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Moderation of Clean Energy Innovation in the Relationship between the Carbon Footprint and Profits in CO_2e-Intensive Firms: A Quantitative Longitudinal Study

Francisco Porles-Ochoa * and Ruben Guevara

Centrum Catolica Graduate Business School, Pontificia Universidad Catolica del Peru, Lima 15088, Peru; rguevara@pucp.pe
* Correspondence: porles.fd@pucp.pe

Abstract: This paper sought to analyze the moderating effect of clean energy innovation on the relationship between corporate carbon footprint and corporate profits in fossil fuel intensive industrial sectors in which it is "hard to abate" CO_2e emissions. We used a longitudinal design consisting of a panel study with a structural equation modeling (SEM) method, based on partial least squares. For the analysis of longitudinal moderation, this paper employed a Bayesian multiple-indicator latent growth curve model (B-LGC model). A global sample was used, consisting of 7827 firm-year observations between 2015 and 2021 for 167 international firms. The results showed that the corporate carbon footprint had a very significant impact on corporate profits and that innovations in clean energy—measured as renewable energy consumption—positively moderate the relationship between Scope 3 value chain greenhouse gas emissions (according to the Greenhouse Gas (GHG) Protocol) and the gross profit margin obtained. In addition to the academic contributions made by the moderating effect of clean energy innovation, these findings imply that a more detailed understanding of total value chain emissions (Scope 3 CO_2e) among executives and managers at high CO_2e-emitting companies offers an effective mechanism for obtaining higher profits and creating competitive advantages, while at the same time achieving a net zero emissions strategy. More importantly, public policymakers will be able to use these results to revise CO_2e-related policies, paying closer attention to the Scope 3 CO_2e emissions produced by these companies to design regulatory and control mechanisms that stimulate clean energy innovation.

Keywords: clean energy innovation; corporate carbon footprint; corporate profits; high CO_2e emissions; longitudinal panel model; latent growth curve (LGC)

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1. Introduction

The mitigation of climate change by reducing greenhouse gas emissions (GHG) is one of the most important challenges facing society today [1]. To this end, the Paris Agreement of 2015 seeks to limit the increase in global warming to less than 2 °C. Among other things, this requires the deep decarbonization of industrial sectors with a high demand for conventional fossil fuels [2,3]. Energy-intensive firms increasingly face demands that they act decisively to reduce these emissions and make a positive impact on climate change [4], since they are considered the largest emitters of anthropogenic carbon dioxide and equivalent GHGs (CO_2e), and thus the main contributors to global warming [1,5–9]. Consequently, these companies face the twofold challenge of generating profits for shareholders while achieving lower CO_2 emissions in their production processes [10–12]. In achieving these goals, clean and renewable energy sources can contribute to deep decarbonization, especially in "hard-to-abate" CO_2 emissions sectors associated with high energy consumption [13,14].

While there is a large body of recent literature with evidence of a direct relationship between environmental performance—measured by using the addition of Scope 1 and Scope 2 corporate carbon footprints—and corporate profits [15–19], the results are still inconclusive. For instance, those studies used absolute metrics associated with Scope 1 and Scope 2 CO_2e emissions, but none used Scope 3 CO_2e emissions to measure total corporate carbon footprints. They also used other relative metrics, such as carbon intensity and environmental, social, and governance (ESG) ratings. Consequently, this study filled an existing research gap, involving the total measurement of corporate carbon footprint in a longitudinal study to measure its impact on corporate profits. This is the first study to do this. Another research gap addressed by this research was the measurement of the moderating effect of clean energy innovation (CEI) on the relationship between corporate carbon footprint (CCFP) and corporate profits (CP).

The relationship between carbon footprint and profits in fossil-based energy-intensive global companies from different sectors and countries is of particular interest to academia and governments. While technological innovation has been widely recognized as an effective means for combating negative environmental impacts [20], technological innovations take time to develop and implement, and their impact on companies' performance is only perceived in the long term [21]. This means that studies with a longitudinal design are a particularly effective means for firm-level research to examine the effect of clean energy innovation on GHG reduction and increased profits. As a result, clean energy innovation has gradually become an important topic in the business field [22].

The literature has so far paid little attention to the potential moderating effect of firms' clean energy innovation on the link between their carbon footprint and profits, particularly among leading CO_2e-intensive global firms in various industrial sectors that are active in different countries around the world [23]. This paper sought to address the gap in the literature and examine the moderating effect of clean energy innovation on this relationship, focusing on large firms from primary industries with the most intensive use of fossil fuel generated energy. To accomplish this, this study developed a moderation model with longitudinal panel data obtained from the Carbon Disclosure Project (CDP) and the Thomson Reuters Refinitiv database, which were then analyzed using a Bayesian growth curve model. This paper contributes to the literature by proposing a longitudinal structural model for the moderation effect of clean energy innovation, using Bayesian multiple-indicator latent growth curve models (B-LGC models), on the link between corporate carbon footprint and corporate profits. This study also highlights the importance of renewable energy consumption as a moderating indicator for measuring clean energy innovation in the relationship between corporate value chain emissions (Scope 3 CO_2e) and gross profit margin (Pr_Mrg) in energy-intensive industries.

2. Theoretical Framework and Hypothesis

The ecological modernization theory (EMT) supports the concept of clean energy innovation. EMT states that ecology and the economy can be combined to achieve a better result for the company, the country, and society [24,25]. It also states that increases in energy and resource efficiency can lead to improved productivity and therefore to more available resources for future growth. This knowledge encourages energy- and pollution-intensive firms to embrace clean energy technologies that allow them to lessen the environmental effect of their economic operations [24]. Similarly, the natural resource-based view (NRBV) theory proposes that competitive advantage is directly related to the company's relationship with the natural environment [26]. It then supports the idea that competitive advantages can be based on institutional capabilities that support natural resources conservation. An example is pollution prevention through the reduction of greenhouse gas emissions as an effective strategy for protecting the environment while also being profitable for business [25]. On the other hand, the anthropogenic theory of global warming predicts that human influence is the dominant cause of global warming and of other adverse impacts of climate change [26–28]. Likewise, [29] suggested that "anthropogenic influence is evident from the emission of greenhouse gases such as CO_2 from human activities" (p. 1141).

2.1. Corporate Carbon Footprint

Corporate carbon footprints are dominated by emissions of carbon and equivalent gases resulting from intensive energy consumption [27], with a size value that is often expressed in absolute CO_2e emissions [28,29]. As a result, one widely accepted taxonomy for accounting and reporting absolute CO_2e emissions is based on the philosophy and classifications of the Greenhouse Gas Protocol (or GHG Protocol, for short) [30,31]. At the corporate level, the World Business Council for Sustainable Development (WBCSD) and the World Resources Institute (WRI) Corporate Accounting and Reporting Standard [32] provide guidance for drafting a GHG emissions inventory. This paper defined three different scopes for CO_2e: Scope 1, Scope 2, and Scope 3. The Scope 1 CO_2e inventory, as defined by the WBCSD and WRI (2015), consists of "direct GHG emissions from sources owned or controlled by the company" [32] (p. 25). Scope 2 CO_2e comprises indirect GHG emissions from electricity [27,30]. More specifically, the WBCSD and WRI (2015) state that Scope 2 CO_2e "accounts for GHG emissions from the generation of purchased electricity consumed by the company" [32] (p. 25). For its part, Scope 3 CO_2e also refers to indirect GHG emissions, in this case from the upstream and downstream supply chain, which are mainly related to the use of goods and services sold [27,33,34]. To this end, the WBCSD and WRI (2011) Corporate Value Chain (Scope 3 CO_2e) Accounting and Reporting Standard [35] permits companies to prepare a GHG emissions inventory that includes Scope 3 CO_2e emissions and to determine where they should focus their activities to reduce these emissions [32].

2.2. Linking Corporate Carbon Footprint and Profits

Drawing from Barney's resource-based view (RBV) of business [36] and Freeman's stakeholder theory [37], it can be argued that reducing their carbon footprint provides companies with a way to achieve greater competitive advantage [38]. Although a significant body of both accounting-based (e.g., profits, sales, ROA, ROE, ROS, EBITDA, etc.) and market-based (e.g., Tobin's Q) empirical investigations [17,18,28,33,39,40] has examined the direct relationship between carbon footprint and certain indicators of profitability, the results are still inconclusive. For instance, some authors have found a statistically significant positive relationship [17–19,28], while others concluded that this relationship was not statistically significant [39,41]. Several authors found mixed results [33,40,42]. Furthermore, essentially all of this research is based on cross-sectional studies, a major limitation when it comes to reaching firm conclusions.

Consequently, there is a clear lack of empirical studies with a longitudinal analysis of the relationship between an (absolute) size value, such as carbon footprint, and a performance indicator based on a monetary metric, such as profit [43]. Thus, the relationship between carbon footprint and profit in energy-intensive global companies was of particular interest in this study. In light of these arguments, the first hypotheses proposed were the following:

H1a. *Scope 1 CO_2e has a positive influence on gross profit margin.*

H1b. *Scope 1 CO_2e has a positive influence on EBITDA margin.*

H1c. *Scope 1 CO_2e has a positive influence on operating margin.*

H2a. *Scope 2 CO_2e has a positive influence on gross profit margin.*

H2b. *Scope 2 CO_2e has a positive influence on EBITDA margin.*

H2c. *Scope 2 CO_2e has a positive influence on operating margin.*

H3a. *Scope 3 CO_2e has a positive influence on gross profit margin.*

H3b. *Scope 3 CO_2e has a positive influence on EBITDA margin.*

H3c. *Scope 3 CO_2e has a positive influence on operating margin.*

H4a. *Scope 1 + 2 CO_2e has a positive influence on gross profit margin.*

H4b. *Scope 1 + 2 CO_2e has a positive influence on EBITDA margin.*

H4c. *Scope 1 + 2 CO_2e has a positive influence on operating margin.*

H5a. *Scope 1 + 2 + 3 CO_2e has a positive influence on gross profit margin.*

H5b. *Scope 1 + 2 + 3 CO_2e has a positive influence on EBITDA margin.*

H5c. *Scope 1 + 2 + 3 CO_2e has a positive influence on operating margin.*

2.3. Clean Energy Innovation

From an operational standpoint, clean energy innovation is defined as "the set of processes leading to new or improved energy technologies that can increase energy resources; enhance the quality of energy services; and reduce the economic, environmental, or political costs associated with the supply and use of energy" [44] (p. 193). More specifically, renewable energy innovations involve "process innovations that lead to a substitution of fossil energy sources with renewable sources within companies," as defined by [45] (p. 405). The concept of clean energy innovation builds upon the evolutionary theory of innovation [46] and Joseph Huber's ecological modernization theory (EMT) [47]. According to the first theory, technological change is driven by the search for better technologies and the selection of successful innovations in the market [48]. However, others argue that a truly competitive industry responds to global environmental challenges by reducing pollution through technological innovations that redesign industrial processes [49]. More recently, the authors of [50] have stated that the neo-Schumpeterian approach (evolutionary model) raises the possibility of clean energy innovation acting as a major driver of radical transformation to a low-carbon economy. For its part, the EMT theory encourages energy intensive (and thus, high-pollution) industries to use clean energy technologies that enable them to reduce the environmental impact of their business activities [51].

2.4. The Moderating Role of Clean Energy Innovation on the Relationship between Carbon Footprint and Profits

The Porter hypothesis [49] asserts that companies that design and execute environmental strategies using innovative pollution prevention technologies can simultaneously improve their environmental performance and increase their competitiveness [52]. Subsequently, [53] argued that, at a corporate level, carbon footprint management promotes cleaner and greener technological innovations. Harangozo and Szigeti [30], meanwhile, claimed that in order to achieve a lower carbon footprint, companies must make greater efforts at clean energy technological innovation.

Ecological modernization theory (EMT), on the other hand, offers an approach to a corporate environmental strategy rooted in innovation and technology, also called "eco-efficient innovation" (or eco-innovation) [51]. Seen from this standpoint, clean energy innovation is a radical innovation that stems from the ecological modernization approach [54]. Indeed, one of the fundamental tenets of this approach is that technological innovation in clean energy helps improve both corporate environmental performance and financial performance [55]. Wedari et al. [19] recently reviewed the current state of research on the relationship between environment-related innovation, on the one hand, and environmental and economic performance on the other. Their findings shed new light on the role of innovation in the adoption of proactive environmental innovation strategies as a source of competitive advantage. According to [23], the influence of clean energy innovation in different industrial sectors has not yet been explicitly tested. Thus, we formulated the following research hypotheses:

H6a *Clean energy innovation positively moderates the relationship between Scope 1 CO_2e and gross profit margin.*

H6b. *Clean energy innovation positively moderates the relationship between Scope 1 CO_2e and EBITDA margin.*

H6c. *Clean energy innovation positively moderates the relationship between Scope 1 CO_2e and operating margin.*

H7a. *Clean energy innovation positively moderates the relationship between Scope 2 CO_2e and gross profit margin.*

H7b. *Clean energy innovation positively moderates the relationship between Scope 2 CO_2e and EBITDA margin.*

H7c. *Clean energy innovation positively moderates the relationship between Scope 2 CO_2e and operating margin.*

H8a. *Clean energy innovation positively moderates the relationship between Scope 3 CO_2e and gross profit margin.*

H8b. *Clean energy innovation positively moderates the relationship between Scope 3 CO_2e and EBITDA margin.*

H8c. *Clean energy innovation positively moderates the relationship between Scope 3 CO_2e and operating margin.*

H9a. *Clean energy innovation positively moderates the relationship between Scope 1 + 2) CO_2e and the gross profit margin.*

H9b. *Clean energy innovation positively moderates the relationship between Scope 1 + 2 CO_2e and EBITDA margin.*

H9c. *Clean energy innovation positively moderates the relationship between Scope 1 + 2 CO_2e and operating margin.*

H10a. *Clean energy innovation positively moderates the relationship between Scope 1 + 2 + 3 CO_2e and gross profit margin.*

H10b. *Clean energy innovation positively moderates the relationship between Scope 1 + 2 + 3 CO_2e and EBITDA margin.*

H10c. *Clean energy innovation positively moderates the relationship between Scope 1 + 2 + 3 CO_2e and operating margin.*

Figure 1 presents an overview of the conceptual model used in this paper.

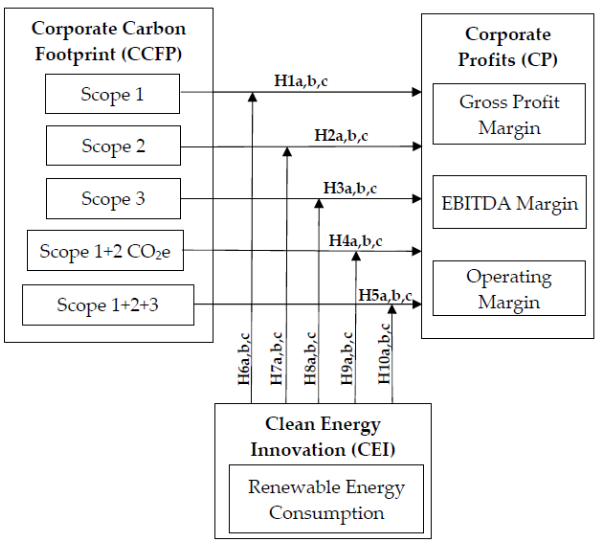

Figure 1. Conceptual model.

3. Research Methodology

3.1. Data and Sample

The sample used consists of a set of the world's largest companies that are included in CDP reports and that have a significant impact on climate change due to their high CO_2e emissions. Data on CO_2e emissions and clean energy innovation were collected from the database of the CDP, a well-known international organization dedicated to improving the quality of available data on corporate carbon emissions worldwide [56]. Detailed financial data were taken from the Thomson Reuters Eikon database. Using the industrial sector-level classification of the Global Industry Classification Standard (GICS), seven energy-intensive primary industries were selected for analysis: materials, consumer discretionary, industrials, utilities, technology, energy, and health care. Table 1 summarizes the composition of the sample of firms by region and industry sector.

The final sample, as shown in Table 2, consisted of 7827 firm-year observations made between 2015 and 2021 among 167 large firms from 27 countries and various energy-intensive industry sectors. This is an unbalanced panel, since the number of firm-year observations is not always the same for each company. The firm-year observations with missing values for more than two consecutive years were removed from the data set. Following previous studies [31,57,58], distortion caused by outliers was taken into account by winsorizing the lowest and highest percentiles of all continuous variables used in the study. Winsorization was performed on 2.41% of the total data points in this research.

3.2. Data Collection

3.2.1. Corporate Carbon Footprint

The independent variable was the corporate carbon footprint (hereafter, CCFP). Following the practices of previous research [17,33,39], this study used absolute metrics to measure the CCFP, specifically absolute firm-level carbon emissions expressed in CO_2 equivalent units, that is, in total tons of CO_2e reported annually. This took into account not just carbon dioxide (CO_2) but other GHGs with a high global warming potential, which were then transformed into carbon dioxide equivalent (CO_2e) [27,59]. This metric is most suitable for precisely measuring the carbon footprint of those companies and industries with a high absolute GHG intensity [60]. Following [29], Scope 1 + 2 CO_2e were added together to capture a company's total annual carbon footprint. Similarly, following the model proposed by [33] for the breakdown of corporate carbon emissions, which expands the firm's total carbon footprint by including indirect Scope 3 CO_2e emissions to account for the entire GHG supply chain, all emissions were added together to obtain an annual snapshot of total absolute CO_2e (Scope 1 + 2 + 3).

Table 1. Distribution of the sample of firms by sector and region.

Region	GICS SECTOR							Total Number of Firms	% of Total
	Consumer Discretionary	Energy	Health Care	Industrials	Technology	Materials	Utilities		
OECD Eurasia							1	1	0.60%
OECD Oceania						1	2	3	1.80%
Non-OECD Americas		2				3		5	2.99%
Non-OECD Asia		1			3	8	1	13	7.78%
OECD Asia	16		1	8	5	12	1	43	25.75%
OECD Americas	8	3		10	3	12	8	44	26.35%
OECD Europe	13	5		8	2	22	8	58	34.73%
Total	37	11	1	26	13	58	21	167	100.00%
% of Total	22.16%	6.59%	0.60%	15.57%	7.78%	34.73%	12.57%	100.00%	

Note: Firms are classified according to the Global Industry Classification Standard (GICS).

Table 2. Sample description.

	Firm-Observations Per Year							Firm-Year Observations
	2015	2016	2017	2018	2019	2020	2021	Total
Region								
OECD Eurasia	6	7	7	7	7	7	7	48
OECD Oceania	20	20	17	21	21	21	21	141
Non-OECD Americas	34	35	31	35	35	35	35	240
Non-OECD Asia	81	89	84	90	83	89	91	607
OECD Asia	282	288	285	299	295	295	301	2045
OECD Americas	272	282	258	299	306	308	304	2029
OECD Europe	374	384	352	402	398	402	405	2717
Total	1069	1105	1034	1153	1145	1157	1164	7827
Sectors								
Health Care	7	7	7	7	7	7	7	49
Energy	70	74	66	77	77	77	77	518
Technology	87	87	81	91	90	91	91	618
Utilities	127	139	130	143	146	147	147	979
Industrials	172	173	159	181	178	178	178	1219
Consumer Discretionary	232	240	229	257	253	258	259	1728
Materials	374	385	362	397	393	400	405	2716
Total	778	798	750	835	824	836	842	7827

3.2.2. Corporate Profits

Given the multidimensional nature of corporate profits (hereafter CP), empirical research on the concept tends to adopt different proxy metrics, with accounting-based performance metrics being the most prevalent [40,61]. Along these lines, [43] distinguished between two types of metrics: money metrics and ratio metrics. For the sake of convenience, and given the current availability of detailed and reliable financial data for the same period (2015–2021) as the corporate carbon footprint panel data, this study measured profits by gross profit margin (Pr_Mrg), EBITDA margin (EBITDA Mrg), and operating margin (Op Mrg). Gross profit margin (Pr_Mrg) was also included because profits are significantly influenced by operating costs [62] and are therefore suitable for examining the effect of corporate carbon footprint reduction. EBITDA—which has been used in similar studies [16,43,63]—was included as a way of capturing the financial cost–benefit ratio for companies resulting from climate initiatives to reduce GHG emissions [64]. Finally, operating margin (Op Mrg) was used because of its prevalence as an indicator in previous studies [18,65,66] but above all because it is an effective financial indicator for managerial decision-making [67].

3.2.3. Clean Energy Innovation

Our model's moderating variable was clean energy innovation (hereinafter CEI), quantitatively measured by renewable energy consumption (RENC) and quantified in billions of kilowatt hours (kWh). While output metrics, such as the number of new technologies used, energy consumption from renewable sources, and the number of patents granted [68–70], are usually used in the final stages of clean energy technology innovation processes [44], not all of these are appropriate. On the other hand, the use of renewable energy sources is a proxy metric for the development of clean energy technology innovation [69]. More importantly, renewable energy consumption is more plausible as an indicator of progress in the adoption of clean energy technologies in energy-intensive industries with a high level of environmental pollution [71,72].

Table 3 contains the definitions and a brief explanation of the metrics being examined.

Table 3. Operational definitions of the variables used in this research.

Variables	Symbols	Details	Data Source
Dependent Variables			
Gross Profit Margin	Pr_Mrg	Ratio of gross profit (revenue minus cost of goods sold) to revenue (%)	Refinitiv Workspace®
EBITDA Margin	EBITDA_Mrg	Ratio of EBITDA (Earnings Before Interest, Tax, Depreciation, and Amortization) to total revenue (%)	Refinitiv Workspace®
Operating Margin	Op_Mrg	Ratio of operating income to revenue (%)	Refinitiv Workspace®
Independent Variables			
Direct Emissions			
Scope 1 Emissions	Scope1 CO_2e	Organization's gross global Scope 1 emissions in metric tons of CO_2e	CDP
Indirect Emissions			
Scope 2 Emissions	Scope2 CO_2e	Organization's gross global Scope 2 emissions in metric tons of CO_2e, including location-based and market-based accounting	CDP
Scope 3 Emissions	Scope3 CO_2e	Organization's gross global Scope 3 emissions, disclosing and explaining any exclusions, in metric tons of CO_2-e	CDP
Moderator Variable			
Renewable Energy Consumption	RENC	Organization's total energy consumption (excluding feedstocks) in MWh from renewable sources	CDP

3.3. Data Analysis

This study used a longitudinal design consisting of a panel study with a structural equation modeling (SEM) method. One approach widely adopted in the literature is the latent growth curve (LGC) model, based on the maximum likelihood estimation (MLE) method [73–75]. We also used a Bayesian multiple-indicator latent growth curve model, which is becoming an increasingly popular specialized model [76], primarily in longitudinal research in the field of developmental psychology [76–78]. The Bayesian LGC approach was adopted for three reasons. First of all, according to [77,79], this method is suitable for improving the accuracy of estimates in the modeling of latent variables. Secondly, compared to the MLE method, Bayesian estimation is a more plausible technique for analyzing longitudinal data sets in small sample sizes [78,79]. Third, the availability of Bayesian computational methods in software packages (e.g., Mplus, Amos, among others) is driving their application in different fields of social research [80], in particular, in social science research on climate change. Finally, we analyzed the longitudinal data collected with version 8.8 of the Mplus statistical software, mainly because it permits the moderation of latent variables.

Bayesian LGC Model Implemented

The statistical model used for the moderation analysis was a Bayesian latent growth curve model (hereafter, B-LGC model) with structural equations [81,82]. Figure 2 presents the longitudinal structural model for this B-LGC model, which includes three continuous latent variables measured by multiple observed indicators. In particular, following the latent growth models proposed by [83–85], this B-LGC model contains six time-changing latent growth predictors, that is, five latent exogenous variables X_i (i = 1,2,3 . . . ,5) and one latent moderation variable Z, as well as three latent growth outcome variables Y_j (j = 1,2,3) and an INT cross-product indicator representing the interaction (moderation) of Z. Because the observed metrics of the predictor variables X_i and Z correspond to the same point in time, the product indicator INT is determined by the cross product of the latent growth factors (slopes) ξ_2 and ξ_4 of X_i and Z, respectively. For their part, η_{j1} and η_{j2} correspond to the initial level (intercept) and the rate of change (slope) of Y_j. In this case, being a linear growth model, all intercept factors are restricted to a constant value of 1 as a starting point (initial state) for any change (growth) over time. Likewise, all slope factors are specified using fixed-value restrictions (i.e., 0, 1, 2, 3, . . . , 6) that represent straight-line growth in order to capture the rate of change in the trajectories over time [83]. On the other hand, the X_i and Z growth curve factors interact with each other to influence the Y_j endogenous growth factors. Lastly, the model's three latent variables (X_{it}, Z_t and Y_{jt}) were measured in total with 63 observed variables, each measured at seven equidistant points in time ($t_1,\ t_2,\ t_3, \ldots t_7$).

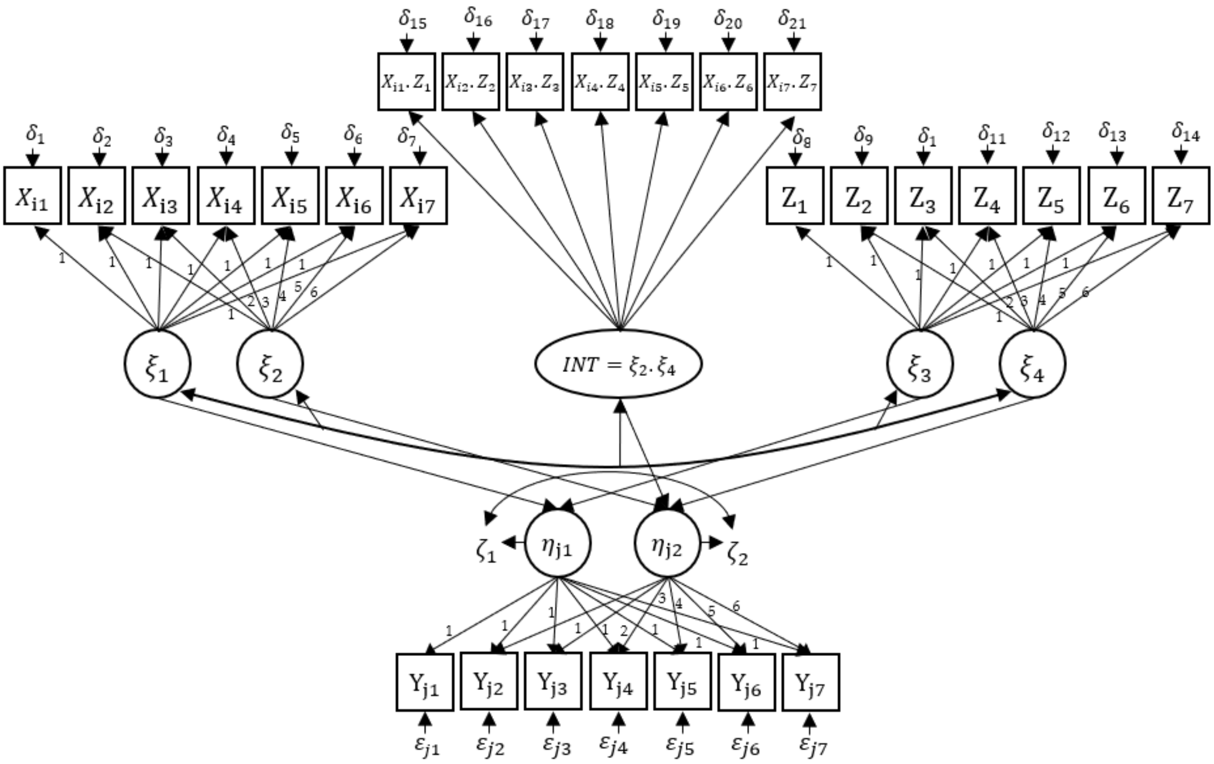

Figure 2. Path diagram of the b-lgc model for a latent growth curve model for three constructs and seven time points (t = 1,2, . . . ,7). *Note*: Y_{jt} = latent growth outcome variables (j = 1,2,3); X_{it} = latent growth predictor (i = 1,2,3, . . . ,5); Z = latent moderation variable; ξ_3, ξ_4 = intercept and slope factors for Z; η_1, η_2 = intercept and slope factors for Y_{jt}; INT = latent product indicator for slope factor of moderating interaction term; ζ_1, ζ_2 = latent residual variables; ε, δ = measurement error variables. Adapted with permission from [85]. Copyright © 2014, Taylor & Francis Group, LLC. by Z. Wen.

Appendix A contains the full formula needed to estimate the hypothesized B-LGC model, specifically for relationships between corporate carbon footprint (Scope 1 CO_2e), clean energy innovation (RENC), and profits (Pr_Mrg). Appendix A also provides the Mplus-specific syntax for this multiple-indicator measurement model, which describes the relationships between latent moderation (Z), latent interaction terms ($INT1$ and $INT2$), the latent growth predictor (X_{it}), and latent growth outcome (Y_{jt}), as well as the structural model specifications, using Mplus commands. For the distribution parameters (priors) used in the Bayesian estimation, this study adopted previous non-informative priors, that is, Mplus default priors [79].

4. Empirical Results

4.1. Diagnostic Testing of B-LGC Model Fit

To verify the reliability of the results of the B-LGC model, this study employed two diagnostic tools. First, posterior predictive checks were used together with posterior predictive *p*-values (PPP) [77,79,80]. Essentially, this approach is based on the idea that Bayesian *p*-values seek to assess the quality of the model, that is, to ensure that the data generated by the model closely resemble the observed data. Any deviation would suggest an incorrect specification of the model [86,87]. For the proposed B-LGC model, the model's fit is acceptable for calculated PPP greater than zero and close to 0.5 [79,80].

Secondly, from a Bayesian perspective, using Markov chain Monte Carlo (MCMC) algorithms, we examined whether the B-LGC model converges correctly, using the potential scale reduction (PSR) factor [86], which is a specific numerical measurement of the default convergence criterion in Mplus [74,88]. The B-LGC model is estimated using a larger number of MCMC iterations (between 20,000 and 30,000) in which PSR values close to 1 are considered evidence of convergence, which "means that convergence is achieved when the between-chain variation is smaller than the within-chain variation" [79] (p. 335). However, it is recommended to examine model convergence using other diagnostic tools, such as trace plots, autocorrelation plots, and posterior parameter distribution plots [80].

4.2. Hypothesis Testing

The numerical results of the analysis are shown in Table 4 (a) and (b). Both tables provide the standardized parameter estimates of the B-LGC model for each of the proposed hypotheses. For example, the fifth column presents the mean obtained from the posterior distribution in each simulation. The sixth column contains the posterior standard deviation (SD) for the mean of each interaction. In the seventh column, one-tailed PPP, based on posterior distribution, is provided for the significance tests of each of the proposed hypotheses. For each interaction parameter, the posterior probability interval [79,80], also known as the Bayesian 95% credible interval (CI), is shown. Finally, the level of statistical significance is shown for each of the proposed hypotheses. In a Bayesian context, "significant interaction" must be inferred when the credible interval does not contain zero [79].

Table 4 (a) shows the results of the hypotheses of direct interaction between CCFP and CP. In this table, we can see that the PSR measurements dropped rapidly to values close to 1.0 and remained at 1.0 between 10,000 and 20,000 MCMC iterations, which indicates that the convergence of the B-LGC model was achieved in all the MCMC hypotheses. Moreover, all the point estimates of the mean slope parameters reached PPP values greater than zero and below 0.05, which indicates an absolute fit of the B-LGC model in the Bayesian framework. With respect to the statistically significant results of the direct CCFP→CP interaction, only hypotheses H1b, H3a, H4b, H4c, H5a, H5b and H5c obtained plausible values at a significance level of 5%, since their corresponding CIs [−0.602, −0.101], [0.167, 0.643], [−0.647, −0.101], [−0.512, −0.020], [−0.521, −0.004], [−0.635, −0.098] and [−0.501, –0.014] do not contain zero.

Table 4 (b) presents the results for the longitudinal moderation of clean energy innovation (CEI) on the direct CCFP→CP relationship. All hypotheses achieved convergence for the estimated parameter (mean), including hypothesis H8c, which reached a PSR value of 1.048 at 29,300 iterations. However, according to [79], PSR values less than or equal to 1.1 are also considered evidence of convergence. Similarly, all PPP values indicated the good fit of the B-LGC model and the moderating effect of the CEI construct on the relationship between the exogenous (corporate carbon footprint) and endogenous variables (corporate profits). In fact, only hypothesis H8a showed the statistical significance of the moderating effect of the CEI construct, measured by the continuous observed moderator variable RENC, on the direct relationship between the observed variables Scope3 CO_2e →Pr_Mrg, given that its Bayesian 95% CI of [−0.991, −0.774] does not include zero, implying a positive intervention (moderation) effect. Figure 3 shows the standardized solution, confidence intervals, variance estimates, and standard errors provided by the Mplus diagram for H8a. This output diagram shows a value of 0.886 and a confidence interval of (−0.991, −0.774) for $INT2$. However, hypotheses H7a, H7b, and H8c displayed a PPP of 0.405, 0.490, and 0.357, respectively—all close to 0.5 but with a very narrow CI that includes zero. These can be interpreted as marginal effects caused by the moderating interaction of the CEI variable [79].

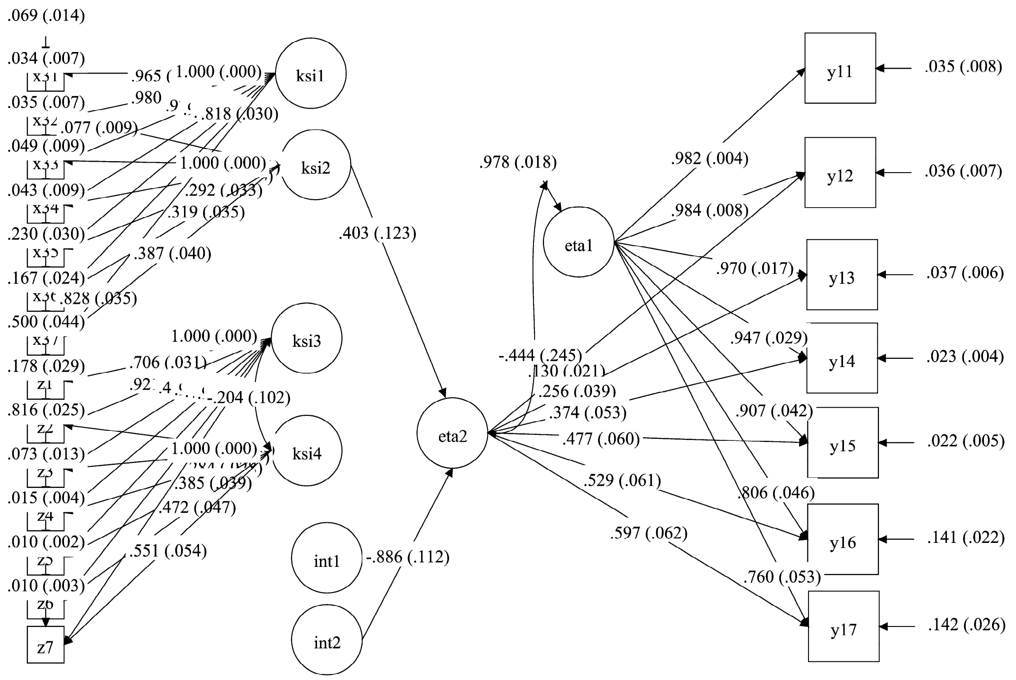

Figure 3. Mplus output diagram obtained for B-LGC model examined in hypothesis H8a.

4.3. Graphic Illustrations of Longitudinal Moderating Effect

Figure 4 shows the Bayesian trace plot of each chain of the MCMC process during the 20,000 iterations, which indicates a proper convergence of the autoregressive slope parameter corresponding to the moderating interaction term (INT) of the B-LGC model. This can be seen by the fact that there are no trends or large fluctuations in the trace plot, which confirms that there were no abnormalities in the model's convergence [89]. On the other hand, Figure 5 presents the autocorrelation plot for the autoregressive slope parameter, also corresponding to the interaction term INT, where the autocorrelation value is shown on the y-axis and the time lag between the 20,000 MCMC iterations on the x-axis. More specifically, this plot shows a relatively high autocorrelation (just over 0.5) for shorter lags between iterations. As the time lag increases, however, the autocorrelation becomes smaller (close to zero). This is a positive result, considering that "ideally, each MCMC iteration should result in independent information for the posterior distribution of a parameter (autocorrelation of zero)" [74] (p. 267). Finally, Figure 6 shows the posterior distribution of the mean slope parameter of the INT term. As we can see, this distribution is roughly symmetric. In fact, these distributions do not need to be normal or symmetrical in Bayesian analysis [88]. The mean, median, and mode were 0.886, 0.902, and 0.927, respectively. The posterior SD was relatively small (0.112), indicating negligible uncertainty about the true value of the mean slope parameter of the INT term. This is reflected in the narrow CI range obtained, which goes from −0.99108 to −0.77367 and does not cover zero. Consequently, it can be argued that the number of data points used (N = 167: 4509 total data points) to test hypothesis H8a was sufficient to obtain low uncertainty and high statistical power.

Table 4. (a) Numerical summary of B-LGC model estimate parameters for direct interaction effects between corporate carbon footprint (CCFP) and profits (CP). (b) Numerical summary of B-LGC model estimate parameters for the interaction (moderating effects) of CEI (measured by RENC) on the CCFP→CP relationship.

(a)

Simulation (Hypothesis)	Direct Interaction Effect (CCFP→CP)	Number of Iterations	PSR Measurement	Estimate (Mean)	Posterior SD	One-Tailed PPP	95% CI Bottom 2.5%	95% CI Top 2.5%	Significance
	Direct CO_2 Emissions								
H1a	Scope1 CO_2e → Pr_Mrg	14,300	1.000	−0.200	0.128	0.058	−0.444	0.057	
H1b	Scope1 CO_2e → EBITDA_Mrg	10,800	1.000	−0.354	0.128	0.004	−0.602	−0.101	**
H1c	Scope1 CO_2e → Op_Mrg	16,200	1.000	−0.226	0.120	0.032	−0.464	0.008	
	Indirect CO_2 Emissions								
H2a	Scope2 CO_2e → Pr_Mrg	9700	1.000	−0.164	0.116	0.082	−0.391	0.061	
H2b	Scope2 CO_2e → EBITDA_Mrg	17,200	1.000	−0.190	0.127	0.071	−0.429	0.066	
H2c	Scope2 CO_2e → Op_Mrg	9400	1.000	−0.005	0.004	0.127	−0.013	0.003	
	Supply-Chain CO_2 Emissions								
H3a	Scope3 CO_2e → Pr_Mrg	14,000	1.000	0.403	0.123	0.003	0.167	0.643	**
H3b	Scope3 CO_2e → EBITDA_Mrg	22,500	1.000	0.213	0.183	0.118	−0.229	0.517	
H3c	Scope3 CO_2e → Op_Mrg	29,300	1.048	0.062	0.261	0.352	−0.464	0.458	
	Direct and Indirect								
H4a	[Scope 1 + 2 CO_2e] → Pr_Mrg	11,700	1.000	−0.259	0.133	0.026	−0.518	0.006	
H4b	[Scope 1 + 2 CO_2e] → EBITDA_Mrg	9900	1.000	−0.374	0.140	0.004	−0.647	−0.101	**
H4c	[Scope 1 + 2 CO_2e] → Op_Mrg	13,700	1.000	−0.264	0.126	0.018	−0.512	−0.020	**
	Corporate Value Chain								
H5a	[Scope 1 + 2+3 CO_2e] → Pr_Mrg	14,700	1.000	−0.260	0.132	0.023	−0.521	−0.004	**
H5b	[Scope 1 + 2+3 CO_2e] → EBITDA_Mrg	18,100	1.001	−0.371	0.137	0.003	−0.635	−0.098	**
H5c	[Scope 1 + 2+3 CO_2e] → Op_Mrg	11,500	1.000	−0.259	0.124	0.018	−0.501	−0.014	**

(b)

Simulation (Hypothesis)	Moderation Interaction Effect of RENC	Number of Iterations	PSR Measurement	Estimate (Mean)	Posterior SD	One-Tailed PPP	95% CI Bottom 2.5%	95% CI Top 2.5%	Significance
	Direct CO_2 Emissions								
H6a	Scope1 CO_2e → Pr_Mrg	14,300	1.000	−0.044	0.033	0.090	−0.109	0.019	
H6b	Scope1 CO_2e → EBITDA_Mrg	10,800	1.000	−0.063	0.035	0.037	−0.132	0.007	
H6c	Scope1 CO_2e → Op_Mrg	16,200	1.000	−0.032	0.031	0.154	−0.095	0.028	
	Indirect CO_2 Emissions								
H7a	Scope2 CO_2e → Pr_Mrg	9700	1.000	−0.016	0.062	0.405	−0.140	0.107	*
H7b	Scope2 CO_2e → EBITDA_Mrg	17,200	1.000	0.001	0.067	0.490	−0.134	0.133	*
H7c	Scope2 CO_2e → Op_Mrg	9400	1.000	−0.001	0.002	0.285	−0.005	0.003	
	Supply-Chain CO_2 Emissions								
H8a	Scope3 CO_2e → Pr_Mrg	14,000	1.000	−0.886	0.112	0.003	−0.991	−0.774	**
H8b	Scope3 CO_2e → EBITDA_Mrg	22,500	1.000	−0.733	0.554	0.111	−0.995	0.914	
H8c	Scope3 CO_2e → Op_Mrg	29,300	1.048	−0.266	0.855	0.357	−0.985	0.960	*
	Direct and Indirect								
H9a	[Scope 1 + 2 CO_2e] → Pr_Mrg	11,700	1.000	−0.050	0.033	0.059	−0.115	0.014	
H9b	[Scope 1 + 2 CO_2e] → EBITDA_Mrg	9900	1.000	−0.060	0.035	0.042	−0.130	0.009	
H9c	[Scope 1 + 2 CO_2e] → Op_Mrg	13,700	1.000	−0.034	0.031	0.135	−0.096	0.026	
	Corporate Value Chain								
H10a	[Scope 1 + 2+3 CO_2e] → Pr_Mrg	14,700	1.000	−0.050	0.032	0.056	−0.116	0.012	
H10b	[Scope 1 + 2+3 CO_2e] → EBITDA_Mrg	18,100	1.001	−0.060	0.035	0.042	−0.130	0.008	
H10c	[Scope 1 + 2+3 CO_2e] → Op_Mrg	11,500	1.000	−0.034	0.031	0.133	−0.093	0.028	

** p-value $\leq$ 0.05 and C.I does not include zero, implying a positive moderating effect. * p-value $\leq$ 0.05 and C.I includes zero, implying a marginal positive moderating effect. Note: All estimates are standardized model results. RENC = Renewable Energy Consumption; Pr_Mg = Gross Profit Margin %; EBITDA = EBITDA Margin %; Op_Mrg = Operating Margin %; CI = Credible Interval; S.D. = Standard Deviation; PSR = Potential Scale Reduction; PPP = Posterior Predictive p-Value.

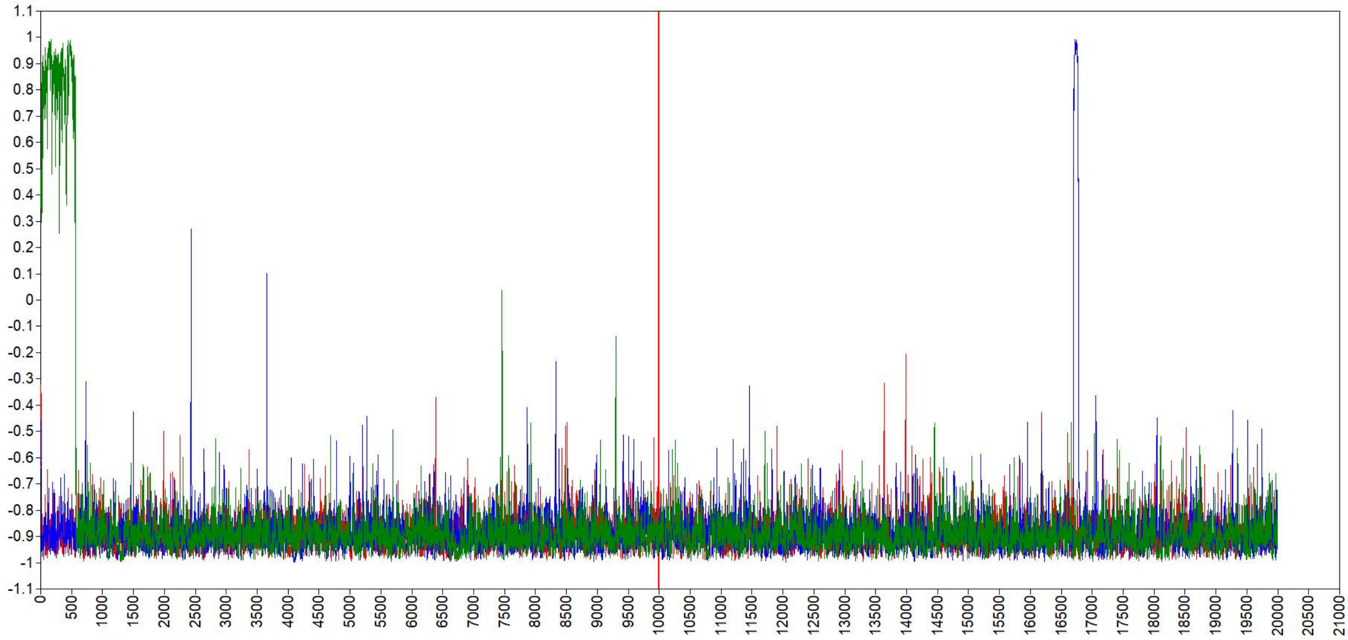

Figure 4. Bayesian trace plot obtained for the slope factor of the moderation interaction term (INT) examined in H8a.

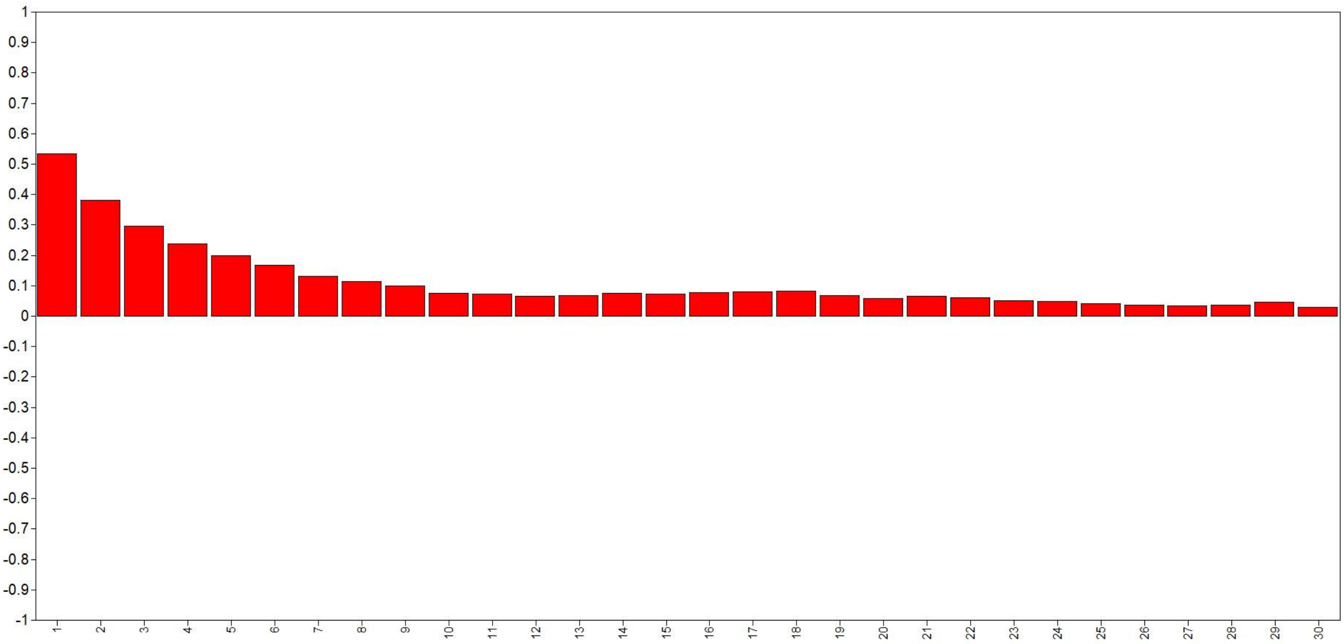

Figure 5. Parameter autocorrelation plot obtained for the slope factor of the moderation interaction term (INT) examined in H8a.

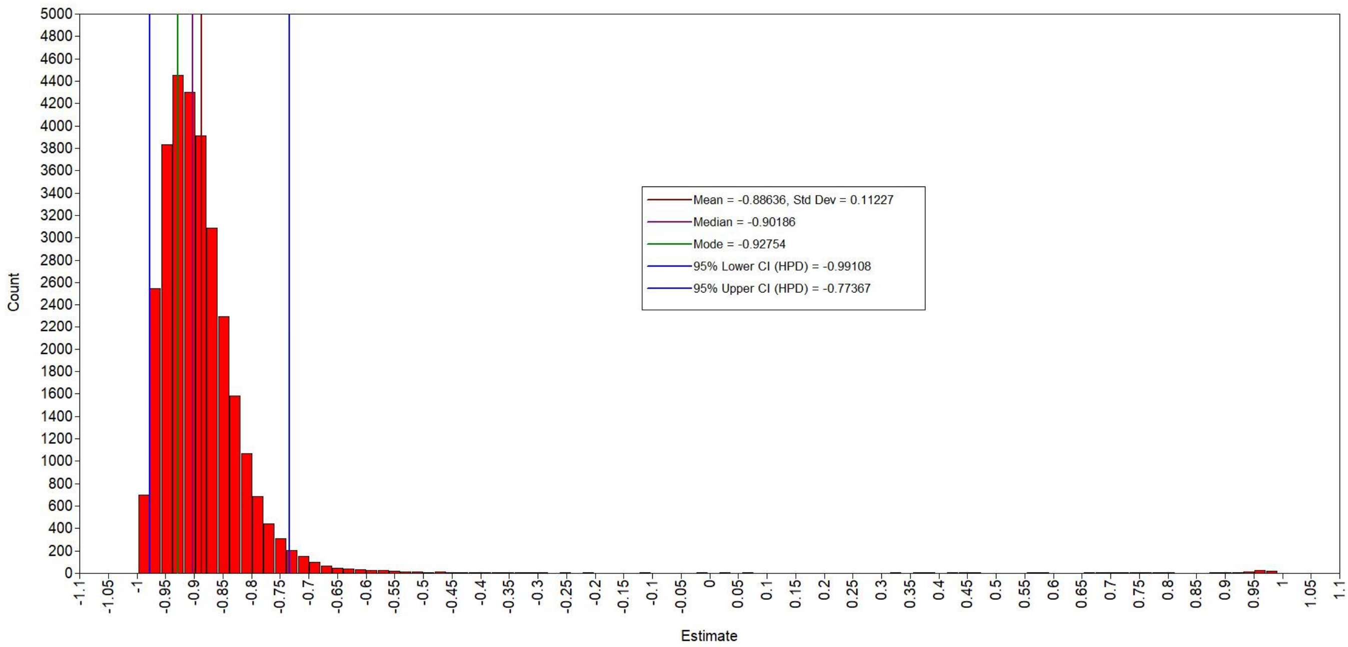

Figure 6. Posterior parameter distribution plot obtained for the slope factor of the moderation interaction term (INT) examined in H8a.

5. Discussion

These results clearly illustrate that the reduction of the CO_2e emissions inventory in those industrial sectors with a high consumption of fossil fuel-based energy sources helps to improve corporate environmental and financial performance. Two conclusions can be drawn from these results. First, continuing to focus on measuring and reducing emissions solely from their own operations (Scope 1 CO_2e) and from their own electricity consumption (Scope 2 CO_2e) continues to be profitable for these companies in the short term. Secondly, the world's largest energy-intensive companies appear to derive greater economic benefits from having a more accurate and detailed understanding of their supply chain's GHG emissions (Scope 3 CO_2e). Consequently, these empirical results are consistent with the resource-based view (RBV) of the firm.

On the other hand, this study suggests that, although clean and renewable energies can aid in the deep decarbonization of the sample of companies studied, the results show that the changeover to new sources of clean and renewable energy is a gradual process that requires considerable capital investment [15], thus dampening the effect of Scope 2 CO_2e and Scope 3 CO_2e emissions reduction on the efficiency of energy- and CO_2e-intensive firms to generate greater profits. Likewise, our results indicate that innovation based on clean and renewable energy technologies, when driven by government environmental policies aimed at reducing corporate value chain emissions (Scope 3 CO_2e), represents an effective mechanism to help these companies achieve the objective of net zero emissions and increase the profitability of their businesses, since value chain emissions (Scope 3 CO_2e) represent most of a company's total carbon footprint [90]. According to ecological modernization theory (EMT), this result is consistent with an "eco-innovation" strategy [51,55].

This paper makes three main contributions to the literature on business and environmental sustainability. First, it integrates two theoretical frameworks—eco-innovation theory [91–93] and ecological modernization theory [51,94]—using a structural equation model which has predictive and explanatory power [95]. Second, it provides empirical evidence of the positive moderating effect of clean energy innovation on the efforts of high-polluting industries to reduce their carbon footprint while generating higher returns for their shareholders, and at the same time reducing this negative impact on climate change. Third, it identifies the importance of technological innovation in clean energy as part of the transition towards deep and accelerated decarbonization in these industries.

6. Conclusions and Implications

The findings reveal that corporate carbon footprint has a significantly positive impact on profits. More specifically, we found a significant positive relationship among the following direct interactions: (a) Scope 1 CO_2e on EBITDA Mrg; (b) Scope 3 CO_2e on Pr_Mrg; (c) Scope 1 + 2 CO_2e on EBITDA Mrg and Pr_Mrg; and d) Scope 1 + 2 + 3 CO_2e on EBITDA Mrg, Pr_Mrg, and Op Mrg. On the other hand, the results of the B-LGC model also support the hypothesis that clean energy innovation, when measured using renewable energy consumption, positively moderates the relationship between value chain emissions (Scope 3 CO_2e) and gross profit margin in energy- and CO_2e-intensive industries. Furthermore, we found only marginal effects due to the moderating interaction of renewable energy consumption on the relationship of Scope 2 CO_2e emissions with gross profit margin and EBITDA margin, as well as the relationship between Scope 3 CO_2e emissions and operating margin.

This paper has several important implications for academics, senior executives of companies with significant fossil CO_2e emissions, and those who make public policy associated with GHG emissions and climate change. For researchers and academics, this study provides empirical evidence of the impact of clean energy innovation on CO_2e-intensive companies in a global context of deep industrial decarbonization, and also substantiates the importance of the concept of eco-innovation taken from the ecological modernization approach [54] in management practices and corporate environmental strategies. For executives and managers of CO_2e-intensive companies, it shows that greater competitive advantages can effectively be obtained by placing importance on the emissions of the firm's entire value chain (Scope 3 CO_2e) and not only Scope 1 and Scope 2 CO_2e emissions. According to [32], carbon reduction policies focus on achieving significant reductions within specific countries or regions. Extrapolating from this, one policy implication is that particular attention needs to be paid to Scope 3 CO_2e emissions produced by CO_2e-intensive firms operating in different industries and countries in order to design regulatory and control mechanisms that incentivize renewable energy consumption. Second, applying greater pressure to energy-intensive firms to disclose their upstream and downstream supply chain emissions (Scope 3 CO_2e) can lead to more effective eco-innovation strategies and greater CO_2e reductions. Third, policies and regulatory frameworks for clean energy innovation must engage in a harmonization process among countries and regions considered high CO_2e emitters by helping CO_2e-intensive companies to build greater environmental benefits and further competitive advantage.

This study had some limitations, however, that can be cleared up by future research. First, given the obviously sparse literature on clean energy innovation metrics at the firm level, we used a single output metric as an indicator for this construct. Future studies could include additional input metrics, that is, those corresponding to the first stages of the innovation process for clean energy technologies. Second, due to the relative lack of reliable statistical data, the time horizon of this longitudinal study was limited to 7 years (2015 to 2021), while the existing literature on longitudinal studies suggests the need for a minimum timeframe of 10 years to counteract random variation [96]. Therefore, future research might explore extensions of this timeframe, even using data containing missing values.

Author Contributions: Conceptualization, F.P.-O. and R.G.; methodology, F.P.-O. and R.G.; software, F.P.-O.; validation, F.P.-O. and R.G.; formal analysis, F.P.-O. and R.G.; investigation, F.P.-O. and R.G.; resources, F.P.-O.; writing—original draft preparation, Francisco Porles Ochoa; writing—review & editing, F.P.-O. and R.G.; supervision, R.G.; project administration, F.P.-O. and R.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Data are unavailable because of privacy restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A Mplus-Specific Syntax for the B-LGC Model

<table>
<tr><td>TITLE: Moderating Effect Analysis Based on the Bayesian Latent Growth Curve (LGC) Model</td><td>Title for the Bayesian analysis to be conducted.</td></tr>
<tr><td>DATA: FILE = w_Data2022_7.dat</td><td>Data file to be used: w_Data2022_7.dat is the name of this data file.</td></tr>
<tr><td>VARIABLE:
NAMES ARE Firm_ID Sector X11 X12 X13 X14 X15 X16 X17 Z4 Z5 Z6 Z7 Y11 Y12 Y13 Y14 Y15 Y16 Y17;
USEVAR ARE X11 X12 X13 X14 X15 X16 X17 Z4 Z5 Z6 Z7 Y11 Y12 Y13 Y14 Y15 Y16 Y17;
MISSING ARE ALL (−99).</td><td>Name of the seven time points (t = 7) of data for observable variables. We called them “X1t” here to represent seven metrics of Scope 1 emissions, “Zt” for renewable energy consumption (RENC) metrics, and “Y1t” for gross profit margin (Pr_Mrg).</td></tr>
<tr><td>ANALYSIS:</td><td></td></tr>
<tr><td>ESTIMATOR = BAYES;</td><td>Request the Bayesian estimator.</td></tr>
<tr><td>TYPE = RANDOM;</td><td></td></tr>
<tr><td>POINT = MEAN;</td><td>Use of mean-centered indicators.</td></tr>
<tr><td>CHAINS = 3;
PROCESSORS = 3;
FBITERATIONS = 20000;
BCONVERGENCE = 0.025;</td><td></td></tr>
<tr><td>THIN = 30.</td><td>By specifying THIN = 30, we request that only every 30th iteration of the post-burn-in phase be used by Mplus to compute the posterior distribution.</td></tr>
<tr><td>MODEL:</td><td>Specification of the measurement model to be tested.</td></tr>
<tr><td>X11-X17*;</td><td>Estimation of residual variances for independent variable X1 (Scope 1) for each time point (t = 7).</td></tr>
<tr><td>Z1-Z7*;</td><td>Estimation of residual variances for moderator variable Z (RENC) for each time point (t = 7).</td></tr>
<tr><td>Y11-Y17*;</td><td>Estimation of residual variances for dependent variable Y1 (Pr_Mrg) for each time point (t = 7).</td></tr>
<tr><td></td><td>The asterisk (*) is used to a free estimation of residual variance parameters of independent variable (X1), moderating variable (Z), and dependent variable (Y1).</td></tr>
<tr><td>KSI1 KSI2 | X11@0 X12@1 X13@2 X14@3 X15@4 X16@5 X17@6;
KSI3 KSI4 | Z1@0 Z2@1 Z3@2 Z4@3 Z5@4 Z6@5 Z7@6;
ETA1 ETA2 | Y11@0 Y12@1 Y13@2 Y14@3 Y15@4 Y16@5 Y17@6;</td><td>Specification of latent growth curve model with two latent growth parameters, intercepts (KSI1, KSI3 and ETA1), and slopes (KSI2, KSI4 and ETA2). All seven data time points (X11–X17, Z1–Z7, Y11–Y17) are used. The numbers to the right of @ indicate an equal time span between the data points, i.e., 0, 1, 2, 3, 4, 5, 6, and 7, reflecting equidistant points in time between 2015 and 2021)</td></tr>
<tr><td>KSI1*; KSI2*; KSI3*; KSI4*; ETA1*; ETA2*;</td><td>Estimation of variances of latent growth parameters.</td></tr>
<tr><td>INT1 | KSI1 XWITH KSI3;</td><td>Definition of interaction (moderation) term. INT1 corresponds to the latent product variable between intersections KSI1 and KSI3.</td></tr>
<tr><td>INT2 | KSI2 XWITH KSI4;</td><td>Definition of interaction (moderation). INT2 corresponds to the latent product variable between slopes KSI2 and KSI4.</td></tr>
<tr><td>ETA1 ON KSI1 KSI3 INT1;</td><td>Structural model specification.</td></tr>
<tr><td>ETA2 ON KSI2 KSI4 INT2.</td><td>Structural model specification.</td></tr>
<tr><td>OUTPUT: CINTERVAL(hpd) TECH8 STDYX.
PLOT: TYPE = PLOT2.</td><td></td></tr>
</table>

by S. Depaoli, H. M. Rus, J. P. Clifton, R. van de Schoot, & J. Tiemensma, 2017, *Health Psychology Review*, *11*(3), 248–264. [76].

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