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ESG Risk Ratings and Stock Performance in Electric Vehicle Manufacturing: A Panel Regression Analysis Using the Fama-French Five-Factor Model

Henry Efe Onomakpo Onomakpo*

Faculty of Economics and Business, University of Gadjah Mada, Indonesia

***Corresponding Author**
Henry Efe Onomakpo Onomakpo, Faculty of Economics and Business, University of Gadjah Mada, Indonesia.

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Abstract

As electric vehicles (EVs) gain prominence in the global shift to sustainable mobility, Environmental, Social, and Governance (ESG) factors are increasingly vital for investment decisions in the automotive sector. This study investigated the link between ESG risk ratings and the financial returns of EV manufacturers, addressing the growing need to understand how sustainability impacts financial performance in this key industry. A panel regression analysis was conducted on a sample of EV firms, categorized by ESG risk, employing entity and time-fixed effects within the Fama-French five-factor model, enhanced with lagged ESG pillar scores. The analysis reveals a context-dependent relationship. For Low ESG Risk firms, strong prior-period governance positively drives stock performance, while prior environmental scores show a negative correlation. Conversely, High ESG Risk firms require broad ESG improvements, especially in governance, to improve market sentiment, though prior ecological and social gains alone do not guarantee immediate return benefits. The Fama-French model's explanatory power varies modestly across ESG risk groups, with firm size consistently significant. These findings are useful and important because they demonstrate the nuanced and non-uniform market valuation of ESG in the EV sector. They suggest that effective ESG strategies and investment decisions in this sector must be context-aware and tailored to specific ESG risk profiles, moving beyond generic approaches. This study contributes to a more refined, actionable understanding of ESG's complex role in EV financial performance, directly informing corporate sustainability strategies and targeted investment approaches critical for achieving a net-zero emissions future.

Keywords: Electric Vehicles (EV), ESG Risk Ratings, Stock Performance, Fama-French Five-Factor Model, Panel Regression, Sustainable Finance, Net-Zero Ambitions, Automotive Industry, Behavioral Finance

1. Introduction

The global transition towards sustainable transportation is rapidly reshaping the automotive industry, with electric vehicles (EVs) at the forefront of this revolution [1]. This shift, driven by growing global environmental consciousness and the urgent need to mitigate climate change, has placed unprecedented emphasis on corporate sustainability [2]. In this context, Environmental, Social, and Governance (ESG) factors have become essential benchmarks for evaluating the overall health and prospects of companies, particularly within the EV manufacturing sector [3]. ESG ratings, provided by specialized agencies, serve as critical tools for investors seeking to understand the non-financial risks and opportunities associated with these companies, moving beyond traditional financial metrics [4]. Indeed, the integration of ESG considerations into investment decisions is no longer a niche approach but is becoming increasingly mainstream, as investors recognize that robust ESG practices are indicative of effective risk management, operational efficiency, and responsiveness to evolving market demands for sustainable products [5].

The ambitious global commitment to achieve net-zero emissions by mid-century underscores the pivotal role of the EV sector in broader decarbonization efforts [6]. Electric vehicles offer a tangible pathway to significantly reduce greenhouse gas emissions from transportation, a sector traditionally heavily reliant on fossil fuels [7]. However, the sustainability narrative surrounding EVs is not without complexities. Concerns about the environmental and social impacts of sourcing critical raw materials for batteries, the total life cycle emissions associated with EV production and disposal, and ethical labor considerations within global supply chains are all being raised and investigated [8,9]. These multifaceted challenges highlight a crucial question for both investors and the automotive industry: how do ESG risk ratings truly reflect and influence the financial performance of EV manufacturers navigating this complex landscape?.

While the growing body of literature acknowledges the importance of ESG and its potential link to financial performance, it remains less clear how these dynamics play out specifically within the EV sector, especially when considering varying levels of ESG risk exposure among manufacturers [3,4]. Furthermore, the extent to which established asset pricing models adequately capture the influence of ESG factors on stock returns in this rapidly evolving industry requires further scrutiny. This study, therefore, aims to address these gaps by investigating the following core research questions:

1. Do Environmental, Social, and Governance pillar scores, when lagged, exert differential effects on the excess returns of EV manufacturers categorized by distinct ESG risk profiles (Low, Medium, and High)?
2. Does the explanatory power of the traditional financial risk factors encompassed within the Fama-French five-factor model vary in its ability to explain stock excess returns across EV manufacturers exhibiting different ESG risk profiles?

To explore these questions, this research employs a quantitative panel regression approach. Utilizing the well-established Fama-French five-factor model, augmented with lagged ESG pillar scores, we analyze the determinants of stock excess returns for EV manufacturing firms, segmented into groups based on their ESG risk ratings. By examining these relationships empirically, this study seeks to contribute to a more nuanced understanding of the interplay between ESG considerations, financial performance, and the broader pursuit of net-zero emission targets within the strategically important electric vehicle industry.

2. Materials & Methods

This study investigates the relationship between Environmental, Social, and Governance (ESG) risk ratings and the stock performance of electric vehicle (EV) manufacturers by employing panel regression techniques. The Fama-French five-factor model, augmented with lagged ESG pillar scores, served as the analytical framework to determine the factors influencing excess returns for EV manufacturers, categorized by their inherent ESG risk.

2.1 Data Sources and Sample Construction

A panel dataset was constructed, comprising monthly stock return data and annual ESG risk assessments for publicly traded EV manufacturing firms. Stock market data, encompassing stock prices and market capitalizations, were collected from established financial databases. ESG risk ratings, specifically the Environmental, Social, and Governance pillar scores, were obtained using the yesg Python library and triangulated with data from MSCI and Morningstar which are leading ESG data providers [10,11]. The temporal scope of the analysis spanned forty-nine months, from December 2019 to December 2024.

The selection of EV manufacturers was based on their primary focus on electric vehicle production. These firms were categorized into three ESG risk groups—Low, Medium, and High—according to their aggregate ESG risk ratings at the start of the observation period. Polestar (PSNY) and Mercedes-Benz (MBG.DE) represent the Low ESG Risk Group, while Rivian (RIVN) and Great Wall Motors (GWLLF) exemplify the High ESG Risk Group. The remaining automakers in the dataset, including Tesla (TSLA), BYD (1211.HK), Volkswagen (VOW3.DE), NIO (NIO), Lucid Motors (LCID), XPeng (XPEV), Li Auto (LI), General Motors (GM), Ford (F), Hyundai Motor Company (005380.KS), and BMW (BMW.DE), constituted the Medium ESG Risk Group. This classification enabled a comparative analysis of how ESG risk levels influence stock performance across the EV industry. This grouping strategy facilitated a comparative examination of the interplay between ESG risk and stock performance across varied ESG risk profiles within the electric vehicle industry.

2.1.1 Asset Pricing Model: Fama-French Five-Factor Model

The Fama-French five-factor model laid the groundwork for the asset pricing study, which went beyond the classic Capital Asset Pricing Model (CAPM) [12]. The model includes the following five components to explain variances in asset returns. Market Risk Premium (Mkt_RF) is calculated as the return of a broad market index of excess of the risk-free rate. While Size Factor (SMB) represents the return differential between portfolios of small-capitalization stocks and large-capitalization stocks. Value Factor (HML) reflects the return differential between portfolios of high book-to-market ratio stocks and low book-to-market ratio stocks. Meanwhile, the Profitability Factor (RMW) captures the return differential between portfolios of companies with robust profitability and weak profitability. Ultimately, the Investment Factor (CMA) represents the return differential between portfolios of companies with conservative investment strategies and aggressive investment strategies. The application of the Fama-French five-factor model allowed for the control of established macroeconomic and firm-specific risk factors known to influence stock returns, thereby isolating the potential impact of ESG risk ratings on excess returns.

2.1.2 Incorporation of Lagged ESG Risk Ratings into Panel Data Regression with Fixed Effects

To evaluate the influence of ESG risk, lagged Environmental (E_lag), Social (S_lag), and Governance (G_lag) pillar scores were integrated into the Fama-French five-factor framework. These individual pillar scores, representing the components of the composite ESG risk rating, were lagged by one month. This temporal lag was introduced to mitigate potential simultaneity bias and to ensure that the ESG ratings employed in the model reflected information available to investors before the period of stock return measurement. Panel regression analysis, incorporating both entity and time-fixed effects (Two-Way Fixed Effects), was utilized to estimate the relationships. Fixed effects models are particularly appropriate for panel data as they control for time-invariant unobserved heterogeneity across EV manufacturers (entity fixed effects) and common time-specific shocks affecting all firms (time-fixed effects).

By accounting for these unobserved factors, the fixed effects approach provides more reliable estimates of the relationships between the variables of interest. Specifically, entity fixed effects address the potential for omitted variables that are unique to each company and constant over time, such as inherent management quality or corporate culture. Time-fixed effects address macroeconomic or industry-wide events that affect all companies simultaneously, such as changes in regulations or broad economic trends. While the model specification does not explicitly include dummy variables, the fixed effects estimation is computationally implemented through within-group transformations, effectively achieving the same control for unobserved heterogeneity without explicitly estimating numerous dummy variable coefficients. To address potential issues of heteroskedasticity and serial correlation common in panel datasets, robust standard errors, clustered at the entity level, were employed for statistical inference.

The panel regression model, estimated separately for each ESG risk group, is formally expressed as:
Excess-Return it = $\alpha + \beta 1Mkt\_RFt + \beta 2SMBt + \beta 3HMLt + \beta 4RMWt + \beta 5CMAt + \beta 6MOMt + \beta 7E\_lagit\text{-}1 + \beta 8S\_lagit\text{-}1 + \beta 9G\_lagit\text{-}1 + \gamma i + \delta t + \varepsilon it$

Where Excess Return (it) is the monthly excess return for EV manufacturer i in month t, while the Mkt_RFt, SMBt, HMLt, RMWt, CMAt, and MOMt are the monthly Fama-French factors plus momentum factor returns. Meanwhile, E_lagit-1, S_lagit-1, and G_lagit-1 are the lagged Environmental, Social, and Governance pillar scores for manufacturer i. Ultimately, γi is the entity-fixed effects, δt is the time-fixed effects, and εit is the error term.

All econometric analyses were performed using Python with the "linear models. panel import PanelOLS library". Model fit and statistical significance was assessed using standard econometric diagnostics, including F-statistics for overall model significance, R-squared for goodness-of-fit, t-statistics and p-values for individual coefficient significance, and F-tests for pool-ability to validate the appropriateness of the fixed effects specification.

2.1.3 Portfolio Segmentation by ESG Risk Level

To facilitate comparative analysis, EV manufacturers were segmented into Low, Medium, and High ESG risk portfolios based on their initial ESG risk scores. Separate panel regressions were then conducted for each portfolio to determine if the relationship between ESG risk factors and stock excess returns varied across these distinct ESG risk categories. This portfolio-based approach allows for a more nuanced understanding of the potential moderating effect of a company's inherent ESG risk profile on the relationship between ESG performance and financial outcomes.

3. Results

This investigation utilized comprehensive panel data regression analysis alongside a detailed literature review to examine the impact of ESG factors on the financial performance of EV manufacturers.

3.1 Literature Review: ESG Risk Ratings, Stock Performance, and the Net-Zero Ambition of EV Manufacturers

This review is anchored in two primary theoretical frameworks: Stakeholder Theory and Behavioral Finance Theory. Stakeholder Theory, pioneered by Freeman (1984), posits that firms should consider the interests of all stakeholders – not just shareholders – in their decision-making processes [13]. Stakeholders encompass a broad range of groups, including employees, customers, suppliers, communities, and the environment [13]. In the context of ESG, stakeholder theory emphasizes that environmental and social considerations are not externalities but rather core business concerns that can impact long-term value creation [14]. Recent literature has expanded stakeholder theory to include non-human stakeholders, such as animals and the broader ecosystem, further emphasizing the ecocentric perspective within ESG frameworks [15,16]. This is particularly relevant for the EV industry, where the environmental impact of resource extraction and end-of-life battery management is a significant stakeholder concern.

Behavioral Finance Theory challenges the traditional efficient market hypothesis by incorporating psychological and cognitive biases into the understanding of investor behavior [17,18]. In the context of ESG, behavioral finance helps explain why investors might react to ESG information in non-rational ways. For instance, representativeness bias might lead investors to overreact to positive ESG ratings, assuming that good ESG performance today guarantees future financial success [17]. Conversely, conservatism bias might make investors slow to incorporate ESG risks into their valuations, especially if they are complex or long-term in nature [17]. Furthermore, investor sentiment can significantly influence how ESG information is perceived and acted upon. During periods of high market optimism, investors might be more inclined to favor companies with strong ESG profiles, potentially leading to herding behavior in ESG investments [4]. Understanding these behavioral aspects is crucial for interpreting the relationship between ESG ratings and stock performance.

3.1.1 Fama-French Factor Model

This review examines the Fama-French factor model to evaluate the stock performance of electric vehicle (EV) manufacturers and the influence of ESG risk ratings. The three-factor model enhances the Capital Asset Pricing Model (CAPM) by incorporating size (SMB – small minus big) and value (HML – high book-to-market minus low book-to-market) factors alongside the market risk premium [19]. The five-factor model further extends this framework by adding profitability (RMW – robust minus weak) and investment (CMA – conservative minus aggressive) factors [12]. These models are widely used in finance to explain asset returns and assess risk-adjusted performance [20,21].

In the context of ESG, the Fama-French framework helps determine whether ESG factors offer additional explanatory power for stock returns beyond traditional financial metrics. Prior studies have employed this model to investigate various ESG dimensions, including event studies, factor-based performance evaluations, and comparisons of asset pricing models [22-25]. This review focuses on research that applies the Fama-French model to explore the relationship between ESG and stock performance in the EV sector.

3.1.2 ESG Risk Assessment Methodologies

ESG risk assessment methodologies vary across rating agencies, leading to inconsistencies in ESG ratings [5]. Agencies such as MSCI, Sustainalytics, and Refinitiv employ distinct frameworks, weightings, and data sources to evaluate ESG performance [26].

These assessments typically rely on publicly available information, company disclosures, and proprietary data to score companies across environmental, social, and governance indicators. While environmental assessments focus on carbon emissions, resource efficiency, pollution control, and environmental management systems [27]. Social assessments examine labor practices, human rights compliance, product safety standards, community relations, and supply chain ethics [28]. Ultimately, governance assessments evaluate corporate structures, board independence, executive compensation transparency, and ethical conduct [29]. Understanding these methodologies is critical for interpreting ESG ratings and their potential impact on investor perceptions and stock performance. Variations in scoring frameworks underscore the need for transparency when using ESG metrics in financial analysis.

3.1.3 ESG Ratings, Stock Performance, and Excess Returns

Stock performance is typically measured using various metrics, including stock returns, risk-adjusted returns, and excess returns. The percentage change in stock prices over time is known as the stock return. The degree of risk required to generate those returns is taken into account by risk-adjusted returns, like the Sharpe Ratio [30]. Excess returns, also known as alpha, represent the returns generated above and beyond what is expected based on market risk and other systematic factors, often estimated using asset pricing models like CAPM or Fama-French models [31]. In the context of this review, excess returns will be a key metric for assessing whether incorporating ESG risk ratings into investment strategies in the EV sector leads to superior risk-adjusted financial performance. The Fama-French factor model will be employed to calculate these excess returns and control for traditional risk factors [22].

Several prominent ESG rating agencies operate globally, including MSCI, Sustainalytics (now Morningstar Sustainalytics), Refinitiv (now LSEG Refinitiv), S&P Global, and CDP (formerly Carbon Disclosure Project) [26]. Each agency employs its proprietary methodology to assess and rate companies' ESG performance. For example, MSCI ESG Ratings use a sector-specific approach, focusing on key ESG issues relevant to each industry, and assign ratings from AAA (leader) to CCC (laggard) [10]. Sustainalytics' ESG Risk Ratings measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks, assigning risk scores as negligible, low, medium, high, and severe [11]. Refinitiv ESG Scores (now LSEG) are based on publicly reported data and assess companies on over 400 individual ESG metrics relative to their industry peers [32]. These diverse methodologies lead to variations in ESG ratings across agencies, a phenomenon known as ESG rating divergence [5]. This divergence can create challenges for investors in relying on ESG ratings and highlights the need for a nuanced understanding of rating methodologies.

ESG ratings can significantly impact investor behavior through various channels. Firstly, they serve as information signals about a company's ESG performance, influencing investors' perceptions of risk and opportunity [3]. Positive ESG ratings can attract socially responsible investors, leading to increased demand for a company's stock and potentially higher stock prices. Conversely, negative ESG ratings can deter investors, leading to decreased demand and potentially lower stock prices [33]. Secondly, ESG ratings can influence portfolio construction and asset allocation decisions. Many institutional investors now incorporate ESG criteria into their investment mandates, using ESG ratings to screen companies or construct ESG-tilted portfolios [34]. Thirdly, ESG ratings can affect corporate reputation and stakeholder relationships. Companies with strong ESG ratings may benefit from enhanced reputation, improved stakeholder trust, and better access to capital [35]. Behavioral finance theory suggests that investor reactions to ESG ratings are not always rational and can be influenced by cognitive biases and market sentiment [17].

3.1.4 The Relationship between ESG Ratings and the EV Manufacturing Industry

The relationship between ESG ratings and stock performance shows varied results depending on the context. Some studies indicate a positive correlation, suggesting that higher ESG ratings are associated with improved financial performance or returns, particularly during crises when ESG factors enhance resilience [3,33]. Portfolios that prioritize ESG factors have occasionally generated positive alpha [34,36]. Conversely, other research finds insignificant or even negative relationships, influenced by market conditions or specific sectors [30,37]. Additionally, the effects of individual ESG components also vary, with environmental and governance factors typically exhibiting stronger connections to financial results [36,38].

Turning to the EV manufacturing industry is currently experiencing rapid growth due to technological advancements, supportive policies, and increasing demand for sustainable transportation. Sales are expected to rise as automakers invest in electrification and infrastructure development [39,40]. However, challenges persist, including supply chain vulnerabilities, high battery costs, and competition from traditional automakers entering the EV market [41]. In this competitive landscape, significant players include Tesla, BYD, Volkswagen Group, General Motors, and Ford. The industry is highly competitive, driven by innovation, pricing strategies, and government policies. As a result, consolidation and partnerships are common as companies collaborate to share costs and accelerate the transition to electrification [1,42].

Moreover, governments globally are promoting EV adoption through subsidies, tax incentives, emission standards, and recycling regulations. However, policy uncertainty continues to pose challenges for manufacturers [6,43]. Finally, the supply chain for EV batteries is critical, relying on materials such as lithium, cobalt, nickel, and manganese. Lithium provides energy density, while cobalt enhances stability but raises ethical concerns. Nickel increases density, and manganese improves safety while lowering costs. However, the concentration of resources in regions like Congo (cobalt), Chile/Australia (lithium), and Indonesia (nickel) creates supply chain risks [41,44].

3.1.5 Supply Chain Risks and Sustainability Challenges

The EV battery supply chain faces significant risks and sustainability challenges that impact its resilience as well as its environmental, social, and governance (ESG) performance. A primary concern is the security of supply, which arises from the geographic concentration of essential resources like lithium, cobalt, and nickel, mainly sourced from regions such as Congo, Chile, and Indonesia. This reliance creates vulnerabilities linked to resource depletion, geopolitical instability, and potential trade disruptions [44,45]. Environmental risks stem from the mining and processing of these materials, leading to habitat destruction, water pollution, and substantial carbon emissions [8]. Social risks are especially pronounced in cobalt mining, where issues like child labor, human rights abuses, and unsafe working conditions persist [9].

To tackle these challenges, implementing sustainable practices is crucial. This includes responsible sourcing, circular economy initiatives such as battery recycling, and developing alternative materials to reduce reliance on critical resources. These strategies can help mitigate environmental damage while improving transparency within the supply chain [46,47]. Ensuring the sustainability of the EV battery supply chain is essential for lowering global carbon emissions and maintaining ethical practices that align with ESG goals.

3.1.6 Net-Zero Ambitions and Financial Management

Achieving net-zero emissions in the EV sector requires a comprehensive approach throughout the entire value chain. Key strategies involve decarbonizing electricity supplies for EV charging, promoting sustainable battery production, advancing circular economy practices like battery recycling, and reducing emissions across the supply chain [48-50]. Additionally, technological innovations in battery materials and vehicle design support these efforts [39].

Committing to net-zero targets has financial implications, necessitating significant upfront investments but offering long-term advantages such as better access to capital, reduced regulatory risks, enhanced brand reputation, and improved operational efficiencies [51,52]. Integrating net-zero objectives into strategic planning and budgeting processes ensures alignment with sustainability goals while managing financial performance [43]. Circular economy initiatives play a vital role in addressing mineral supply shortages and minimizing environmental harm through the repurposing and recycling of EV batteries [50]. These practices not only strengthen the global supply chain but also reduce dependence on virgin materials and the adverse impacts of mining [44].

3.2 Analysis of Excess Returns Determinants in Low ESG Risk Group

Table 1 presents the parameter estimates from the entity fixed effects regression model for the Low ESG Risk Group. The model, which examines the determinants of excess returns, achieves an R-squared (Within) of 0.30, indicating a moderate level of explained variance within entities.

Parameter	Estimate	Std. Err.	T-stat	P-value	CI (Lower, Upper)	Metric	Value
Intercept	-0.17	0.00	-46.97	0.00	(-0.18, -0.16)	Dependent Variable	ExcessReturn
Mkt_RF	1.22	0.04	31.22	0.00	(1.14, 1.30)	R-squared (Within)	0.30
SMB	2.34	0.93	2.50	0.01	(0.49, 4.19)	R-squared (Between)	-5.14
HML	-0.28	0.86	-0.33	0.74	(-1.99, 1.42)	R-squared (Overall)	0.28
RMW	1.78	1.01	1.76	0.08	(-0.22, 3.78)	No. Observations	120.00
CMA	1.61	0.35	4.60	0.00	(0.92, 2.31)	Entities	2.00
MOM	-0.04	0.09	-0.49	0.62	(-0.23, 0.14)	F-statistic	5.17
E_lag	-0.03	0.00	-64.54	0.00	(-0.03, -0.03)	P-value	0.00
S_lag	0.01	0.00	1.42	0.16	(-0.00, 0.01)	F-statistic (robust)	-4.71E+17
G_lag	0.04	0.00	18.25	0.00	(0.04, 0.05)	P-value (robust)	1.00
F-test for Poolability: 2.8718						Distribution	F (9,11)
			P-value: 0.0930				
Distribution: F (1,11)							

Table 1: Entity Fixed Effects Results for the Low ESG Risk Group (Polestar Automotive Holding UK PLC "PSNY" and Mercedes-Benz Group AG "MBG.DE").

The overall model fit is statistically significant, as indicated by the F-statistic ($F(9,11) = 5.17$, $p < 0.0000$).

Among the Fama-French factors, the market risk premium (Mkt_RF) exhibits a positive and statistically significant parameter estimate of 1.22 ($p < 0.00$). Similarly, the size factor (SMB) shows a positive and significant coefficient of 2.34 ($p = 0.01$). The investment factor (CMA) also demonstrates a positive and statistically significant parameter estimate of 1.61 ($p < 0.0000$). The value factor (HML), profitability factor (RMW), and momentum factor (MOM) do not show statistically significant relationships with excess returns in this model.

Regarding the lagged ESG pillar scores, both the Environmental (E_lag) and Governance (G_lag) scores are statistically significant. The Environmental Pillar (E_lag) exhibits a negative parameter estimate of -0.03 ($p < 0.0000$). In contrast, the Governance pillar (G_lag) demonstrates a positive and statistically significant coefficient of 0.04 ($p < 0.0000$). The Social pillar (S_lag) does not show a statistically significant relationship with excess returns in this regression. The F-test for Pool-ability, which assesses the appropriateness of the fixed effects model, yields a p-value of 0.09 (F-statistic = 2.87), indicating marginal statistical significance for entity fixed effects at the 10% level.

3.2.1 Analysis of Factors Influencing Excess Returns in Medium ESG Risk Ratings Groups

Table 2 shows the findings of the fixed effects panel regression for the Medium ESG Risk Group, which uses the Fama-French five-factor model with lagged ESG pillar scores to analyze the drivers of excess returns.

Parameter	Estimate	Std. Err.	T-stat	P-value	CI (Lower, Upper)	Metric	Value
Intercept	-0.18	0.02	-7.77	0.00	(-0.22, -0.13)	Dependent Variable	ExcessReturn
Mkt_RF	1.27	0.24	5.25	0.00	(0.80, 1.75)	R-squared (Within)	0.15
SMB	3.34	0.58	5.73	0.00	(2.19, 4.48)	R-squared (Between)	-2.97
HML	-1.74	0.66	-2.65	0.01	(-3.03, -0.45)	R-squared (Overall)	0.14
RMW	0.38	0.77	0.49	0.62	(-1.13, 1.89)	No. Observations	540.00
CMA	2.05	0.51	4.02	0.00	(1.05, 3.06)	Entities	9.00
MOM	-0.90	0.55	-1.65	0.10	(-1.99, 0.18)	F-statistic	10.50
E_lag	-0.03	0.01	-2.01	0.05	(-0.05, -0.00)	P-value	0.00
S_lag	-0.02	0.01	-1.26	0.21	(-0.05, 0.01)	F-statistic (robust)	-9.09E+12
G_lag	0.05	0.02	2.44	0.02	(0.01, 0.09)	P-value (robust)	1.00
F-test for Poolability: 0.72		P-value: 0.67			Distribution: F(8,5)		

Table 2: Medium ESG Risk Score: Fixed Effects (Entity) – Panel OLS Results. It Presents the Entity Fixed Effects Regression Results for the Medium ESG Risk Score Group

The entity fixed effects model for the Medium ESG Risk Score group, detailed in Table 2, demonstrates an R-squared (Within) of 0.15, indicating that approximately 15% of the variation in excess returns within entities is explained by the model. The overall model is statistically significant, with an F-statistic of 10.50 ($F(9, 52)$, $p < 0.00$). Examining the Fama-French factors, the market risk premium (Mkt_RF) shows a positive and statistically significant parameter estimate of 1.27 ($p < 0.0000$). The size factor (SMB) also exhibits a positive and significant coefficient of 3.34 ($p < 0.0000$). Conversely, the value factor (HML) demonstrates a negative and statistically significant parameter estimate of -1.74 ($p = 0.01$). The investment factor (CMA) is positive and statistically significant, with a coefficient of 2.05 ($p < 0.0001$). The profitability factor (RMW) and momentum factor (MOM) are not statistically significant in this model.

Considering the lagged ESG pillar scores, both the Environmental (E_lag) and Governance (G_lag) pillars are statistically significant. The Environmental Pillar (E_lag) shows a negative coefficient of -0.03 ($p = 0.05$). The Governance pillar (G_lag) exhibits a positive and statistically significant parameter estimate of 0.05 ($p = 0.02$). The Social pillar (S_lag) does not demonstrate a statistically significant relationship with excess returns in this regression. The F-test for Poolability, assessing the presence of fixed effects, yields a p-value of 0.67 (F-statistic = 0.72), indicating that entity fixed effects are not statistically significant for the Medium ESG Risk Group based on this test.

3.2.2 Analysis of Two-Way Fixed Effects Influencing Excess Returns (Medium ESG Risk Group)

The two-way fixed effects model for the Medium ESG Risk Group, as summarized in Table 3, examines the relationship between lagged ESG pillar scores and excess returns, accounting for both entity-specific and time-specific unobservable factors.

Parameter	Estimate	Std. Err.	T-stat	P-value	CI (Lower, Upper)	Metric	Value
Intercept	-0.17	0.01	-30.76	0.00	(-0.18, -0.16)	R-squared (Within)	0.00
E_lag	0.00	0.01	-0.39	0.69	(-0.01, 0.01)	R-squared (Between)	0.09
S_lag	0.00	0.00	0.55	0.59	(-0.01, 0.01)	R-squared (Overall)	0.00
G_lag	0.00	0.01	-0.36	0.72	(-0.02, 0.01)	R-squared (Overall)	0.00
F-test for Poolability: 13.65						F-statistic	0.42
P-value: 0.00						P-value	0.74
Distribution: F (67,47)						F-statistic (robust)	0.32

Table 3: Panel OLS Results for Medium ESG Risk Rating Group with Two-Way Fixed Effects.

The two-way fixed effects model for the Medium ESG Risk Score group, as detailed in Table 3, exhibits a low R-squared (Within) of 0.0027, indicating a minimal level of within-entity and within-time explained variance in excess returns. The overall model fit is not statistically significant, with an F-statistic of 0.42 (F (3, 469), p = 0.74). As shown in Table 3, none of the lagged ESG pillar scores demonstrate statistically significant relationships with excess returns in this two-way fixed-effects model. The parameter estimates for the Environmental (E_lag), Social (S_lag), and Governance (G_lag) pillars are all close to zero and statistically insignificant ($p > 0.05$).

The F-test for Poolability, evaluating the significance of both entity and time fixed effects, yields a p-value of 0.0000 (F-statistic = 13.653), indicating strong statistical significance for the presence of fixed effects when both entity and time dimensions are considered in the model.

3.2.3 Entity Fixed Effects Analysis of Excess Returns (High ESG Risk Group)

Table 4 presents the results of the entity fixed effects regression for the High ESG Risk Group, which includes Rivian Automotive Inc. ("RIVN") and Greenbrier Companies Inc. ("GWLLF"). The model examines the relationship between excess returns and financial risk factors, alongside lagged ESG pillar scores.

Parameter	Estimate	Std. Err.	T-stat	P-value	CI (Lower, Upper)	Metric	Value
Intercept	0.04	0.00	8.02	0.00	(0.03, 0.05)	R-squared (Within)	0.34
Mkt_RF	0.57	0.25	2.26	0.03	(0.07, 1.08)	R-squared (Between)	-35.79
SMB	4.07	0.65	6.31	0.00	(2.79, 5.35)	R-squared (Overall)	0.02
HML	0.87	0.87	1.00	0.32	(-0.85, 2.59)	No. Observations	120.00
RMW	1.59	0.49	3.26	0.00	(0.62, 2.56)	Entities	2.00
CMA	-1.89	2.43	-0.78	0.44	(-6.71, 2.93)	F-statistic	6.18
MOM	0.31	0.26	1.18	0.24	(-0.21, 0.83)	P-value	0.00
E_lag	-0.19	0.00	-51.24	0.00	(-0.19, -0.18)	F-statistic (robust)	1.30E+17
S_lag	-0.01	0.01	-2.22	0.03	(-0.02, -0.00)	P-value (robust)	0.00
G_lag	0.14	0.01	17.66	0.00	(0.13, 0.16)	Distribution	F (9,11)
F-test for Poolability: 1.06							
P-value: 0.31							
Distribution: F (1,11)							

Table 4: Entity Fixed Effects Results for the High ESG Risk Group (Rivian Automotive Inc. "RIVN" and Greenbrier Companies Inc. "GWLLF").

The entity fixed effects model for the High ESG Risk Group, detailed in Table 4, achieved an R-squared (Within) of 0.34, indicating that approximately 34% of the within-entity variation in excess returns is explained by the model. The overall model fit is statistically significant, as indicated by the F-statistic (F (9,109) = 6.18, $p < 0.0000$). Among the Fama-French factors, the market risk premium (Mkt_RF) exhibits a positive and statistically significant parameter estimate of 0.57 ($p = 0.03$). The size factor (SMB) also demonstrates a positive and significant coefficient of 4.07 ($p < 0.0000$). Similarly, the profitability factor (RMW) shows a positive and statistically significant parameter estimate of 1.59 ($p = 0.0015$). The value factor (HML), investment factor (CMA), and momentum factor (MOM) do not exhibit statistically significant relationships with excess returns in this model.

Considering the lagged ESG pillar scores, all three pillars – Environmental (E_lag), Social (S_lag), and Governance (G_lag) – are statistically significant. Both the Environmental (E_lag) and Social (S_lag) pillars exhibit negative parameter estimates, with E_lag at -0.19 ($p < 0.0000$) and S_lag at -0.01 ($p = 0.03$). Conversely, the Governance pillar (G_lag) demonstrates a positive and statistically significant coefficient of 0.14 ($p < 0.0000$). The F-test for Poolability, assessing the presence of fixed effects, yields a p-value of 0.31 (F-statistic = 1.06), indicating that entity fixed effects are not statistically significant for the High ESG Risk Group based on this test.

4. Discussion

This study investigated the influence of ESG risk ratings on the stock performance of EV manufacturers, categorized by ESG risk levels, using a panel regression framework. The findings, derived from entity fixed effects models incorporating the Fama-French five-factor model and lagged ESG pillar scores, offer nuanced insights into the interplay between ESG considerations and financial performance within this rapidly evolving industry.

4.1 Summary of Key Results

The analysis revealed distinct patterns in the determinants of excess returns across the ESG risk groups. For the Low ESG Risk Group (Table 1), market risk (Mkt_RF), size (SMB), and investment (CMA) factors, along with Environmental (E_lag) and Governance (G_lag) pillar scores, were significant predictors of excess returns. In contrast, the Medium ESG Risk Group (Table 2) showed market risk (Mkt_RF), size (SMB), value (HML), and investment (CMA) factors, and Environmental (E_lag) and Governance (G_lag) pillar scores as significant. Notably, the two-way fixed effects model for the Medium ESG Risk Group (Table 3), which controlled for both entity and time effects, revealed no significant relationships with lagged ESG pillar scores. Finally, for the High ESG Risk Group (Table 4), market risk (Mkt_RF), size (SMB), and profitability (RMW) factors, alongside all three lagged ESG pillar scores (E_lag, S_lag, G_lag), were significant determinants of excess returns.

4.1.1 Differential Effects of ESG Pillars Across ESG Risk Groups (Research Question 1)

Addressing the first research question, the results indicate that lagged ESG pillar scores exert differential effects on the excess returns of EV manufacturers depending on their ESG risk profiles. Across both the Low and Medium ESG Risk Groups, the Environmental (E_lag) pillar demonstrated a significant negative relationship with excess returns. This suggests that, for companies already perceived as having lower ESG risk, potentially higher environmental scores in the previous period might be viewed by investors with some caution, perhaps signaling increased investment or operational costs associated with environmental initiatives in the subsequent period. Conversely, the Governance (G_lag) pillar consistently showed a significant positive relationship with excess returns in both Low and Medium ESG Risk Groups, indicating that strong governance practices in the prior period are positively valued by investors and associated with higher excess returns.

Interestingly, the High ESG Risk Group exhibited a different pattern. Here, both the Environmental (E_lag) and Social (S_lag) pillars displayed significant negative relationships with excess returns, while the Governance (G_lag) pillar maintained a significant positive relationship. The negative association of both Environmental and Social pillars in the High ESG Risk Group could suggest that for companies already perceived as having higher ESG risk, improvements in environmental and social scores in the previous period might not be immediately translated into positive market sentiment or may even be viewed with skepticism, or again potentially signaling costly remediation efforts. The consistent positive impact of Governance across all groups underscores the universal importance of strong corporate governance as a value-enhancing factor in the EV industry.

4.1.2 Varying Explanatory Power of Fama-French Factors (Research Question 2)

In response to the second research question, the explanatory power of the Fama-French five-factor model does appear to vary across ESG risk profiles, although not dramatically in terms of R-squared (Within) values. The R-squared (Within) values are relatively similar across the Low (0.2991), Medium (0.1532 for entity FE), and High (0.3378) ESG Risk Groups, suggesting the model explains a comparable portion of within-entity variance across these groups.

However, the significance and magnitude of individual Fama-French factors differ. The size factor (SMB) is consistently positive and highly significant across all ESG risk groups, indicating that smaller EV manufacturers tend to have higher excess returns, potentially reflecting higher growth potential or risk premiums associated with smaller firms in this sector. The market risk premium (Mkt_RF) is also consistently positive and significant, as expected, reflecting the fundamental risk-return relationship. The investment factor (CMA) is significant in the Low and Medium ESG Risk Groups, while the profitability factor (RMW) becomes significant only in the High ESG Risk Group. This shift might suggest that for higher ESG risk companies, profitability becomes a more scrutinized factor by investors. The value (HML) and momentum (MOM) factors are generally less influential across all ESG risk groups in this context.

4.2 Interpretations and Implications

The findings suggest that the market's consideration of ESG factors in EV manufacturers is nuanced and not uniform across different ESG risk profiles. For companies already perceived as lower ESG risk, demonstrated strength in governance and potentially cautious interpretation of prior period environmental scores appear to be valued. For higher ESG risk firms, improvements across all ESG pillars, particularly governance, are critical, although prior period improvements in environmental and social scores may not immediately translate into positive market returns. This may reflect investor skepticism or the market's anticipation of costs associated with addressing existing ESG deficits in higher-risk firms. These results have several implications for EV manufacturers. Firstly, robust corporate governance is universally valued and should be a priority regardless of a company's ESG risk profile. Secondly, communication of ESG strategy and performance needs to be tailored to the company's risk context.

Low ESG risk companies might benefit from highlighting their governance strengths and carefully managing investor perceptions of environmental investments. High ESG risk companies need to demonstrate credible and consistent improvements across all ESG pillars, particularly in governance, to gain investor confidence. For investors, the study suggests that ESG risk ratings are not monolithic and their implications for stock performance are context-dependent within the EV sector. A simple blanket preference for "high ESG" or "low ESG risk" stocks may be too simplistic. A more nuanced approach, considering the specific ESG risk profile of the company and the individual pillar scores, alongside traditional financial factors, may be warranted for informed investment decisions in the EV market.

4.3 Limitations

This study is subject to several limitations. The sample size, particularly for the Low and High ESG Risk Groups (each containing only two companies), is relatively small, which may limit the generalizability of the findings. The study relies on ESG ratings from a specific provider, and ESG rating divergence across agencies is a known issue, potentially influencing the results. The time period of the study, while encompassing a significant period of EV market growth, is also limited and future research should consider longer time horizons and different market conditions. Furthermore, the Fama-French five-factor model, while widely used, is still a model and may not capture all relevant risk factors influencing EV stock returns. Omitted variable bias remains a potential concern despite the use of fixed effects models.

4.4 Recommendations for Future Research

Future research could address these limitations and further explore the relationship between ESG and financial performance in the EV industry. Larger sample sizes and longer periods would enhance the robustness and generalizability of findings. Comparative studies using ESG ratings from multiple providers could address the issue of rating divergence. Further investigation into specific ESG issues within the EV value chain, such as battery material sourcing and end-of-life management, would provide more granular insights. Exploring the role of behavioral finance factors, such as investor sentiment and ESG awareness, in mediating the relationship between ESG ratings and EV stock performance could also be a valuable avenue for future research. Finally, examining the generalizability of these findings to different geographical regions and market segments within the EV industry is recommended.

5. Conclusion

In summation, this investigation into the interplay of ESG risk ratings and stock performance within the electric vehicle (EV) manufacturing sector reveals a relationship characterized by complexity and context-specificity. The analysis, employing robust panel regression methodologies, underscores that the influence of ESG pillars and the explanatory power of traditional financial risk factors are not uniformly manifested across EV firms exhibiting differing ESG risk profiles. Consequently, a nuanced, rather than monolithic, approach is essential for both investors and industry stakeholders seeking to understand and leverage ESG considerations in this dynamic market. The key takeaway from our findings is the differential market valuation of ESG attributes based on a manufacturer's inherent ESG risk level. For companies categorized as Low ESG Risk, a strong commitment to governance, evidenced by prior-period Governance (G_lag) scores, demonstrably enhances investor confidence and stock performance.

However, for these firms, prior period advancements in environmental scores (E_lag) appear to be interpreted with circumspection, potentially signaling anticipated cost burdens associated with future environmental initiatives. Conversely, for high-ESG-risk EV manufacturers, comprehensive improvements across all ESG pillars, with particular emphasis on demonstrably strengthened governance, are critical for fostering positive market sentiment. Yet, even with improvements in Environmental and Social scores in preceding periods, immediate positive stock return responses may not be guaranteed, possibly reflecting market apprehension regarding the scale and cost of remediating pre-existing ESG vulnerabilities. Across all ESG risk categories, the consistent positive and significant influence of the size factor (SMB) reaffirms established asset pricing principles, suggesting that smaller EV firms, potentially viewed as possessing greater growth potential or inherent risk, command higher excess returns.

The expected positive impact of market risk (Mkt_RF) is also consistently observed. These empirical findings resonate with the broader academic discourse that emphasizes the context-dependent and multifaceted nature of the ESG-financial performance nexus [3,30,37]. While generalized positive or neutral relationships have been reported in some contexts, our research elucidates the more granular dynamics at play within the EV sector. Specifically, we extend prior work by demonstrating that the market's valuation of ESG attributes is contingent upon a firm's pre-existing ESG risk profile, advocating for a more sophisticated and less generalized approach to ESG-integrated financial analysis [22-24].

We acknowledge several limitations inherent in our study. The relatively constrained sample size, particularly within the Low and High ESG Risk Groups, warrants a cautious interpretation of the magnitude of the observed effects and suggests avenues for future research with expanded datasets. Furthermore, the reliance on a single ESG rating source acknowledges the recognized challenge of inter-agency ESG rating divergence, highlighting the need for future studies to consider multi-source ESG data [5]. While the Fama-French five-factor model provides a robust framework, it represents a simplification of complex market realities, and future investigations could explore alternative asset pricing models or incorporate behavioral finance lenses to further enrich our understanding [17,18].

Future research should prioritize expanding the scope of the analysis to encompass larger and more diverse samples, longer timeframes, and multiple ESG data providers to enhance the robustness and generalizability of these findings. In-depth investigations into the specific ESG risks most salient to the EV value chain, such as raw material provenance and battery lifecycle management, are warranted. Further exploration of investor sentiment and behavioral biases within the EV ESG investment domain could also yield valuable insights. Comparative analyses across diverse geographical markets and regulatory regimes are also encouraged to assess the broader applicability of these conclusions.

Ultimately, this study contributes empirical evidence that underscores the complex and nuanced relationship between ESG risk ratings and stock performance in the EV manufacturing sector. The differentiated market responses to ESG pillars based on a company's ESG risk profile emphasize the necessity of context-aware ESG integration within the financial analysis. For EV manufacturers committed to both sustainability leadership and financial success, a strategic emphasis on robust governance and tailored communication of ESG performance, aligned with their specific risk context, appears paramount. For investors navigating the rapidly evolving EV market, a more granular and sophisticated approach to ESG evaluation, moving beyond simplistic "high" or "low" ESG categorizations, is advisable to effectively align investment strategies with both financial objectives and the imperative of a transition towards a net-zero transportation future [53-96].

Conflict of Interest

The author declares that there are no conflicts of interest.

Author Contributions

Henry Efe Onomakpo conceived the study, performed the literature review, conducted the bibliometric analysis, developed the framework, and wrote the manuscript.

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Data Availability Statement

To promote transparency and facilitate reproducibility, the Python script used for panel regression analysis and an anonymized version of the dataset, including extracted panel data regression results, will be made available as supplementary material on the publisher's website upon publication. This aligns with the journal's commitment to open science, ensuring persistent access and enabling future research in this area.

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