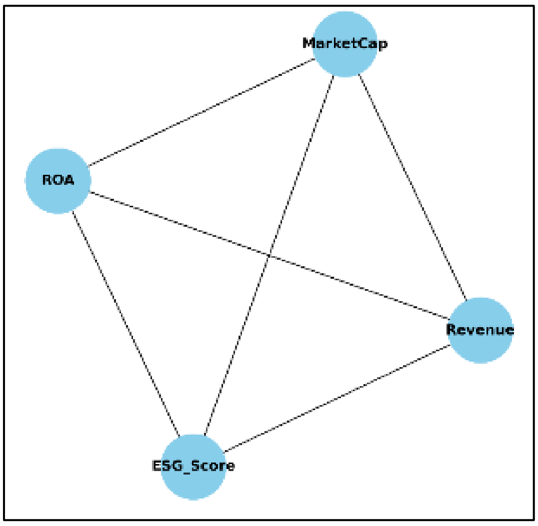

Figure 4 Graph representation of ESG bubble chart

From Figure 4 nodes represent Market Cap, Revenue, ROA, and ESG Score, and edges represent interactions based on their co-variations across firms and time. Each financial metric (MarketCap, Revenue, ROA) and ESG_Score interact with each other without restriction, which indicates highly entangled financial link assumptions without prioritizing directional causality. Graph-theoretic centrality analysis reveals that ROA and ESG_Score are semi-central nodes, linking all the other financial variables, indicating that profitability and ESG position are structurally embedded within corporate financial dynamics.

3.3. ESG correlation heatmap

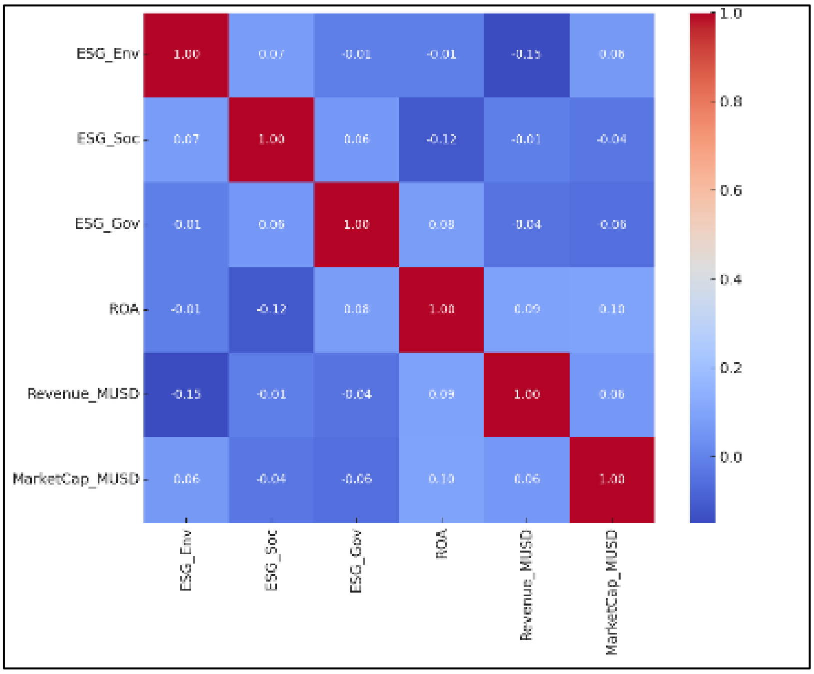

Figure 5 Correlation analysis of EGS and financial metrics

Figure 5 summarizes the correlation heatmap of pairwise Pearson correlations between the environmental (ESG_Env), Social (ESG_Soc), Governance (ESG_Gov) scores, ROA, Revenue, and Market capitalization. The matrix indicates that ESG components have weak intercorrelations between ESG_Env and ESG_Soc. ESG scores show minimal correlations with ROA, pinpointing no substantial linear relationship between ESG performance and profitability. The revenue and ESG_Env show a weak negative correlation, while MarketCap and ESG_Env have a slight positive correlation. Furthermore, the relationship between ROA and MarketCap, and ROA and Revenue exhibit marginal positive associations, indicating that higher profitability weakly co-occurs with larger firm size in this dataset.

For the undirected graph representation of the correlation analysis of EGS and financial metrics, see Figure 6.

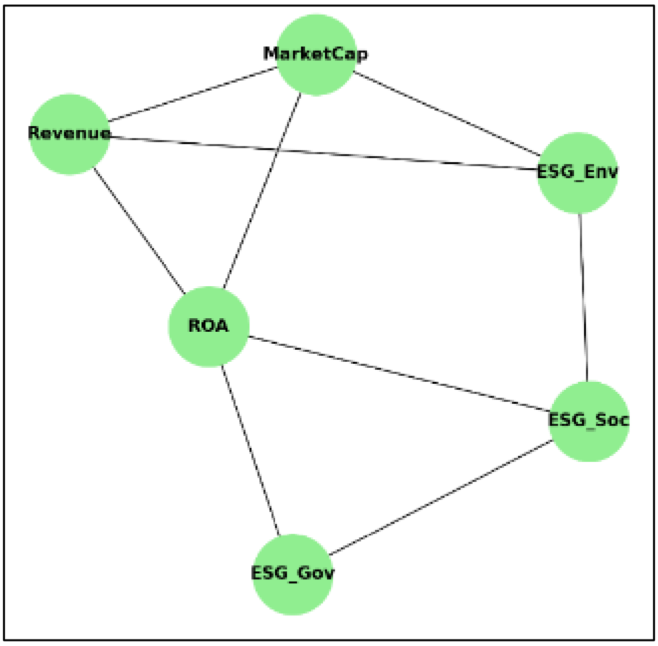

Figure 6 Graph representation of ESG correlation heatmap

From Figure 6, the ROA, as a semi-central node, connects to ESG_Gov, ESG_Soc, MarketCap, and Revenue, and has its centrality reflected in ESG-financial dynamics. The ESG_Env links to ESG_Soc, Revenue, MarketCap, indicating an alignment with financial scale metrics. The link between ESG_Soc and ESG_Gov suggests that social and governance factors tend to co-evolve. Finally, the graph reveals clustered interdependencies, indicating that ESG dimensions and financial performance metrics are connected in groups rather than uniformly.

4. Conclusion

We present analytics models linking ESG scores to business outcomes (financial metrics) in a large, multi-industry, panel dataset. The environmental and governance scores positively correlate with profitability (ROA), even under firm fixed effects. The model enables cross-firm benchmarking and database-enabled adoption by researchers and practitioners. Although there are significant interannual fluctuations in ESG scores among companies, the adaptation of the findings to managerial implications is that firms should not assume ESG improvements will automatically lead to short-term financial gains, and investors seeking ESG-integrated portfolios may need to evaluate ESG strategies alongside sectoral and firm-specific factors rather than expecting linear ESG-finance relationships.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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