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The Relationship Between Corporate Environmental Performance and Firm Value

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This is to certify that the doctoral study by

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Walden University
2024

Abstract

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MBA, Norwich University, 2020

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

The increasing scrutinization of polluting industries raises concern for corporate leaders responsible for sustaining profitability while reducing environmental impacts. Nested in the enlightened value maximization theory, the purpose of this quantitative correlational study was to examine the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and firm value. The participants were 140 publicly listed industrial companies that disclosed corporate environmental impacts to environmental rating agencies. The results of the multiple linear regression were significant, $F(3, 136) = 4.51$, $p < .01$, $R^2 = .09$. In the final model, two independent variables were significant, greenhouse gas emissions ($t = –2.21$, $p = .03$, $\beta = –.187$) and waste and hazardous materials management ($t = 2.62$, $p = .01$, $\beta = .227$). A fundamental recommendation emerging from this study is for industry leaders to establish a robust environmental impact disclosure strategy that accounts for sustainable production and long-horizon value maximization. The implications for positive social change include the potential to minimize an industry’s environmental footprint while jointly enhancing ecological stability, human flourishing, and environmentally responsible products and services.

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Dedication

I dedicate this work to my beautiful wife, Shari; your boundless love and support have always brought me to great heights.

Acknowledgments

I want to express my sincere gratitude to my chair, Dr. Charlie Shao, for your thoughtful guidance and recommendations that allowed me to pursue a higher level of scholarship. I also thank my methodologist and committee member, Dr. James Glenn, for your valuable insights toward my research endeavors. I also thank my colleague, Dr. Malcolm McLelland, for the erudite discussions throughout this excellent journey. Lastly, I acknowledge the U.S. Army 1st Special Forces Regiment; this distinguished institution ingrained in me the resilience and fortitude to never quit.

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Section 1: Foundation of the Study

Over the past few decades, managing the carbon footprint of emerging and established businesses has increasingly become the focus of numerous stakeholders. While climate concerns warrant global cooperation and coherent climatic research, the current framework associated with corporate environmental reporting reveals a discordant space occupied by social and scientific researchers, corporate leaders, policymakers, regulators, investors, and the media (Epstein, 2022; Liu et al., 2021; Spencer, 2008; Taliento et al., 2019). The extant literature and research on organizational attempts at improving strategic positioning, branding, and market share through implementing environmental initiatives yield mixed results (Gillan et al., 2021; Harahap et al., 2019; Signori et al., 2021). Adding to the vagueness of firm value and their potential environmental mitigation strategies are government policy decisions concerning time horizons for businesses to eliminate carbon outputs (Mahoney & Mahoney, 2021). Indeed, industry abatement of harmful environmental outputs is a material issue. How a company reports nonfinancial environmental data while concurrently maximizing value creates a gap worthy of further examination.

Measuring corporate environmental outputs relative to a firm's value is not new. The current construct, which considers the environmental, social, and governance (ESG) framework as outlined in the 2005 United Nations Environment Programme Initiative (UNEPI) (Freshfields Bruckhaus Deringer, 2005), emphasizes the quantification of ESG factors as a required element in investment decision-making and corporate sustainability (Bilyay-Erdogan et al., 2023; Raimo et al., 2020). During the 19 years since the introduction of the UNEPI ESG framework, the legitimacy of rating agencies and the consequent market value of businesses remain illusory (Escrig-Olmedo et al., 2019). My study intends to redress corporate environmental performance declarations' fundamental yet conflicting nature to determine if a firm's environmental sustainability ratings share a relationship with profitability and value.

Background of the Problem

Corporate financial statements provide organizational leaders with an assessment of how well and to what extent the company may perform (Gardi et al., 2021). Shifts in annual financial and registration statements from voluntary to mandatory nonfinancial reporting (see U.S. Securities and Exchange Commission, 2022, Deloitte Touche Tohmatsu Limited, 2022, and Warren, 2023 concerning standardized climate disclosure rules) appear to be a significant factor in maintaining credibility across a firm's broad range of stakeholders (Aureli et al., 2020a; Escrig-Olmedo et al., 2019). The integration of environmental reporting in financial statements represents a nonfinancial metric that, despite claims of rating agencies' comprehensive analysis, continues to confound researchers and organizational leaders with respect to a firm's competitive advantage. The need for disentangling the often-confusing relationship between environmental performance and firm value persists (Uyeda, 2023). At a time when businesses face unprecedented scrutiny concerning their polluting outputs, leaders of these organizations must discover how best to balance abatement initiatives while attempting to increase the firm's long-term value.

The dissemination of climate science data appears overwhelmingly one-sided, suggesting that industrial carbon emissions will inevitably cause catastrophic suffering to ecosystems and society (Epstein, 2022; Mörner, 2018). These assumptions further pressure businesses to align with a widespread carbon-neutral policy shift. The industry's reliance on fossil fuels to support the consumer needs of the globe continues to demonstrate why organizational leaders can only attempt to mitigate their carbon footprint incrementally. Faced with this business problem, executive leaders must assess the costs and benefits of such compliance. Indeed, not every firm will successfully satisfy exogenous demands from within, yet addressing the internal problem of environmental challenges and their long-term value is integral to their survivability (Le Thanh et al., 2022). Given the background of this business problem, a deeper understanding of the problems companies face concerning sustainability decision-making and value creation follows.

Problem and Purpose

As investors and stakeholders increasingly scrutinize corporate commitments toward sustainability, business leaders will need to employ adaptive strategies to manage the environmental impacts of their industry while concurrently maximizing the firm's market value (Busch et al., 2020). In 2020, global sustainable investment assets exceeded $35 trillion (Global Sustainable Investment Alliance, 2020), with an additional $500 billion added in 2021 (Wu, 2022). Nevertheless, environmental reporting data remains inconsistent, leaving business leaders questioning how their reporting adds to market value and investment incentives (Vitolla et al., 2019). The specific business problem is that some industrial-organizational leaders are unaware of the relationship between: (a) greenhouse gas emissions, (b) waste and hazardous materials management, (c) water and wastewater management, and market value added (MVA). Therefore, this quantitative correlational study examines the relationship between greenhouse gas emissions, waste and hazardous materials, water and wastewater management, and MVA. The independent variables are greenhouse gas emissions, waste and hazardous materials management, and water and wastewater management. The dependent variable is the MVA of firms. The targeted population comprises transnational industrial companies trading on the New York Stock Exchange (NYSE).

Population and Sampling

The target population for this study consists of transnational industrial firms traded on the NYSE. All listed firms disclosing environmental impact data in the industry sectors represent the study's sample population of 140. The NYSE dates back 225 years, listing and making markets in 8,000 securities traded on U.S. exchanges (Intercontinental Exchange, Inc., 2023). The NYSE equity listings expose investors to a broad range of equity assets. Integral to the sample population's environmental assessment is the mapping of 2022 ranking data from the Sustainability Accounting Standards Board (SASB), a nonprofit organization developing corporate sustainability accounting standards and assessments for disclosure to investors, researchers, and policymakers (Hughes et al., 2021; International Financial Reporting Standards, 2023).

In conjunction with the SASB, the FactSet Truvalue Labs rating agency maps composite SASB data for environmental and econometric analysis (Goldberg & Mouti, 2022; Truvalue Labs, 2023). All financial statements associated with the study's constituent companies are sourced through the SEC EDGAR government site (U.S. Securities and Exchange Commission, 2023) and FactSet Truvalue Labs. My academic licensing agreement with the SASB and FactSet Truvalue Labs enables access to data associated with the target and sample populations. Each company in the sample reports nonfinancial performance data and company financial filings, which provides information for assembling a robust, verifiable, and replicable dataset for examination.

Nature of the Study

The quantitative method is appropriate for this study based on the need to examine continuous numerical data. For researchers, the quantitative approach yields numerical results and quantifiable relationships that can describe changes in a target population, provide historical and predictive trends, monetize nonfinancial data, and elucidate causal relationships (Amrhein et al., 2019; Unerman et al., 2018). Conversely, the qualitative methodology is inappropriate for this study because the subjectivity and interactions with the population in question are central to this method (Aspers & Corte, 2019). Applying the mixed-method approach is equally impractical for this study because its combination of qualitative and quantitative research is informed by conceptual positions, which deviate from a purely deductive quantitative reference frame (Timans et al., 2019).

I consider the correlational design optimal for addressing this study's research question. The correlational design allows researchers to examine the stability and directionality of relationships between variables of interest (Bücker et al., 2018).

Leveraging the quasi-experimental design to approach the research question is not applicable because this design implies that select variables are manipulated across control groups or participants within a non-randomly assigned target population. Similarly, the experimental design does not effectively support this study because its central focus relies on evaluating the effectiveness of implementation strategies (Miller et al., 2020). Support for my correlational design consideration is derived from archival secondary data (Cheng & Phillips, 2014; Olabode et al., 2018), which can serve to test the effect of environmental performance initiatives and their relationship to a firm's MVA

Research Question

What is the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and market value added?

Hypotheses

Null hypothesis (H_0): There is no statistically significant relationship between (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management and market value added.

Alternative hypothesis (H_1): There is a statistically significant relationship between (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management, and market value added.

Theoretical Framework

The theory binding this study is the enlightened value maximization theory (EVMT). Developed by Jensen (2002), the central premise of the EVMT suggests the long-term maximization of corporate value and the reduction of negative externalities, such as those caused by water and air pollution (Agle et al., 2008; Zhang, 2022). EVMT utilizes the structure of stakeholder theory but stresses the maximization of the long-run value of the firm as a precondition when balancing tradeoffs among its stakeholders (Cooray et al., 2020; Lund, 2021; Wry & Zhao, 2018; Xue et al., 2020). The EVMT focuses on managerial accountability while adhering to internal and external governing actions that affect the firm's value-enhancing outcomes (Javeed & Lefen, 2019). The EVMT framework differs from normative stakeholder theory's proposed multipurpose corporate initiatives, which can broadly distribute the firm's strengths across numerous areas where management attempts to satisfy all stakeholder interests (Keay, 2019).

Jensen (2002) argued that balancing multiple objectives versus optimizing firm value results in accountability problems, mainly because optimizing one objective function precludes optimizing another. Based on this proposition, Jensen alludes to the hypothesis that long-run firm value can conditionally be maximized while concurrently satisfying stakeholder interests. In an article by Agle et al. (2008), Jensen argued that reducing the costs of environmental externalities–such as this study's independent variables of: (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management–requires the collective action of local, state, and national government alongside corporate entities to form a system of environmental compliance. Such a meta-governance system may support companies attempting to maximize long-term value while reducing their carbon footprint. The theoretical precepts of EVMT address the nature of this study, its research problem, and its purpose by investigating the relationship between the externalities and outputs of a–c above and the market value added of the firm.

Operational Definitions

Market value added: MVA is the difference between a firm's capital, as provided by all its shareholders and bondholders, and its market value. A high MVA suggests that the intrinsic value of effective management and optimal operational capacity exceeds the firm's debt and equity valuation and market perceptions (Baydaş et al., 2022; Kostin, 2018).

Enlightened value maximization theory: The EVMT stresses that the long-term maximization of corporate value is the sole function of a firm and is mainly dependent upon organizational leaders' capacity to initiate stakeholder tradeoffs to action value creation (Xue et al., 2020). The value maximization proposition of this theory relies on the origins of economics and finance spanning more than 200 years (Jensen, 2010).

Corporate sustainability: Corporate sustainability is synonymous with environmental stewardship (Folke et al., 2019; Woo & Kang, 2020) and involves a firm's expansion of economic growth and shareholder value (Meuer et al., 2020; Simangan et al., 2021). Corporate reputation, job creation, and the quality of a firm's products and services also form the fundamental elements integral to a corporation's sustainable practices (Jensen et al., 2012).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are proposals of ideas researchers consider accurate or plausible yet lack verification. Because assumptions inherently contain risk, it is necessary to address them accordingly (Hu & Plonsky, 2021). Herein, it is assumed that organizational leaders provide accurate financial and nonfinancial information when they assemble reports in accordance with the Securities and Exchange Commission (SEC). A second assumption is that environmental data provided by the Sustainability Accounting Standards Board (SASB) in conjunction with FactSet Truvalue Labs contains accurate information.

Limitations

Limitations refer to the potential weaknesses of the study, which the researcher cannot control. Under these constraints, limitations can influence the study's end-state and internal validity (Theofanidis & Fountouki, 2019). Numerous environmental, social, and governance (ESG) rating agencies assess the firms under investigation in this study. Employing the secondary SASB and FactSet Truvalue Labs data implies that a company's environmental performance data aligns with other rating agency measurements. The homogeneity of ESG metrics across sustainability rating agencies is irregular, thus posing a limitation for this study. Secondly, the potential for emergent errors in the statistical model can be problematic, regardless of systematic checks and transparency efforts on behalf of the researcher (Hu & Plonsky, 2021). Lastly, the findings revealed in this study cannot form a consensus outside the boundaries of industrial firms examined during 2022 whose equity shares trade within the United States.

Delimitations

Delimitations clarify the scope or boundaries of the study, which researchers decide upon and have control over (Fetzer, 2022; Roberts & Hyatt, 2019). In this study, three environmental output measurements represent the independent variables. Other measurable outputs standard to this area of research are organizations' social and governance capacity, but these elements of sustainability are not part of this study. By delimiting the broader construct of ESG metrics, I can narrow the scope of this study to the relevant environmental factors that may impact the target population.

The range of this study covers corporate sustainability and financial performance reporting for 2022 and represents the national market exposure for the industries and industry sectors under examination. The decision to leverage only those constituent industrial firms traded on the NYSE, along with the FactSet Truvalue Labs industry rating data, best narrows the research scope while supporting the purpose of the study. Lastly, the specific selection of industrial firms for this study implies an industry dependent on natural resources, which, at a minimum, are obligated to comply with environmental regulatory standards and financial reporting functions.

Significance of the Study

This study is significant and timely because organizational leaders frequently face challenges maximizing a firm’s value. To be sure, Battilana et al. (2022) and Henderson (2021) explained that the value of any firm begins and ends with specific tradeoffs, such as the willingness of firms to focus on specific organizational stakeholders despite the concurrent demands of other stakeholders. Compliance with industry environmental standards while satisfying stakeholder demands introduces such tradeoffs. Organizational leaders seek to minimize environmental impacts to maximize the firm’s value and maintain sustainability across their corporate enterprise (Pham & Kim, 2019; Toha et al., 2020). Further, this study is significant to business practice because it may provide a practical model for accurately understanding the relationship between the reduction of environmental impacts of corporate outputs and a firm’s value.

A reliable and predictive model can guide and support leaders in gauging the extent of environmental reduction initiatives while maximizing the firm's long-term market value. The outcome of such a model can potentially lead to a company’s optimal pro-environmental capability and long-term economic sustainability. Collateral benefits may emerge for stakeholders while innovative firms work to sustain ecosystems due to corporate environmental impact abatement. The implications for positive social change may include the potential to provide significant knowledge to organizational leaders for minimizing the firm’s environmental footprint while jointly enhancing ecological stability and environmentally sustainable products for regions where these entities operate.

A Review of the Professional and Academic Literature

This correlational study concerns the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and the market value of firms. In this review, I investigate the extant works concerning the expansion of a firm's market value under the lens of environmental reporting by adopting the EVMT as a theoretical basis for process improvements. Managerial decision-making actions, such as strategic tradeoffs, are integral to this relationship. The empirical research contained in this review addresses the research question: What is the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and MVA? Peer-reviewed journal articles, government publications, and books central to this question form the basis of information for this literature review.

Organizational Structure of the Literature Review

The structure of this academic literature review is chronological and thematic, beginning with the theoretical framework of the EVMT and its background. The EVMT's development, propositions, tenets, and axioms contribute to the exploration of strategic decision-making criteria for managers to maximize the long-term market value of organizations while dealing with contemporary environmental externalities, such as carbon transition risk (Zhang, 2022). I further review and discuss competing and complementary theories of the EVMT and its relationship to managerial finance, economic externalities, the environmental sciences, and corporate strategic decision-making.

The review continues by examining the environmental independent variables of greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and the dependent variable of MVA. I evaluate the applicability of quantifying corporate environmental reporting by addressing each independent variable and its nonfinancial integration with a firm's financial reporting mandate. The desired end state of this review is to comprehensively evaluate recent management and economic literature concerning the efficacy of environmental reporting and its propensity to either enhance or diminish MVA. I conclude the review with a brief description of secondary data analysis and its application in this study.

Search Criteria for the Literature Review

I employ a targeted search to analyze the empirical literature for this study. The search for extant research leverages the following databases: ABI/INFORM Complete, Business Source Complete, FRASER, SAGE Journals, JSTOR Arts & Sciences Collections I-VII, JSTOR Sustainability, Science Direct, MathSciNet, Academic Search Complete, Nexus Uni, ProQuest Science, eBook Collection (EBSCOhost), Emerald Management Journal, SAGE Premier, Business Market Research Collection, Gale OneFile: Economics and Theory, NYSE Industrial Materials and Processing Index, Sustainability Accounting Standards Board, FactSet Research Systems, Truvalue Labs, U.S. Securities and Exchange Commission: Edgar Search and Access, Green File, MarketLine, S&P Global-Market Intelligence, Thoreau, Social Science Research Network Journal, and Google Scholar. The keywords associated with this search strategy are *enlightened value maximization theory, market value added, economic value added, environmental, social, and governance pillars, environmental performance and financial performance, carbon transition risk, carbon footprint, economic externalities, environmental stewardship, corporate sustainability, sustainable finance, sustainable development, corporate social responsibility, corporate social performance, pro-*

environmental performance, competitive advantage, value creation, corporate value maximization, normative stakeholder theory, and institutional theory.

Other topics of integral research included the triple bottom line, green economics, slack resources, carbon reporting, carbon leakage, weak and strong sustainability theory, relative and absolute carbon emissions, economic responsibility, economic externalities, and environmental stewardship. The comprehensive literature search and keyword truncation revealed additional primary source literature, totaling more than 600 references; 567 were integral in supporting this study. Eighty-three percent of this review's content contains peer-reviewed research articles from 2019–2024, illustrated in Table 1—the remaining content leverages seminal publications mainly supporting this study's theoretical framework and econometric analysis.

Table 1

Details of the Literature Review According to Publication Year

	Older than five years	2019	2020	2021	2022	2023	2024	Total
Peer-reviewed articles	49	85	110	89	77	55	3	468
Government documents	1		1	1	4	5		12
Books	15	5	2	3	2	1		28
Other sources		5	10	10	15	18	1	59
Total	65	95	123	103	98	79	4	567

Enlightened Value Maximization Theory

Underpinning this study is the enlightened value maximization theory (EVMT). The EVMT is attributable to economist and educator Michael C. Jensen and was first published in 2000 in the book *Breaking the Code of Change*, edited by Michael Beer and Nitin Nohria. A second, more interpretive publication in 2002 came from a Business Ethics Quarterly article, which included a comprehensive review and debate concerning stakeholder theory–the premise that firms acknowledge all of their constituencies. While Jensen yields to the stakeholder theory's capacity for value maximization, he reveals significant shortfalls in its ability to satisfy all constituent demands while concurrently generating enterprise value. Constituents in this context include but are not limited to the firm's workforce, shareholders, creditors, customers, communities, suppliers, government, and the environment (Freeman, 1984; Starik,1995). The premise that companies adopt a single objective function–maximizing the firm's market value–above all constituent needs is central to the long-run sustainability of the corporation and embedded in the tenets of the EVMT.

The Tenets of EVMT

Often taken as strata from shareholder primacy and agency theory, which corporate law continues to recognize (see Lipton, 2019; Lund, 2021; Strange, 2018 for amplification), the EVMT encompasses a one-dimensional approach to strategic decision-making. At its core, the EVMT posits that the long-run value maximization of a corporation should constitute a firm's single objective (Dang et al., 2019; Queen, 2015). The theory proposes that decision-making must account for strategies and changes that facilitate rising values to achieve maximum market value. According to Jensen (2002), a requisite value scorecard must be deployed in ways that define decisions yielding results that align best with value creation and avoidance of those that diminish a firm's value. A consequence of Jensen's suggested value scorekeeping is purposeful decision-making, regardless of the self-interests of a firm's agents (Cooray et al., 2020). As Jensen (2002) reasoned, the end-state of coherent value-based scorekeeping ultimately enlightens and guides firms, allowing leadership to maximize long-term market value while advancing social welfare.

Because value may not readily be observable or easily quantifiable across many enterprises, save for market exchanges (Unerman et al., 2018), keeping a ledger of value-seeking activities may provide managers with a posteriori knowledge to justify future strategic decisions. As tradeoffs across a firm's stakeholders fluctuate, so does the chronological recording of the value creation score and the identification of material value drivers (Edmans, 2022; Kostin, 2018). In assembling such a stakeholder-value-creating paradigm, Pichet (2011) pointed to two interests that organizational actors pursue when considering the value creation construct: its measurement and choices made among stakeholders. The first dictates that the organizational citizenry seek involvement in such an enterprise because they have a vested financial interest or material stake in the firm (Margolis & Walsh, 2003). The second concerns the inextricable connection between the firm and its stakeholders, which, if left unattended, may degrade value creation.

The idea of maximizing value while having regard for a firm's stakeholders is a subject of much debate across academia, management, and government policymakers (Keay, 2019). Indeed, satisficing stakeholders in place of a value stream strategy is thought to produce corporate mediocrity (Madden, 2020). Attempting to maximize value in more than one dimension is, on the one hand, impossible (de Bussy, 2018; Griffin, 2017; Jensen, 2002). On the other hand, orienting corporations toward managing integral stakeholder communication is considered a necessary link in establishing firm sustainability and competitive advantage (Calabrese et al., 2019).

Achieving a balance between long-term corporate value creation and stakeholder interests will likely remain difficult in otherwise non-uniform industries (Battilana et al., 2022; Lipton, 2019; Mahoney & Mahoney, 2021; Margolis & Walsh, 2003). Organizational theorists contend that combining economic and ethical frameworks may reduce the institutional complexity inherent in the firm's purpose while potentially moving managers and directors toward purposeful decision-making (Demers & Gond, 2020; Hengst et al., 2020). Supporting these inherent challenges, the EVMT builds on more than two centuries of economic and financial research (Jensen, 2002). The theory acknowledges a firm's constituent base as a potential lever for value creation and seeks a single objective for firms to establish economic and socially sustainable practices. For this reason, it is helpful to summarize the salient features of Jensen's (2002) presuppositions in Appendix A. To better understand the EVMT and the decades-old conjecture surrounding stakeholder theory's role, the following section aims to elucidate some of the embedded friction and complementarities.

Stakeholder Theory and EVMT

Stakeholder theory calls upon an innate and fervent commitment to family and society. For millennia, tribal members who chose not to comply with this familial orthodoxy did not survive (Jensen, 2002). Indeed, security in numbers could better provide for members of the group, consequently increasing their survivability. While infallible as a social mechanism for the longevity of human flourishing, the fragmentation of this social doctrine became evident as manifest free markets and property rights emerged over the last 400 years (Dutta, 2021; Shaffer, 2021). The displacement and fracturing of the tribal ideology are due in part to the eventual rise of hierarchical institutions like the military, state-sponsored colonization, segmented bureaucratic states, and economic markets reacting to supply and demand dynamics (Murray, 2022; Ronfeldt, 1996).

Unpacking contemporary stakeholder theory is often complicated due to the numerous variants of the theory given by social science researchers and business ethicists since 1970 (Hendry, 2001; Margolis & Walsh, 2003; McGahan, 2020; Valentinov & Hajdu, 2019; Vitolla et al., 2019). Nevertheless, stakeholder theory continues to gain support across a universe of academic and organizational theorists as a viable approach to managing a firm’s social responsibility, management, and decision-making functions (Ferri et al., 2022; Freeman et al., 2021). At its core, stakeholder theory identifies those constituents–employees, customers, suppliers, shareholders, creditors, government, and environmentalists–that affect or are affected by the firm (Freeman, 1984). Stakeholder theory attempts to inform corporations about stakeholder management and dialogue (Ferri et al., 2022). Considering the multitude of stakeholder paradigms, corporate agents remain concerned when determining optimal managerial actions and communications across a multidimensional stakeholder enterprise (Harrison et al., 2020; Pies et al., 2021; Queen, 2015; Tsai & Wu, 2022). Despite broad support for the stakeholder management archetype, legal scholars, shareholder groups, and management theorists continue to question a firm's material stakeholder responsibilities and their presumed value-delivering outputs (Battilana et al., 2022; Bebchuk & Tallarita, 2020; Bebchuk & Tallarita, 2022; McGahan, 2020; Vitolla et al., 2019). The EVMT addresses this gap between value initiatives, balancing corporate constituents through purposeful decision-making and acknowledging that stakeholder claims carry merit conditional on enhancing the firm's long-term value (Gersel & Johnsen, 2020; Jensen, 2002; Pies et al., 2021).

Knowing the net effects of each constituency across the firm is fundamental for stakeholder management and deliberation in decision-making. For this reason, Minning (2021) suggested that firms need to recognize ten types of stakeholders composing three domains: internal and external, primary and secondary, and direct or indirect. Still, when considering the multitude of stakeholder classifications, Minning stressed that satisfying all of these groups is impossible when a firm ultimately seeks value and growth. Relegating the multidimensional stakeholder approach to management until the firm's market value and capacity can absorb extraneous demands leaves corporates with a single objective to maximize the firm's value. With this singular financial objective in mind, both Jensen's EVMT and Freeman's stakeholder theory center on value maximization and trade while combining time-tested economic and ethical theories (Clark, 2019; Freeman et al., 2010; Jensen, 2002). While similar in their value-creating objective, the theories remain divided in their approach to this end.

Despite disagreement among management practitioners and scholars concerning stakeholder tradeoffs and multi-stakeholder initiatives (Arenas et al., 2020; Battilana et al., 2022; Mitnick et al., 2021b), both Freeman and Jensen advocate for value added activities across publicly traded companies (Muldoon et al., 2022). Nevertheless, the stakeholder theory has shortcomings. Fundamentally, the theory introduces politics within a firm, potentially leaving its managers freedom to act on their desires and divert the company's resources away from its owners and employees and toward external non-obligatory causes and non-economic objectives (Friedman, 2002; Jensen, 2002; Tencati et al., 2020). The EVMT departs from stakeholder theory at the intersection of multi-objective versus single-objective corporate activity, maintaining a route toward long-term market value. For this reason, the lens under which this study examines a firm's market value is best guided by the precepts of EVMT, which does not entirely discount the stakeholder paradigm but aims to offer insight into whether and how a firm's long-term generation of market value may moderate stakeholder and environmental externalities.

EVMT and the Principle-Agent Dilemma

The EVMT coincides with earlier precepts of the separation of corporate ownership and control, as suggested by Berle and Means (1930). The separation of corporate ownership and control centers on the authority to direct management, policies, and an organization's governance via stock ownership by stockholder proxy voting (Condon, 2020; Jensen & Ruback, 1983). The EVMT aligns with the separation of ownership and control by suggesting that shareholders vote their shares in ways that promote wealth maximization. In the decades to follow, the separation of ownership and control inexorably gave rise to the agency problem–which outlines inherent issues between shareholders (principal owners) and corporate managerial executives (agents)–as illustrated by Ross (1973) and further elucidated by Jensen and Meckling (1976), and Fama and Jensen (1983b). The current debate over the agency problem continues among legal, regulatory, investment, and academic circles.

Agency problems emerge when a firm's agents execute decisions within a nexus of corporate contracts without assuming the potential revenue effects of their actions (Dang et al., 2019; Kasbar et al., 2023; Ross, 1973; Strange, 2018). When disjointed decisions, unilateral preferences, information asymmetry, and self-serving actions of corporate agents degrade the value of a company, the principal owners ultimately bear this agency cost, consequently inciting moral hazard problems, onerous contractual obligations, and a higher cost of equity capital (Benlemlih & Cai, 2020; Fama & Jensen, 1983a; Lanza et al., 2020; Mitnick, 2021a). The EVMT seeks to mitigate the agency dilemma by viewing the corporate enterprise under an aggregate stakeholder lens with value enhancement and agent mutual monitoring as a primary principal-agent goal (Fama & Jensen, 1983a; Li, 2019; Styhre, 2018). While principal-agent conflict and agency costs tend to be ubiquitous under all management models, the underlying integrity of principal and agent surfaces as a pivotal element in leveraging the fundamental doctrine of EVMT (Cheffins, 2020; Erhard & Jensen, 2013; Erhard et al., 2022; Jensen, 2003; Muldoon et al., 2022).

EVMT and Long Horizon Value-Based Management

The EVMT does not subscribe to short-term profit-seeking, often called short-termism (Fried & Wang, 2021; Gu et al., 2020; Jensen, 2003; Keum, 2021; Louche et al., 2019; Lund, 2021). In contrast to firms that focus on transient quarterly earnings through sharp reductions in research and development and investment opportunities (Janicka et al., 2020; Madden, 2020; Varas, 2018), the EVMT seeks value creation over a longer horizon by identifying and recording positive managerial value drivers. Conceptually, value creation stems from companies seeking to advance their governance, social, environmental, and financial performance through robust management strategy and value-driven actions (Rumelt, 2011; Schoenmaker & Schramade, 2020). Comparatively, Richards and Giovanni (2022) and Qian et al. (2023) noted that while short-termism may provide transitory wealth for shareholders and quarterly earnings increases, the net effect of these short-term gains comes at the expense of long-run value generation for future internal and external stakeholders. In short, the EVMT discourages sacrificing corporate innovation (Yang & Zhao, 2023), future value-based investments, demonstrable market resilience, and industry competitiveness in lieu of short-term gains.

EVMT: Applications Across Research Fields

Several research fields, deliberately or otherwise, employ value maximization precepts as previously described. In the management and law literature, research tends to investigate value drivers with respect to a company or industry's empirical value creation within standard legal parameters (Lund, 2021). Management practitioners, such as Alsayegh et al. (2020), found that interdependencies among economic, social, and environmental initiatives support value creation. While the study by Alsayegh et al. leverages a shared value theoretical framework, the researcher's results suggested a positive correlation between environmental performance and firm value, which jointly supports the EVMT's argument for value-creating activities. Conversely, many legal researchers maintain that increasing shareholder value is decisive for building long-term enterprise value. To be sure, Bebchuk and Tallarita (2022) indicated that numerous high-level corporate proposals–intended to embrace multiple stakeholder needs–appear void of any decision to alter their current shareholder value maximization principles.

The environmental research field maintains a verifiable investigative connection to value maximization theory. Moreover, the environmental research domain comprises subordinate fields, including but not limited to energy, geoscience, and infrastructure. Within the broader environmental research area, profound discoveries of environmental harm committed by polluting firms propagate value degradation. Shapira and Zingales (2017) examined an example of environmental and economic fallout in the DuPont Corporation, where toxic chemicals, such as polytetrafluoroethylene used in the company’s manufacturing process, were discharged into the Ohio River and dumped in nearby landfills along the border of West Virginia and Ohio. The subsequent class action lawsuit cost DuPont $670M, not to mention destroying its long-standing reputation as a firm committed to stakeholder management and environmental safety. Such breakdowns between publicly listed firms and environmental regulators proliferate stricter policy actions regarding pollution abatement and future energy use. In the field of renewable energy research, Duygan et al. (2022) noted an asymmetrical response from 680 organizations otherwise committed to alternative energy sources beyond fossil fuels.

Research indicates that targeting firms’ negative environmental outputs by government regulators, environmental groups, and citizens has accelerated significantly in the last two decades and shows no sign of subsiding (Cai & Ye, 2020; Costa, 2021;

Graafland & Bovenberg, 2020). As a result, companies face environmental externalities, which drive further scrutiny through environmental reporting policies, industry compliance, increasing costs concerning research and development, and innovation technology (Unerman et al., 2018; Yang & Zhao, 2023). On the one hand, firms may adopt robust environmental policies for an inevitable low-carbon transition and early compliance. Paradoxically, firms that merely report engagement in environmental initiatives may perform just as well as those embracing intensive environmental expenditures (Li et al., 2020; Turulja & Bajgoric, 2019). At first glance, this situation is not readily intuitive nor reconcilable to managers, investors, practitioners, and scholars.

The findings from these studies question the relationship between capital expenditures toward corporate environmental enhancements and long-term profitability. Is this relationship consistently linear, and to what extent do investments in environmental commitments exhibit material value? In the following sections, I investigate this paradox among a broad range of extant value maximization literature and economic research fields.

Future Direction of EVMT

The EVMT can be integrated into many value-based frameworks (Boscolo et al., 2020; Božič & Dimovski, 2019; Gleißner, 2019) because the theory applies mainly across a corporate finance and management ecosystem. Readily apparent in the theory's future direction is the firm's long-standing purpose, which is to maximize value, remain sustainable, and be competitive (Kantabutra & Ketprapakorn, 2020; Kudratova et al., 2018). Striking a sustainable balance between economic growth and environmental protection presents thorny issues, often displaying disjointed empirical coverage across economic, ecological, social science, and industrial research fields (Caniglia & Mayer, 2021; Chan, 2023; Simangan et al., 2021). Whether or not firms implement a rigorous effort toward material enhancements for the environment and the firm's innovative capacities, the principal scope of the EVMT is to maintain long-term profitable operations with an eye on qualitatively and quantitatively assessing the value of the firm's assets (Edmans, 2022).

The enlightenment element of the EVMT emanates from theory building. From a pragmatic management point of view, the EVMT is a platform for revelations concerning process approaches, laws, and generalizations that influence and inform enterprise decision-making (Kantabutra & Ketprapakorn, 2020). The streams of theoretical research on value creation would appear infinitely beneficial to finance and management scholars so long as free and efficient markets remain. In short, value-based theory and metrics tell managers and directors which decisions positively impact the enterprise. In turn, managers and directors shape value-based decisions according to initiatives accelerating market value.

The narrowing of theoretical vision helps keep the social sciences moving; the EVMT is no exception. The EVMT's longevity is partly due to interspersed organizational crises and paradigms that bring theory closer to fact (Kuhn, 1976). For this reason, value maximization has fundamentally withstood political, regulatory, economic, and technological headwinds acting on publicly traded firms dating back to the first industrial revolution (Jensen, 2010). Nevertheless, value creation is not an end in itself but rather a means toward an enlightened end state for all organizational stakeholders. The last two decades further demonstrate why value creation plays a significant role in firms' sustainability. A model example of value maximization can be seen in the Corning Corporation, a glass manufacturer established in 1851. Corning manufactures and supplies industrial materials, products, and research for e-commerce, telecommunications, ceramics, and optical fiber networks. The company's market value is driven mainly by innovation via significant expenditures in research and development, as is consistent with a priority single-objective function (Corning Incorporated, 2022). Instances of firms exhibiting value influenced practices like Corning are given consideration later in this review.

EVMT and Negative Externalities

The EVMT primarily centers on a firm's value accumulation over time. The value of a firm may not be fully priced by markets due to economic impacts driven by negative externalities and the firm's position on their mitigation (Lu et al., 2022). A negative externality, such as a firm's carbon emissions, emerges when an economic agent's effects on another are not accounted for by markets (Chatziioannou et al., 2020; Fernandes et al., 2021; Griffiths et al., 2019). According to Lehmann et al. (2019) and da Silva Rocha and Salomão (2019), these externalities occur when a polluting company produces goods based only on their direct costs without considering the indirect costs to those negatively affected by the pollution. Measuring the external cost of pollution remains complicated despite technological advances since the inception of the EVMT (Kaufman et al., 2020; Rode et al., 2021). Addressing these exogenous costs requires variables accurately capturing an industry’s indirect costs and the societal benefits that may emerge due to their attenuation.

The three predictor variables of this study represent negative externalities to society and the environment. In the discourse of Jensen’s (2002) EVMT, he asserted that companies must lead markets to the resolution of their policies and consequent cash flows over time, which can include transparency on how firms mitigate polluting outputs. At the same time, the EVMT stresses that no single firm or industry can unilaterally implement policies that attenuate externalities without governmental rule-setting intervention (Dées, 2020; Di Bartolomeo et al., 2023; Fernandes et al., 2021). The reasoning behind government intervention follows Jensen’s argument that firms will act in their best interest and choose not to internalize the social costs of the air, water, and soil pollution they create. When companies fall short of compliance, regulatory agencies and environmental protection groups will seek stricter emissions policies and taxation (Currie & Walker, 2019; Xiao, 2023). As pollution concerns continue, the question remains whether government intervention is stifling economic growth or not accelerating it enough.

Companies engaging in pollution abatement actions and technologically advanced production schemes may dilute their competitive edge and revenue streams over time when other firms refrain from bearing their commensurate share of the production externality. According to the U.S. Department of Justice Environment and Natural Resources Division (2023), most environmental crime prosecutions center on firms that dismiss environmental stewardship due to the associated costs or extensive work required for regulatory compliance. The EVMT explains how these infractions affect future decision-making through a value scorecard, explicating what is better and what is worse for the firm.

Suppose a company increases its market value over time by reconciling its pollution outputs as a function of government regulation, internal policies, procedures, and pollution reduction technologies (da Silva Rocha & Salomão, 2019). In this case, the firm's value scorecard registers this action as a contribution to the single objective of value-seeking. Under these parameters, Jensen (2002) argued that social welfare is created when all firms maximize value in an economy. This archetype stems from firms producing sustainable goods that maintain value to customers above a company's costs to produce them. Given that the EVMT represents linkages between externalities–a function of a firm's outputs, regulatory actions of governments, and costs or benefits to society–and total market value, it is not unfounded that a company focuses on value streams through the instrumentality of these domains. To reinforce the theoretical motivations of the EVMT and the inevitable headwinds due to production externalities, I provide an economic example of price, quantity, and the net effects of negative production externalities.

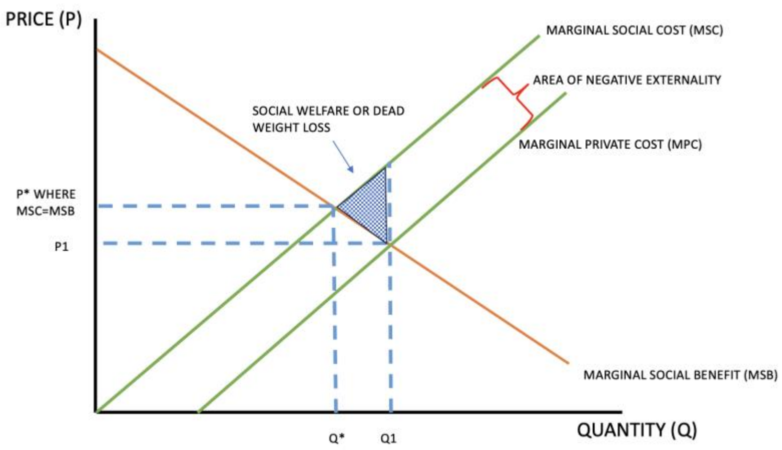
Negative Production Externalities

Eliminating pollution is not possible due to increasing socioeconomic requirements for resource extraction, farming and ranching operations, electrical power generation, and goods manufacturing (Dées, 2020; Hellegers et al., 2022; Kartal, 2022; Mateer & Coppock, 2023; Pajewski et al., 2020; Radukić & Perović, 2019; Yi et al., 2022). For this reason, the effects of externalities reside in the microeconomic discipline where production, consumption, and investment decisions of companies and households can indirectly affect others who are not a part of the economic transaction. The effect is known as the marginal social cost or benefit (Kaufman et al., 2020; Rode et al., 2021). While these indirect effects are minor–the burden of costs and returns fall only to those engaged in the transaction–when they become disproportionally high, the returns and costs spill over to whole societies (Ziolo et al., 2019). Government intervention to curb negative or subsidize positive externalities is commonly initiated when social disparities occur. As a negative example, the marginal social cost increases commensurate with increases in water and air pollution, as illustrated in Figure 1.

For this study, negative externalities are a direct function of production externalities, where the production of goods and services generates polluting outputs, coinciding with each independent variable examined in this study. The economic effects of production externalities on firms and the indirect costs borne by society can affect the marginal cost of production and consequently impact profits (Di Corato & Maoz, 2019).

Figure 1

Price and Quantity Externalities



Note. The representation of marginal social cost as a function of price and quantity. Q* illustrates the optimal intersection of marginal social benefit (MSB) and cost (MSC). Given an appropriate government externality tax on production quantity, firms will internalize this tax as a marginal private cost (MPC), narrowing the negative externality area while correcting the price from P1 to P*. Correcting negative externalities via government intervention where MSC=MSB is difficult due to inaccurate measurements of pollution-to-production output ratios. Figure adapted from Intelligent Economist, by P. Agarwal, 2022, https://www.intelligenteconomist.com/negative-externalities.

The EVMT considers the equilibrium pricing of all goods firms produce under conditions excluding externalities. According to Jensen (2002), social welfare is maximized when each firm maximizes its market value. Within this framework, negative externalities, such as groundwater contamination from over-fertilization and greenhouse gas emissions from industrial production, are regulated through government policy intervention and emissions taxation via state and federal environmental agencies (Folke et al., 2019; Leeson & Rouanet, 2021). Jensen's pricing equilibrium exempting externalities is not new; others before him, such as Pigou (1924), wrote of the merits of state intervention to prevent private enterprise failure and maximize the national economic dividend. As recent as the Great Recession and the COVID-19 pandemic, government intervention may only reduce negative externalities, not eliminate them.

The relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and MVA form my research question. To thoroughly examine each independent variable implies a reliance on market price discovery, the underpinnings of the EVMT, corporate financial and nonfinancial reporting, and the potential for government intervention to appropriately reduce negative externalities (Li et al., 2020; Paniagua & Rayamajhee, 2023). The negative production externalities discussed here add complexity to this relationship because firms under investigation in this study may act in their self-interest rather than engaging fully in pollution abatement policies.

Each independent variable described in this study is mutually exclusive in its characteristic measurement, environmental impact, and associated business risks; they share an interrelationship common to sustainability goals and corporate reporting disclosures (Caputo et al., 2019; Fiandrino & Tonelli, 2021; Gerged et al., 2021). Introducing these variables aims to provide a tangible overview of material factors that contemporary firms must manage in the current business environment. The variability of greenhouse gas emissions, waste and hazardous materials management, and water and wastewater management serve as a potential barometer for assessing a firm's market value (Khanifah et al., 2020). The EVMT acknowledges each predictor variable as an externality while jointly proposing that firms execute tradeoffs among their stakeholders and regulators that aim to increase the firm's market value through reconciling external outputs.

Variables for Analysis

In this study, I examine three environmental variables and one financial variable as a path toward statistical investigation and discussion (Hammoudeh et al., 2020). While all three environmental impact variables constitute the potential outputs of a firm's atmospheric, terrestrial, and aquatic pollutants, greenhouse gas emissions encompass firm-based outputs and naturally occurring greenhouse gases in the environment (see Malyan et al., 2022; Prairie et al., 2018 concerning waterborne greenhouse gases). The remaining two environmental impact variables, waste and hazardous materials management and water and wastewater management are the environmental variables examined through a company's operational upstream demand and downstream outputs.

The initial selection criteria for these variables centers on industry pollutant emissions and environmental waste impacts; the top five industry groups are energy generation, transportation, manufacturing, food production, and processing (Botto, 2019; Lamb et al., 2021). Statistical analysis using archival secondary data helps unpack each variable's characteristics and propensity to act upon a firm's market value. In addressing each independent environmental impact variable, a discussion of its origin, impacts on the environment, and emissions quantification in terms of environmental rating methodologies is provided (Milanés-Montero et al., 2022). Descriptions of each variable throughout this study aim to provide insights into their materiality factors–the issues influencing critical stakeholder decision-making–which appear consistent across much of the extant environmental, financial, economic, and industry analyses.

The dependent variable, MVA, is a market-based financial metric (Firk et al., 2019) that measures the wealth firms create, capture, or degrade for their primary stakeholders. MVA deals explicitly with a long-term view of the company's market value and performance versus the often shorter-term outlook of financial accounting profitability measures (Cardao-Pito, 2020; Dobrowolski et al., 2022; Gras & Krause, 2020; Mariyani et al., 2023). In the dependent variable narrative, I discuss how MVA is calculated and why it is a viable metric when considering a firm's wealth management, executive decision-making, investing, and academic analysis.

Greenhouse Gas Emissions

An explanation of greenhouse gases (GHG) is best prefaced with a brief description of the greenhouse effect–a term originated by the physicist Svante Arrhenius circa 1896–which takes into account the warming of the Earth's surface and tropospheric temperatures via the accumulation of water vapor (H_20), methane (CH_4), carbon dioxide (CO_2), nitrous oxide (N_2O), and ozone or trioxygen (O_3), hereafter and collectively (GHG) (Mikhaylov et al., 2020; Wang et al., 2023). The net greenhouse effect occurs when heat is trapped near the Earth's surface due to releasing the above-listed gases, thus increasing terrestrial and near atmospheric temperatures.

GHG emissions are an inherent consequence of the industrial complex, which is integral to established and expanding economies (Fang et al., 2022; Habert et al., 2020; Lamb et al., 2021). Dependence on industry is a precondition for global economic growth. According to Khan et al. (2023) and Miller (2018), demand for concrete, a consistent contributor to the industrial sector, takes second place only to water as the most consumed material by humans worldwide. The concrete manufacturing process–the cementitious materials that bind concrete–accounts for 2–3% of global energy demand and releases significant GHGs (Rissman et al., 2020).

Achieving an ecological and economic balance between GHG emissions, sustainable population growth, mitigating harmful environmental emissions, and measuring GHG variability remains elusive (Boesch et al., 2021; Humpage et al., 2018; Karion et al., 2020; Kaufman et al., 2020; Prairie et al., 2018; Yaman, 2020). Further GHG measurement complications emerge due to inconsistent GHG measurement methodologies, which require differentiation of in situ GHG production from anthropogenic contributions of GHG.

Disparate views concerning the release and future impacts of terrestrial, aquatic, and atmospheric GHG emissions are relatively transparent in the climate sciences–an epistemological commonality and expectation of the scientific method (Augustine et al., 2019). Literature in policymaking, environmental management, and journalism suggests a reduction paradigm. These climatic hypothetical views portray an inescapable Earth-system dystopia, which discounts a natural origin or teleological view of the universe (Alibašić, 2023; Carroll, 2006; Epstein, 2022; Ferris et al., 2020; Leidenhag, 2021;

Spencer, 2008; Stern & Stiglitz, 2021). At the same time, trends in the financial management literature tend to align with extant literature, stressing immediate corporate pollution abatement (Aczel et al., 2022; Aureli et al., 2020a; Dechezleprêtre et al., 2022; Lu et al., 2021; Pizzi, 2018). Taken together, the academic, government, and industry literature attempt to inform the universe of companies on material relationships between standard financial reporting and existential carbon transition risk exposure. Quantifying such relationships can be complex, if not illusory, save for a unified facility-level environmental reporting method that reveals a singular carbon footprint metric (Busch et al., 2020).

Mitigating the effects of GHG and relative industrial environmental impacts, such as water and waste management, brings financial markets and corporate disclosure into focus by revealing quantifiable environmental inputs relative to market perceptions and asset pricing. Recent work by Louche et al. (2019) signaled that the ongoing shifts in capital flows supporting GHG reduction and low-carbon economies would persist, suggesting that financial markets are decisive in environmental transformation. The research by Louche et al. (2019) challenges the current financial market's capacity, which centers on short-sighted logic, such as short-termism, disconnectedness between asset pricing and environmental uncertainties, value predictability via price discovery, and the lack of a dynamic carbon risk premium associated with risk-adjusted returns.

The nuance of market returns and corporate accountancy underwent examination by Huang et al. (2023), who employed ordinary least squares regression and corporate disclosure project (CDP) environmental reporting data (Corporate Disclosure Project,

2023) to investigate relationships between corporate environmental stewardship (Folke et al., 2019) and the financial ratios of return on assets (ROA) and Tobin's Q. The researchers found that impacts on ROA were significant at $p < 0.01$ (3.915) and Tobin's Q at $p < 0.01$ (–3.547). In effect, the results from Huang et al. support a hypothesis that financial constraints decrease as corporate carbon disclosures increase. Still, this hypothesis emphasizes a firm's disclosure principles and rhetoric concerning stewardship while discounting the potential granularity of measurable corporate carbon emissions.

Research focusing on the relationship between corporate carbon emissions and asset valuations builds on whether markets are presently pricing carbon risk, and if so, what is the magnitude of a carbon risk premium that investors demand for accepting risk associated with polluting firms. Bolton and Kacperczyk (2021) tested the carbon risk premium hypothesis on 3,421 transnational firms for the period 2005-2017. While the cross-sectional regression coefficients concerning total emissions and emission intensity were unremarkable, along with a winsorization of 2.5% across all carbon data to account for numerous outliers, Bolton and Kacperczyk found a statistically significant positive relationship between polluting or brown firms and a carbon risk premium embedded in U.S. equity markets; $p = 0.043$, significant at 5%, $R^2 = 0.2$. The market-driven risk premium suggests that shareholders will remain invested in polluting firms to the extent they are compensated for the added risk of holding the securities of brown firms. The implications of a non-standardized carbon risk premium influencing the asset prices of industrial firms can, by Bolton and Kacperczyk's definition, affect the MVA of firms in this sector.

GHG disclosure is particularly scrutinized in the industrial sector mainly due to its reliance on fossil fuels as a primary source of production. In most countries, climate-related disclosures remain voluntary but are rapidly transitioning to a mandatory disclosure framework. In the U.S., the state of California quickly aligned with many of the disclosure requirements drafted by the Securities and Exchange Commission at the Federal level (Robinson, 2022; Rothman et al., 2023: U.S. Securities and Exchange Commission, 2022) and are slated for enactment in 2026. Even as GHG emissions and other environmental impact disclosures are significantly increasing under a broader sustainability context (Bui et al., 2021; Datt et al., 2019; Haque & Ntim, 2022), the relationship between disclosure and profitability, particularly concerning long-term market value, remains blurred in the recent literature.

A significant determinant of profitability across industrial sectors centers on cost management and establishing an optimal capacity utilization rate. The addition of pollution abatement requirements and climate disclosure demands begin to question the long-run profitability of these sectors. Quantitative research by Larasati et al. (2020) examined the relationship between profitability (return on assets), media exposure of corporate disclosure, and carbon emission disclosure (CED) of 27 non-service industrial companies over three years. The researcher's profitability findings were insignificant ($p = 0.42 > 0.05$) with a standardized regression coefficient of .086. Media exposure, included as a moderating variable, returned a significant result at ($p = 0.001 < 0.05$) against a dependent variable of CED. Larasati et al. (2020) noted that the costs of reducing facility-level carbon outputs exceed the potential for increasing profitability. Still, the researchers dismiss the impact of the statistical model's coefficient of determination (R^2) of 0.195, which resembles the lower coefficients found in the Bolton and Kacperczyk (2021) study. The small sample research by Larasati et al. also suggests that transparency in disclosure can affect profitability without any material improvements in pollution abatement.

Corporate environmental disclosure can be elusive and question the transparency of the disclosing source. The recent work by Andrus et al. (2023) suggested that a firm's disclosure may lack transparency or be construed as greenwashing. *Greenwashing* is a term that implies a firm's attempt to report an unsubstantiated claim of environmental stewardship or through false GHG reduction disclosures (Westerman et al., 2022). The Andrus et al. research samples 1,026 firms using CDP data from 2010–2015, to which multivariable analysis supported the hypothesis that the market value of firms increases as the completeness and clarity of environmental nonfinancial data disclosure increases; $p = 0.007$ and $p = 0.05$, significant at 1% and 5% respectively. As stakeholder demands and government pressure through regulatory action persist in holding firms accountable for GHG disclosures and abatement actions, the field of environmental science remains mixed on whether an industry is disproportionally responsible for climate change.

Climate change trends are not disputable, nor are the trends conspicuously measurable. Changes in nature have proven to vanish as rapidly as they emerge (Adrian et al., 2022; Gleick, 2008; Goklany, 2015; Piao et al., 2019). For some organizations, the significant proliferation in climate generalizations represents changing systematic and non-systematic financial risks (Sciarelli et al., 2023), the former attributable to the broader market (Bannier et al., 2022). From a systematic viewpoint, environmental externalities, such as GHG emissions, can widely impact an industry's attractiveness toward investors (Falcone, 2020; Sciarelli et al., 2023; Tashman et al., 2022). Alternatively, the non-systematic risk of latent decision-making in a systematically driven market may leave corporate agents searching for leading indicators that coherently shape their industry sector. According to Dechezleprêtre et al. (2022), emerging environmental regulations add to the systematic effects of competitiveness across industries but may pose barriers to entry for specific industries.

Nevertheless, researchers lack measures to empirically demonstrate which industries and populations are most impacted (Folke et al., 2019; Sieber et al., 2022). Approaches to mitigating enterprise risk for organizational managers and directors are challenging and require additional resources. From a pecuniary standpoint, the sustainability preferences of private and public investors–accounting for more than $30 trillion in assets–add a ubiquitous sense of urgency for firms to manage their GHG emissions (Cornell, 2020). Determining a unified metric for how firms collectively perform and report financially and environmentally remains debatable across financial and legal domains (Busch et al., 2020). This paradox is mainly driven by framework discontinuities associated with government policy and lawmakers, environmental groups, top-tier fund activists, academic circles, and publicly traded companies (DesJardine & Durand, 2020; Uyeda, 2023; Wang & Wang, 2021; Yunus et al., 2020).

Current reporting methodologies align with various corporate sustainability principles and come in the form of private and nonprofit third-party environmental, social, and governance (ESG) rating agencies. The primary function of ESG agencies is to analyze and collect significant amounts of data to quantitatively and qualitatively assess a firm's ESG performance and materiality risk (Lund, 2021). The data collection efforts aim to provide insight to investors and other relevant stakeholders about the firm's material sustainability characteristics and carbon risk exposure (Freiberg et al., 2019; Hughes et al., 2021; Larcker et al., 2022). Presently, ESG rating firms total more than 600 globally, with most possessing heterogeneous rating schemes in pairwise analyses (Berg et al., 2022; Zhu et al., 2023). Considering the prolific coverage of corporate sustainability ratings and the high cost of access, one may gather that rating frameworks across agencies are highly correlated. On correlation and potential measurement unification, researcher Kevin Prall (2021) noted that correlation across some of the larger ESG rating firms is less than 50%, a statistically significant shortfall when comparing debt rating agencies reporting on the same industry sectors at 94%.

The gap between debt rating accuracy and ESG ratings is decreasing despite the intent of debt rating agencies, such as Moody's, which focus on credit market characteristics that rank order firms on their ability to service debt and avoid default across a $133 trillion debt market (Cantor et al., 2004). The corporate debt ratings are derivations of credit risk calculated using universally accepted accounting standards. Alternatively, ESG ratings can be multidimensional, applying rank order to firms using nonfinancial data across the environmental, social, and governance domains through non-standardized factors by more than 600 rating agencies (Kölbel et al., 2023; Larcker et al., 2022).

The division between numerous ESG rating agency rankings versus the ratings of the big three credit rating agencies of Moody's, Standard & Poor's, and Fitch only suggests that different risk factors exist between ESG and credit market assessments. To be sure, recent advances in ESG rating firm technology, such as artificial intelligence resources and extensive data-gathering algorithms, signal the mutual inclusion of a company's credit ratings and environmental ratings as material factors in broad rating methodologies (Capucho, 2022; S&P Global Ratings, 2023). As ESG and credit rating enterprises continue to amalgamate material risk factors, the variance in rating correlation between them should diminish while simultaneously providing quantitative researchers with robust statistical accuracies.

Measures from atmospheric science and agency-based environmental ratings suggest accurate assessments of a firm's GHGs. The Environmental Protection Agency (EPA) monitors total greenhouse gas emissions driven by facility measurements from the GHG reporting program (GHGRP). The GHGRP, initiated in 2009 to measure facility-level GHGs above 25,000 metric tons or more, tracks these gases by state, county, and emitting facility (Environmental Protection Agency, 2023). Accordingly, the corporate GHG emission inventory measures tons of CO_2 equivalent (tCO_2e) because CO_2 constitutes the majority of GHG outputs (Bakay & Ağbulut, 2021; Yaman, 2020). Truvalue Labs (TVL), the data source used in this study, collects and analyzes GHG emission data through artificial intelligence, which generates corporate ratings for all reporting firms (Hughes et al., 2021). For instance, a multinational firm like Coca-Cola's 2021 annual scope one and scope two GHG emissions are 5.17 million tons of CO_2

equivalent (MtCO_2e) (Global Data, 2022), which rendered a 2021 TVL GHG rating of 64.9 on a 1–100 ratio scale (FactSet Research Systems Inc., 2023). GHG values may differ depending on the rating firm used in a research study.

One rating agency provides a total company ESG rating of 37.7 on a quintile scale, with ratings above a threshold of 40 suggesting a high risk to potential investors (Sustainalytics, 2023). Nevertheless, decomposing the aggregate 37.7 high-risk total ESG rating to a specific GHG component is unobtainable, leaving researchers fused to all three ESG factors when pursuing statistical and financial analyses. For this reason, I focus on specific environmental ratings that do not include the social or governance portions of ESG. The GHG, waste and hazardous materials, and water and wastewater variables reveal comprehensive yet mutually exclusive environmental predictors of performance. While GHG ratings by ESG rating providers may differ due to proprietary data collection methodologies, TVL stands out as one of the most consistent and accurate providers for over two decades.

Waste and Hazardous Materials Management

The variability of waste and hazardous materials is broadly distributed across industries. Waste and hazardous material (HAZMAT) distribution have direct pollution impacts on air, soil, and water (ASW). Contamination of ASW resources perpetuates the need for robust solid waste management programs and systems at all levels of local, state, federal, and international agencies (Nižetić et al., 2019). The World Bank (2022) estimated the global waste generation rate to be 0.79 kilograms per person daily. This rate is forecasted to increase by 73% over the next 30 years. Economic and health care shocks can accelerate waste and hazardous material pollution, which is why this variable represents a material factor in society and business.

The solid waste disposal of medical supplies during the COVID-19 pandemic significantly accelerated global waste production (Tripathi et al., 2020; Yousefi et al., 2021). Industries apart from health care are also significant contributors to solid waste generation (Das et al., 2019). For example, industries associated with ground extractives and minerals processing, commonly found in lithium mining for electric vehicles and other battery-powered units, are responsible for polluting water basins and exhausting freshwater resources across expansive regions where these minerals are mainly concentrated (Dunlap & Riquito, 2023). Tampering with global water cycles due to lithium mining threatens the displacement and health of expansive human population zones and permanently destroys entire ecosystems in mineral-rich regions (Chow, 2022; Frederiksen & Banks, 2023). The commonality of ASW polluting industries suggests that industry fixed effects may elicit further insights into which sectors contribute most to ASW pollution.

Other corporate solid waste pollutants are increasing the concern of policymakers and solid waste management enterprises. Electronic waste (e-waste) such as computers, cellular phones, video players, copiers, fax machines, and cryptocurrency mining hardware form the nexus of these pollutants. E-waste primarily introduces hazardous heavy metals, such as lead, cadmium, chromium, and copper, and toxic chemicals into soil, polluting the Earth’s air and water (Ankit et al., 2021; de Vries & Stoll, 2021; Faibil et al., 2023; Li et al., 2020). In short, e-waste, as mentioned by Mowla et al. (2021), is forecast to increase globally to 120 million metric tons by 2050 unless significant abatement measures are taken. Increases in e-waste point to industries that are jointly responsible across the supply chain. These sectors represent non-energy and energy mineral extracting companies, process manufacturing firms, and downstream users of electronic components.

Single-use plastic (SUP) constitutes another source of HAZMAT pollution and possibly the most detrimental worldwide, particularly at the manufacturing stage and the downstream consequences driven by society. SUP includes but is not limited to plastic cups, utensils, water bottles, plastic bags, and microbeads. The pollution rate for SUPs entering oceans is between 5 and 13 million metric tons per year (Adam et al., 2020; G. Wang et al., 2020b). Industrial materials and processing companies significantly contribute to these sources of pollution (Budzinski et al., 2022; Law et al., 2020). The implications of continued SUP production due to high consumption rates point to consumers adding to the waste at the end of the product's lifecycle via solid waste landfill disposal or outright littering (Zambrano-Monserrate & Ruano, 2020). The volume of upstream and downstream SUP pollution is negatively impacting the planet's oceans, seas, and land masses at an alarming rate, leaving entire ecosystems and aquatic life to perish.

Many nations have implemented bans on SUPs and other plastic packaging materials in the last decade. Research indicates that plastic bans have decreased pollution marginally (Herberz et al., 2020). Adding to the abundance of waste and HAZMAT pollution is the manufacturing of single-use items during the COVID-19 pandemic.

Personal protective items such as gloves, masks, face shields, shoe coverings, eyewear, respirators, and related packaging were produced at a staggering rate (Nugnes et al., 2022). According to the World Health Organization (2020), the monthly production of 89 million protective masks was required to guard against virus transmission in medical facilities. Considering industrial increases in waste and hazardous material pollution, economic shocks precipitated by the COVID-19 pandemic suggest temporal effects that may be isolated by year, such as 2022, where net economic and financial effects of 2020-2021, a period saddled with plummeting revenues and supply chain constraints (Gunay & Kurtulmuş, 2021)–may shed light on environmental and financial outcomes.

While the solid waste and hazardous material pollutants mentioned in this section do not represent an exhaustive list, they remain potent in two ways. First, the pollutants threaten the sustainability of the natural environment as both developed and emerging economies continue expansion. Secondly, the pollutants trigger abatement policy action across corporate and governmental entities. As a result, the ratio of waste and HAZMAT pollution to enterprise value forms a relationship in the outcome of this research. I intend to analyze this class of pollution intensity across the sample population following the same data-driven path described in the GHG variable section.

Water and Wastewater Management

Water constitutes the planet's most precious natural resource, and groundwater demand far exceeds its replacement rate (Breulmann et al., 2022). The obligation to conserve water falls not only to industry but societies worldwide. While only 3% of the Earth's freshwater supply is available for consumption, a 55% increase in demand for the resource is expected by 2050 (Boretti & Rosa, 2019; Colella et al., 2021; Ungureanu et al., 2020). Considering the negative environmental outputs of industry, concerted conservation efforts by corporations and government agencies are required to sustain and recycle water. Two central problems are attributable to freshwater scarcity: surging population growth and water pollution (Gautam et al., 2020; Hernández-Chover et al., 2022; Minos, 2022). Therefore, the inextricable link between water and wastewater drives current lifecycle techniques and principles toward adopting a circular economy concerning this resource (Del Borghi et al., 2020).

Although the water scarcity issues appear alarming due to the preponderance of climate impact research, measures to strengthen water quantity and quality appear promising. For example, digitized remote sensing, which analyzes large bodies of water for stream flows, terrestrial water storage, and reservoir levels, may further assist water and wastewater management agents in determining natural source constraints before emergencies arise (Chawla et al., 2020). The need for sustained industrial and scientific investment in remote sensing is essential, requiring governmental assistance in funding and research advancement.

Accounting for water consumption at upstream utility providers is straightforward due to metering. Metering enables utilities to control water loss, forecast demand, and adjust consumption rates accordingly (Bragalli et al., 2019; Gautam et al., 2020). The industrial draw on water resources exceeds residential demands, making technological advances in remote sensing and metering integral to environmental variable measurement. Variations in consumption and wastewater management among industry sectors, such as energy-producing mineral extraction, goods processing, production manufacturing, and utility providers, constitute a principal portion of this research.

Industrial recovery of water resources fosters sustainable development and leads to a circular economy (Sotelo et al., 2021). Save for the agricultural sector, the industrial sector is the largest consumer of water (Bierkens et al., 2019; Dolan et al., 2021). Government programs, such as the United Nations Environment Programme (UNEP), establish sustainable system guidelines and goals tracing back to 1972 (UNEP, 2021). Since its inception, UNEP and similar organizations have generated pressure on industry sustainability transparency and material goals concerning water and other natural resource consumption (Cournoyer & Bazinet, 2023; Trianni et al., 2019). For these firms, plant-level consumption data is considered the most optimal method of water use measurement (Najjar & Cherniwchan, 2021).

Despite global measurement standards, heterogeneity exists within and across industrial sectors regarding how firms manage water and wastewater resources. Moreover, the parallel between economic expansion and increasing water consumption places firms and government policymakers at odds with how a sustainable environmental equilibrium is achievable (Aragòn-Correa et al., 2020; Trianni et al., 2019; Xiang et al., 2021). This gap in definitive solutions concerning water and wastewater management warrants further academic and governmental research, which I aim to narrow by focusing on consumption data elicited through environmental ratings.

The scarcity of potable water brings to light Poor Richard's Almanack of 1746, where Benjamin Franklin stated, "When the Well's dry, we know the Worth of Water"

(Franklin, 1961, pp. 60–67). However poignant almost three centuries ago, modern industrial firms increasingly understand the legitimacy behind Franklin’s words. The systemic and non-systemic risks associated with water scarcity can harm industry sectors; hence, I include water and wastewater management as a significant predictor variable in this study.

Market Value Added

Over the last five decades, much has been published concerning the sole purpose of a corporation. Some economic theorists maintain that a manager’s singular purpose is to maximize the firm's market value for its owners' benefit. Others, such as business ethicists, disagree, insisting that a manager must account for the interests of all stakeholders, i.e., employees, suppliers, public officials, the environment, and communities (Jensen, 2002). Maximizing the long-run value of firms is a subject of interest and debate for investors, managers, and stakeholders alike. Conjecture aside, a firm’s economic security and financial sustainability depend on advancing its market value (Baydaş et al., 2022; Lund, 2021), which is why I elect the multifaceted metric of MVA as the criterion variable for this study.

There are several dimensions of complexity in monitoring the MVA of a company. At the value assessment–economic security nexus, Zinina and Olentsova (2020) proposed a system of inequalities presumed requisite for the sustainability of an enterprise, which considers

$$rc < rr < rp < rac < rit$$

where *rc* is the growth rate of production costs; *rr* is the rate of revenue growth; *rp* is the growth rate of profits; *rac* is the growth rate of advanced capital; and *rit* is the growth rate of technological innovation. While the economic implications of this system of inequalities are straightforward from the perspective of sustainability, the advancement of capital growth, *rac*, and its application, appears least understood by management practitioners, specifically during times when competing stakeholder demands redirect capital advancements away from long-term value maximizing activities in attempts to solve short-term social dilemmas (Battilana et al., 2022; Han, 2023). These short-term advancements suggest a misappropriation of capital and a long-term destabilizing effect of capital growth.

In such cases where the distribution of investment capital appears misappropriated, management practitioners can return to the tenets of the EVMT, specifically the fifth, which stresses that the fundamental function of market value maximization means spending an additional dollar of resources to satisfy the requests of each constituency as long as the firm's constituents value the result at greater than one dollar (Jensen, 2002). Alternatively, the framework can fail when the result of expenditures generates no gains in long-term value. In other words, once believed to be a catalyst for value creation, key enterprise performance indicators can no longer sustain long-term growth. This dilemma, while not immediately intuitive, may shift the foci of management back to the third tenet of the EVMT, where pursuing multiple objectives results in no objective. Keeping score of which actions develop or degrade value–the tenth EVMT tenet–via the quantitative measurement of MVA provides a decisive scoring method.

Researchers, investors, and financial analysts measure a firm's tangible and intangible value under the context of MVA and economic value added (EVA). MVA and EVA help quantify a firm's capital management aptitude and consequent wealth generation for shareholders (Gras & Krause, 2020). In the comprehensive study by Lee and Kwon (2019), contrasting back propagation neural networks and multiple regression models revealed that manufacturing firms' environmental stewardship and transparent reporting accounted for a 41% increase in MVA as these strategic predictor variables were elevated on a one-percent incremental basis. I use MVA as the dependent variable in this study, which is contextually consistent with the Lee and Kwon study, save for the corporate reputation variable. In this study, MVA was chosen as response variable over EVA due to internal and external factors that differentiate the two.

The multidimensionality of MVA, which can exhibit deviations across the universe of global equities, considers the elementary calculation of debt, equity, and market capitalization. As a result, MVA can represent different outcomes based on each firm's industry alignment, environmental, social, and governance characteristics, management structure, debt maturities, persistent fluctuations in equity holdings, market perceptions, information asymmetries, and historical measures of volatility (Carini et al., 2017; González-Rodríguez et al., 2021; Gupta & Das, 2022). At its core, MVA provides characteristic long-term value insights as measured against industry environmental performance.

Allocating a firm's capital resources toward projects that maximize its long-term economic value is integral to corporate decision-making. As value measures, EVA and MVA complement each other when managers attempt to clarify the intrinsic and extrinsic value of strategic opportunities (Arnold et al., 2023). MVA and its predecessor EVA were developed in the 1980s by Stern Stewart & Co. In its calculation, Stewart (1999) noted that EVA is simply a firm's operating profits minus the cost of the firm's capital, which is leveraged to produce the profits. By employing the EVA measure, managers may examine the company's residual profitability, or net profit after tax (NOPAT), after subtracting its cost of debt and indirect cost of equity capital, known as the weighted average cost of capital (WACC).

MVA is a function of EVA in terms of long-run returns on equity, save for the substitution of book values of debt (BVD) and equity (BVE) with market values of debt (MVD) and equity (MVE) (Kostin, 2018). Markets, on average, provide a reasonable price discovery mechanism for all securities worldwide (Wang, 2022). For this reason, MVA can vary particularly during broader market peaks and troughs or through industry sector price discovery. The key takeaway is that MVA is a systematic reflection of value perceived by markets. In contrast, EVA is a non-systematic firm-level snapshot of how well management utilizes the company's capital. Table 2 amplifies the difference between EVA and MVA.

Table 2

Differences between EVA and MVA

Value Measure	Calculation	Purpose	Advantage	Disadvantage
Economic Value Added (EVA)	EVA = Net operating profit after taxes (NOPAT) – (invested capital x Weighted average cost of capital (WACC)).	An internally-oriented performance-based measure of a company's economic advance or decline over time.	Provides a historical barometer of economic profit and estimates the opportunity cost of different investments or projects.	Relies on invested capital and established tangible assets for accurate measure.
Market Value Added (MVA)	MVA = Market value of equity (MVE) + market value of debt (MVD) – all contributed capital from investors.	An external wealth-based measure of the company's market value above or below its invested capital by bond and shareholders.	Reflects the market perception of how well a firm has managed capital resources and wealth creation for shareholders.	Management cannot influence broad market securities pricing or industry trends, which can exogenously impact a firm's market value.

MVA can be negatively affected when value creation becomes less of a priority than social dimensions. For example, in a manufacturing company study, Lucía Sabogal-De La Pava et al. (2021) found that increased dispersion among stakeholders, specifically across raw material suppliers and distribution locations, reduced the MVA of the firm significantly under all sensitivity analyses. These findings reinforce the need for financial accounting agents to closely monitor and report the firm's EVA and MVA calculations to corporate steering committees.

While there is no shortage of research studies concerning corporate environmental performance and its potential effects on shorter-term profitability ratios (Algarni et al., 2022; Hang et al., 2019; Li et al., 2020; Nizam et al., 2019), few studies examine relationships between corporate environmental performance and MVA (Garcia-Castro et al., 2011; Mamilla & Vasumathi, 2020; Sabogal-De La Pava et al., 2021), which as mentioned above, is the difference between a company's market value–the firm's equity share price multiplied by the total shares outstanding–and the capital contributions of all its investors. MVA is helpful to investors because it is a forward-looking measure that centers on a firm's market value created (destroyed) above (below) its invested capital (Apreku-Djan et al., 2023; Lee & Kwon, 2019). A higher MVA indicates a market premium set above the capital provided by all of the firm's investors and provides a forecast of a company's value. This premium fundamentally amplifies Jensen's (2002) value-maximizing framework, stressing the employment of longer-term value measures.

In value-based analyses, some researchers will further examine the nonfinancial performance of companies under the lens of their leadership or, more broadly, its characteristic governance (Kasbar et al., 2023). Other researchers employ value measurement criteria concerning a firm's social and environmental capacities (Dhar et al., 2022). The strand of research covering firms' ESG attributes has become a mainstay of academic and financial inquisition since its inception in 2004 (Edmans, 2022; Li et al., 2020; Lund, 2021). When management pursues a single-valued objective, MVA may shed light on how nonfinancial environmental metrics relate to value-based accounting and market perceptions (Cardao-Pito, 2020). The evolution of corporate valuation models demonstrates that MVA represents a viable approach toward clarifying value-based profit over a given period (Baydaş et al., 2022; Rahman, 2020). Therefore, the purpose of incorporating MVA as this study's dependent variable is to investigate the relationship between the previously mentioned environmental independent variables and the intrinsic value added for the firm's owners.

Because the indicators of value are latent and do not appear immediately recognizable to a firm's management, agents are faced with determining whether and how corporate decisions foster growth and value (Kostin, 2018; Zhang & Cui, 2020). Accordingly, finance and risk managers serve substantial roles in a company's decision-making process and value-based judgment (Firk et al., 2019; Willumsen et al., 2019). Thus, the quantitative integration of risk and financial management elucidates the net effects of a company's decisions toward capital structure, capital flows, research and development, product improvements, and organizational processes (Boisjoly et al., 2020; Singh & Bagga, 2019).

While financial and risk management serve functions in the corporate domain, their forecasting scope is limited to historical data emerging from past accounting statements and previous risk assessments. Annual MVA amplitudes can help reveal all the present values of a firm's expected future economic value added (EVA), including value creation associated with integrated reporting of nonfinancial environmental impacts across all industries (Dobrowolski et al., 2022). Measuring MVA is straightforward through inspection of a firm's balance sheet, income statement, and the current market value of the firm's equity shares and debt instruments. Using an example fictional firm whose current market value is $4 million (500,000 shares outstanding x $8.00 current market price per share), with debt and equity valued at $1.7 million, suggests an MVA of $2.3 million. Thus, MVA = the market value of equity + the book value of debt – all capital provided by investors.

In summary, iterating between the theoretical basis of value maximization, reporting environmental impacts, and the periodic functions of data-driven financial reporting can allow managers to build on known value drivers to enhance value for all enterprise stakeholders (Carini et al., 2017; Han, 2023; Hitt et al., 2021; Klein et al., 2019). As the current economic shift in investment preferences tends toward environmental sustainability concerns, the potential for corporate agents to lose sight of enterprise value maximization generates concern for the long-run sustainability of firms (Kong et al., 2020; Sahrul & Novita, 2020). Equally concerning is the ability of researchers and practitioners to efficiently investigate the relationship between nonfinancial variables and classical financial accounting measures (Arif et al., 2021; Kristi & Yanto, 2020). MVA aggregates present and future economic values while orienting corporate leaders' focus on multidimensional objectives that obscure a single-valued corporate objective.

Secondary Data Analysis

Utilizing secondary data allows quantitative and qualitative researchers to access published data from other entities, such as the U.S. Securities and Exchange Commission, which I employ in this study. The cost of leveraging secondary data can range from inexpensive open-source access to costly for specific commercial purposes (Olabode et al., 2018). Nevertheless, accessing the data can expedite the researcher's collection efforts for analysis pertinent to a doctoral study. Accessing secondary data eliminates the need to create new data, save for the tertiary data conversion for my research purposes (Gelman et al., 2021; Johnson et al., 2019), which optimizes a researcher's time spent on quantitative analysis (Saunders et al., 2016). Conversely, secondary analysis can pose potential disadvantages, such as time-consuming activities in locating secondary data appropriate for the researcher's needs and ability to support the research question (Wickham, 2019). Other pitfalls include but are not limited to data validity, e.g., a greenhouse gas variable with values applicable only to hydrochlorofluorocarbons, and reliability, a concern for both the researcher and others who desire reproducibility in follow-on research (Cheng & Phillips, 2014).

Using multiple source document secondary data from FactSet Truvalue Labs and open-source financial statement data from the Securities and Exchange Commission allows an appropriate basis of analysis for this study. Bai et al. (2020) found that collating insightful archived secondary data best supports the study of sustainable industry development goals in a quantitative value function matrix. Similarly, Wamba-Taguimdje et al. (2020) employed secondary data to elucidate firms' financial performance relative to process improvements via artificial intelligence. The studies by Bai et al. (2020) and Wamba-Taguimdje et al. (2020) employ large data samples, a practical benefit of secondary data resources, and are similarly helpful for conducting this study. Although secondary data analysis cannot replace principal approaches used in other research domains, such as medicine (Wickham, 2019), I exploit financial and environmental economics in this study, which is congruent with correlational research designs.

Transition

Sustainable investment and development are central to capital flows and can financially impact numerous firms' market value. In the management field, adverse environmental impacts due to industry outputs represent an area of concern for corporate stakeholders, frequently due to an increasing mobilization of external factors such as investors, government regulatory policies, and interest groups pressuring firms to adopt meaningful environmental stewardship. Consequently, some management practitioners are tipping the scales away from pollution-centric practices toward environmental accountability.

Questions remain about whether managerial actions toward stewardship are profitable in terms of long-run market value. According to my academic and professional review of the literature, the answer remains mixed, leaving a gap that warrants a further examination of the relationship. For this reason, I employ a multiple regression model alongside the theoretical premises of the EVMT to gain added insight concerning this relationship.

With the foundation of the study complete, Section 2 follows with a description of the project. This section provides a restatement of the study's purpose, my role as a researcher concerning data collection, the constituent firms under analysis, my chosen research method and design, the target population and sampling, ethical research considerations, data collection instruments and techniques, data analysis, and research validity.

Section 2: The Project

The enlightened value maximization theory (EVMT) catalyzes management to decide on required tradeoffs between multidimensional objectives and a single value-maximizing objective. The success criteria of this project concerned connecting and demonstrating the theoretical concepts of the EVMT with practical environmental and financial observations. For this reason, I draw on the research method and design I employed in this quantitative correlational study to examine the relationship between corporate environmental performance and firm value. Within this section, I discussed the following topics: (a) the purpose statement, (b) the role of the researcher, (c) the constituent firms and industry sectors under analysis regarded as participants, (d) the research method, (e) research design, (f) population and sampling technique, (g) ethical research considerations, (h) data collection methods, and (i) examination of the data and validity. Section 2 concluded with a transition and summary.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management and firm value. The target population comprised all U.S. publicly traded transnational industrial companies. The independent variables were derived from: (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management. The dependent variable was MVA.

Role of the Researcher

My role as researcher for this quantitative correlational study adhered to the criteria outlined in Walden University's quantitative study research handbook and the institutional review board's compliance requirements. I collected one year of secondary data (Olabode et al., 2018) supporting the environmental performance and firm value nexus coinciding with my independent and dependent variables. Integral to the data collection is a researcher's ability to assess and ensure the data quality is appropriate for analysis. According to McLaughlin et al. (2021) and Moore et al. (2021), researchers may sacrifice end-state statistical robustness should they fail to account for data quality assurance and control, such as the means of collection, maintaining measurement quality, detection and correction of errors, and cautious significance testing. It follows that for the researcher, the quality of a quantitative study is proportional to the time spent immersing oneself in the data.

Given the importance of data quality, I confirmed my data sourcing through FactSet Truvalue Labs and the Securities and Exchange Commission as the researcher responsible for this study. My archival data collection principally centered on retrieving a 2022 corporate annual financial report from FactSet and the U.S. Securities and Exchange Commission via the open-source site known as the electronic data gathering, analysis, and retrieval (EDGAR) system to confirm the numerical values required for calculating the dependent variable of MVA. Loukas et al. (2021) drew upon natural language processing to enhance the EDGAR system so that researchers could rapidly access specific elements of company financial reports. In addition to leveraging EDGAR and FactSet, I retrieved environmental data that principally formed the study's three independent variables from FactSet Truvalue labs, which specializes in collating company environmental insight data for commercial distribution to investors, institutional pension and hedge funds, and academics (Truvalue Labs, 2023). The cost of the FactSet Truvalue labs data was high and assumed by the researcher to ensure data accuracy, statistical generalization of the representative population, validity, and reliability (Pesämaa et al., 2021). Despite scholarly attempts to validate the secondary data for this study, its suitability can be relied upon but is never absolute.

My engagement in quantitative analysis followed Franklin (2022), who argued that quantitative analysis retains an uncertainty constant, such as the unobservable elements embedded in the residual error term of a regression. My aim was to deliver a comprehensive yet temporally bounded study to mitigate a worldview by presenting an impartial representation of a statistical relationship nested in correlation (Gregersen et al., 2020). With these ends in mind, I was not concerned with the receptiveness or ambition of a company's adoption of environmental stewardship but rather with whether corporate environmental performance shared a statistical relationship with firm value. I did not include human participants in this study to mobilize this impartiality. Instead, I collected secondary archival data made available through open-source sites and commercial data aggregators (Lam et al., 2020; Wamba-Taguimdje et al., 2020). The participant data collection approach recognizes and adheres to the ethical guidelines of the Belmont Report, a comprehensive government report that outlines mandatory ethical principles that warrant a researcher's compliance when studying human subjects (U.S. Department of Health and Human Services, 1979). The report stresses: (a) respect for persons, (b) beneficence, and (c) justice. Lastly, I employed the econometric statistical software known as Stata (Stata, 2023) via my annual student licensing subscription to effectively analyze the required data points for the study.

Participants

The participants for this study were the constituent industrial firms traded on the NYSE whose financial data and performance are publicly available through EDGAR or a FactSet Research Systems academic account. There were no human subjects under investigation in this study. Participant action was exclusively governed by the release of continuous numerical secondary data associated with publicly traded entities to answer the research question in correlational terms (Frost, 2020; Mohajan, 2020). The industrial companies I investigated centered on firms in the following industry sectors with FactSet industry codes in parentheses:

1. Producer Manufacturing Sector (1200)
2. Energy Minerals Sector (2125)
3. Process Industries Sector (2200)
4. Electric Utilities (4705)

Industry sectors offer a way to examine broader industrial firms among their sectors that may perform similarly in various economic settings, which is integral in many regression-based studies employing similar industry data (Broadstock et al., 2021; Zhang et al., 2023).

I based the selection of these sectors on environmental and energy-intensive impacts characteristic of industrial production, energy mineral extraction, manufacturing, goods processing, and utility providers (Brundage et al., 2018; Dechezleprêtre et al., 2022; Gerged et al., 2021; Oreggioni et al., 2021). I also considered these sectors relevant to the rapid acceleration in climate change assumptions. Indeed, climate change issues and emission reduction policies have been ongoing since the mid-1970s. At no other time than in the last half-century has climate-related discussion and scientific modeling received more political and scientific attention than in the last five years. Among the target population, I excluded automobile manufacturers due to the upstream dependence on supply chain firms producing their final component materials (Mohammad Ebrahimi & Koh, 2021; Nygaard, 2023), which can further complicate environmental impact estimations.

All firms in the sample population are publicly traded on the NYSE, with market capitalizations ranging from $35 million to $184 billion (Folke et al., 2019). Each participant firm provided at least two years of corporate environmental disclosures captured by environmental rating agencies (Truvalue Labs, 2023; Value Reporting Foundation, 2022) and more than five years of financial reporting data. The industry sectors, financial marketplace, and data sources provided the analytic structure to map participant firms to corporate profitability.

Research Method and Design

Research Method

The decision to employ the quantitative method for this study stemmed from the need to numerically examine and conduct hypothesis testing on the relationship between environmental impact variables and firm value (Frost, 2020; Mohajan, 2020). The rationale behind using the quantitative method supported the study's two primary goals–including linking my research objectives to a suitable research method. The first objective aligned with the systematic quantification of numerical data, which Rahman (2017) and Slaney and Tafreshi (2021) described as advantageous for research generalization applicable to a broader population. The second goal addressed potential management knowledge gaps using measurable variables in a statistical setting (Amrhein et al., 2019; Rezaei et al., 2021). For these reasons, and others expressed across the social sciences and scientific community concerning inferential findings via deductive reasoning (Borgstede & Scholz, 2021; Proudfoot, 2023; Sanyal et al., 2022; Suryansyah et al., 2021), my selection of the quantitative method–in comparison with qualitative and mixed-method research methodologies (Dewasiri et al., 2018)–was an optimal means of conducting this research project.

Applying a qualitative research method could further the goal of answering my research question and add potential contributions to the field of study and theory building. Recent research by Lo et al. (2020) demonstrated the effectiveness of the qualitative method in the business and management field, particularly concerning the employment of fuzzy-set qualitative comparative analysis (fsQCA), where inputs of causal conditions often translate to effectual outcomes. Similarly, Rodrigues et al. (2020) leveraged fsQCA to illuminate specific elements of corporate governance that coincide with higher research and development performance. I decided against using the qualitative method because it does not support the primary function of numerical analysis in the environmental and financial space.

Mixed-method studies can also enhance the value of this research field and show promise in similar fields of study. To be sure, Sarfo et al. (2022) employed the mixed-method approach to adeptly illuminate the relationships, sensitivities, and interactions between land use and regional surface temperature variations using expert interviews and numerically driven geostatistical resources. Mixed methods assemble quantified participant surveys or other numerically measured data and participant interview data to meet conditional research objectives, reveal purposeful results, and generate sound decisional criteria (Eicke & Goldthau, 2021; Gibson, 2017; Villena et al., 2021). Despite the usefulness of mixed-method research, it did not support the intent of my study, which exclusively involved examining numerical data to gain insights on the environmental-financial nexus.

Gaining added knowledge through qualitative and mixed-method examinations of the individual experiences of managers implementing value-based metrics within their respective firms provides beneficial insights otherwise unobservable in pure quantitative analysis (Arnold et al., 2023; Dewasiri et al., 2018). Nevertheless, the research goals I intended to achieve for this study focused on numerically driven environmental impact variables and their relationship to firm value, which call for the quantitative research method.

Research Design

The theoretical framework and the research question formed the basis for conducting this research and interpreting the study, which quantified the strength and direction of relationships between variables using statistical regression nested in a nonexperimental design (Frost, 2020; Siedlecki, 2020). Dewasiri et al. (2018) and Roberts and Hyatt (2019) argued that researchers must consider the research design selection early in the research process as the theoretical framework, research problem, purpose, and question materialize. Given these considerations, my nonexperimental approach was appropriate for accomplishing this research goal.

Three types of research designs punctuate social science research. The first represents experimental studies, which test cause-and-effect relationships. That is, the researcher separates the cause from the effect by injecting counterfactual causation–the method of providing specific treatment to one randomly assigned group while withholding the treatment from another–and assesses the mean effects or differences between the groups (Pattison et al., 2019; Reed et al., 2021). The second design is quasi-experimental, similar to the experimental paradigm, except treatment groups are divided using nonrandom factors (Andrade, 2021; Pattison et al., 2019; Waardenburg et al., 2020). The last type of research concerns the nonexperimental design, where there is no manipulation of variables and no intent to infer causal linkages regarding the research question (Allan & Skinner, 2020; Siedlecki, 2020).

The nonexperimental paradigm was suitable for this study given my research criteria, which advocated non-causal applications of correlation and statistical regression to examine the relationship between the variables. Multivariable analysis accomplished the initial research goal of this study (Duan & Luo, 2022; Loaiza et al., 2021; Rosoff et al., 2020), where I measured the strength and direction of each participant firm's MVA using the independent variables discussed in pages 33–47.

Population and Sampling

Population

The population for this study comprised transnational industrial firms listed for public trading on the NYSE. From this target population, a sample of 140 firms provided their annual financial reporting to the U.S. Securities and Exchange Commission (SEC) and further proprietary information to environmental rating agencies concerning environmental impacts (Gensler, 2022). Numerous firms from the target population do not voluntarily provide their environmental impact data, which creates a forcing function for convenience sampling (Fulop & Avvisati, 2022; Griffith et al., 2020) and the subsequent 140 participant company sample result.

The principal factor in selecting this target population of industrial firms was driven by my research question to examine the relationship between environmental performance and firm value. I deployed convenience sampling to assess the relationship of the study's variables, which centered on energy reliant industries mainly responsible for economic growth and production (Ateba et al., 2019; Matubatuba & De Meyer-

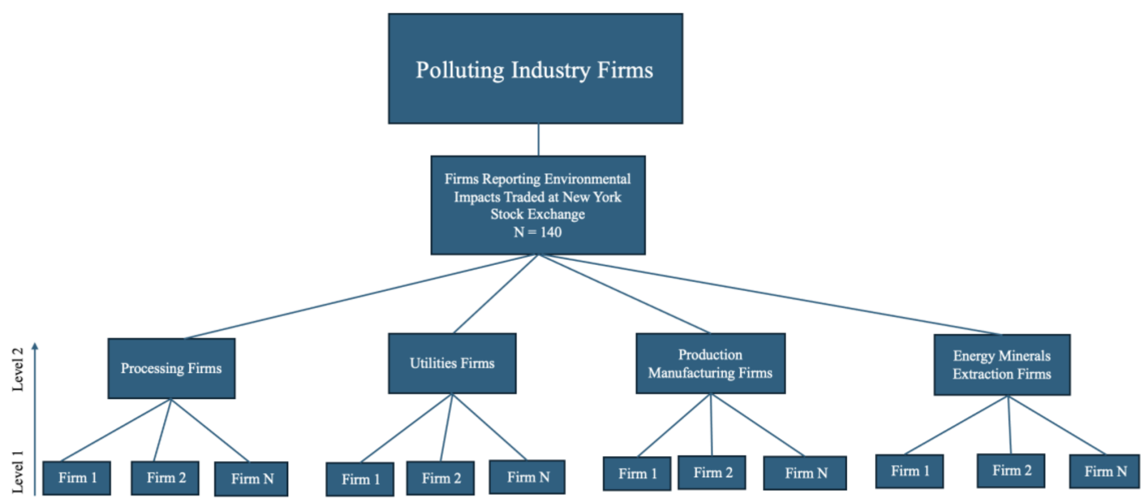
Heydenrych, 2022l; Zhao et al., 2023). All firms in the target population encompassed the four industry sectors listed on page 61, which represent:

1. Producer manufacturing companies, such as firms that purchase goods and transform them into other products for downstream use.
2. Energy mineral companies extracting minerals such as coal.
3. Process industry companies providing food, beverage, and pharmaceutical goods.
4. Utility companies providing electricity and natural gas to homes and businesses.

I selected all firms providing nonfinancial environmental data from these four industry sectors, which formed the sample size and the sampling frame of 140 available firms spanning the industry sectors. Figure 3 illustrates the hierarchy of firms, which were examined for the year ending 31 December 2022.

Figure 2

Sample Segmentation



Sampling

Methods of sampling can be divided between probability and nonprobability selection strategies. The former relies on random selection, while the latter is based upon a researcher's specific criteria, judgement, or availability. Tutz (2023) argued that while probability sampling offers a concrete basis for the computational accuracy of estimates, the nonprobability method of sampling is rapidly gaining widespread use among researchers due to the ability of sample manipulation using calibration weighting and enlarged regression residuals for more robust results. The key takeaway in differentiating between probability and nonprobability methods is that probability samples are desirable in research due to reductions of systematic bias in representation (Sandstrom-Mistry et al., 2023). Alternatively, nonprobability sampling limits empirical inference but is more cost effective than probability sampling.

Probability and nonprobability sampling methods comprise the echelons for the types of sampling that fall below them. Because I chose the nonprobability method for this study, it was important to select the appropriate type of sampling from the common types available. These nonprobability sampling types include convenience, volunteer, judgmental, and quota. Of these sampling types, I deployed convenience sampling due to the ease of access and the existing industrial companies that rank highest in polluting outputs. Compared to other sampling types, convenience sampling, also called availability sampling, derives its advantages from an affordability, accessibility, and timeliness standpoint. To be sure, Szcześniak and Tułecka (2020) employed convenience sampling in a nonexperimental correlational study to assess relationships of behavioral tendencies, to which their accessible sample online population provided a low-cost alternative and timely access to the desired participants. While Szcześniak and Tułecka's (2020) convenience sampling method was voluntarily chosen, other researchers may be involuntarily channeled into this sampling method. For instance, Asiamah et al. (2022), Castro-Martín et al. (2022), and Stratton (2021) all noted that convenience sampling methods, while statistically constrained by selection bias and consequent generalizability, are often required for researchers conducting studies where the supply of participant data is preconditional and determining relationships versus point estimates is emphasized (Fulop & Avvisati, 2022), which applies to the industry sectors I investigated.

Convenience sampling can affect research outcomes depending on a researcher's goals (Maravelakis, 2019; Pobee, 2022). When the principal research intent is identifying trends or relationships without concern for probabilistic causation (Glynn, 2011), the approach is helpful due to the ease and fractional cost of accessing the data. According to Lehdonvirta et al. (2021), exploratory research concerning policy issues is gaining the attention of researchers in a big data era where large sample sizes tend to control the parameters of research criteria, making the convenience sampling a means to report tentative trends. Further use of convenience sampling concerning market price indices and industry reporting was studied by Seljak et al. (2018), who noted only slight variation in standard error estimation between probability and nonprobability sampling procedures; 1.06 vs. 1.46 percent over 12 data reporting quarters, respectively. In support of the convenience sampling approach, I drew on the work of Hubbard et al. (2019), who argued the indispensability of convenience sampling, where the preponderance of scientific knowledge is reported through nonrandom strategies. Given the finite population of publicly traded firms in the industries under investigation and my resulting sample size of 140 natural resource-consuming firms who voluntarily reported their proprietary environmental impact information, selecting the convenience sampling approach provided a suitable mechanism for this study.

Convenience Sampling and Environmental Data

The convenience sample I used in this study centers on polluting industry sector companies that make their environmental impact data available. From a statistical analysis view, data from a convenience sample can cause inconsistencies in ordinary least square estimators (Hirschauer et al., 2022; Wooldridge, 2019) due to the potential divergence from a normal distribution. Despite the propensity for measurement problems coinciding with the convenience sampling typology, the availability of firms that report their environmental impact data elicits two key factors suggesting that the firm-level data I collected is a robust and testable sample. The first factor accounts for firms' self-selection (Choudhury, 2023) in a rapidly expanding population that reports their natural resource usage and commitment to resource preservation.

The second factor concerns the regression function of a convenience sample. Wooldridge (2019) and Gelman (2021) argued that the regression function is the same for any population subset using the same independent variables, with the only constraint being smaller sample sizes. Despite the unbiased measurement argument associated with convenience samples, Hirschauer et al. (2021) noted that the inherent unmeasured confounders in a convenience sample prohibit empirical inferences, an approach avoided in this correlational study.

Determining Sample Size With G*Power

Determining the minimum sample size for this correlational study traced back to my initial research outline, which proved to be an iterative process as firms within the industry are subject to altering their environmental impact reporting (Deloitte, 2022). Notwithstanding the nuances of corporate reporting policies, I noted an increase in targeted industry firms reporting environmental impacts, the densest and most relevant data reported in 2022. Thus, the increased environmental data reporting influenced my analytical focus on the 12 months ending 31 December 2022.

For the research question and two-tailed hypothesis test (Cohen, 1992), I used a significance level (α) of 0.05 with an effect size of 0.15 and a statistical power (1– β) of 0.95. Using G*Power software, version 3.1.9.6 (Faul et al., 2009), I performed an a priori power analysis (Linear multiple regression: Fixed model, R^2 deviation from zero) for a resulting suggested sample size of $n = 119$. My sample collection of 140 available companies exceeded the suggested sample size of 119 by 21 companies.

The significance level (α) I selected stands for how strong the sample evidence must be to confirm that an effect exists in the population (Frost, 2020), with power parameters (0.05, 0.15, 0.95) aligning with regularly accepted levels across social science and econometric research (Hansen, 2022a; Gelman et al., 2021; Salvatore & Reagle, 2002; Wooldridge, 2019). The effect size numerically measures the strength or magnitude of the relationship between variables or the size of differences between group means as ordered by the discrepant elements of the null and alternative hypotheses (Aiken & West, 1991; Cohen, 1992; Schäfer & Schwarz, 2019; Sullivan & Feinn, 2012). My effect size selection of 0.15 followed Cohen (1988, 1992), who considered the 0.15 level moderate. Statistical power (1– β) refers to the probability of a hypothesis test detecting a true effect if an effect exists (Baguley, 2004; Frost, 2020). This study's statistical power parameter (0.95) considered the interrelationship between my sample size, population variability, and effect size (Frost, 2020; Hansen, 2022a; Kang, 2021; Lakens, 2022; Salvatore & Reagle, 2002).

Researchers can input different a priori statistical power parameters in G*Power to approximate the probability of rejecting (or failing to reject) the null hypothesis (Lakens & Caldwell, 2021). Considering these probability approximations, Kang (2021) and Baguley (2004) argued that research is rife with statistical power and sample size issues due to the need for baseline statistical knowledge, which a researcher needs before establishing initial power parameters or estimations of a finite population. The power parameter selection for this study preceded my initial research plan, becoming iterative in G*Power as the number of predictor variables, research designs, and access to relevant samples were contemplated and eventually determined suitable for dispatch. I illustrate my G*Power analysis in Figures 3a and 3b, which graphically represent the approximate parameters required for the study.

Figures 3a and 3b

*G*Power Parameters and Power as a Function of Sample Size*

Figure 3a

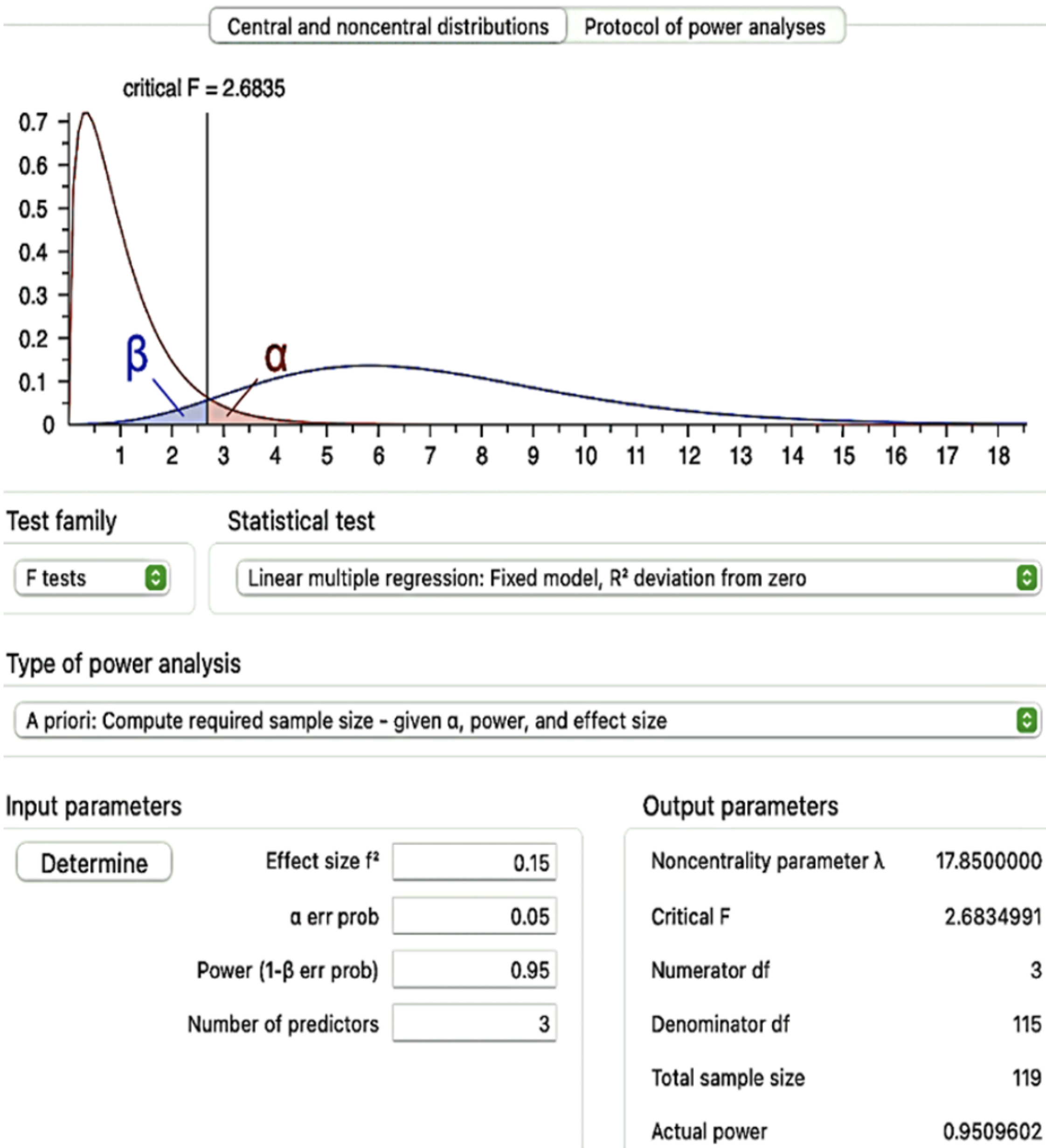
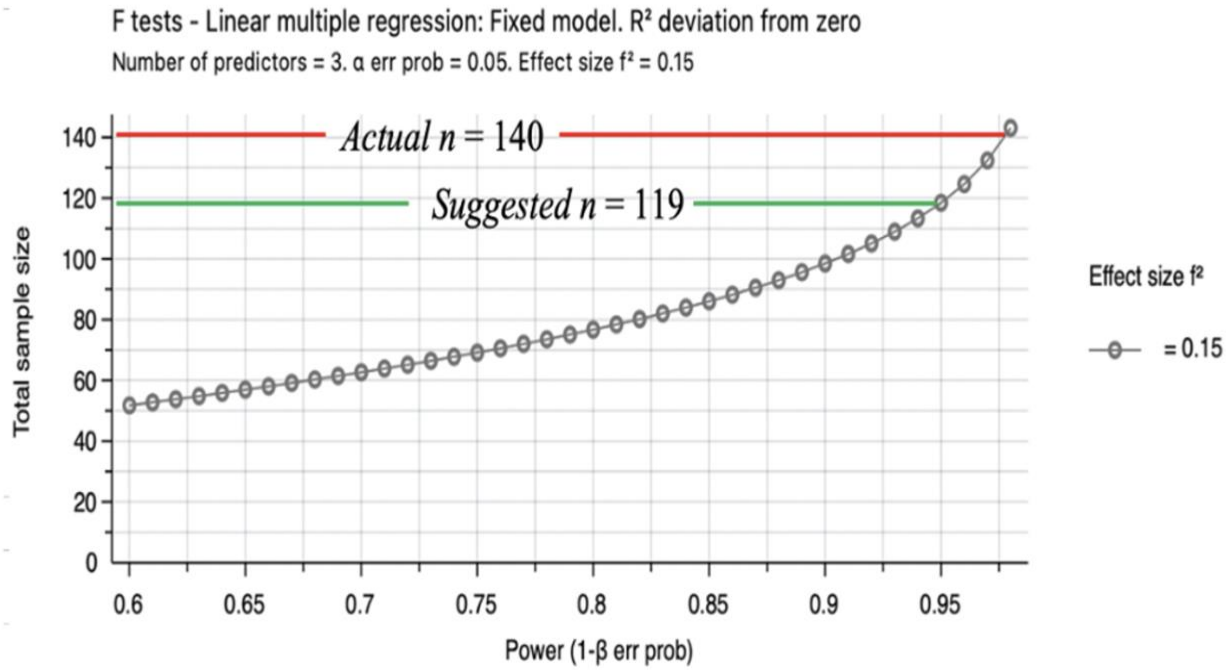


Figure 3b



Note. Figure 3a illustrates the input-output parameters for approximating sample size using G*Power software with my chosen parameters of effect size (0.15), significance level (0.05), power (0.95). In Figure 3b, the X, Y intersect indicates an a priori suggested sample size of 119 (21 cross-sectional observations less than my sample) with a statistical significance threshold of 0.05, an effect size of 0.15, and power of 0.95. For the model, I used three predictor variables (*GHG, WHZ, WAT*). In this study, I tested the relationship between these independent variables and MVA in two directions, implying a two-tailed hypothesis test. As such, the significance level percentage ($\alpha = 0.05$), which represents the probability of rejecting a correct null hypothesis, is equally applied between both tails of the distribution. From "Sample size justification," by Lakens, D, 2022, *University of California Press, 8*(1), p. 5 (https://doi.org/hqbs).

Ethical Research

As is common in human participant research, ethical considerations are scrutinized. While the awareness of ethical dimensions in research is clearly defined in the Belmont Report (U.S. Department of Health and Human Services, 1979). Zgaga (2020) argued that researchers view the current ethical review system equivocally. Indeed, ambivalence toward the present model can center on various asymmetries between researchers and participants, such as those punctuated by differences in status and age (Thomson & Berriman, 2023). Despite these tensions, a majority of the literature suggests that researchers coherently inform participants concerning their role, consent, confidentiality, anonymity, and their right to withdraw during the research process (Mannheim et al., 2019; Montreuil et al., 2021; Sim & Waterfield, 2019).

Within the scope of human participatory research, the secure storage and transmission of participant data is required. To be sure, Adeoye-Olatunde and Olenik (2021), Edwards et al. (2020), and van Zoonen (2020) stressed the importance of securely storing participant data across all research fields, with particular emphasis on healthcare, municipal, and educational domains. Ethical compliance concerning secondary data analysis is also a requirement. Considering the acceleration of artificial intelligence and big data collection schemes, the potential for erroneous personal and organizational data transmission increases (Chang, 2021; Munoko et al., 2020). To reduce the risk of ethical issues centering on secondary data collection, I retrieved numerical financial and nonfinancial data publicly available through open source and data aggregation entities, namely, the U.S. Securities and Exchange Commission and FactSet Research Systems.

As such, I did not engage in human participatory research in this study; therefore, there is no psychometric assessment of intelligence, aptitude, or personality traits (O'Connor et al., 2019) enclosed.

I collected data representing constituent firms publicly traded on the NYSE, which accounts for shareholder equity and debt holdings, market capitalization figures, and the aggregation of environmental impact information. Due to the discrete numerical characteristics of the data I collected, organizational data, such as company names, agents, or other proprietary information, is withheld in this study to achieve anonymity, confidentiality, and ethical compliance with institutional review board (IRB) and university policy guidance concerning research participants. I adhere to Walden University's research policy, where all collected data is stored in a password-protected digital storage device for a minimum of five years, after which data destruction will occur on the first day of the 73rd month. Lastly, I obtained approval from Walden University's IRB before analyzing data derived from the participant firms. The university's IRB approval number is 03-08-24-1038985, with an expiry date of 8 March 2025.

Data Collection–Instruments

The primary predeveloped instrument supporting data collection for this study was the FactSet Research System, a data and software company providing global research and analysis for investors, financial professionals, pension and hedge funds, and academia. FactSet was founded in 1978 and headquartered in Norwalk, Connecticut, with other offices spanning the U.S. and the globe. The company, whose market value is $15 billion, sources raw data from numerous financial information services, providing single-source online portal features to registered users (Aw et al., 2022; Financial Times, 2023; Sato & Mizuno, 2022). Notable companies and banks like JP Morgan Chase and Wells Fargo financial services subscribe to FactSet content for financial analyses and client portfolio management (Corporate Finance Institute, 2021). FactSet is a reputable firm that provides robust global data for assessing the market-based dependent and environmental independent variables central to this study.

FactSet and Truvalue Labs Integration

An in-depth description of the FactSet Research System is appropriate for the future replicability of this study. FactSet acquired Truvalue Labs, Inc.–a leader in artificial intelligence-driven environmental, social, and governance data (ESG)–on 20 October 2020. The acquisition of Truvalue Labs allows FactSet to provide over 185,000 users with detailed ESG ratings and other financial information for decision-making and investment analysis (FactSet, 2023c). The data aggregation service intends to reveal ESG industry leaders and laggards while informing FactSet users of real-time industry materiality risks across the investment universe (Beheshti et al., 2020; Hughes et al., 2021). FactSet integrates data from Truvalue Labs bellwether data aggregation technology using proprietary neural language processing algorithms and artificial intelligence capabilities to codify component environmental assessments in numerical format (FactSet, 2023a). This aggregation results in a FactSet Truvalue long-term environmental Insight score for each firm in my sample population.

Insight Score

FactSet Truvalue Labs Insight scores represent a company's sustained environmental performance over time. An Insight score employs an exponentially weighted moving average (EWMA), which is frequently used in technical analysis and clinical assessments (Smit et al., 2023; Sukparungsee et al., 2020). Further driven by the FactSet Truvalue Labs Pulse Score–a quantitative index of continuously updated values extrapolated by FactSet Truvalue Labs proprietary systems–the EWMA assesses contextual time-series data of long-term firm performance and calculates this average.

The Insight scores used for this study's intended participant firms reflected FactSet Truvalue Lab's environmental aggregation of 140 firm observations for 2022. The Insight score values ranged from 0 to 100, representing measurement on a ratio scale with a defined zero point. A score of 100 suggests the highest level of environmental stewardship, and a score of zero is also meaningful, explaining a total lack of corporate environmental responsibility (FactSet, 2023b). The Insight scores are initially derived from TruValue Labs (TVL) through the Sustainability Accounting Standard Board's firm-internal assessment of sector-specific corporate materiality and sustainability reporting criteria. Hughes et al. (2021) and Consolandi et al. (2022) further described the materiality-financial nexus as corporate sustainability issues that inherently invoke long-term relevance to financial stability. Given the preponderance of concern for corporate environmental performance, investors and institutional fund managers reference Insight scores when considering portfolio additions, divestment, or balancing (Aureli et al., 2020b; Consolandi et al., 2022; Hughes et al., 2021; Wu et al., 2023). The Insight scores are most relevant to this study compared to other data providers because of their numerical ranking of the specific independent variables I chose for this research.

Independent Variables and Insight Scores

Each environmental predictor variable in this study received a mean annual TVL Insight score that separately assessed greenhouse gas emissions, waste and hazardous materials management, and water and wastewater management for 2022. TVL, a subsidiary company of FactSet, collects unstructured data from more than 100,000 sources, aggregates relevant environmental data, normalizes the data, and provides environmental performance Insight scores (FactSet, 2023b). For greenhouse gas emissions, the TVL Insight score is measured based on a firm's absolute gross greenhouse gas emissions generated during the firm's reporting period, which is measured in accordance with the Greenhouse Gas Protocol Corporate Standard and expressed in metric tons of CO_2 equivalent (International Financial Reporting Standards, 2022a). Each monthly TVL Insight score is averaged for the year ending 2022, which generated the cross-sectional data points for analysis.

Reporting entities may exceed or fall short of their forecasted goals to reduce greenhouse gas emissions, which generates a TVL Insight score between 0 and 100 using a ratio scale based on these outcomes. Waste and hazardous materials management is measured by the percentage of waste and hazardous materials generated versus recycled or repurposed for operations, which is also tracked in metric tons and assigned a similar TVL Insight score using a ratio scale as the greenhouse gas emission materiality category. Lastly, and similar in its assignment of the TVL Insight score, is the water and wastewater management materiality category. In this category, firms disclose their percentage of water recycled as the volume used, measured in thousands of cubic meters, divided by the volume of water withdrawn. Further, any volume of water reused multiple times is counted as recycled each time it is recycled and repurposed (International Financial Reporting Standards, 2022b).

In sum, all of the predictor variables I have discussed here are assessed quantitatively in metric tons or thousands of cubic meters, which are then converted to the TVL Insight score (a data point between 0–100 on a ratio scale), a numerical value based on a firm's capacity to improve upon their environmental impacts. I presented Table 3 for the purpose of describing all variables in the study, which utilized the TVL Insight scoring methodology (FactSet., 2023b) for the independent variables in this study. For the dependent variable, I collected year-end financial accounting data from FactSet and the EDGAR databases. These publicly accessible accounting figures were reported in billions of U.S. dollars and measured on a ratio scale that differed only in terms of environmental assessment versus the pecuniary measure of MVA.

Table 3

Variable Analysis

Independent Variable	Unit of Measure	Scale	Instrument	Purpose
Greenhouse gas (GHG)	Measurement of absolute gross GHG emissions generated during the firm's reporting period per the Greenhouse Gas Protocol Corporate Standard expressed in metric tons of CO_2 equivalent.	Ratio (0–100), e.g., 41.1, 41.2, 41.3...with a ranking scale of zero indicating the worst possible performance.	FactSet-TVL Insight score via the Sustainability Accounting Standard Board's firm-internal assessment.	Use of the GHG variable assesses the corporate environmental impact during 2022.
Waste and Hazardous Materials (WHZ)	The percentage of waste and hazardous materials generated versus recycled or repurposed for operations expressed in metric tons.	Ratio (0–100), e.g., 41.1, 41.2, 41.3...with a ranking scale of zero indicating the worst possible performance.	FactSet-TVL Insight score via the Sustainability Accounting Standard Board's firm-internal assessment.	Use of the WHZ variable assesses the corporate environmental impact during 2022.
Water and Wastewater Management (WAT)	Volume of water measured in thousands of cubic meters, divided by the volume of water withdrawn.	Ratio (0–100), e.g., 41.1, 41.2, 41.3...with a ranking scale of zero indicating the worst possible performance.	FactSet-TVL Insight score via the Sustainability Accounting Standard Board's firm-internal assessment.	Use of the WAT variable assesses the corporate environmental impact during 2022.
Dependent Variable				
Market Value Added (MVA)	The U.S. dollar sum of a firm's market capitalization less shareholder equity and long-term debt.	Ratio with negative values indicating negative MVA.	FactSet and EDGAR financial data.	Assess the 2022 value of sample firms.

TVL Insight scores supported this study's full range of statistical tests, aligning with many financial and econometric research studies (Consolandi et al., 2022; Goldberg & Mouti, 2022; A. Hughes et al., 2021; Saini et al., 2022; Serafeim & Yoon, 2022). Recent research by Sato and Mizuno (2022) employed the FactSet Research System and TVL Insight scores to map shock propagation on individual companies relative to endogenous supply chain events. Using big data via FactSet, the researchers concluded that internal supply chain issues are less impactful than macroeconomic factors, such as geopolitical tensions and adverse tariff policies between nation states. Adding to the usefulness of these consolidated ratings, Goldberg and Mouti (2022) heavily employed the TVL Insight scores as a long horizon sentiment indicator for analysis of longitudinal returns and maximum securities drawdown parameters.

Application Programming Interface Training and Cost

Due to extensive data and assembling procedures, I enrolled in FactSet’s available training in August and September 2023. The training was held between a FactSet data specialist and me on the Microsoft Teams platform, explicitly addressing my research goals and data collection intent. The cost of accessing the FactSet API and all associated proprietary support for August 2023–August 2024 was $10,000. The contractual agreement specified my academic status as a doctoral candidate at Walden University and assistant professor in the North Dakota University System, which granted my use of the database while also requiring appropriate attribution of all FactSet intellectual work, data curation, and repository ownership (Wood-Charlson et al., 2022) in this manuscript.

U.S. Securities and Exchange Commission–EDGAR Site

The SEC EDGAR site is a secondary existing instrument developed and launched by the SEC in 1992 (U.S. Securities and Exchange Commission, 2023) that I used to confirm the accuracy and reliability of FactSet's secondary data. Using EDGAR, I cross-validated the archived corporate financial filing data points retrieved from the FactSet Research System platform. The year-end financial reporting data assembled from FactSet is cross validated using EDGAR for 2022. While time-consuming, the confirmation effort confirmed secondary data accuracy and reliability. To be sure, Sousa-Zomer et al. (2020) noted that the government SEC EDGAR site is an extensive resource for data collection of publicly traded companies in the U.S. The completeness and quality of the SEC EDGAR data stems from federal standardization laws requiring company filings to be in accordance with specific accounting criteria that assure accuracy from the primary filing source (Wouters et al., 2020).

The FactSet Research System and the EDGAR database represented the primary and secondary instruments I used for this study. Both instruments have been and continue to be integral to economic, financial, and environmental research fields. Recent empirical literature shows evidence of the research practicality coinciding with FactSet and EDGAR (Azar et al., 2021; Larcker et al., 2022; Loukas et al., 2021), making the reliability and validity of the instrumentation I used for this study's measurement properties suitable for quantitative research, which, for reference purposes, I included as a database overview in Appendix B (Tables B1 and B2).

Data Collection Technique

Financial and accounting-based research generates numerous possibilities for answering a research question. For this study, the underlying research questioned the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and MVA. Linking the research question to a viable theoretical framework influenced my decision to map the study to existing taxonomies that demonstrate an empirical approach to answering the research question (Kundisch et al., 2022). In doing so, I discovered that many studies approach similar market-based questions using deductive reasoning and quantitative analysis nested in nonexperimental correlational design (Cho et al., 2019; Seeram, 2019; Turner & Deng, 2020). Such methodologies and designs require systematic and structured data analysis collection protocols and statistical tests suitable for hypothesis testing (Pesämaa et al., 2021). I further describe the data collection plan in this section.

Active Collection Period

The main collection technique was iterative and required accessing the primary (FactSet) and secondary (EDGAR) data instruments for structured records. The collection took place between August 2023 and March 2024. The rationale behind this collection technique was driven by the advantages associated with the availability of the data, the convenience of accessing the data in the FactSet single source API, and the efficient integration of the data in a coherent format for statistical analysis (Bacilieri & Austudillo-Estevez, 2023; Cheng & Phillips, 2014; Goldman et al., 2020; Olabode et al., 2018).

Despite the convenience of the primary and secondary collections, shortfalls in accessing structured data were inevitable, like limitations of use, the cost of access, the pervasive issue of missing data, and the delisting of companies publicly traded among global stock exchanges (Bessler et al., 2023; Hughes et al., 2019; IBM Cloud, 2021).

Screening

Within the structured data domain are two types of tabular data (numerical or categorical), where rows and columns containing numerical values are retrievable (Ontañón, 2020; Shwartz-Ziv & Armon, 2022). Central to this study is the retrieval of numerical data, which represented the continuous values I retrieved for all variables in this study. To satisfy the collection method and the assembly of structured observations, I built a company screening platform within FactSet's application programming interface (API) containing public firms traded on the NYSE, constituting the population of firms across the industry sectors noted on page 62. From this broader sample of firms, I further screened for all firms containing numerical environmental and financial accounting values, which revealed 140 companies with annual data for 2022, reflecting the analysis of all predictor variables and the dependent variable I employed in this study.

Variable Calculation

I disaggregated the financial market capitalization (*MC*), shareholder equity (*SE*), and long-term debt (*LTD*) of each firm in the sample ($n = 140$) and programmed for the calculation of market value added (*MVA*), e.g., $MVA = MC – SE + LTD$. Once the MVA values were assembled, I added them to a worksheet containing the independent variable columns.

I derived all numerical values through online platforms, leveraging archived data from two reliable sources. This method of examining collected data differs from others, such as a pilot study, where qualitative research is often preceded by a small-scale test of methods and procedures without hypothesis tests to validate the feasibility of a more comprehensive study (Charlesworth et al., 2020; Malmqvist et al., 2019; Ng, 2022). As such, a pilot study was unnecessary due to the predetermined feasibility and accessibility of secondary data.

Data Analysis

The research question for this study asks: What is the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and market value added? By denoting a 0.05 statistical significance threshold (two-tailed), the subsequent null and alternative hypothesis test is Null hypothesis (H_0): There is no statistically significant relationship between: (a) greenhouse gas emissions; (b) waste and hazardous materials management; and (c) water and wastewater management, and market value-added, and the alternative hypothesis (H_1): There is a statistically significant relationship between (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management, and market value-added.

Approaching the question and hypothesis required a statistical inquiry utilizing multivariable analysis. The statistical procedures I used were correlation (Dodanwala & Santoso, 2022) and multiple regression (Gelman et al., 2021; Hsiao, 2014; Wang & Cheng, 2020; Wooldridge, 2019). Based on the regression analysis results, I determined the efficacy of the regression model using the results given by the *F*-test, which is an overall test determining whether the independent variables in the model can explain the variance in the dependent variable. If the *F*-test returns a significant result at the 0.05 level ($p < 0.05$) allowing rejection of the null hypothesis, a researcher can proceed with testing each of the regression coefficients in the model (Sureiman & Mangera, 2020). Hence, the null hypothesis associated with the regression can be rejected if the probability value (*p*-value) is less than or equal to 0.05 ($\alpha \leq 0.05$). Conversely, a *p*-value greater than 0.05 constitutes a failure to reject the null hypothesis (Frost, 2019).

Defining an appropriate statistical procedure implies considering factors integral to the research question, such as the scale measure of each variable and whether data is discrete or continuous, among other parameters (Šimkovic & Träuble, 2019). In this study, I leveraged multiple linear regression analysis using ordinary least squares (OLS) because of its usefulness in modeling the linear relationship between an outcome variable (Y) and two or more independent variables (X) (Frost, 2019; Hsiao, 2014; Maulud & Abdulazeez, 2020; Wooldridge, 2019). In keeping with the linear regression construct, I examined the relationship between three independent variables and MVA in this study.

Analysis of Variance

Other statistical analysis procedures for hypothesis testing are suitable in various circumstances. Analysis of variance (ANOVA) is one type of statistical test used to determine if a statistically significant difference exists between three or more samples or groups (Wang et al., 2020a). According to Gelman (2005) and Lairgi et al. (2023), ANOVA models data structures by batching groups of categorical predictor variables and their coefficients, returning the mean and *p*-value of each predictor. While the intercept generated from multiple regression can be subtracted from the means of ANOVA to gather the regression coefficients, the statistical technique of ANOVA was not appropriate for use in this study because I focused on multiple regression's continuous outputs based on three continuous independent variables which return a single mean as an intercept and each independent variable's coefficient. My decision to adhere to multiple regression as a statistical technique for answering the research question centers on multiple regression's usefulness in analyzing the relationship between a single dependent variable and several independent variables (Gelman et al., 2021; M. Li, 2015).

My observational approach employed correlational output without conditions for causal inference (Lorenz-Spreen et al., 2022; Moland & Michailidou, 2023). The multiple regression analysis proved a suitable statistical approach to assess the relationship between the independent variables and MVA. For this reason, I learned from Alduais (2023), who demonstrated that the multiple regression technique provides an optimal statistical approach to the environmental-financial nexus and is integral for answering the research question.

Within the data analysis domain, statistical techniques and tests have inherent strengths and weaknesses, with multiple regression having its share. The principal advantage of multiple regression, however, is its ability to determine the influence of predictor variables on response variables and make light of the collective relationships among independent variables (Frost, 2019; Ray, 2019; Wooldridge, 2019). Conversely, the disadvantages of multiple regression mainly stem from the data used in the analysis, which, without data cleansing and quality control procedures, likely produce erroneous, degraded, or obscure results (Cohn et al., 2022; FactSet Research Systems Inc., 2022; Gelman et al., 2021). In large datasets, missing or incorrect values can dispatch erroneous regression interpretations and outlying data points. For this reason, researchers can take precautionary actions before employing regression by familiarizing themselves with the five assumptions of multiple regression (Aiken & West, 1991; Arenhart et al., 2022; Gelman et al., 2021; Hsiao, 2014; Kim, 2019; Wooldridge, 2019), which are covered in the following sections and illustrated in Appendix C.

Variables of GHG, WHZ, WAT, and MVA

I attribute three predictor variables (GHG (X_1), WHZ (X_2), WAT (X_3)) and one outcome variable (MVA (Y_1)) for use in the hypothesis testing in conjunction with pending probability values. All independent variables in this study are continuous numerical variables forming monthly data representing a ratio scale of statistical measure with a defined and meaningful zero point (Beard et al., 2019; Rau et al., 2019). The dependent variable of MVA is measured on an annual constant monetary ratio scale in billions of U.S. dollars (Wooldridge, 2019). MVA can result in negative and positive accounting values and yield statistical relationships integral to this data analysis.

Data Cleaning and Addressing Missing Data

Like most research worth pursuing, my time allocation for collecting and examining the data for this study was significant. As with other data types, it is common for monthly and annual data to contain erroneous values and high-leverage outliers (Beard et al., 2019; Jadhav et al., 2019). Corrales et al. (2020) noted that having a suitable data analysis technique can mean the difference between timely confirmation of data accuracy and spending an inordinate amount of time preprocessing the data. While the time spent pre-processing the data was protracted, e.g., identifying and removing any discrepancies, standardizing data for analysis, data consolidation, variable transformations, integrity check tasks, and safe storage actions, the provisional confidence in the data I retrieved from FactSet decreased the cleansing procedure times.

FactSet employs more than 5,000 content collection specialists who monitor both qualitative and quantitative content sets, which affords researchers a high level of assurance that data redundancies and discrepancies are eliminated before the initial collection process (FactSet Research Systems Inc., 2022). As the researcher, I was responsible for the quality and reliability of the data I collected, regardless of a data provider's assurances of quality data curation and oversight (dos Santos et al., 2022). For this reason, I addressed common issues in data analysis, particularly the assumptions of multiple regression, with approaches to potentially resolve or alleviate these issues, ensure replicability, and optimize the statistical analysis.

Missing Data

Missing data values are abundant in data analysis and a significant cause of concern for researchers (Beard et al., 2019; Wooldridge, 2019), mainly when using datasets initiated via machine learning, despite their robust validation schema for checking errors and biases (Tucker et al., 2020). In the FactSet proprietary collection process, error checking and appropriate data curation are preconditions before clients receive the data (Reilly, 2021). Despite conditional reassurances of FactSet's data, I searched for missing attributes and subsequent high-leverage values associated with the continuous numerical variables of GHG, WHZ, WAT, and MVA.

To safeguard against missing data, I primarily deferred to the FactSet Research System specialists to conduct a query for retrieving any missing data I encountered. In the data pre-processing stage, my sample of 140 firms contained all independent and dependent variable values for appropriate statistical measurement. Using this information and the EDGAR database as a cross-checking resource, I further consolidated the FactSet data into an Excel worksheet to finalize all financial numerical data concerning the dependent variable MVA.

Assumptions of Regression

To gather the best possible coefficient estimates in my model, I follow five multiple regression assumptions that Wooldridge (2019) emphasized as 1. linearity, 2. independence, 3. normality, 4. equality of variances, and 5. no multicollinearity. These assumptions are closely analogous to the classical Gauss-Markov assumptions in ordinary least squares regression for obtaining the best linear unbiased estimator (Hansen, 2022b; Portnoy, 2022). I explain each assumption below regarding impacts on the study's multiple regression analysis and my inherent compliance with these assumptions.

Linearity

Linearity assumes that the regression process aligns with a model that is itself linear. This assumption is delineated by the regression equation $Y = \beta_0 + \beta_1 Xi_1 + \beta_2 Xi_2 + \beta_3 Xi_3 + u_t$, where a one-unit increase in X_1 changes the expected value of Y by the approximated value of the independent variable coefficient β_1. Further, (u_i: $i = 1,2,. . .,n$), where u_i indicates the sequence of errors and n is the number of observations in the model (Wooldridge, 2019). According to Gelman et al. (2021), the assumption of linearity in regression is the most critical mathematically, and its violation would inaccurately predict a statistical relationship.

I visually checked for linearity using fitted line plots depicting the linear relationship between MVA and each independent variable. Inspection of the fitted line plots reveals the negative and positive relationship associated with the collective contribution of all independent variables in the multiple regression model. I further examined the linearity assumption using a residual versus fitted plot in Stata, inspecting for any discernable patterns–such as emergent cone or fan shapes–between the fitted values and the residuals contained in the regression model. There should be no identifiable patterns if linearity is present in the plot (Lee, 2022). If the assumption is violated, expansion of the model using a cubic root transformation of the dependent variable and transformation of all negative MVA values using the absolute value of the highest negative MVA observation (Frost, 2019; Gelman et al., 2021; Lee, 2020; Wooldridge, 2019) is feasible, ensuring a suitable data fit. The cubic equations depicted in Appendix D provide examples of the dependent variable transformation and back-transformation.

Independence

The independence of observations assumption states that measurements for each data point from each sample firm are not influenced by other sample firms (Arenhart et al., 2022; Kim, 2019; Osborne & Waters, 2019; Ploton et al., 2020). I visually checked for the independence of observations by plotting the residuals against each covariate. A scatterplot with no deterministic pattern suggests the presence of independence of errors (Frost, 2019; Wooldridge, 2019). Due to the hierarchical importance of this assumption, I also conducted a Durbin-Watson d-test for first-order autocorrelation. This test generates values between 0 and 4, with a value around 2 indicating non-serial correlation (Durbin & Watson, 1971; Turner, 2020). If the assumption is violated after inspection of the plots and the Durbin-Watson test, I consider the random removal of a participant firm in cases where values are redundantly identical or directly influenced by another.

Normality

The normality assumption states that errors u_t are independent of X and are independently and identically distributed as normal (Wooldridge, 2019). Non-normal errors can bias parameter estimates, skew confidence intervals, and degrade hypothesis tests (Hansen. 2022a). A normal probability plot (P-P) graphically illustrates whether a dataset approximately resembles a normal distribution (Frost, 2019; Rodu & Kafadar, 2022). Distributions of the expected and observed cumulative probabilities in the plot should adhere to an approximate straight line diagonally (Wooldridge, 2019), which is rarely the case. Instead, the points tend toward a slight curvature, landing above or below the fitted line or both (University of Wisconsin–Madison, 2021). The normality of the residuals is a precondition for valid hypothesis testing, although, as demonstrated by Knief and Forstmeier (2021), strict adherence to normality is rarely achieved in econometric data. I visually inspected for normality using a P-P plot.

As a secondary confirmation of normality, I deployed the numerical Jarque-Bera (J-B) Lagrange multiplier test for assessing normal skewness and kurtosis. The J-B test is a goodness-of-fit test that examines whether sample data reflect skewness and kurtosis corresponding to a normal distribution (Dare et al., 2022), its null hypothesis implies that normality is present. Using the graphical and numerical approaches of the P-P plot and the J-B Lagrange multiplier test provided insight on whether the assumption of normality satisfied. In the event the assumption of normality is violated, I will perform the dependent variable transformation described in the linearity assumption.

Equality of Variances

The assumption of the equality of variances is analogous to homoscedasticity, which implies that the error term u_t and independent variables $X_{1\text{-}n}$ are independent and that the variance (u_t) is constant over time (Wooldridge, 2019). A violation of the homoscedasticity assumption implies the presence of heteroscedasticity, which can distort the model's findings (Alabi et al., 2020). While heteroskedasticity does not significantly bias parameter estimates, it can point to other violated regression assumptions in the model (Kim & Li, 2023). I tested the homoscedasticity assumption using the Breusch–Pagan/Cook–Weisberg and White's tests for heteroscedasticity. A failure to reject the null hypothesis of these tests implies that residual error variances are equal, suggesting the presence of homoscedasticity (Huang et al., 2023).

When heteroscedasticity is present in the data due to nonlinear relationships and variance interactions embedded in the data (Ruza & Caro-Carretero, 2022), a transformation of the model's variables is advisable. Gelman et al. (2021) noted that variable transformations help explain growth models with inherent initial uneven variances. For this reason, the dependent variable transform indicated in the previous assumption is considered.

Multicollinearity

This assumption presumes that no independent variables exhibit perfect collinearity or multicollinearity with any other independent variables under examination (Wooldridge, 2019). Two independent variables (IVs) are considered perfectly collinear when their correlation coefficients are +/– 1.0, which can cause regression estimation challenges, inflated standard errors, and unstable parameter estimates (Jweihan, 2023). I tested for multicollinearity using the variance inflation factor (VIF), which tests the severity of collinearity among the variables (Kyriazos & Poga, 2023; Lindner et al., 2020; Marcoulides & Raykov, 2019; Sulaiman et al., 2021; Tamura et al., 2019). The VIF statistic is the ratio of total variance divided by the proportion of unique variance and expressed as $1/(1–R^2)$, where R^2 is the IV coefficient of determination (Kyriazos & Poga, 2023). Redundancy in each independent variable occurs when VIF values exceed 10.0 (Kline, 2016). If the set of IVs display extreme collinearity, I consider the removal of a highly correlated variable from the set.

In summary, regression analysis can reveal insightful relationships and potential inferences for researchers to expand. Still, the researcher's comprehensive knowledge of the subject and use of robust theoretical foundations are needed when deciding whether and how interpretations of statistical results coherently apply to the research question (Mishra et al., 2019). Testing for the five assumptions of multiple regression warrants a comprehensive understanding of the subject matter and a firm grasp of data analysis and foundational statistical techniques. Appendix C includes the five multiple regression assumptions in table format.

Integral Data Interpretation

For researchers and statisticians, data analysis encompasses numerous pre-processing procedures, such as data collating, cleansing, consolidation, and organization, before any statistical investigation is underway. Once the sample data is deemed valid for statistical analysis, it is transformed into descriptive and inferential statistical outputs for summarizing and potentially generalizing conditions relative to the population (Salvatore & Reagle, 2002; Wooldridge, 2019). Researchers conduct post-regression estimation and diagnostic inquiry using numerical and visual results (Jawad et al., 2021; Khemet & Richman, 2021). Principally, researchers can better understand regression outputs through graphical plots of residuals and patterns of relationships between predictor and outcome variables (Ravindra et al., 2019). These statistical tools can be helpful in model selection. The statistical tests and consequent model selection criteria can differ with every research study (Lv et al., 2019; Midway et al., 2020), depending on the descriptive and inferential statistics.

Descriptive Statistics

I generated descriptive statistics for this study using Stata statistical software, Version 18. Descriptive statistics provide insights into the dataset characteristics (Salvatore & Reagle, 2002; Wooldridge, 2019), which in this study represented 140 participant firms with an average annual TVL Insight score for 2022 measuring greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and the year-end MVA value for 2022. I used Stata statistical software to develop the descriptive statistics by running the command *summarize MVA GHG WHZ WAT,* which yields the summary statistics for all variables yielding: (a) the number of observations (*n*), (b) the minimum and maximum values of each variable, (Min / Max), (c) the mean of each variable (*M*), (d) the standard deviation of each variable (*SD*), and (e) 95% confidence intervals.

My interpretation of descriptive statistics focused on values such as the total number of observations and the proportional spread of the data across each variable. I examine the central tendency of each variable, particularly the mean, to determine its location across the data distribution (Frost, 2020; Salvatore & Reagle, 2002). Lastly, I inspected the measures of dispersion within the sample, namely the standard deviation, as these values represent the square root of the variance and constitute values in scaled units of the original distribution (Gelman et al., 2021). Given this dataset snapshot, I gained insight into the composition of the data and interpreted it contextually.

Inferential Statistics

I assembled inferential statistics for this study using the Stata statistical software tool. Researchers use inferential statistics to estimate population generalizations from a representative sample (Frost, 2020; Mondal et al., 2022; Salvatore & Reagle, 2002). Inferential statistics naturally introduce a sample error, which is the difference between the sample statistic and the population values (Frost, 2020; Gelman et al., 2021). I used multiple regression and hypothesis testing as inferential statistical tools. For this study, I intended to address the research question by testing the probability of rejecting or failing to reject my null hypothesis. To do this, I examined the statistical results of the regression to assess the statistical validity of the model and the subsequent relationship existing among the variables I used in this study. The previously mentioned parameters I selected consisted of a medium effect size of 0.15 at a 95% confidence level, with a *p*-value of 0.05. These parameters provided the criteria governing my decision whether to fail to reject the null hypothesis if the *p*-value is greater than 0.05 ($p > 0.05$) or reject the null hypothesis ($p < 0.05$), concluding that there is a statistically significant relationship between: (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management, and market value-added.

Further examination of the statistical analysis brings to light the *F*-test or an intercept-only model, which, as Frost (2020) defined, compares the overall significance of two hypotheses that the variances of two populations are equal. The null hypothesis in an *F*-test indicates a regression model having no independent variables that fit the data equally as well as a model that includes the independent variables. The alternative *F*-test hypothesis states that my developed model fits the data more appropriately than a model void of independent variables. The *F*-test formula in my non-directional hypothesis test is H_0: $\sigma^2{}_1 = \sigma^2{}_2$ and H_1: $\sigma^2{}_1 \neq \sigma^2{}_2$, where $\sigma^2{}_1$ is the variance of the first population and $\sigma^2{}_2$ is the variance of the second population (NIST, 2012). Using this criterion, I compared the resulting *p*-value for the *F*-test of overall significance to my significance level (0.05). If the *p*-value is less than my 0.05 significance level, it indicates the unlikelihood that all the independent variable coefficients equal zero.

Study Validity and Reliability

Researchers conducting in-depth studies must account for the attributes of validity and reliability, which equally apply to quantitative and qualitative inquiries. Failure to precisely demonstrate the reliability of a measurement instrument's yield and the study's outcome in ways that transparently convey trustworthiness can be deleterious to holistic research (FitzPatrick, 2019; Lavee & Itzchakov, 2023; Leung, 2015). Validity in research constitutes external and internal elements. To be sure, the articles by Mulisa (2022) and Beets et al. (2020) provided a distinction between external and internal validity, whereby quantitative research seeks appropriate external validity by demonstrating generalizability–where the study's conclusions can effectively map to the broader population or transfer to other studies (Fusch et al., 2018). Conversely, internal validity is central to the qualitative research paradigm, which aims to reveal a particular phenomenon correctly. FitzPatrick (2019) avoided discussing the often-mentioned instrument validity in qualitative research, opting for a Maxwellian linkage that suggests validation procedures be carried out during the study, not afterward.

In this study, I allay external and statistical validity threats by providing a sample size of 140 firms to foster generalizability (Delios et al., 2022); the sample selection was dictated by the availability of reporting companies. Further, this study adopts the nonexperimental design, to which internal validity is not applicable. The potential reduction of this study's external validity stems from the unobservable universe of firms operating globally (Hill et al., 2020). Hence, the true population parameter is unclear under the lens of generalizability. My intent in clarifying potential validity weaknesses is not to dissuade a researcher from replicating this study. Instead, it attempts to adhere to the guidance of Secchi (2022), who argued that replicability and justification of methods narratives in methodology sections of research studies lack the adoption of consistency without deviations and robust conveyance of quantitative methods to express validity and reliability coherently.

The rationale for justifying the industries and constituent firms in this study's sample flowed from the recent acceleration of environmental-economic research and geopolitical policies. Explanations of disparities often emerge as to whether science is driving environmental and economic policy or whether politics is maintaining influence over real scientific research that may not appear as evident. Nevertheless, the degree of confidence in data, interpretation, and methods used in qualifying scientific research can point societies on a robust path toward human flourishing. The nexus of environmental impacts, the profitability of firms, and the theories that underpin them influenced this research. For this reason, discovering a testable quantitative vector between corporate environmental stewardship and firm value justified the inclusion of known polluting industrial firms and their relative value in my sample. While Secchi's (2022) four guiding principles of replicability, justification, consistency, and robustness may not have surfaced as they could in this quantitative study, I found the design, sample size, and data assumptions an appropriate segue for dispatching additional research in this field.

Statistical Conclusion Validity

The potential rejection of the null hypothesis in this study implied that there is a statistically significant relationship between (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management, and market value-added. A Type I error or false positive concerns the probability of rejecting the null when it is true. Type I errors can be problematic and degrade statistical validity, mainly when sample size estimates are too small or excessively large (Kang, 2021; Madhan et al., 2022). Moreover, Meckler and Boal (2020) and Harvey and Liu (2020) argued that Type I errors and their inverse (Type II errors) could completely derail financial and organizational value due to decision-making driven by mistaken statistical results.

Hypothesis testing is the prevailing approach toward substantiating knowledge advancement in quantitative research (Johnson et al., 2019) and leverages sample data to make inferences about the characteristics of a broader population (Frost, 2020). By design, an a priori power analysis can aid researchers in estimating a sample size by integrating a power level, hypothetical effect size, and alpha (Lakens, 2022; Quintana, 2023). By setting a low significance level, type I errors–the erroneous rejection of the null hypothesis when no statistically significant difference exists–are reducible (Gohary, 2019). Inversely, type II errors that reject the alternate hypothesis due to the lack of statistically significant results are not reducible by manipulating the significance level, effect size, or power (Frost, 2020; Hill et al., 2020). According to Frost (2020), *p*-values near 0.05 have a false positive error rate between 23-50%, which may influence researchers desiring more substantial reproducibility characteristics to adopt lower *p*-values at or near .0027.

My initial proposal concerning this study's significance level (Type I error probability) of 0.05 (two-tailed) with an effect size of 0.15 and statistical power (1– β error probability) of 0.95 was taken from G*Power software (Faul et al., 2009), which frequently appeared in the extant literature concerning similar financial research (Bui et al., 2021; Busch et al., 2020; Dobrowolski et al., 2022; Louche et al., 2019). While I concur with Frost (2020) and Halsey (2019) on the relative weakness of *p*-values near 0.05 and their propensity for inflating Type I errors, I augmented potential weaknesses by maintaining the most extensive available sample size coupled with background knowledge of financial markets and a novel approach to environmental science to gain closure concerning the statistical results and their ability to reinforce the external validity and reliability contained herein.

Transition and Summary

Section 2 of this study discussed the motive and plan for administering this research to determine the relationship between corporate environmental performance and firm value. Using known polluting industries as a proxy for investigating the type of relationship that exists when environmental reporting is available, the sample of 140 exchange-listed firms emerged by applying the convenience sampling approach. This sampling approach and the curated data from FactSet Research Systems cross-validated via EDGAR confirmed no missing data values during the cleansing process, thus confirming a balanced dataset. Stata's statistical software is the primary platform on which the analysis of secondary numerical data is calculated to yield regression results. Lastly, addressing regression assumptions as a precondition for providing valid purpose and reliability for this study's overall outcome extends the research to Section 3, which presents the statistical results, amplifies the data analysis, and suggests opportunities for future research along with implications for social change.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative, correlational study was to examine the relationship between greenhouse gas emissions, waste and hazardous materials management, water and wastewater management, and firm value**.** The independent variables were: (a) greenhouse gas emissions (GHG), (b) waste and hazardous materials management (WHZ), and (c) water and wastewater management (WAT). The dependent variable was market value added (MVA). The null hypothesis (H_0), indicating that there was no statistically significant relationship between GHG, WHZ, and MVA, was rejected, prompting the acceptance of the alternative hypothesis (H_1) that there was a statistically significant relationship between GHG, WHZ, and MVA. Conversely, I failed to reject the null hypothesis (H_0) described above for WAT, indicating that there was no statistically significant relationship between WAT and MVA. All the findings mentioned above were associated with the cross-sectional secondary data analysis for the year 2022.

Presentation of the Findings

For the following subsections, I present the relevant descriptive statistics followed by a robust evaluation associated with the assumptions of multiple regression. Following these preliminary tests, I report the results of the inferential statistics using graphical and numerical results derived from my secondary data analysis. Lastly, I revisit my research question and hypothesis, map them to my findings, and include a theoretically linked clarification of the findings. The section concludes by summarizing the analysis regarding the statistical model performance and my research objective.

Descriptive Statistics

During the data preprocessing stage, there were no missing values or any other erroneous numerical attributes that would disrupt the statistical analysis coinciding with this study. The cross-sectional data analysis spanned 140 company observations during 2022. The mean for MVA was 39.22, which, when back-transformed, is the equivalent U.S. dollar amount of $22.372 billion. This value and its transformation criteria are found in Appendix D.

The mean TVL Insight scores for GHG, WHZ, and WAT were 68.28, 56.46, and 44.43, respectively. The dispersion (SD) of the TVL Insight values about the sample mean is lowest for GHG (8.68) and highest for WAT (18.24). Relative to the sample of 140 firms, the 95% confidence interval spread for GHG, WHZ, and WAT were 2.90, 5.37, and 6.10, respectively. To maintain quantitative continuity, I transformed the continuous values of the dependent variable to allow a condensed and appropriate fit relative to the continuous independent variables. Table 4 depicts the descriptive statistics of the variables under analysis.

Table 4

Means and Standard Deviations for Quantitative Study Variables

Variable	M	SD	Min.	Max.	95% CI
MVA	39.22	17.27	1.0	78.0	[36.34, 42.11]
GHG	68.28	8.68	36.86	89.73	[66.82, 69.72]
WHZ	56.46	16.05	0.33	89.69	[53.77, 59.14]
WAT	44.43	18.24	0.06	86.25	[41.38, 47.48]

Note. $N = 140$.

Tests of Underlying Multiple Regression Assumptions

The assumptions of linearity, independence of errors, normality, equality of variances, and multicollinearity were examined using the Stata statistical software tool, version 18. All instruments used in this analysis were robust, valid, and reliable. Due to the numerical heterogeneity inherent between the dependent and independent variable numerical values, I fit the data using a cube root transformation of the dependent variable. This transformation, as depicted in Appendix D, is due to MVA values quoted in billions of U.S. dollars, while each independent variable contained two-digit nonnegative values.

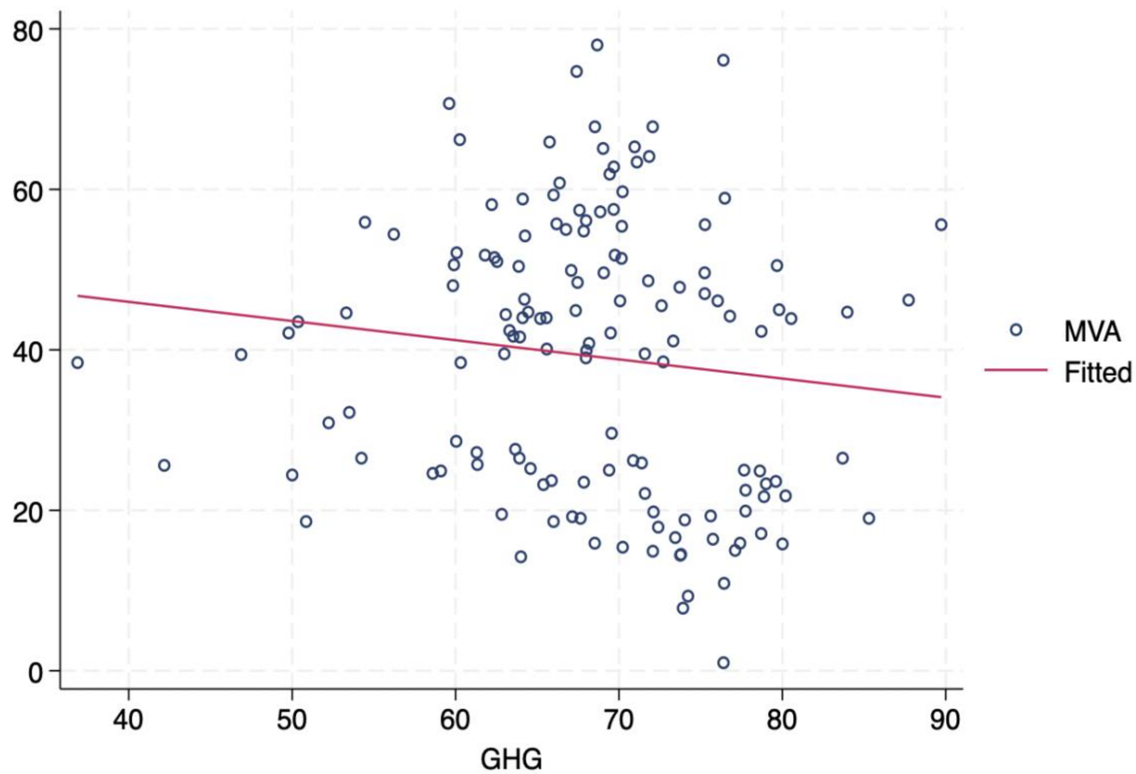
Linearity

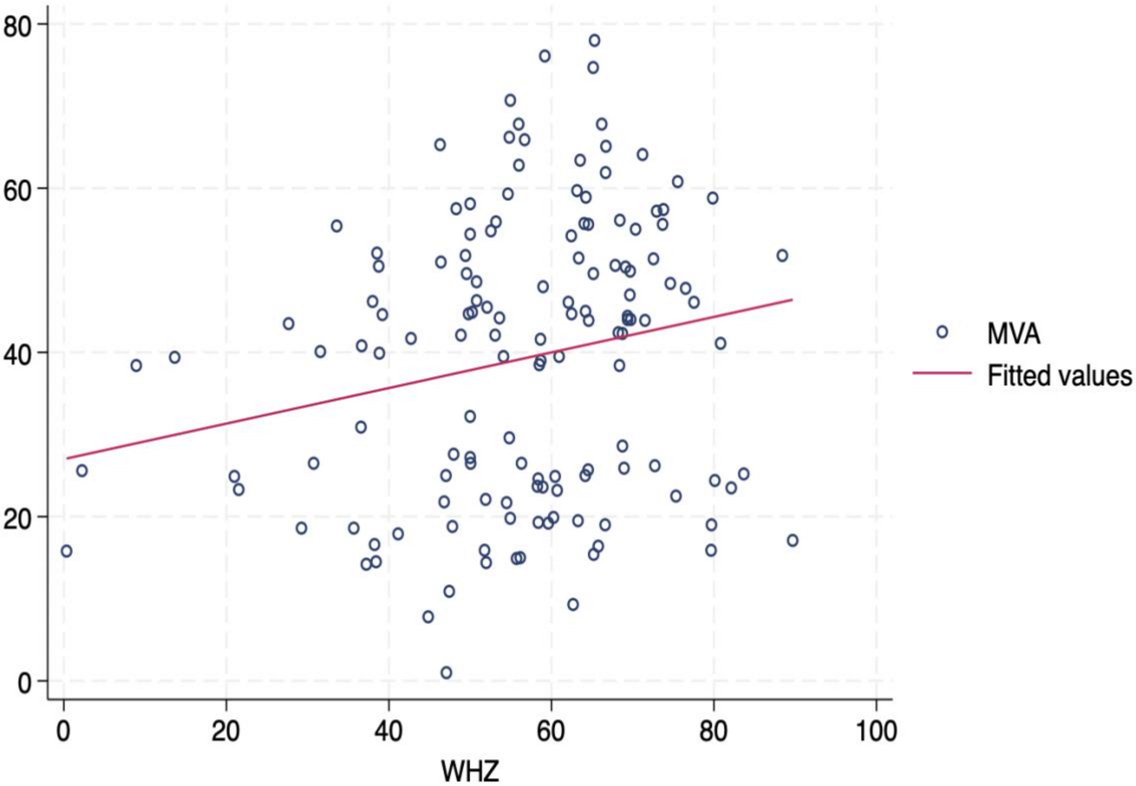
Using a multiple linear regression model posits that the average outcome is linearly related to each term in the model when holding all others fixed (Hohberg et al., 2020). I evaluated linearity by surveying fitted line plots for MVA as measured by each independent variable. The fitted line plots in Table 5 indicate a negative linear relationship with GHG and positive linear relationships associated with WHZ and WAT.

Additionally, I generated the residuals versus fitted value plot shown in Figure 4 to examine emergent or systematic patterns between the residuals and fitted regression values. The plot is broadly scattered, void of a discernable pattern, and supportive of linearity in parameters.

Table 5

Fitted Line Plots




80
60
40
20
0
0
20
40
60
80
100
WHZ
MVA
Fitted values

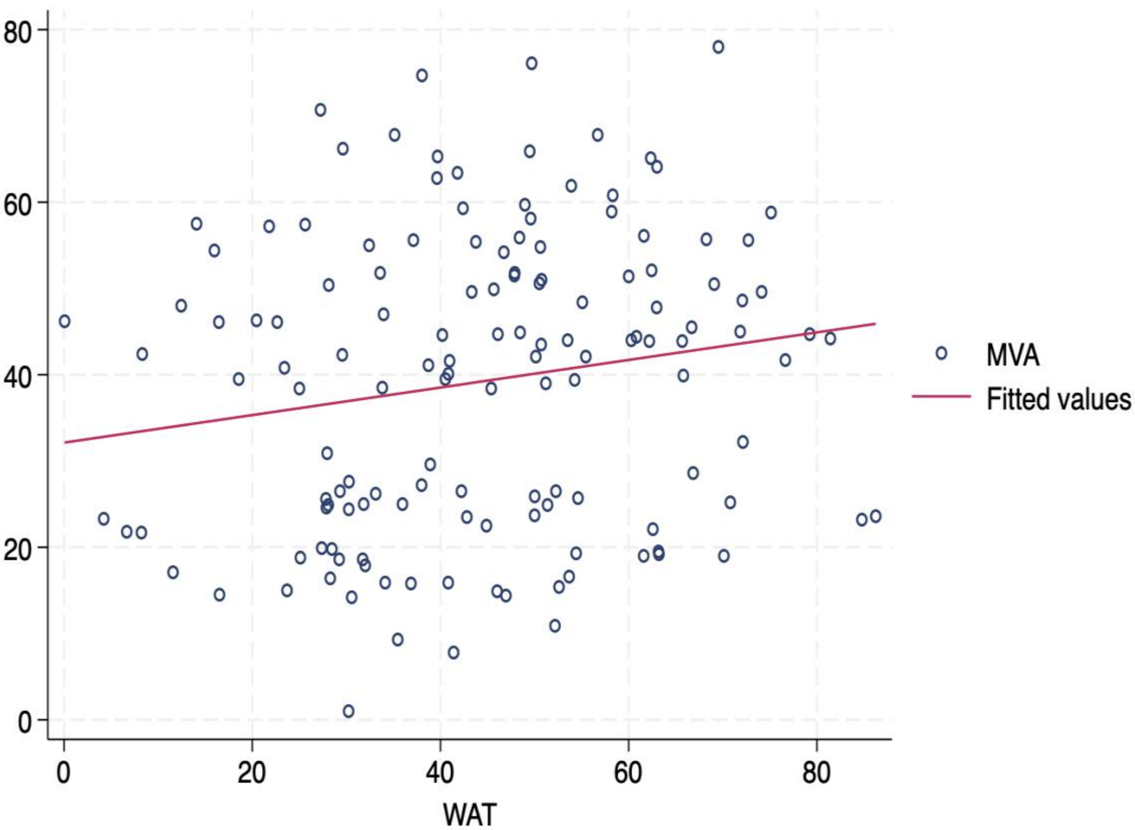
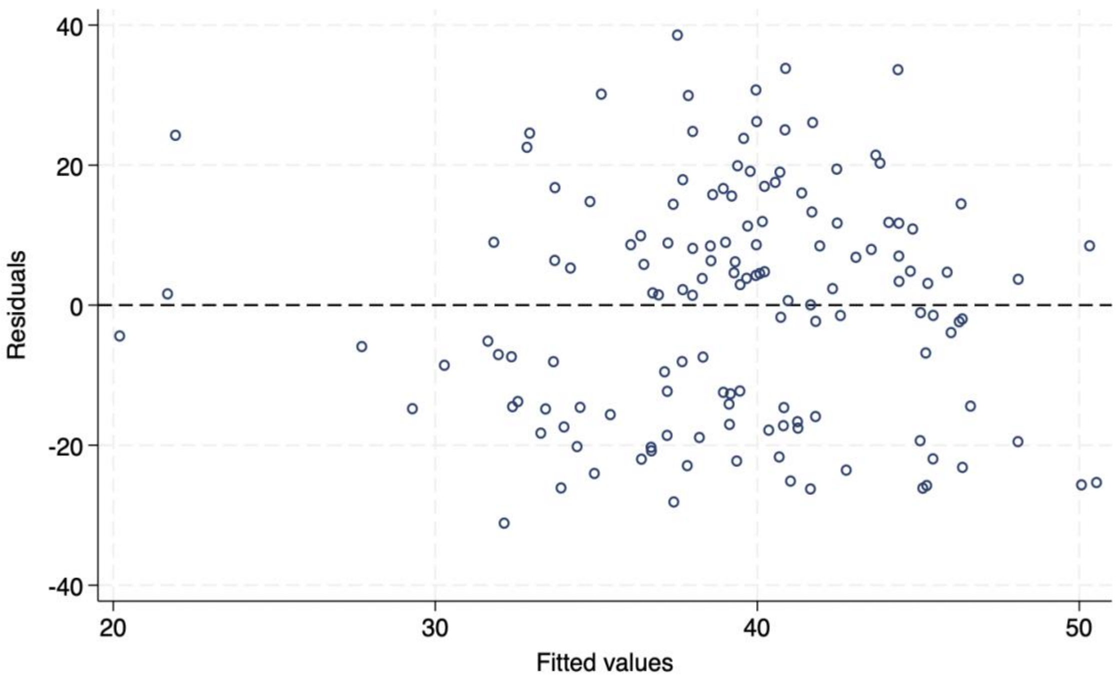

80
60
40
20
0
0
20
40
60
80
WAT
MVA
Fitted values

Figure 4

Residuals vs. Fitted Values Plot



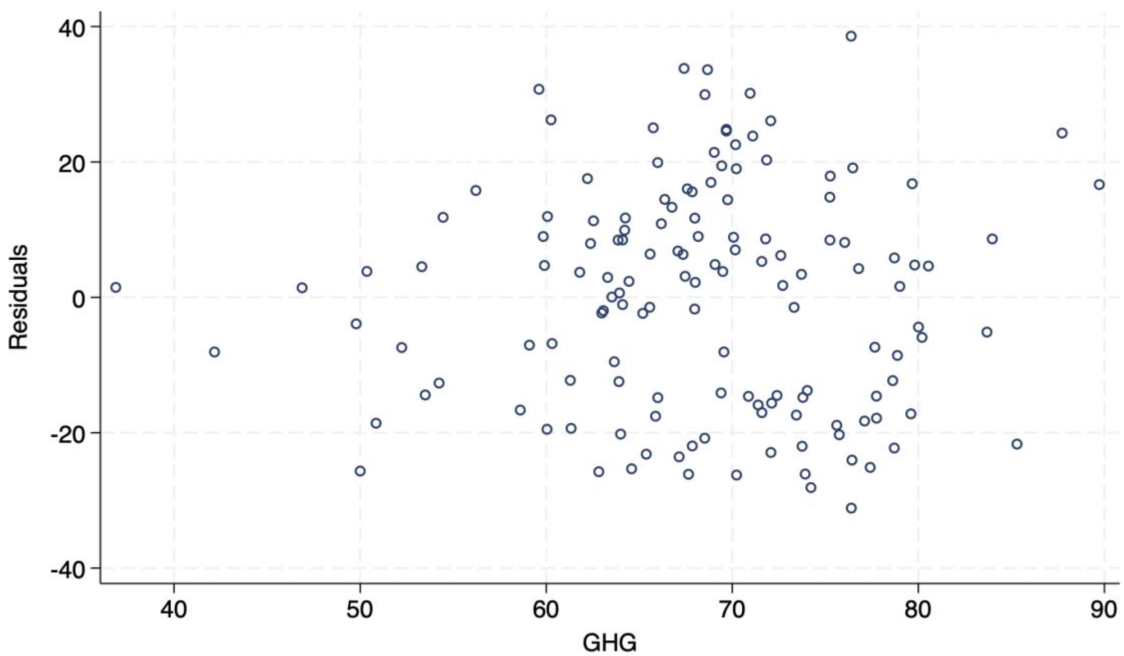
Independence of Errors

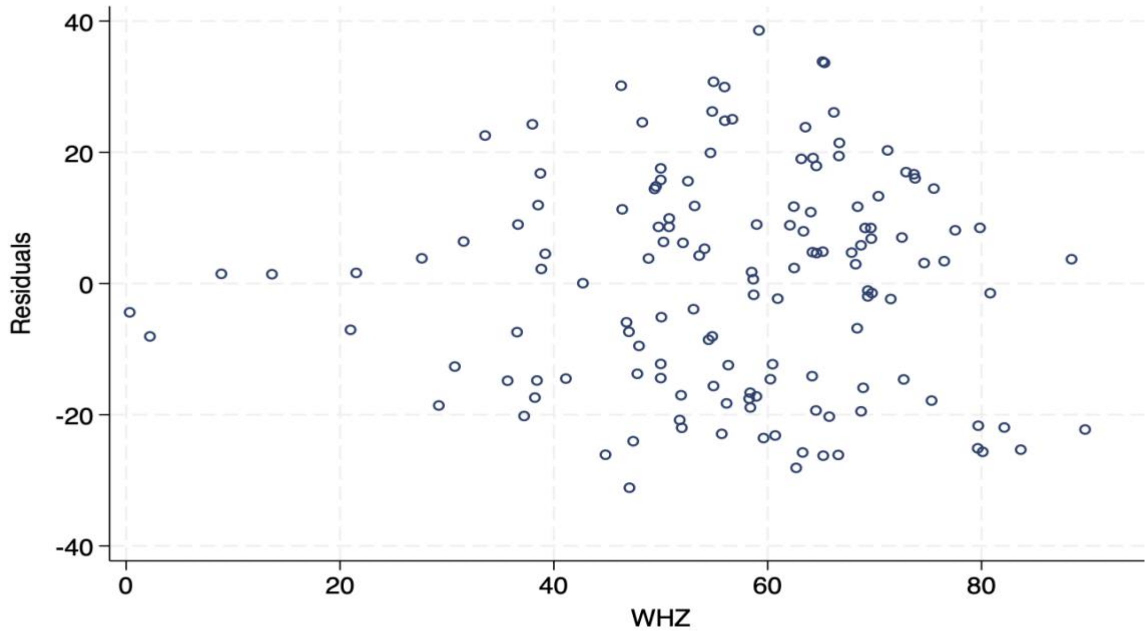
This assumption presumes that one observation's value does not predict another observation's value (Arenhart et al., 2022; Kim, 2019; Osborne & Waters, 2019; Ploton et al., 2020). I evaluated three residual versus independent variable scatter plots using the command *scatter* in Stata to interpret the independence of errors across GHG, WHZ, and WAT. The scatter plots in Table 6 aid in visually exploring the independence of residuals. Similar to the residuals versus fitted values plot, there should be no visual indication of systematic patterns in Table 6. The plots only provide an approximation because residuals will always sum near zero.

In addition to the visual analysis of the independent variable scatter plots, I performed the numerical Durbin-Watson (D-W) statistical test to confirm that autocorrelation is suppressed in the model. The resulting D-W *d-statistic* in Stata is compared to a table of published lower and upper bound values, which consider the number of observations and independent variables in the model. A failure to reject the null hypothesis of the D-W test suggests autocorrelation is not an issue. I provide the d-upper bound value and the d-statistic in Table 7. The data met the assumption of independent errors with a value of 2.179, supporting adherence to this multiple regression assumption.

Table 6

Residuals vs. Independent Variables




40
20
0
-20
-40
Residuals
0
20
40
60
80
WHZ

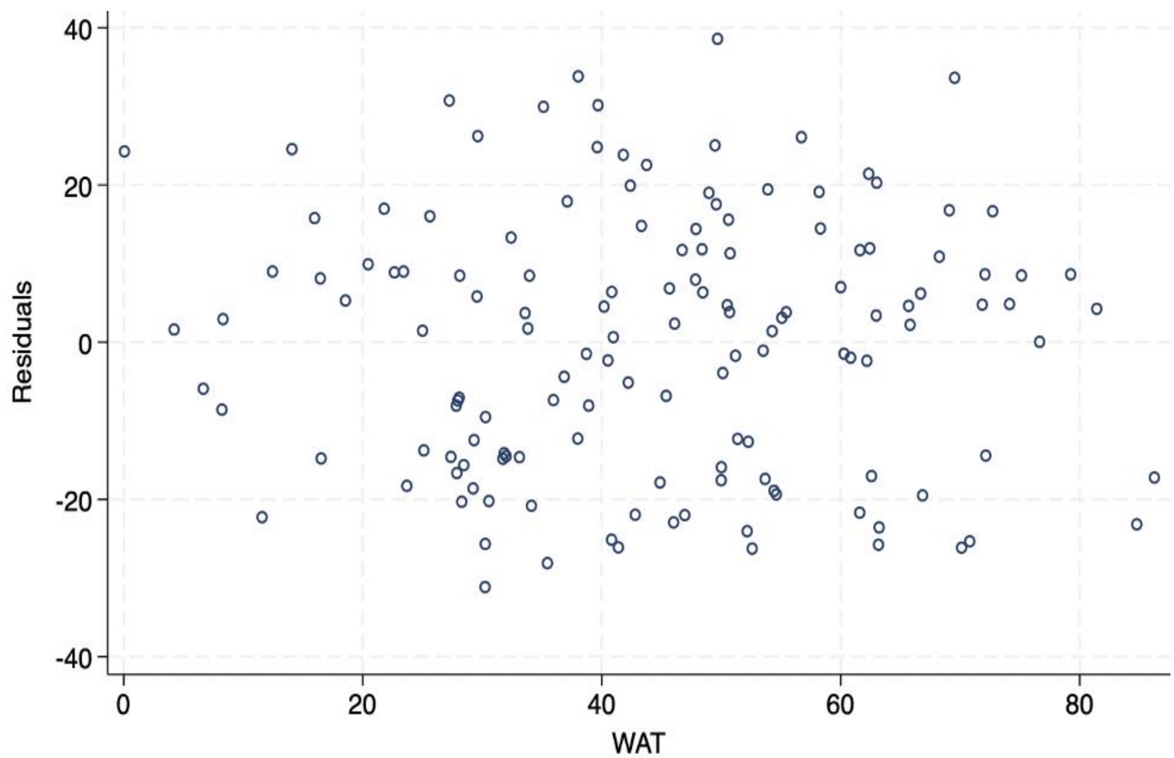

40
20
0
-20
-40
Residuals
0
20
40
60
80
WAT

Table 7

Durbin-Watson Test for Independence of Errors

D-W Test Statistic	d-Upper Bound	$p > 1.679$
2.179	1.679	2.179 > 1.679

Note. $N = 140$.

Normality

I conducted a visual check using a normal probability plot (P-P) and the numerical Jarque-Bera test for normality to test for data normality. Each variable returned values above the test's 0.05 null hypothesis threshold. The plot in Figure 5 and the values depicted in Table 8 support the presence of normality.

Table 8

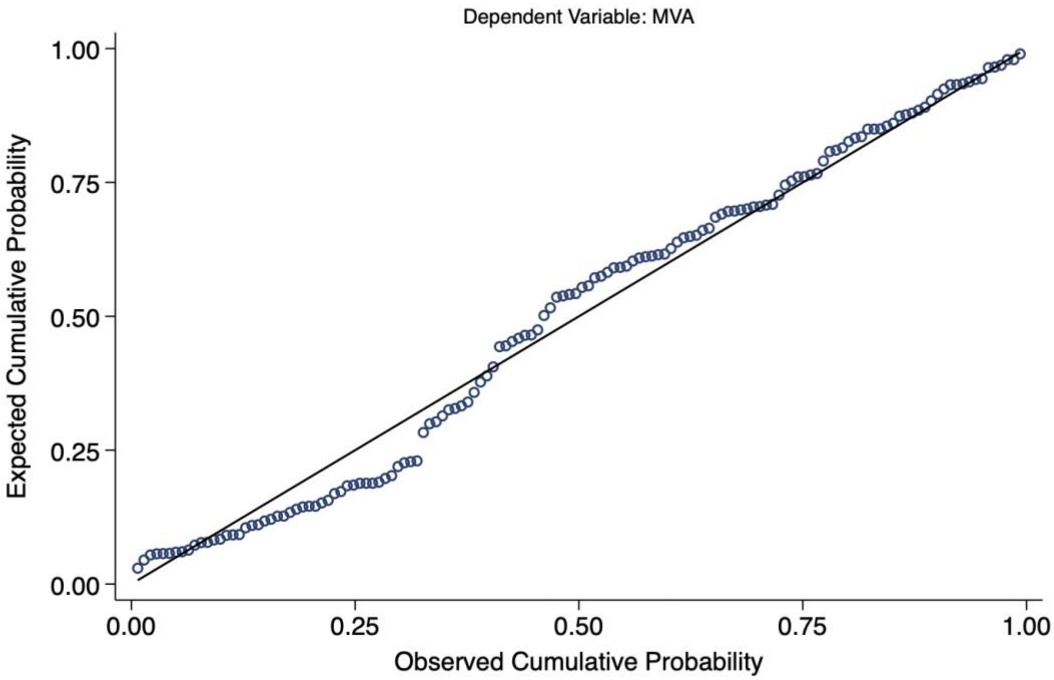
Jarque-Bera Lagrange Multiplier Test

Variable	$p > 0.05$
MVA	0.06
Residuals	0.09
Standardized Residuals	0.08

Note. $N = 140$.

Figure 5

Normal Probability Plot (P-P) of the Regression Standardized Residuals



Equality of Variances

Equality of variances is analogous to homoscedasticity, which implies that the error term u_i and independent variables $X_{1\text{-}n}$ are independent and that the variance (u_i) is constant over time (Wooldridge, 2019). In Table 9, the Breusch–Pagan/Cook–Weisberg test and White's test returned non-significant results at 0.8826 and 0.4256, respectively. Hence, *p*-values were greater than 0.05, prompting a failure to reject the null for both tests, suggesting equal variance is present.

Table 9

Homoscedasticity Tests

Test Type	$p > 0.05$
Breusch-Pagan / Cook-Weisberg test for heteroscedasticity	0.8826
White's test for heteroscedasticity	0.4256

Note. $N = 140$.

Multicollinearity

The multicollinearity assumption infers that no independent variables exhibit perfect collinearity or multicollinearity with any other independent variables under examination. As Jacob and Varadharajan (2023) noted, multicollinearity can render estimations and interpretations of coefficients problematic. The variance inflation factor (VIF) data in Table 10 shows that each independent variable falls well below the inflationary threshold of 10.0 with a mean VIF of 1.08; hence, the absence of multicollinearity is present.

Table 10

Variance Inflation Factor Statistics

Variable	*VIF*	*1/VIF*
WHZ	1.12	.890
GHG	1.08	.924
WAT	1.04	.961

Note. $N = 140$.

Inferential Results

The purpose of this quantitative, correlational study was to examine the relationship between: (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management and firm value**.** Simultaneous multiple linear regression, $\alpha = .05$ (two-tailed), was used to examine this relationship. The environmental independent variables were greenhouse gases (GHG), waste and hazardous materials (WHZ), and water and wastewater management (WAT). The dependent variable was market value added (MVA). The null hypothesis was that GHG, WHZ, and WAT would not show a significant relationship with MVA. The alternative hypothesis was that GHG, WHZ, and WAT would show a statistically significant relationship with MVA. Prior analyses assessed five multiple regression assumptions: linearity, independence of errors, normality, equality of variances, and multicollinearity. Each assumption was tested without significant violations.

The regression model summary, detailed in Table 11, was able to significantly demonstrate a relationship with MVA, $F(3, 136) = 4.51$, $p < .01$, $R^2 = .09$. The R^2 (.09) value showed that approximately 9% of variations in MVA are accounted for by the linear combination of the model's independent variables. While the model's significance *F* implied that the GHG, WHZ, and WAT variables helped predict the relationship with MVA, testing the regression coefficients returned mixed results. These results showed a statistically significant negative relationship noted between GHG and MVA ($t = –2.21$, $p < .03$, $\beta = –.187$) and a statistically significant positive relationship between WHZ and

MVA (t = 2.62, p < .02, β = .227). Conversely, WAT was not a statistically significant relationship predictor of MVA; the final regression equation was:

MVA = 45.416 –.374(GHG) + .244(WHZ) + .124(WAT). Table 12 illustrates the regression analysis summary for the independent variables of GHG, WHZ, and WAT.

Table 11

Regression Model Summary

Statistic	Value
F-Value	4.51
P-Value	0.004
R Square	0.0904
Adjusted R Square	0.0704

Note. N = 140.

GHG Insight

The negative standardized beta (β) coefficient associated with the independent variable of GHG (–.187) relative to the dependent variable of MVA suggested that one standard deviation (8.68) increase in the GHG TVL Insight score lowers the standard deviation of MVA (17.27) by –.187 when holding all other independent variables constant.

WHZ Insight

The positive standardized beta (β) coefficient associated with the independent variable of WHZ (.227) relative to the dependent variable of MVA suggested that one standard deviation increase in the WHZ TVL Insight score increases the standard deviation of MVA (17.27) by .227 when holding all other independent variables constant. In short, WHZ demonstrated a dominant absolute value relationship with MVA.

Table 12

Regression Analysis Summary for Independent Variables

Variable	*B*	*SE*	*β*	*t*	*p*	95% CI
GHG	–.374	.169	–.187	–2.21	0.029	[–.708, –.039]
WHZ	.244	.093	.227	2.62	0.010	[.060, .429]
WAT	.124	.079	.131	1.58	0.117	[–.032, .281]

Note. $N = 140$.

Analysis Summary

The purpose of this quantitative correlational study was to examine the relationship between: (a) greenhouse gas emissions, (b) waste and hazardous materials management, and (c) water and wastewater management and firm value. I used simultaneous multiple linear regression to assess the above relationships on MVA. My assessment of the assumptions integral to the cross-sectional analysis using multiple linear regression yielded no significant violations.

Holistically, the model was able to demonstrate a relationship with MVA, $F(3, 136) = 4.51$, $p < .01$, $R^2 = .09$. The *p*-value associated with the independent variable of water and wastewater management (WAT) was .117, $p > .05$, indicating that the independent variable of WAT did not express a significant relationship with MVA. Alternatively, the *p*-value associated with the independent variable of greenhouse gases (GHG) suggested a statistically significant negative relationship with MVA, $p = .029$. Lastly, the *p*-value associated with the independent variable of waste and hazardous material management (WHZ) showed a statistically significant positive relationship at the 95% confidence level with MVA, $p = .010$.

Theoretical Discourse on Findings

EVMT Linkages

Returning to the theoretical framework supporting these findings shows that value-maximizing actions within polluting industries are elusive. Agents' pollution abatement actions to enhance a firm's long-term value can be complex, exhibiting meaningful relationships for some sustainability practices and yet unobservable instances for others (Plunge et al., 2023). Stakeholder constituencies add a level of intricacy to the value maximization paradigm as Jensen (2002) argued that the fundamental function of value maximization infers spending an additional dollar of resources to satisfy the requests of each constituency so long as the firm's constituents value the result at greater than one dollar. This tenet begs the question of exactly which constituency matters most. Can management act in favor of the Earth's finite natural resources, or does a firm's monetary value take precedence over all constituents?

Profits before the planet continue a ubiquitous climb in polluting industries and all industries (Davis, 2021; Simangan et al., 2021). The relevant takeaway is that regardless of which enterprise firms interact with, they can employ the EVMT to their benefit, transcending to social well-being and conserving finite natural resources (Sheth & Parvatiyar, 2021). The requisite sustainability warning here is that firms realize, with the aid of value-added scorekeeping, how much value environmental stewardship yields in a single value-maximizing dimension. Indeed, the tradeoffs that agents encounter along the path to value maximization may often be blurred, calling on government intervention and empirical research to mollify negative externalities inherently created by industries and society.

Statistical Linkages

The findings of this data analysis can be processed in myriad ways. From a legal perspective, the positive relationship between WHZ and MVA (t = 2.62, p < .05, β = .227) is plausible and potentially generalizable to the broader industry population because companies know the heavy penalties they could incur if negligent hazardous dumping is committed. Avoiding these fines may insulate a firm's bottom-line revenue while enhancing long-run value; however, this is beyond the scope of this research. Not surprisingly, Patra et al. (2022) validated this view, noting that while the preponderance of illegal industrial waste dumping exceeded other pollution sources by 23%, accelerating penalties and the recodification of stricter dumping laws are causing firms to rethink illegal forms of hazardous waste disposal.

From a value-based perspective, the negative relationship between GHG and MVA derived from this analysis (t = –2.21, p < .05, β = –.187) relates closely to research from Mahmudah et al. (2023), who noted that polluting industrial sectors' profitability is negatively impacted when carbon outputs are publicly disclosed (t = –3.99, p < .001). Disconfirming these findings, however, is the study conducted by Tomar (2023), who found that industrial firms reporting GHG impacts are prone to reduce total GHG emissions by 7.9% when near-peer firms are also reporting. Similarly, Choi and Luo (2021) noted that for every thousand metric ton increase in carbon emissions, industrial firms forego $200,000 in value. However, there is value in mentioning that R^2 values across these empirical studies similarly coincide with this study's R^2 of .09, potentially reducing the overall efficacy of a meaningful model regardless of *t*-values exceeding +/– 1.96. Citing (Hollingsworth et al., 2017), Al Frijat et al. (2024) noted the predictive capacity of statistical models by delineating strong R^2 as greater than or equal to 0.75, moderate between 0.25 and 0.75, and weak at 0.25 and below.

Despite the weak R^2 of this study, the findings may suggest that various risk and cost-benefit analyses are necessary before embarking on an environmental impact disclosure strategy. This corporate due diligence may also include peer industry benchmarking, which was empirically explained by Tomar (2023) and may guide corporate agents in determining what is better or worse for incrementally improving MVA. Once a firm accepts an environmental strategy that is appropriate for generating positive impacts to its value added and its stakeholders, benchmarking among peers intuitively furthers the need for similar data analysis to explicate relationships between environmental impact management and MVA (Gelman et al., 2021; Shafer, 2021; Thomas et al., 2022).

My interpretation of the findings from this study is impartial, given that my study centers on a nonexperimental research design that attempts to isolate a single dependent variable cross-sectionally over one year. Therefore, the relationships concerning GHG, WHZ, WAT, and MVA are transient, requiring further empirical analysis in the research field before capital expenses are allocated to any long-term strategy (Gleißner et al., 2022).

This study used the EVMT and a single statistical model to hypothesize a profitability relationship with environmental TVL Insight Scores. The unobservable elements of this research concern the decisions made by corporate agents that either embraced or abandoned environmental disclosure. The choice of abandonment centers on firms that merely comply with minimum current environmental regulations governed by environmental agencies (Busch et al., 2024), which may also be ignorant of scientific validation of Earth's natural climate cycles (Epstein, 2022). Conversely, embracing disclosure and stewardship takes a much different path–perhaps less traveled–which may enlighten corporate agents in ways that enhance the value of their enterprise and the well-being of societies through socioeconomic sustainability–the ultimate goal of the EVMT.

Applications to Professional Practice

The acceleration of stakeholder demands to reduce corporate environmental impacts in the last five years is extensive (Vázquez-Brust et al., 2023). It follows that polluting industries commit to fostering sustainable profitability while concurrently satisfying stakeholder demands (Busch et al., 2024; Kantabutra & Ketprapakorn, 2020). Satisfying all stakeholder demands as they arise is impossible, and those agents who are familiar with the EVMT know that pursuing multiple objectives equates to no objective (Jensen, 2002). Pollution abatement and myriad other corporate objectives may pose challenges for firms that lose sight of the single objective of the firm, which is maximizing its value. In effect, maximizing value in a single dimension should, over the longer term, allow for other multidimensional objectives to be resolved.

The integration of MVA in the strategic management of a firm is well-understood, particularly for firms that adhere to a value-maximizing paradigm (Long & Bryant, 2007). Business leaders can use MVA and economic value added (EVA) as optimal performance metrics to incrementally monitor the outcome of difficult management tradeoffs in the face of environmental capital expenditures. Leaders may adopt these metrics as part of a broader value-maximizing scorecard.

The findings given in this study suggested that reductions in GHG may pose a marginal negative relationship with MVA, and fostering WHZ exhibits an opposite relationship. Material improvements in GHG may seem counterintuitive to industry stakeholders at first glance; however, it is well-known that natural carbon resources still provide a significant energy source for all industries in this study's target population. Until such carbon resources entirely transition to alternative energy-producing resources, such as nuclear fusion, fission, and carbon capture schemes (Nicholas et al., 2021), industry leaders will remain reliant on carbon energy sources for production.

Business leaders associated with the industry sectors I investigated in this study recognize the carbon-to-clean energy transition as both a point of friction and a value chain proposition (Eisenreich et al., 2022), where exogenous pressures and market perceptions have the potential to influence company trajectories. For this reason, agents of firms can draw on this study to comprehensively assess the tradeoff risk between lower capacity utilization and higher emission outputs. Such tradeoffs may steer corporate agents toward cultivating innovative pollution abatement technologies (Yang & Zhao, 2023) and adopting the value-maximizing paradigm discussed throughout this study.

Implications for Social Change

The confluence of investor and stakeholder perceptions centering on the scrutinization of polluting firms strengthens year over year. This corporate surveillance is inescapable due to accelerating concern for the climate and critical Earth systems, which negligent polluting companies continue to degrade (Green, 2023). To mitigate the effects of detrimental climatic tipping points, Lenton et al. (2022) argued for the operationalization of positive tipping points–discrete interventions introduced through sustainable behaviors and pro-environmental technology that, over time, result in significant positive social change–where corporate environmental stewardship dominates short-term profit-seeking.

This study calls on industry leaders to adopt positive tipping points across their enterprises and advance genuine socioeconomic improvement. Recently, the scales have incrementally tipped in favor of diverse communities and investors who regularly speak out on behalf of Earth's precious finite resources, prompting industries to rethink their operational practices (Laffoley et al., 2021; Reynolds & Ciplet, 2023; Sheth & Parvatiyar, 2021). Regulatory agencies and public-private organizations have also played a crucial role in enforcing industry-wide pollution limits by increasing carbon-neutral goals (UNFCCC, 2023). Provided there are also reductions in pervasive over-consumerism, the unification of all these forces can continue providing a sustainable pathway to positive social change.

Recommendations for Action

Although further comprehensive research is needed, the outcome of this study suggests that environmental stewardship and impact disclosure share a relationship, albeit mildly, with corporate financial performance. My recommendations for the industry sectors I covered follow two mutually beneficial paths. The first involves further research in value-maximizing activities, including developing proprietary accounting principles focused on the net present value of environmental capital expenditures already underway. This way, organizational leaders can equip themselves and other stakeholders with internally driven data that captures an inflection point where the maximum value derived from environmental research and development, pollution abatement, and impact disclosures is finally identified. Any investments beyond this point are considered a decreasing return on deployed capital.

The second path concerns the often-frenetic activity associated with satisfying all stakeholder demands. As industry leaders sift through these commonly exogenous demands in what Mhlanga (2022) called stakeholder capitalism, which of these needs point dimensionally toward shaping the company's intrinsic value and which do not? This latter path is likely the most nebulous, requiring a value-maximizing scorecard that, while latent in its ability, can guide leaders and their organizations away from multidimensional activities that degrade value.

Nevertheless, my academic efforts to advance this research question continue. I intend to expand my statistical model, adding supportive theories and using longitudinal data that may shed light on otherwise unobservable areas in this research study. Despite this field's labyrinth of preliminary and post-publications, I remain committed to publishing meaningful and socially impactful research that may advance the socioeconomic and environmental sciences.

Recommendations for Further Research

I described the limitations of this study in Section 1, which may guide researchers and professional practitioners toward investigating the environmental-firm value relationship further. While the environmental-economic research may appear saturated in the extant literature, the related business problems may remain valid for some time. For this reason, researchers can add economic value added (EVA) as a second dependent variable for statistical testing, potentially enhancing the model's weak predictability while eliciting the intrinsic and extrinsic differential between EVA and MVA. Additionally, a random sampling methodology and multi-year longitudinal data may prove purposeful once more constituent firms provide their environmental disclosures. Lastly, the heterogeneity of ESG metrics across sustainability rating agencies may be addressed by adding another reputable rating agency's data for cross-examination. I used FactSet Truvalue Labs due to its robust collection and rating methodologies, which were self-funded, imposing financial limitations that did not allow further expenditures for additional data.

Conclusion

To be ranked as the most polluting firm in an industry is not a desirable corporate identifier during the massive shift in investor and stakeholder sentiment favoring a circular economy. Many industry sectors have begun investing in long-term measures to reduce greenhouse gases, manage waste responsibly, and conserve water. At the same time, some organizational leaders tasked with strengthening the value of their firms have adopted public environmental disclosure policies to showcase their environmental stewardship. Firms that fail to disclose can face divestiture of equity shares and the loss of a socially responsible reputation. Creating value amid this socioeconomic paradigm shift is hard, causing business leaders to reflect on past environmental strategies and retool their approaches to meet the future comprehensively prepared. I examined these relationships and concluded that sustaining robust MVA among these industry sectors is crucial when environmental frictions are added to other stakeholder demands. The environmental demands are not merely perfunctory but materially meaningful, affecting financial wealth and the social well-being that hangs in the balance.

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Appendix A: 12 Tenets of the EVMT (Jensen, 2002)

1. Corporations must identify and maintain a single-valued objective.
2. Maximizing market value in more than one dimension is impossible.
3. Pursuing multiple objectives equates to no objective.
4. Total market value of a publicly traded firm is the sum of the market values of its debt, equity, and any contingent claims outstanding.
5. The fundamental function of market value maximization means spending an additional dollar of resources to satisfy the requests of each constituency so long as the firm's constituents value the result at greater than one dollar.
6. No single constituent group is more privileged than another.
7. Value maximization is compatible with stakeholder theory only under conditions where stakeholder theory can provide criteria for what is better and what is worse.
8. Communicating with and motivating managers, directors, partners, and employees is difficult.
9. Value maximizing offers nothing to employees or managers on how to create superior strategies, initiatives, or ventures that create value.
10. Value maximization explains how a firm measures value creation through a scorecard.
11. EVMT does not recognize short-term profit-seeking; its only focus is long-run total market value accumulation.
12. Numerical goals for management destroy value.

Appendix B: Database Overviews

Table B1

Overview of FactSet Research Systems Database

Database	FactSet Research Systems
Website	www.factset.com

Summary
The FactSet Research System performs automated collection and indexing of financial and nonfinancial company data within an open programming platform for investors, analysts, financial enterprises, and academic use. FactSet leverages artificial intelligence, machine learning, and data science to provide users with a programmatic environment for tailored analysis (United States Securities and Exchange Commission, 2023)

Data sourcing
FactSet aggregates the universe of public and private company data.

Comprehensiveness
FactSet is a leading provider of financial information and analytic applications. While a fraction of private company data may be inaccessible for collection by FactSet due to proprietary disclosure policies, their access to the universe of globally traded companies listed on all exchanges represents one of the most comprehensive databases available.

Measures
Market capitalization (*MC*), shareholder equity (*SE*), and long-term debt (*LTD*).

Data usage
I retrieved *MC*, *SE*, and *LTD* for the sample population of firms to calculate market value added (*MVA*).

Validity and reliability
FactSet provides a reliable information source for firm-level financial and nonfinancial data, linking diverse content sources to ensure consistency, transparency, and data integrity (United States Securities and Exchange Commission, 2023). FactSet specialists review each materiality issue and data point to ensure alignment and consistency with its reporting methodology while data is further vetted via automated systems for internal data checks.

Table B2

SEC EDGAR Database Overview

Database	EDGAR
Website	www.sec.gov/edgar

Summary
The electronic data gathering, analysis, and retrieval (EDGAR) system provides an open-source platform for users which collects, validates, and indexes millions of company and individual filings. The company filings are legally required in accordance with Securities Act of 1933, the Securities Exchange Act of 1934, the Trust Indenture Act of 1939, and the Investment Company Act of 1940 (U.S. Securities and Exchange Commission, 2023).

Data sourcing
All firm financial filings are available in EDGAR.

Comprehensiveness
All publicly traded firms are required to submit their filings through the EDGAR system. The system processes approximately 3,000 filings per day, making the site one of the most comprehensive publicly available resources associated with U.S. listed companies.

Measures
Digital data mining and cross-referencing via company standard industry classification code.

Data usage
I retrieved *MC*, *SE*, and *LTD* for the sample population from EDGAR to cross-validate the reliability and validity of the FactSet Research System platform.

Validity and reliability
EDGAR is a reliable source of information for accessing primary financial filings from publicly listed companies. This reliability carries over to the cross-validation of other third-party data from numerous providers. Due to the legal requirement for firms to directly file with the SEC, the EDGAR database and its agents ensure that firm-level data is available and standardized to appropriate quality specifications (U.S. Securities and Exchange Commission, 2023).

Appendix C: Multiple Regression Assumptions

Assumptions 1–5	Description	Interpretation/Impacts	Application to this study	Test/Mitigate
Linearity	The regression process aligns with a model that is itself linear.	Examine the regression equation to conclude that $Y = \beta_0 + \beta_1 Xi_1 + \beta_2 Xi_2 + \beta_3 Xi_3 + u_t$, where a one-unit increase in X_1 changes the expected value of Y by the approximated value of the independent variable coefficient β_1.	The 2022 data are delineated by 140 firms, whose values are additive and multiplicative in a linear parameter function.	Visual check for linearity using a residual-versus-predictor plot and fitted line plots. If violated, consideration for transforming the dependent variable via cube root transformation.
Independence	Measurements for each data point from each sample participant are not influenced by other sample participants	Studies where an intervention is based on a segment of the sample receiving the intervention and another that does not receive intervention.	All data should represent IV and DV values that are never duplicated nor influenced by another firm.	Visually check for the independence of observations by plotting the residuals against each covariate. Add Durbin-Watson test for enhanced testing. Consider removal of a participant firm in cases where values are identical or directly influenced by another.

Normality	The normality assumption states that errors u_i are independent of X_i and that they are independently and identically distributed as normal.	Non-normal errors can bias parameter estimates, skew confidence intervals, and degrade hypothesis tests.	Similar to independence assumption, e.g., normality should also appear evident.	Test for normality using the P-P plot and the numerical Jarque-Bera test. If the assumption is violated, I considered transforming the dependent variable through cube root transformation.
Equality of variances	Assumes the error term u_t and independent variables $X_{1\text{-}n}$ are independent, and that the variance (u_t) is constant over time.	Heteroskedasticity does not result in biased parameter estimates; however, it can indicate the presence of other violated regression assumptions in the model.	A violation of the assumption is possible in an OLS model with a small sample size ($n < 50$).	Employ the White's test and Breusch-Pagan / Cook-Weisberg test, which tests the null hypothesis of assumed homoscedasticity. I considered transforming the dependent variable through cube root transformation.
Multicollinearity	Two or more IVs that are highly correlated with each other.	Analytical problems emerge when a trying to determine which IV is contributing to the variance in the DV.	Each IV influence on the DV output is assumed independent of other IVs due to the dichotomous nature of each IV being a separate and distinctly different measure of pollution.	Testing of multicollinearity using the variance inflation factor (VIF). If violated, consider removing a highly correlated variable from the set.

Note. Information concerning the five assumptions of regression is adapted from *Regression and other stories*, by A. Gelman, J. Hill, and A. Vehtari, 2021, *Multiple regression*, by L. S. Aiken and S. G. West, S. G., 1991, *Analysis of panel data* 3rd Ed., by C. Hsiao, 2014, and *Introductory econometrics*, by J. M. Wooldridge, 2019.

Appendix D: Dependent Variable Transformation

The cubed root transformation of the dependent variable of market value added (MVA) allows for quantitative continuity associated with the non-negative TVL Insight Score values of greenhouse gases (GHG), waste and hazardous materials management (WHZ), and water and wastewater management (WAT). The rationale for the transformation of MVA is twofold. The first reason for the transformation concerns the measured units of MVA, which are quoted in billions of U.S. dollars (USD), e.g., $37,956,700,000, which differ from an example independent variable values, e.g., 41.5.

The second reason for the transformation of MVA concerns the negative values of MVA inherent in the dataset, e.g., –$37,956,700,000, which following the cubic transformation, allows for all data encompassing the datset to represent non-negative values. The forward cubic transformation of the largest negative value of MVA in this study's dataset is given below.

- –$37,956,700,000 / 1,000,000 = –$37,956.7 (divide initial MVA by 1,000,000)
- –$37,956.7$^{(1/3)}$ = –33.60697961 (take the cubed root of this reduced value)
- –33.60697961 + 34.60697961 = 1 (add the absolute value +1 to the negative cubed value)

The above transformation effectively sets this company's cubic MVA value to 1, while all other MVA values in the sample dataset (*n* =139) are raised by 34.60697961.

A back transformation example for a company in the sample dataset with a positive MVA of $36,487,505,447.96 is given below.

- 67.77462967–34.60697961 = 33.16765171 (subtract the initial cube root value, minus 1, of the highest negative cubed MVA from the dataset)
- 33.16765171^3 = $36,487,505,447.96 (take the cube of this value to arrive at the example firm's actual MVA in billions of USD.